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Subscription information:

Institute of Forestry and Engineering,
Estonian University of Life Sciences
Fr.R. Kreutzwaldi Str. 56,
51006 Tartu,
ESTONIA
e-mail: timo.kikas@emu.ee

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Effect of shade treatment on the growth and vitality of cloudberry *Rubus chamaemorus*

L. Āboliņa^{1,2,*}, A. Karlsons¹ and A. Osvalde¹

¹Latvia University of Life Sciences and Technologies, Faculty of Agriculture and Food technology, Lielā street 2, LV-3001 Jelgava, Latvia

²University of Latvia, Institute of Biology, O. Vācijas street 4, LV-1004 Riga, Latvia

*Correspondence: laura.abolina@lu.lv

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Abstract. Cloudberry *Rubus chamaemorus* is a promising new berry species for cultivation in Latvia. This study aimed to assess how different shade levels influence cloudberry growth and vitality in semi-controlled conditions. Cloudberry (variety ‘Nyby’) were planted in enclosed planting area and grown under four shading treatments, using shading nets: control (no shade), 30%, 50%, and 80% shade for two years. Non-destructive SPAD measurements were taken weekly during the growing season (from May to August) in both years. Leaf size was measured at the end of August in both years, while leaf density and leaf nutrient concentrations were determined at the end of August in 2024. The results revealed significant differences between treatments for all of the measurements, with the highest values observed in plants under the 80% shade in both years. In the second year, the 50% and 80% shade treatments had similar results. Overall, the highest plant vitality was observed under 50% and 80% shade, demonstrating that netting effectively protects cloudberry from excessive sunlight. While larger leaves might improve light capture, they also require additional energy, potentially reducing resources available for fruit production. Thus, we suggest the 50% shade to be the most effective for cloudberry in the Latvian climate, as it balances protection with optimal energy conservation. Additionally, optimal fertilizing in the field could improve plant health and yield, therefore further studies regarding the combined effects of shade and fertilization on cloudberry production are required.

Key words: berry cultivation, chlorophyll content, leaf nutrient content, netting, shade adaptation.

INTRODUCTION

Cloudberry *Rubus chamaemorus* is a perennial herbaceous plant. In Latvia, cloudberry are harvested in the wild, and their cultivation remains in the experimental stage. In northern regions, cloudberry can form abundant fields in ombrothropic bogs (Hébert-Gentile et al., 2011). Although Latvia has a milder climate, cloudberry are still found in sphagnum peatlands throughout the country. Their distribution in Latvia is concentrated in the northern and central regions, with significantly fewer records in the eastern continental areas (Laiviņš et al., 2009).

Rising annual temperatures, along with milder winters and longer summers, contribute to wild plant adaptations. During wild cloudberry field studies from 2020 to 2022 in Latvia, the authors observed that cloudberries predominantly grew in forested peat bogs with trees and low shrubs, rather than in fully exposed peatlands (Āboliņa et al., 2023). This suggested that in a moderate climate, cloudberries might prefer at least partial shade rather than full sun exposure.

Light conditions is one of the main ecosystem productivity drivers (Niinemets, 2010). However, prolonged periods of high temperatures and low precipitation during summer increase the risk of crop failure, particularly in fields with insufficient irrigation possibilities (Fatima et al., 2020). Drought and high temperatures significantly reduce plant photosynthetic activity, thus inhibiting carbon accumulation (Ashraf & Harris, 2013). Cloudberry cold hardiness and overall growth relies on sufficient carbon storage in rhizomes (Gauci et al., 2009). In the wild, cloudberries typically grow in high moisture ecosystems such as bogs, while cultivated cloudberries are often grown in cutover peat fields (Bussi res et al., 2015), where irrigation can be challenging during droughts. Even in their natural habitat, climate change affects wild cloudberries in Northern regions, with events as higher temperatures at the beginning of the year and subsequent drought conditions (Crawford, 2008).

In forest ecosystems, the understorey tends to be cooler during the day, and warmer at night due to shade from plant canopies. In its natural habitat, wild cloudberry can reach 25 cm in height (Thiem, 2003). In Latvia, cloudberries are often found growing alongside bilberries *Vaccinium myrtillus* and lingonberries *Vaccinium vitis-ideae*, which can reach higher growth, respectively, 90 cm and 30 cm, thus potentially limiting light availability for smaller herbaceous species nearby (Gustavsson, 2001; Gail te et al., 2019;  boliņa et al., 2023).

Wild plants tend to require more light than those grown in controlled environments, due to the environmental complexities and variables that are not present in fully or partly controlled conditions (Valladares et al., 2016). While low light exposure can limit plant growth, both shade and non-shade species develop adaptations for growing in the shade, including increased leaf area to optimize light capture (Valladares & Niinemets, 2008; Gommers et al., 2013). Cloudberries exhibit phenotypic variations depending on their growing conditions. Large leaves and longer shoots are typically associated with shaded environment, while smaller plants are found in open areas ( gren et al., 1989). Berry quality also depends on the level of exposure to sunlight. Cloudberries are known for their fruit high in anthocyanins and elagitannins (Hykkerud & Uleberg, 2018). Wild cloudberry fruits produced in shaded areas have been found to be sweeter and lighter coloured than fruits in open areas (Jaakkola et al., 2012).

The photosynthetic rate of plants fluctuates throughout the growing period and varies by species. Lingonberry was found to maintain relatively high photosynthetic rate until October, whereas blueberry photosynthetic rate levels declined in September, indicating photoinhibition (Lundell et al., 2008; Percival et al., 2012). High exposure to sunlight and drought stresses can lead to plant dehydration and photoinhibition, thus limiting plant performance (Akashi et al., 2008; Valladares & Niinemets, 2008). Plant protection mechanisms for light and drought stresses require significant resources. Netting can mitigate these stressors by reducing excessive soil temperatures and radiation, increasing minimum temperatures to protect flowers from frost, and shielding plants from hail and heavy rainfall (Shahak et al., 2004; Retamal-Salgado et al., 2017).

In Latvia, one of the concerns during the growing season is the combination of prolonged drought and high temperatures. Minimizing soil water evaporation in such conditions could be a significant factor in maintaining favourable conditions for berry cultivation. Additionally, cloudberries are susceptible to frost damage (Gauci et al., 2009). Considering that cloudberry flowering in Latvia coincides with potential late spring frosts in May (Latvian nature S.a.; LEGMC, 2025), netting might contribute to flower protection.

Nets differ not only by the shade level but also by the transmitted light wavelength, which vary depending on the net material and colour (Kotilainen et al., 2018). The overall current knowledge regarding the netting impact on plant physiology is limited, particularly on berry crops. The aim of this study was to assess how different shade levels influence cloudberry growth and vitality in partly controlled conditions, imitating cultivation in a peat field in temperate climate. The findings will be used in developing a growing technology for cloudberries in Latvia.

MATERIALS AND METHODS

Design and conditions of the experiment

The experiment was located in Riga, Latvia, at the Institute of Biology, University of Latvia, for two vegetation seasons from May to August of 2023 and 2024.

The mean temperature and monthly solar radiation data for May, June, July and August in Riga (Fig. 1) was provided by SLLC ‘Latvian Environment, Geology and Meteorology Centre’ archives (LEGMC, 2025).

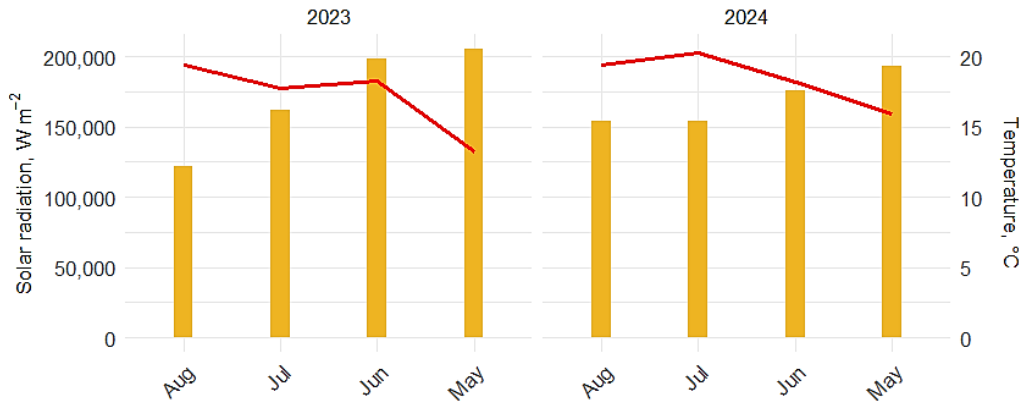


Figure 1. Mean monthly solar radiation ($W m^{-2}$) and temperature, ($^{\circ}C$) for the vegetation seasons of 2023 and 2024 in Riga, Latvia.

Solar radiation total sum was similar between years (686,753 and 676,134 $W m^{-2}$, respectively). While in 2023 the trend for solar radiation was decreasing over the summer months, in 2024, July and August had similar total radiation. Temperatures were higher for May and July in 2024 than in 2023, other months were similar between years. Additionally, 2023 and 2024 both were on average hotter than the previous climatic norm (+1.0 $^{\circ}C$ and +1.9 $^{\circ}C$, respectively) following the climatic warming trend.

Cloudberry cultivar ‘Nyby’ was used in the experiment. Substrate from combined milled raw peat and peat substrate for forest seedlings (Ltd. LaFlora, Latvia), in a ratio of 2:1, degree of decomposition H2–H5, was used for propagation. Cloudberryes were propagated in spring of 2022: rhizomes were sectioned in 15 cm parts and planted in 1 L pots with the peat substrate. In autumn, cloudberryes with visible living rhizomes were transplanted in enclosed planting area (beds) with milled raw peat. The area was divided in four sections, each section measuring 2 m in length, 0.80 m in width, and 0.50 m in depth. In each section 24 plants were taken out of the pots and planted with identical gaps between plants. Beds were isolated from surrounding soil with water-permeable agrotexile. Milled raw peat substrate agrochemical characteristics before transplantation outside are given in Table 1.

Table 1. Milled raw peat substrate nutrient concentrations, pH and EC before shading experiment establishment

Plant available nutrient concentrations, mg L ⁻¹ (1 M HCl extraction)												pH _{KCl}	EC _{H2O} , mS cm ⁻¹
N	P	K	Ca	Mg	S	Fe	Mn	Zn	Cu	Mo	B		
7	<5	31	391	108	3.15	38.55	2.7	2.6	0.3	0.02	0.1	3.48	0.09

Green shading nets with shading factors of 30%, 50% and 80% were used in the experiment to assess the effect of shade on cloudberry growth and vitality. The percentages indicate the proportion of sunlight (solar radiation) that is blocked by the shading net. A control variant (C) was left fully exposed to sunlight. No other natural or artificial shade affected the area (Fig. 2).



Figure 2. Experimental cloudberry beds with nets of different shading factors (from left to right): A – control (full sun exposure) and 30% sunlight blocking net; B – 50% and 80% sunlight blocking nets (taken on May 18, 2023).

In May of 2023 and 2024, 100 g of complex fertilizer (NPK 12–8–16 + micronutrients) was added to each bed as a base fertilizer. During the vegetative months from May to August, watering frequency was adjusted based on soil moisture level and weather patterns. Once a week, peat samples from 5–10 cm below the surface were taken and squeezed by hand into a ball. Optimal moisture was assumed if the peat retained its shape and was moist without dripping water. If the peat crumbled, treatments were watered with tap water to increase moisture.

Nutrient analysis

To determine plant-available nutrient (N, P, K, Ca, Mg, S, Fe, Mn, Zn, Cu, Mo, B) concentrations in substrate, peat samples were extracted with 1 M HCl in a volume ratio of 1:5. Peat reaction (pH) was measured in 1 M KCl mixture (in a peat-extractant ratio of 1:2.5). The electrical conductivity (EC) of the substrate was measured in a distilled water extraction (in a peat-water ratio of 1:5). For leaf tissue nutrient analysis, approximately 30 g of cloudberry leaves were collected from each treatment at the end of vegetation season of 2024. Samples were fully dried at +60 °C in a drying oven, and finely ground using a laboratory mill. Ground samples were then dry-ashed in concentrated HNO₃ vapours, and then redissolved in 3% HCl to detect K, P, Ca, Mg, Fe, Cu, Zn, Mn, B, and Mo via microwave plasma atomic emission spectrometry (MP-AES Agilent 4210). Wet digestion was used to determine N (in H₂SO₄) and S (in HNO₃). The contents of P, Mo, N, and B were determined via colorimetry, S – via turbidimetry, as previously described in Karlsons et al. (2021). Nutrient content was determined in triplicate for all samples.

Plant measurements

The beginning of cloudberry growth in 2023 was recorded at the end of April. The first leaves were fully developed by the second decade of May, measurements were conducted from May 22 to August 31. For each treatment, leaf total *a* and *b* chlorophyll concentration was measured weekly on randomly selected leaves (*n* = 10) with a chlorophyll meter SPAD–502Plus. In 2024, SPAD was measured between May 23 and August 28.

For all treatments, leaf size (in cm) was measured at the end of the growing season in both years (in 2023 – on August 31; in 2024 – on August 30). Leaves were selected randomly and two measurements (width and length) for each leaf were taken to calculate the average size (*n* = 10).

At the end of summer 2024 we also measured leaves per 10×10 cm² quadrats (*n* = 6 for each treatment) to compare cloudberry density after two years of growth. Quadrats were placed randomly in each bed without overlapping.

Statistical analysis

Data were analysed and visualized with R programming language. To determine significant differences (*P* < 0.05) between shading treatments for SPAD, leaf size and density, and leaf tissue nutrient concentrations, one-way ANOVA with post-hoc Tukey HSD test, and descriptive statistics were conducted. Mann-Kendall's τ (tau) test was used to determine significant trends in SPAD readings throughout the vegetation season.

RESULTS AND DISCUSSION

In our previous studies in Latvia, less wild cloudberries were observed in areas that are fully exposed to the sun, than in shady or partially shaded areas (Āboliņa et al., 2023). In the northern Finland and Sweden, wild cloudberries have been found to have larger leaves in shaded conditions, as well as longer rhizomes and higher seed mass as compared to exposed areas (Ågren, 1989). Optimally reduced light and temperature conditions under protective covers have been reported to increase yield and quality of other berries grown in an acidic environment (Matamala et al., 2023). This led to the idea that in temperate climates, cloudberries might require at least partial protection from sunlight during the summer months. The issue is also relevant in the context of global warming. Although typical temperate climate conditions of Latvia are favourable for cloudberries, the warming climate might have its negative effect on local plant vitality. Generally, for the last years the average temperatures have been above, and precipitation levels below the climatic norm in Latvia (LEGMC, 2025).

At the beginning of the first year, the cloudberry shading experiment did not indicate any noticeable trends in cloudberry photosynthetic activity, however, significant differences ($P < 0.05$) were observed at the end of the season (Fig. 3).

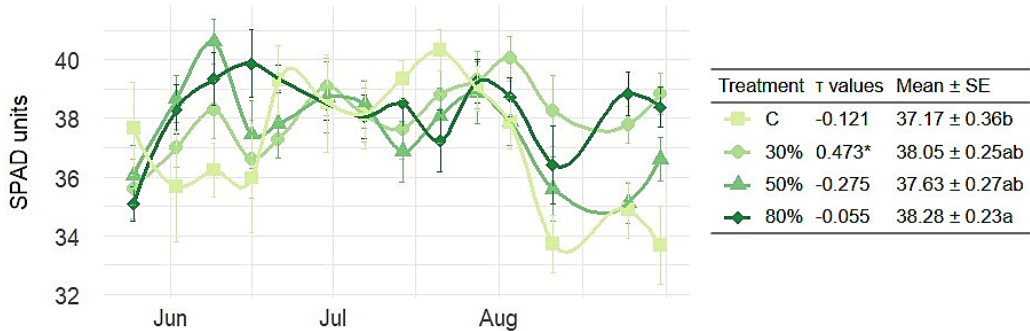


Figure 3. Shading level effect on chlorophyll content (in SPAD units) of cloudberry leaves from May to August 2023.

*Significant trend ($P < 0.05$). Means and standard errors (SE) of each treatment represent chlorophyll data of the whole season. Significant differences between treatments are indicated by small letters ($P < 0.05$; a > b).

Specifically, the last three weeks of SPAD measurements revealed significantly different results between the treatments. For these last three measurements, the control treatment had the lowest SPAD results, which differed significantly from treatments of 30% and 80% shade. The overall season means for each treatment revealed differences consistent with the end of the season results - control treatment had significantly lower SPAD indices than treatments 30% and 80%. Among the treatments, only the 30% shading showed a significant yet moderate positive trend in total chlorophyll content over the season.

In the second year, a trend was observed for the SPAD values to decrease over the season, as all four treatments showed strong negative trends over the observed period, as indicated by tau values ($P < 0.05$) (Fig. 4).

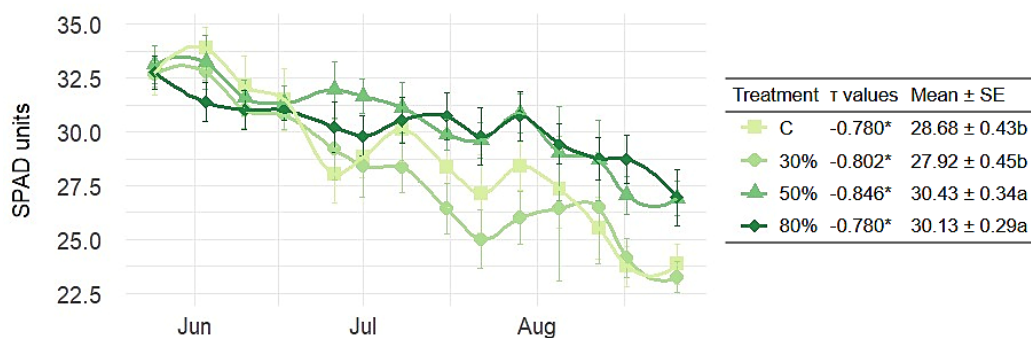


Figure 4. Shading level effect on chlorophyll content (in SPAD units) of cloudberry leaves from May to August 2024.

*Significant trend ($P < 0.05$). Means and standard errors (SE) of each treatment represent chlorophyll data of the whole season. Significant differences between treatments are indicated by small letters ($P < 0.05$; a > b).

It was also evident that for all of the treatments the chlorophyll content was lower in the second year, indicated by significantly lower SPAD results (weekly treatment means ranging 23.24–33.90) as compared to the first year (weekly treatment means ranging 33.68–40.61). Significant differences between groups were observed three times during the season, once at the end of July and then again at the last two weeks of August. In all three weeks, the 80% shade treatment had significantly higher SPAD indices than the 30% treatment. The overall season SPAD means were consistent with these differences, as control treatment and 30% SPAD results were significantly lower than for treatments 50% and 80%.

In the second year of our experiment, SPAD indices showed a consistent and significant decline in total chlorophyll content over the course of the season for all treatments. Decrease in total chlorophyll, also observed visually as yellowing of the leaves, was noticeable by second half of July 2024 for the two most exposed treatments - control and 30% shade. Thus, the visual indications generally corresponded to the SPAD readings. July and August 2024 had similar total sun radiation, which may have further contributed to late summer photodamage of cloudberries in treatments more exposed to the sun.

In both years of the experiment, the largest leaves corresponded to the darkest shade treatment of 80%. In the first year, the smallest leaves were observed in the control and 50% shade treatments, in the second year – in control and 30% shade treatments (Fig. 5). Noticeably, the second year revealed higher variation of leaf size in all of the treatments, as well as an overall decrease in size was observed. Size decrease in the second year was confirmed significant for the 30% shade treatment ($P < 0.05$).

Shade-tolerant plants have larger leaves, reduced chlorophyll a/b ratio, higher total chlorophyll content - adaptation responses to shade conditions, which contribute to carbon gain optimization (Lobos et al., 2012, Gommers et al., 2013, Lambers & Oliveira, 2019). Our study results were consistent with these responses as well, as the largest leaves were confirmed for the 80% shade treatment in both years, and for 50% shade treatment as similar on the second year.

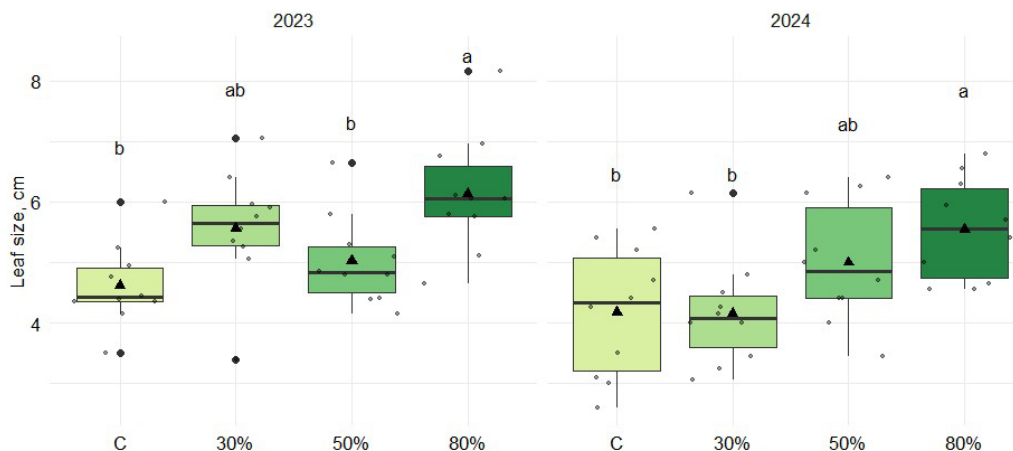


Figure 5. Cloudberry leaf size in different shading treatments for both years of the shading experiment (2023 & 2024). Triangles show group means, grey dots show individual measurements, letters indicate significant differences ($P < 0.05$; $a > b$) between treatments.

It was also evident that between treatments, the shaded plants had higher survival rates at the end of the experiment. Leaves per quadrat were measured at the end of 2024 season to assess the density of developed cloudberry ramets after a two-year period for each treatment (Figs 6 and 7). Differences were significant between the control and 80% shade treatments, thus following the overall trend for the 80% shade treatment to have higher results. The lower density observed for the control also corresponded to other plant health indicator results.

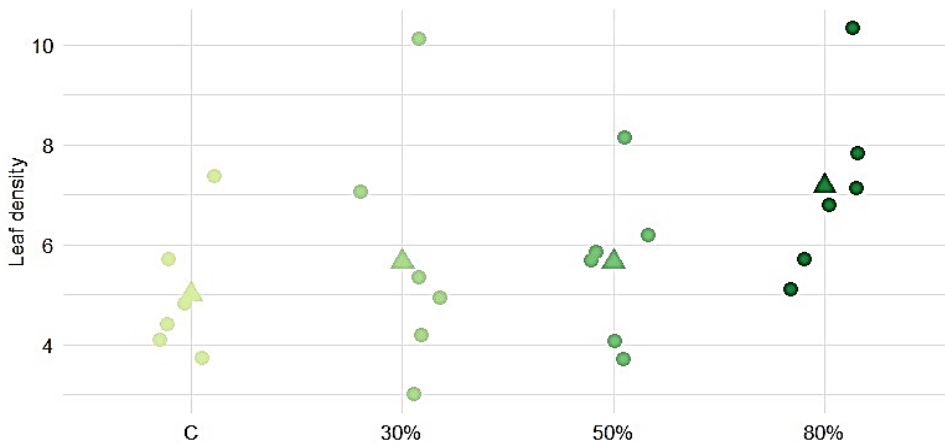


Figure 6. Cloudberry leaf density per $10 \times 10 \text{ cm}^2$ quadrats in different shading treatments ($n = 6$), measured at the end of August 2024. Triangles show group means, dots show individual measurements.

The higher leaf density in late August for the shaded treatments is explainable by reduced exposure to sunlight, thus reducing high temperature and radiation stress. Shade-tolerant plant leaves have a higher dry matter percentage and carbon

concentration, which make the leaves more sufficient at resisting damage and they last longer in shady environments (Pons & Poorter, 2014). Longer surviving leaves allow the plant to photosynthesise continuously without replacing them frequently due to photoinhibition or combined damage. Thus, the study results suggest that in a typical summer, as the climate warms, radiation levels may be higher than optimal for cloudberry if they are exposed to full sun. Data on photosynthesis rates, leaf size and density confirms that cloudberry is a shade-tolerant plant and also suggests that physiological characteristics of the hermaphroditic variety ‘Nyby’ could generally correspond to wild cloudberry phenotypes in different habitats. Comparison between wild plants and the cultivated variety could initially help to develop a cultivation technology, particularly from the aspects of cloudberry nutritional requirements.



Figure 7. Visual comparison of cloudberry growth under different sun exposure levels: A – control (full exposure) and B – under 80% sunlight blocking net. Taken on July 28, 2024.

Plant nutrient content was analysed to compare shading treatments and additionally, cultivated cloudberry ‘Nyby’ with wild plants. Significant differences were observed between shading treatments for N, Fe and Cu (Table 2). The highest concentrations of these nutrients were determined for cloudberry leaves under the 50% and 80% shade treatments, although only the 80% shade treatment reached leaf N concentrations consistent with the range of wild cloudberry. P, K, Mg, Zn, Cu, and Mo concentrations of all treatments generally fell within the range observed for wild cloudberry. The concentrations of Ca, S, Fe, Mn, and B were higher for cultivated cloudberry in the shading experiment than for wild plants, which could be mainly due to the base fertilizer applied in both years of the experiment. The substrate used in the experiment was similar to previously described wild cloudberry peat in terms of decomposition level and nutrient concentrations described in Āboliņa et al. (2023).

Table 2. (A) Mean nutrient concentration in air-dried leaves of cloudberry leaves grown in different shading treatments (2024); (B) Nutrient concentration in air-dried wild cloudberry leaves in Latvia, 2020–2022

Nutrient	A. Shading treatments, means				B. Wild cloudberry nutrient content (Āboliņa et al., 2023)
	K	30%	50%	80%	
Macronutrients, %					
N	1.31	1.20	1.83*	1.98*	1.90–3.00
P	0.09	0.08	0.09	0.10	0.08–0.27
K	0.72	0.96	1.10	0.84	0.75–1.75
Ca	1.44	1.41	1.3	1.44	0.15–0.90
Mg	0.42	0.48	0.49	0.50	0.26–0.72
S	0.30	0.31	0.31	0.30	0.07–0.23
Micronutrients, mg kg ⁻¹					
Fe	120	126	145	204*	34.67–129.00
Mn	1,581	1,678	1,761	1,639	50.95–660.00
Zn	109	112	111	126	43.61–121.00
Cu	3.80	4.54	5.18	6.79*	2.50–17.20
B	44	50	50	58	8.00–29.00
Mo	0.20	0.25	0.20	0.20	0.10–0.75

*Significantly higher concentrations than for other treatments ($P < 0.05$).

As nutritional status also affects every aspect of plant physiology, especially photosynthesis, we also consider the nutrient supply results as indicators of cloudberry vitality. Shading nets can reduce ambient and leaf temperatures and thus prevent leaf damage, which is important for CO₂ assimilation and thus photosynthesis (Lobos et al., 2012). Nitrogen use is optimized as it is allocated to light-harvesting complexes (Eichelmann et al., 2005). Strong positive N and chlorophyll index correlations have been reported in other berry species, even for different varieties (Pinzón-Sandoval et al., 2023). Soil N deficiency has been shown to significantly reduce total chlorophyll contents in berry leaves (Yang et al., 2023a; Yang et al., 2023b). However, the level of sensitivity to N deficiency depends on the cultivar (Yañez-Mansilla et al., 2015). According to Hallik et al. (2009), chlorophyll and N correlation is species specific among herbaceous plants, rather than universal. Considering the higher N and chlorophyll concentrations in cloudberry leaves under the shaded treatments could be an adaptation to enhance chlorophyll production and light-harvesting capacity. Studies have shown that this helps to maximize photosynthesis under limited light conditions (Lambers & Oliveira, 2019), further confirming cloudberry responses characteristic to a shade-tolerant plant. In addition to N, higher Fe and Cu concentrations in cloudberry leaves were also determined in the 80% shading treatment. These microelements play a vital role not only in maintaining the overall health and vitality of plants - Fe is also directly involved in N fixation and chlorophyll development, and Cu acts as a catalyst for photosynthesis and respiration (Lambers & Oliveira, 2019).

Our study focused on the agronomic aspects of netting as a means of plant protection from overexposure to sunlight and its effects on cloudberry. As the most optimal plant status results were observed in the 80% shade treatment, we consider shade as an effective factor contributing to cloudberry vitality over the summer season in Latvian climate. However, we also consider the hidden aspects of netting on plant

development and growth. For berry cultivation, it is important to understand how the plant $\times$ environment interaction impacts potential yield size and quality, as well as overall management of the berry crop (Senger et al., 2022). Problems related to the use of netting on cultivated berries may include reduced pollinator activity and decreased plant water stress, both of which significantly influence the overall chemical composition and quality of the fruit (Brown & McNeil, 2009; Mikulic-Petkovsek et al., 2015; Karppinen et al., 2016). Habitat openness, temperature and exposure to sunlight were suggested as the main factors affecting yield and chemical composition of cloudberry fruits (Jaakkola et al., 2012). Lower stress levels during flowering and fruiting are associated with increased yield, but may lead to reduced secondary metabolite content in the fruits. Zoratti et al. (2015) found that shading increased anthocyanin content in bilberries, but decreased their content in blueberries. Considering this, the lowest yet effective shade factor might be applied to achieve desirable cloudberry growth and berry quality. Several studies have shown that, depending on the species, reducing solar radiation by 50% to 70% can improve plant vitality (Dai et al., 2009; Schwerz et al., 2017). As leaf size was confirmed significantly larger for the 80% shade treatment in both years, 80% shading for cloudberries could be excessive, as the plants might use the most energy for green mass growth at the expense of other physiological processes. Meanwhile, in 2024, leaf size between the other treatments did not differ, while SPAD results were significantly higher for plants under both 50% and 80% shade. This suggests that plants under 50% shade would not spend significant energy resources to develop larger leaves whilst maintaining optimal chlorophyll content. The mechanical protection is also considerable as a positive shading effect during the experiment. Netting considerably decreases the negative effects of insects and birds on berry crops (Kuesel et al., 2019). Reduced weed growth was also observed under the shaded treatments, as compared to the control.

Current study of shading effect on cloudberries revealed healthier plants for longer periods in shaded treatments as compared to the fully exposed control variant. Higher cloudberry vitality was indicated by SPAD results and leaf density, as well as leaf colour during on-site assessment. Based on the findings of this research, we consider the cloudberry to be able to maintain optimal photosynthetic activity and leaf growth under 50% shade netting, which will help maintain optimal temperature and irradiance for the plant in temperate climates. It is worth noting that optimal fertilizing would also improve plant vitality and possibly yield, therefore further studies regarding shade and fertilizer combined effect on cloudberry production are required.

CONCLUSIONS

Cloudberry is a promising new berry species for cultivation in Latvia, particularly given the vast areas of cutover peat bogs where it naturally occurs. Our study focused on the agronomic benefits of netting, which is known to mitigate extreme temperatures and protect plants from excessive solar radiation. The highest plant vitality was observed under 50% and 80% shade, demonstrating that netting effectively shields cloudberries from overexposure to sunlight and enhances overall plant health. However, we also considered the plant physiological adaptations to lower irradiance – increased leaf size, which were significant for cloudberries under 80% shade. While larger leaves may improve light capture, they also require valuable energy, potentially reducing resources

available for fruit production. Although both 50% and 80% shade treatments improved cloudberry vitality, we suggest the 50% shade netting to be most effective for cloudberry in the Latvian climate, as it balances protection with optimal energy conservation. These findings will contribute to the development of cloudberry cultivation technologies in Latvia.

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The role of ICT and animal welfare concerns in Estonian food purchasing channel preferences

O. Aleksandrova¹, A. Põder^{1,2,*}, M. Kukk¹, A.-H. Viira^{1,3} and H. Tamm²

¹Estonian University of Life Sciences, Institute of Agricultural and Environmental Sciences, Chair of Rural Economics, Kreutzwaldi 1a, EE51006 Tartu, Estonia

²Estonian Dairy Cluster, Aretuse 2, EE61406 Märja, Tartu, Estonia

³The Centre of Estonian Rural Research and Knowledge, Agricultural Research Department, J. Aamisepa 1, EE48309 Jõgeva, Estonia

*Correspondence: anne.poder@emu.ee

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Abstract. The modern consumer is now more attentive to animal welfare practices, and this is an important factor when making food purchasing decisions. Different levels of concern for animal welfare as well as the use of information and communication technology (ICT) affect consumer food consumption and purchasing decisions and information access. This study explored both consumer preferences for food purchasing channels by using principal component analysis and regression analysis as well as the interaction between ICT use and animal welfare concerns. To analyse consumer preferences for food purchasing channels, we utilised data from a survey on the use of various retail outlets, such as buying online, retail stores, local markets, directly from producers, and organic or specialised shops. We used the varimax rotation method in principal component analysis to find the main factors in consumer choices related to animal health and welfare. Results from five generalised linear models indicated that Estonian consumers are more willing to purchase products of animal origin directly from producers or in organic or specialised shops when they pay attention to animal health and welfare. Animal health and general welfare practices aimed at ensuring the safety of food in large-scale production and distribution are significant for retail shop users. More frequent ICT use does not translate to a preference for online food shopping over more traditional retail purchasing. Compared with other age-gender groups, younger women prefer to buy food directly from producers. Older individuals in particular favour purchasing food from traditional retail stores rather than online. Consumers who prefer to buy food online are more concerned about animal health and welfare.

Key words: agri-food, animal welfare, consumer behaviour, ICT, online grocery shopping.

INTRODUCTION

Dietary habits and food purchasing behaviours are undergoing significant shifts, as consumers are increasingly voicing concerns related to the ethics and various consequences of their consumption choices (Roubík & Mazancová, 2017; Hölker et al., 2019; Hyland et al., 2022; Reeh et al., 2023). Animal welfare, environmental

sustainability, and human health concerns are expected to drive consumer demand for alternative foodstuffs and products that are perceived as higher value items as well as a reduction in meat consumption and shifts in dairy consumption, all of which will have a considerable impact on agricultural production practices (OECD, 2023). Digitalisation is another major driver of change, and it is anticipated that its technological opportunities, as well as its economic and social implications, will fundamentally transform agri-food value chains as well as consumer behaviours. Digitalisation is expected not only to boost productivity and efficiency in the agri-food sector and help tackle sustainability challenges (Kukk et al., 2022) but also to assist producers in adapting to changing customer needs (Atkočiūnienė & Papšienė, 2023). Digitalisation facilitates the collection and dissemination of copious amounts of information and rapid development of more – and more advanced – tools, and it also shapes the consumer's decision-making process itself (Linkiewicz & Bartosik-Purgat, 2022). The benefits of digitalisation, such as access to more information, multiple channels, and experience sharing (Linkiewicz & Bartosik-Purgat, 2022); convenience, time, and money savings; a wider variety of product offerings (Blitstein et al., 2020); and individually customised offers (Prause et al., 2021), allow consumers a more comprehensive analysis before making purchase decisions (Linkiewicz & Bartosik-Purgat, 2022).

The welfare of farm animals is under increasing public scrutiny due to public scandals, animal disease outbreaks, increased news and social media coverage, and expansion and visibility of animal protection organisations (Miele et al., 2011; Autio et al., 2017; Alonso et al., 2020). Consumer interest in sustainability and animal welfare issues is affected by a variety of factors, including sociodemographic factors such as age, gender, and place of residence (Verbeke, 2009; Alonso et al., 2020; Boatey & Minegishi, 2020; European Commission: Directorate-General for Health and Food Safety et al., 2022; Hyland et al., 2022; Ammann et al., 2024). Studies have shown that consumers have considerable interest in animal welfare issues; however, their awareness of modern farming and animal welfare practices is very limited (Kupsala et al., 2010; Autio et al., 2017; European Commission: Directorate-General for Health and Food Safety et al., 2022; Fonseca & Sanchez-Sabate, 2022). Animal welfare labels on products are designed to convey information quickly to consumers, but these labels are often confusing for consumers (Di Pasquale et al., 2014; Autio et al., 2017; Thibault et al., 2022; Ingenbleek & Krampe, 2022). Digitalisation has the potential to facilitate both the sharing of this kind of information and interaction between the producers and consumers, thus improving the transparency of production practices and helping to address animal welfare issues (Fielke et al., 2020; Shepherd et al., 2020).

Consumer preferences for food shopping channels are influenced by convenience, with large discount stores, supermarkets, and online shopping channels growing rapidly as food retailing methods, while other channels such as traditional markets are in decline (Cho et al., 2020). The demand for online food purchasing options grew particularly during the COVID-19 pandemic (Alaimo et al., 2020; Benedek et al., 2021; Tyrväinen & Karjaluoto, 2022), which resulted in the rapid expansion of various online ordering and delivery options (Hobbs, 2020; Alaimo et al., 2022). Subsequent research has indicated that customers returned to traditional retail shopping channels after the pandemic (Brüggemann & Olbrich, 2023); however, some effects are expected to be

more permanent with online retail continuing to grow (Verhoef et al., 2022). Sociodemographic characteristics, especially age, have also been key variables affecting the adoption of and proficiency with ICT use as well as attitudes and expectations regarding digital tools (Linkiewicz & Bartosik-Purgat, 2022) and the uptake of online shopping channels (Zatz et al., 2021).

Shopping channels offer different types of interaction and information on animal welfare. Direct food distribution channels enable direct personal interaction with food producers and provide consumers with opportunities to learn about both the food and the producer; consequently, this will impact how much trust they build in vendors (Fehrenbach & Wharton, 2012). The information exchanged in such interaction is relatively limited and focused. However, online channels and new digital tools, including those integrated into traditional channels, offer opportunities to collect and exchange copious amounts of information (Linkiewicz & Bartosik-Purgat, 2022). The use of information to make informed purchasing decisions will depend on the consumer's ability to sift through a high volume of information and critically judge the sources, as well as on their ability to utilise digital tools for information gathering.

The aim of the present article is to analyse the interrelationship between Estonian consumer preferences regarding food shopping channels, ICT use, and animal welfare attitudes. Digitalisation has considerable potential to enhance consumer decision-making in the animal welfare context; however, the topic has received relatively limited research attention (Jose et al., 2025). To the authors' knowledge, no one has previously researched this topic in the Estonian context. The analysis utilised a dataset from a nationally representative study on Estonian consumers and explored what characterises their selection of food purchasing channels, how their attitudes on animal welfare interact with this selection, and their ICT use.

MATERIALS AND METHODS

Data collection

The data were collected in 2022 with a nationwide, cross-sectional, online questionnaire. The survey focused on Estonian consumers' attitudes toward animal welfare, dietary habits, and purchasing behaviours related to products of animal origin. Questions on food purchasing also addressed the kind of shopping channels consumers used for products of animal origin and the respondents' ICT use.

Execution of the survey was contracted to a professional public opinion polling company, which drew the sample from their virtual panel of 70,000 Estonian residents. The sample was designed to be representative of the Estonian population aged 18–74 years based on selected demographic and geographic variables, such as age, gender, language (Estonian, Russian), place of residence (capital, other urban area, or a rural area), and region of residence (northern, southern, central, western, and north-eastern Estonia). Data were collected from 1,000 respondents.

The questionnaire was divided into four parts. The first addressed sociodemographic characteristics including nationality (Estonian, other), level of education (basic, secondary school, vocational, undergraduate, graduate); average monthly household income (less than €1,000; €1,000–2,000; €2,001–3,000; €3,001–4,000; €4,001 or more). The second part of the questionnaire contained questions

on attitudes towards animal welfare. These included the following questions (see Appendix 1, Tables A1–A3):

- A1. For which of the following animal health and welfare aspects are you willing to pay more? (yes, no)
- A2. Which aspects of animal health and welfare are important to you when buying food (1 = not important ... 5 = very important)
- A3. How important to you are the following attributes in making purchasing decisions about food products? (1 = not important ... 5 = very important)

The third part of questionnaire measured food purchasing behaviour, specifically what kind of shopping channels the respondents used to purchase food of animal origin and how often they used the channels. The response options were buying online, retail stores, local markets, buying directly from producers, and buying from organic or specialised shops. Respondents rated their preference for each retail type on a Likert scale ranging from 1 (never) to 5 (always). The fourth part inquired about ICT use. This included the question What device do you normally use to access the internet? in which respondents assessed their use of mobile phone, tablet, laptop, and desktop personal computer (PC) in the Likert type (1 = never ... 5 = regularly).

Data analysis

Consumer behaviour analysis

To determine the main factors related to animal health and welfare influencing food purchasing behaviour, we conducted a principal component analysis (PCA) using the varimax rotation method. PCA is a technique used to analyse large datasets and helps to identify a new reference system that maximises the variance of the variables represented along the axes.

First, we applied Bartlett's test of sphericity to evaluate the suitability of the data for PCA (Costillas et al., 2016). Bartlett's test statistic follows an approximate chi-squared (χ^2) distribution. Bartlett's test assesses whether the correlation matrix significantly deviates from an identity matrix, indicating the presence of sufficient intercorrelations among variables for PCA. Second, we assessed sampling adequacy using the Kaiser-Meyer-Olkin (KMO) measure. A high KMO value suggests strong correlations between variables, which enhances the reliability of PCA or factor analysis (Blanc et al., 2020).

PCA simplifies data by transforming the original variables into new, uncorrelated components (or factors), thereby reducing the dimensionality while retaining as much of the variance as possible. The total variance of the variables is divided into components, which can be reduced based on the amount of variance each component explains. PCA was conducted for three sets of questions on animal welfare: willingness to pay for animal welfare attributes (A1), importance of animal welfare in purchase decisions (A2), and importance of general food purchase attributes (A3).

These questions had 14, 13, and 12 variants of responses, respectively (Appendix 1, Tables A1–A3). In the PCA, the goal was to reduce the dimensionality of the data and identify the principal components that would be included in subsequent regression analyses for the dependent variable.

In PCA, factors emerge that are described by a participation ratio. This ratio indicates how much a set of data influences the factor formed. If the participation ratio is less than 0.35, the factor is considered nonsignificant and is rejected. A ratio between 0.5 and 0.7 is considered satisfactory, while values above 0.7 indicate that the factor is well supported (Vlontzos et al., 2018).

Following PCA, we used the participation ratios (factor loadings) to identify the importance of each variable in each component. The analysis was conducted using R program, with the `principal()` function from the `psych` package, and factor rotations were done using the varimax method.

Econometric analysis

To examine the factors influencing the frequency of purchasing food of animal origin via different retail channels, we employed generalised linear models. Five separate regression models were constructed, each corresponding to a different retail channel based on the kind used to buy products of animal origin: online; retail stores; local markets; directly from the producer; and organic or specialised shops.

Each of the five models was specified as (Wooldridge, 2009)

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon_i \quad (1)$$

where Y_i is the frequency of purchasing via a specific retail outlet; X_i (1,2,... n) denote the independent variables, including sociodemographic factors (e.g. age, gender, income, education); ICT usage (described below); and principal components received from PCA; β_i (1,2,... n) are the estimated coefficients; and ε_i is the error term.

For ordinal categorical outcomes (1 = never to 5 = often), ordinal logistic regression was employed using the proportional odds model.

To measure ICT use, the question on what devices (mobile phone, tablet, laptop, and desktop PC) and how often (ranging from 1 to 5) was used. For each respondent, the device with the highest score was identified. A binary variable was then created, indicating whether at least one device received a score of 4 or 5. If any device met this threshold, the variable was coded as 1 (high ICT usage); otherwise, it was coded as 0 (low ICT usage). To see how the effect of one variable (e.g. age) on the outcome (e.g. preference for buying directly from the producer) differed depending on response to another variable (e.g. gender), we added the interaction term in Eq. (1).

Regression analysis was conducted in R using the `clm()` function for multiple ordinal regression models from the `ordinal` package. `Clm()` function in R is related to cumulative link models, which is relevant if survey responses are on an ordinal scale.

RESULTS AND DISCUSSION

Sociodemographic characteristics and use of ICT and shopping channels

Of the 1,000 respondents, 547 were women (Table 1). The average age was 47.5 years, and 70.4% were Estonian. Just over half of the respondents had either a secondary school (26%) or a vocational education (27.6%), while 42.2% had completed an undergraduate degree. In all, 42.7% reported a monthly household income in the range of €1,001–2,000.

The main shopping channel for purchasing of food of animal origin was retail stores as 86.5% of respondents indicated that they always or mostly (5 and 4 in the Likert scale of 5, mean score 4.42) used this channel, followed by local markets (34.8%, mean score 2.93; Table 1). Overall, 75.5% of respondents indicated that they never used online shopping for food products of animal origin, while a third selected that they never bought directly from producers or from specialised shops. The main devices for internet use were mobile phones (mean score 4.23 in the Likert scale of 5) and laptops (mean score of 3.73).

Table 1. Descriptive statistics

Variable	Description	Result	
		%	Mean
Gender	Male	45.3%	
	Female	54.7%	
Age	Age in years		47.57
Nationality	Estonian	70.4%	
	Other	29.6%	
Level of education	Basic	4.2%	
	Secondary school	26.0%	
	Vocational	27.6%	
	Undergraduate	23.2%	
	Graduate	19.0%	
Average monthly household income	Less than €1000	30.1%	
	€1001–2000	42.7%	
	€2001–3000	16.7%	
	€3001–4000;	6.3%	
	€4001 or more	4.2%	
Shopping channels for purchasing food of animal origin	Online		1.46
	Retail stores		4.42
	Local markets		2.93
	Directly from producer		2.29
	Organic or specialised shop		2.20
Use of devices	Mobile		4.23
	Tablet		2.08
	Laptop		3.73
	Desktop PC		2.78

Results of PCA on animal welfare considerations

The results showed $KMO > 0.9$ (Table 2) for all subsamples (A1–A3), indicating excellent adequacy (Kaiser & Rice, 1974). Bartlett's test of sphericity was significant for all subsamples, which confirmed that the correlation matrix was not an identity matrix and thus appropriate for PCA.

Table 2. Suitability of data for PCA

Subset/question	Test	Result	Interpretation
A1. Willingness to pay for animal welfare attributes	KMO	0.94	Excellent (≥ 0.90 indicates sampling adequacy)
	KMO per item (range)	0.88–0.96	All items above acceptable threshold (≥ 0.50)
	Bartlett's test of sphericity	$\chi^2 = 398.19$, df = 13, p -value < 0.001	Significant correlations are adequate for PCA
A2. Importance of animal welfare in purchase decisions	KMO	0.97	Excellent sampling adequacy (≥ 0.90)
	KMO per item (range)	0.96–0.98	All items above the 0.50 threshold
	Bartlett's test of sphericity	$\chi^2 = 14\,700.51$, df = 78, p -value < 0.001	Significant correlations adequate for PCA
A3. Importance of general food purchase attributes	KMO	0.87	Very good (≥ 0.80)
	KMO per item (range)	0.70–0.92	All above acceptable threshold
	Bartlett's test of sphericity	$\chi^2 = 4892.19$, df = 66, p -value < 0.001	Significant appropriate for PCA

Note: df mean degrees of freedom.

After confirming factorability with Bartlett's test and a high KMO measure, PCA with varimax rotation was performed (Appendix 1, Tables A4–A6).

Table 3. Summary of principal component analysis

Subset	Principal components	Variance explained	Rotated loadings summary
Subset A1 (Willingness to pay for animal welfare attributes)	three components (RC1.1, RC1.2, RC1.3)	61%	RC1.1 and RC1.2 explain most of the variance for most items.
Subset A2 Importance of animal welfare in purchase decisions	three components (RC2.1, RC2.2, RC2.3)	83%	RC2.3 and RC2.1 are highly related to most items, RC2.2 contributes less.
Subset A3 (Importance of general food purchase attributes)	three components (RC3.1, RC3.2, RC3.3)	62%	RC3.1 captures most variance, with RC3.2 and RC3.3 contributing less.

The PCA results (Table 3) revealed three principal components based on the correlation matrix of the data for each data subset (A1–A3) (Table 2). To ensure clarity and prevent confusion in the interpretation of regression equations and further analysis, the components were renamed (RC1.1, RC1.2, RC1.3 for Subset A1; RC2.1, RC2.2,

RC2.3 for Subset A2; and RC3.1, RC3.2, RC3.3 for A3). For Subset A1, A2, and A3, these three components together explained 61%, 83%, and 62% of the total variance, which was considered sufficient for further analysis.

Following the results presented in Table 3, we included in the regression equations the RC1.1 and RC1.2 components from Subset 1, the RC2.3 and RC2.1 components from Subset 2, and the RC3.1 component from Subset 3.

RC1.1 was strongly connected to consumer willingness to pay more for general good animal husbandry practices (transport times, lifespans, low mortality, normal behaviour). RC1.2 captured overall willingness to pay more (including high negative loading of response that the consumer was not willing to pay) for an animal's lack of pain and suffering and species-appropriate husbandry, and thus, we interpreted it as willingness to pay for ethical concerns. Regarding which attributes of animal health and welfare were important to consumers, RC2.3 was strongly correlated with good housing conditions, short transportation times, normal feeding and rumination behaviour, and lack of pain, damage, and stress; these can be summarised as daily animal welfare practices. RC2.1 can be interpreted as animals' physical health as it has high loadings from response items related to low use of medication, lifespan, species-appropriate care and behaviour, and low calf mortality. RC3.1 from the question (A3) on what considerations were important when making food purchasing decisions reflects ethical and sustainability concerns (high loadings for recognisable animal welfare features: sold sustainably, organic, regionally produced, product traceability, fewer additives or preservatives).

Econometric results

As Table 4 shows, there were no significant effects of RC1.1 (willing to pay more for general good animal husbandry practices) on any food purchase channel preferences (Y_1 to Y_5), as all confidence intervals include zero. Principal component RC1.2 (willingness to pay for ethical considerations) had a significant effect on Y_1 (online) and Y_5 (organic and specialised shops). Principal component RC2.3 (daily animal welfare practices) positively influenced preferences for Y_2 (retail stores) and Y_5 (organic and specialised shops). The results indicate that higher RC2.1 (animals' physical health) was linked to a higher likelihood of choosing Y_2 (retail shops). Higher RC3.1 (general ethical and sustainability consideration in general food purchasing behaviour) was associated with greater Y_1 (online), Y_3 (local markets), Y_4 (directly from producer), and Y_5 (organic or specialised shops) preferences but lower Y_2 preference (retail stores). Consumers of Estonian nationality were more likely to prefer Y_4 (directly from producer) and Y_5 (organic and specialised shops) when purchasing animal-origin products, compared to consumers of other nationalities. This can be explained by better contact networks, particularly for buying directly from producers, who usually do not specifically advertise their produce in other languages and with whom contacts are often established through word of mouth in rural communities.

Table 4. Regression analysis results: influence of principal components on food purchase preferences for animal-origin products

Dependent variable	Y ₁ Online	Y ₂ Retail stores	Y ₃ Local markets	Y ₄ Directly from producer	Y ₅ Organic or specialised shops
RC1.1	-0.01 (-0.16, 0.13)	-0.003 (-0.13, 0.12)	-0.01 (-0.13, 0.11)	-0.05 (-0.17, 0.07)	-0.04 (-0.16, 0.08)
RC1.2	0.21*** (0.05, 0.36)	-0.03 (-0.17, 0.10)	0.01 (-0.10, 0.13)	-0.01 (-0.13, 0.12)	0.21*** (0.08, 0.33)
RC2.3	-0.07 (-0.25, 0.12)	0.17** (0.02, 0.32)	0.01 (-0.12, 0.14)	-0.05 (-0.18, 0.09)	0.16** (0.02, 0.30)
RC2.1	-0.14 (-0.31, 0.03)	0.24*** (0.10, 0.39)	-0.04 (-0.16, 0.09)	0.03 (-0.10, 0.16)	0.04 (-0.09, 0.18)
RC3.1	0.31*** (0.12, 0.51)	-0.29*** (-0.45, -0.13)	0.20*** (0.06, 0.34)	0.40*** (0.25, 0.54)	0.70*** (0.54, 0.86)
Nationality	-0.13 (-0.45, 0.20)	-0.14 (-0.42, 0.14)	0.04 (-0.21, 0.29)	1.21*** (0.94, 1.48)	0.94*** (0.67, 1.22)
Income	0.13* (-0.02, 0.28)	-0.06 (-0.19, 0.07)	0.09 (-0.03, 0.20)	0.005 (-0.11, 0.12)	-0.002 (-0.12, 0.12)
Age	-0.04*** (-0.06, -0.03)	0.02*** (0.005, 0.03)	0.01 (-0.004, 0.02)	-0.002 (-0.01, 0.01)	0.004 (-0.01, 0.02)
Gender	-0.36 (-1.35, 0.63)	-0.01 (-0.88, 0.85)	0.01 (-0.75, 0.78)	-0.78* (-1.58, 0.03)	0.07 (-0.74, 0.89)
Education	-0.01 (-0.14, 0.13)	0.02 (-0.09, 0.13)	-0.04 (-0.14, 0.06)	-0.12** (-0.22, -0.02)	0.003 (-0.10, 0.11)
ICT usage	-1.09*** (-1.83, -0.35)	1.55*** (0.81, 2.29)	0.25 (-0.42, 0.92)	-0.21 (-0.90, 0.47)	-0.55 (-1.22, 0.12)
I(age * gender)	0.01 (-0.02, 0.03)	-0.003 (-0.02, 0.02)	0.002 (-0.01, 0.02)	0.01* (-0.002, 0.03)	-0.003 (-0.02, 0.01)
Observations	1,000	1,000	1,000	1,000	1,000
Log likelihood	-808.51	-1,004.86	-1,544.55	-1,408.28	-1,309.49

Note: 95% confidence intervals are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

There was a small positive association between higher income and Y₁ (online) preferences. This is consistent with the argument that higher income consumers are more capable of purchasing food with higher welfare standards, which may be more expensive or require greater access to specialised outlets. Older individuals were less likely to prefer Y₁ (online shopping) but more likely to prefer Y₂ (retail stores). Thus, younger people are more likely to prefer buying food online and less likely to prefer buying food from stores compared to older individuals. Gender was associated with significantly lower preference for Y₄: women are less likely to prefer buying food directly from producers compared to men, which may be linked to gendered preferences regarding convenience and time constraints. However, it is worth noting that younger women tended to show a higher likelihood of preferring to buy directly from producers, which potentially reflects a greater openness to sustainability-oriented and ethical purchasing habits in younger generations, as suggested by Hyland (2022). Higher education levels were linked to lower preferences for Y₄ (directly from producer).

The results suggest that individuals who are online more often using various ICT tools, particularly mobile phones, tended to show a lower preference for online food purchasing Y_1 but were more inclined to prefer alternative purchasing methods, such as buying from stores Y_2 . This finding may reflect the fact that younger individuals, who are more adept at using digital technology, may prefer to engage in more hands-on, direct forms of food purchasing, especially if it aligns with their ethical preferences for animal welfare. Alternatively, the lower uptake of online food purchasing may be due to an underdeveloped online food retail infrastructure.

The interaction suggests that younger women might have a higher likelihood of preferring to buy directly from producers (Y_4), compared to other age-gender groups: while women generally prefer not to buy directly from producers, younger women might prefer this more than men or older women. This potentially indicates that the effect of age is context-dependent as suggested by Boaitey & Minegishi (2020). Similarly to studies by the European Commission (2022), Hyland (2022), and others, our results confirm that women generally express a stronger preference for animal welfare-friendly products than men. This finding agrees with the work of Amiot and Bastian (2017), who suggested that women typically show greater concern towards animal welfare issues.

CONCLUSIONS

This study examined consumer preferences in Estonia for food purchasing channels and their associations with attitudes towards animal health and welfare.

Results from multiple ordinal regression indicated that consumers who were more willing to pay for animal welfare based on their ethical beliefs were more likely seek out specific shopping channels such as online channels and organic or specialised shops. The expectation is that these channels are more likely to ensure higher transparency for their products and better traceability. Online channels offer opportunities to transmit a large amount of information directly to consumers easily and at low cost, and consumers filter and base their purchasing decisions on that information (Linkiewicz & Bartosik-Purgat, 2022). Consumers shopping in organic or specialised shops exchange less information and instead place trust in the belief that these shops uphold the values they advertise.

The main shopping channel for food purchases remains traditional retail shops. While traditional retailers are under increasing pressure (Brüggemann & Olbrich, 2023), it can be expected that they will continue to be the primary food purchasing channel for some time. Our analysis indicated that consumers had different expectations regarding animal welfare information. For users of retail shops, significant considerations were animal health and general welfare practices aimed at ensuring the safety of food in large-scale production and distribution.

Consumers for whom various ethical and sustainability considerations were important were more willing to seek out alternative, specialised shopping channels that could provide more direct interaction or specific information to assure them that production practices aligned with their values. As Estonia is expected to follow a trend similar to, for example, that of the Nordic countries - where consumers demand more information on animal welfare (European Commission: Directorate-General for Health and Food Safety et al., 2022) - retail shops are also coming under increasing pressure to provide this information, not only the specialised shopping channels.

Our findings highlight the significant role of sociodemographic factors, including gender, age, education, income, and nationality in the selection of food purchasing channels. As the demand for ethical and sustainable food choices is expected to grow, these sociodemographic factors will play a pivotal role in driving changes in the food supply chain and influencing market trends and consumer demand. Compared with other age-gender groups, younger women preferred buy food directly from producers. Older age groups preferred purchasing food from conventional retail stores and not from online outlets. However, consumers who used online food purchasing options more often indicated that they paid more attention to animal health and welfare issues.

More frequent ICT use did not translate into a preference for online food shopping over more traditional retail purchasing. Our interpretation is that unlike the case of non-food items, online channels for food items are less developed and include various considerations related to food perishability, logistics, convenience of use, and selection; and thus, active ICT use at this point in the Estonian context does not translate into active use of online shopping for food products of animal origin.

As with most cross-sectional and survey-based research, the reliance on self-reported data introduces the potential for social desirability bias, where participants may respond in a manner they perceive as favourable or acceptable while their actual purchasing behaviour and willingness to pay may differ from their answers. Despite this limitation, the survey captured responses from a large and demographically representative sample of the general population, lending robustness and credibility to the findings. In addition, future research could incorporate longitudinal or experimental designs and examine actual consumer behaviour through purchase tracking or behavioural experiments.

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APPENDIX 1

Table A1. Willingness to pay for animal welfare attributes: For which of the following animal health and welfare aspects are you willing to pay more?

Item	
A1_01	I am generally not prepared to pay more
A1_02	The animals have no disorders or diseases
A1_03	The animals do not have any pain, damage, suffering or stress
A1_04	The animals show normal rumination and feeding behaviour
A1_05	Good housing climate, ventilation, and hygiene and appropriate noise level
A1_06	Short transportation times (e.g. journey to slaughter)
A1_07	The animals have a good physical condition
A1_08	Species-appropriate husbandry system
A1_09	Low calf mortality
A1_10	The animal can perform species-specific behaviours
A1_11	Low use of medication
A1_12	Species-appropriate feeding, nutrition and pasture use
A1_13	The animal reaches its anticipated average lifespan (dairy cattle)
A1_14	The animal does not show any behavioural abnormality

Table A2. Importance of animal welfare in purchase decisions: Which aspects of animal health and welfare are important to you when buying food? (1 = not important ... 5 = very important)

Item	
A2_01	The animals have no disorder or diseases
A2_02	The animals do not have any pain, damage or stress,
A2_03	The animals show normal rumination and feeding behaviour
A2_04	Good housing, climate, ventilation, hygiene and noise level
A2_05	Short transportation times (slaughter)
A2_06	The animals have good physical condition
A2_07	Species-appropriate husbandry system
A2_08	Low calf mortality
A2_09	The animals can perform species-specific behaviours
A2_10	Low use of medication
A2_11	Species-appropriate feeding, nutrition and pasture use
A2_12	The animal reaches their anticipated average lifespan (dairy)
A2_13	The animal does not show any behavioural abnormality

Table A3. Importance of general food purchase attributes: How important are the following attributes to you in making purchasing decisions about food products? (1 = not important ... 5 = very important)

Item	
A3_01	Price
A3_02	Practicality
A3_03	Taste
A3_04	Appearance
A3_05	Texture
A3_06	Nutrition value
A3_07	Fewer food additives or preservatives
A3_08	Information on the source of products (Traceability)
A3_09	Organically produced
A3_10	Regionally produced
A3_11	Recognizable animal welfare features
A3_12	Sold sustainably

Table A4. PCA with varimax rotation. Subset 1: ‘Willingness to pay for animal welfare attributes’

Item	RC1.1	RC1.2	RC1.3	h ²	u ²
A1_01	-0.03	-0.75	-0.40	0.72	0.28
A1_02	0.16	0.32	0.77	0.72	0.28
A1_03	0.24	0.70	0.21	0.59	0.41
A1_04	0.69	0.20	0.21	0.56	0.44
A1_05	0.59	0.45	0.12	0.56	0.44
A1_06	0.71	0.09	0.26	0.58	0.42
A1_07	0.52	0.27	0.43	0.53	0.47
A1_08	0.38	0.66	0.16	0.61	0.39
A1_09	0.75	0.25	0.16	0.65	0.35
A1_10	0.65	0.43	0.02	0.61	0.39
A1_11	0.27	0.22	0.71	0.63	0.37
A1_12	0.45	0.52	0.23	0.53	0.47
A1_13	0.75	0.33	0.04	0.67	0.33
A1_14	0.70	0.03	0.37	0.64	0.36

Note: communality (h²) values were high across all items, indicating strong representation by the extracted components; uniqueness (u²) values were generally low, suggesting little unexplained variance in most items.

Table A5. PCA with varimax rotation. Subset 2: ‘Importance of animal welfare in purchase decisions’

Item	RC2.1	RC2.2	RC2.3	h ²	u ²
A2_01	0.32	0.87	0.32	0.95	0.05
A2_02	0.35	0.39	0.72	0.79	0.21
A2_03	0.34	0.32	0.79	0.84	0.16
A2_04	0.39	0.28	0.80	0.87	0.13
A2_05	0.43	0.12	0.76	0.78	0.22
A2_06	0.54	0.31	0.64	0.80	0.20
A2_07	0.65	0.26	0.59	0.85	0.15
A2_08	0.63	0.21	0.62	0.83	0.17
A2_09	0.71	0.22	0.55	0.85	0.15
A2_10	0.75	0.44	0.22	0.81	0.19
A2_11	0.76	0.30	0.44	0.87	0.13
A2_12	0.73	0.21	0.52	0.84	0.16
A2_13	0.63	0.20	0.56	0.75	0.25

Note: communality (h²) values were high across all items, indicating strong representation by the extracted components; uniqueness (u²) values were low, suggesting little unexplained variance in most items.

Table A6. PCA with varimax rotation. Subset 3: ‘Importance of general food purchase attributes’

Item	RC3.1	RC3.2	RC3.3	h ²	u ²
A3_01	-0.02	0.09	0.93	0.87	0.13
A3_02	0.30	0.41	0.37	0.39	0.61
A3_03	0.06	0.67	0.23	0.50	0.50
A3_04	0.17	0.83	-0.08	0.72	0.28
A3_05	0.26	0.77	0.05	0.67	0.33
A3_06	0.59	0.32	0.24	0.51	0.49
A3_07	0.69	0.25	0.20	0.58	0.42
A3_08	0.76	0.22	0.10	0.63	0.37
A3_09	0.80	0.14	0.00	0.66	0.34
A3_10	0.76	0.10	-0.10	0.60	0.40
A3_11	0.82	0.11	-0.03	0.68	0.32
A3_12	0.81	0.12	0.05	0.67	0.33

Note: The communality values (h²) ranged from 0.39 to 0.87, indicating that most items were well-explained by the three extracted components; uniqueness (u²) values were generally low, suggesting little unexplained variance in most items.

Seasonal and farm-specific variations in milk fat percentage: impact on quality and economic performance in dairy production

Xh. Bytyçi¹, N. Hasanaj^{2,*}, M. Zeqiri¹, F.C. Ajazi¹, S. Makolli¹ and S. Aliu¹

¹Department of Food Sciences and Biotechnology, University for Business and Technology, Kalabria, XK10000 Prishtina, Kosovo

²Department of Food Science, University ‘Haxhi Zeka’ KLA Str., XK30000 Peja, Kosovo

Correspondence: xhavit.bytyci@ubt-uni.net

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Abstract. This study investigated the seasonal dynamics of milk fat percentage and its economic implications across 83 small-scale dairy farms in the Istog region of Kosovo over one year. A total of 1,616 valid raw milk samples were collected and analyzed twice monthly per farm using the *Gerber* method. The average annual milk fat content was 3.75%, ranging from 2.90% to 4.00%. Statistically significant monthly differences were observed (*Friedman* test, $p < 0.001$), with May showing the highest average fat percentage ($3.807 \pm 0.133\%$) and August the lowest ($3.682 \pm 0.220\%$). While *Spearman's* correlation did not indicate a significant relationship between ambient temperature and milk fat percentage, seasonal comparisons revealed significantly higher fat values in spring than in winter ($p = 0.009$, $rrb = 0.543$). Farm-level analysis showed considerable variation, with fat content ranging from 3.35% to 3.92%, likely reflecting differences in general management practices and potential variations in breed and feeding. An economic model based on €0.075 per 1% fat per liter of milk and an annual production of 36,000 liters per farm revealed income disparities of up to €1,539 per year due to fat percentage differences. These findings underscore the importance of improving farm-level practices and implementing seasonal management strategies to stabilize milk fat content and reduce economic losses, particularly during warmer months when fat levels tend to decline. Future research should further investigate the specific effects of cow breed, feeding regimes, and environmental management on milk composition.

Key words: milk fat, samples, averages, seasonal variation, heat stress, economic impact.

INTRODUCTION

Milk fat is a valuable energy source and largely contributes to the taste and texture of many milk products and other foods (Hoffmann, 2011). The fat content of milk is of economic importance because price formulas for milk are functions of the fat content. Compared to other milk macronutrients, fat is the most variable component in the milk of different ruminants, so compared to cow milk, buffalo milk was richer in fat, lactose, protein (especially caseins), and minerals such as calcium, magnesium, and inorganic

phosphate. (Ahmad et al., 2008). Milk fat concentration differs considerably among bovine breeds. For example, *Jersey* cows typically produce milk with a fat content of around 5.09%, whereas *Holstein-Friesian* cows yield milk averaging 3.79% fat, with crossbred cows often exhibiting intermediate levels around 4.45% (Palladino et al., 2010; Claeys et al., 2014). The *Simmental* milk contained 4.02% fat, and the *Holstein* milk contained an average of 3.72% fat. The superiority of the *Simmental* cows over the *Holstein* cows throughout the year was statistically significant (Khastayeva et al., 2021). Barłowska et al. (2011) reported significantly higher ($p \leq 0.01$) milk fat in Jersey cows (5.41%), while other breeds, such as White-Backed (3.98%) and Polish Red (4.25%) displayed lower fat percentages. National data from Poland also indicate that the Jersey breed produced milk with an average fat content of 5.26% in 2010. In another comparative analysis, milk from *Holstein-Friesian* cows averaged 4.69% fat, whereas Jersey milk reached as high as 7.02% (Czerniewicz et al., 2006). Breed-related differences are not only genetically determined but also reflect the influence of farm structure and milking systems. Studies have shown that tie-stall farms housing various cow breeds tend to achieve higher fat concentrations (4.74%) compared to farms using automatic milking systems dominated by Swedish *Holstein* cows (4.32%) or milking parlors (4.47%) (Priyashantha et al., 2021). These inter-breed and management-related differences underscore the complexity of milk fat variation, particularly in production systems where pricing is closely tied to fat percentage.

Nutrition is the single factor having the greatest influence on the milk production performance of dairy animals. The results demonstrate how different feeding systems can affect the gross and elemental composition of milk. (Gulati, A., 2018). Protein and fat content can also be changed due to the physical form of the forage being fed. Milk fat is more sensitive to dietary manipulation than other milk constituents and has received great attention on nutritional control of milk fat content and fatty acid composition (Olika, 2021). Bovine milk's nutritional quality and processing capabilities are closely associated with milk composition (Sundekilde et al., 2013). Milk from pasture-fed cows (grass and clover) had significantly higher concentrations of fat, protein, true protein, and casein (Callaghan et al., 2016).

Thermal stress expressed a significant influence on milk composition, particularly the fat content. Under conditions of heat stress, milk fat levels can decline markedly by approximately 0.3 to 0.6 percentage points according to various studies. For instance, reductions have been observed from 4.05% to 3.58% (Toledo & Thatcher, 2022) and from 3.61% (spring) and 3.80% (winter) to 3.20% in summer (Kabil et al., 2015). Conversely, during thermoneutral conditions, milk fat percentages tend to remain stable or even increase, supporting the hypothesis that elevated temperatures impair lipid synthesis in the mammary gland. Bauman et al. (2011) reported a consistent decline in milk fat concentration as daily maximum temperatures rose from 8 °C to 35 °C, highlighting the sensitivity of milk composition to climatic conditions. Similarly, O'Brien et al. (2011) emphasized the effects of ambient climate on milk fat content. Seasonal variations in milk composition have also been confirmed by several studies, which consistently link higher milk fat content to colder periods. Heck et al. (2009) and Chen et al. (2014) both identified fat content as a key component affected by seasonal changes. In Ethiopia, Shibru et al. (2009) observed higher fat percentages during the dry season, while Lakew et al. (2019) reported significantly greater total solids in milk collected during the winter months. A large-scale study by Nam et al. (2009), based on

over 160,000 milk samples collected over six years in South Korea, confirmed that milk fat content was significantly higher in winter than in other seasons ($p < 0.05$). Similarly, Smith et al. (2013) found that *Holstein* cows experienced reductions in milk fat percentage under moderate and severe heat stress compared to periods of mild heat stress.

Economic loss due to variations in milk composition alone in the summer months was substantial. In this context, it is imperative to implement a support pricing strategy for dairy farmers during the summer months to overcome financial losses (Thomas & Sasidharan, 2015). As can be observed, numerous animal, dietary, and environmental factors influence milk fat content and yield in dairy cows. Because of the current pricing system, it is critical to reevaluate some of these factors and consider the economic implications of manipulating milk fat content with the ultimate goal of increasing milk fat yield profitably (Santos & De Vries, 2019).

The aim of this study is to analyze the seasonal and farm-specific variations in the milk fat percentage of raw cow milk produced in the Istog region of Kosovo over the course of one year. The research seeks to determine whether environmental temperature and other farm-level factors influence milk fat content and, consequently, the economic performance of dairy farms. This is particularly important in Kosovo, where milk pricing is directly tied to fat percentage, as regulated by Administrative Instruction MA-No. 20/2006.

MATERIALS AND METHODS

Study Area

The study was conducted in the Municipality of Istog in Kosovo. The farms are small farms that mainly breed from 2 to 20 cows and deliver milk to the collection point to generate income for the family as a form of self-employment. The farms are of the tied system where the cows are tied and housed in stalls with dimensions of 80–100 cm wide and 1.75–2 meters wide. Ventilation is mainly natural through windows, with average lighting, while the roof in 90% of cases is made of sheet metal, which allows for the increase of temperatures in the stable in the summer months. Cows are milked twice a day (morning and evening), and this is done in about 95% of them through automatic milkers. Farmers are forced to deliver their milk, with their vehicles, twice a day to the collection point and as soon as possible (at the latest 2 hours after milking), considering that about 90% of them do not have cooling equipment (*lactofreeze*) for milk.

Monthly average temperature data for the Istog region were sourced from the publicly available climate platform Weatherspark.com, which compiles data from multiple meteorological datasets (Weather Spark, 2025). These values represent long-term monthly means and were used as proxies for ambient environmental conditions during the sampling period (January to December). For each calendar month, corresponding temperature averages (°C) were matched with the monthly average of % milk fat values across all farms. This allowed for a comparative assessment of thermal influence on milk composition.

While no on-farm temperature sensors were installed, the regional climate data adequately reflect the macroenvironment affecting dairy herds in the Istog municipality. Months were also implicitly categorized by seasonal temperature characteristics: Winter

(Dec–Feb), Spring (Mar–May), Summer (Jun–Aug), Autumn (Sep–Nov). This alignment permitted the analysis of thermal stress patterns in milk fat fluctuations.

The dominant breed of cattle on all farms surveyed is *Simmental*, representing approximately 60% of the total cow population. *Holstein* cows account for about 30%, while the remaining 10% are crossbreds. Due to practical constraints, detailed breed-level data (e.g., exact breed distribution per farm, individual productivity) were not available, which limits the ability to perform breed-specific statistical analyses.

Feeding practices vary significantly by farm size and season. Farms up to 5 cows often allow cows to graze during the spring and summer months, with the duration of grazing depending on the farmer's management preferences. During the winter, feeding is mainly based on roughage such as hay and alfalfa and ground corn (as concentrates). In contrast, farms with 6 to 20 cows generally keep cows indoors all year round in connected housing systems. In the spring, short-term feeding with fresh grass and vetch (*Vicia ervilia*) is common. From summer to winter, the main feed includes roughage hay and alfalfa, while from autumn to spring, the main roughage is corn silage, including, in smaller quantities, hay and alfalfa. In contrast to farms up to 5 cows, these farms constantly use concentrated feed, either home-prepared (corn mixed with soybeans, sunflower meal, and mineral premix) or purchased as commercial milk concentrate.

Although general feeding patterns are known, the lack of standardized feed formulations and accurate nutrient content data limits the possibility of direct statistical correlation between feed type and milk fat percentage. However, the breeds of cows, feeding regimens, and zoo hygienic conditions are likely to contribute to the seasonal and farm-level variations in milk fat content observed in this study. Future research could benefit from collecting more detailed data on individual animal feeding and breed productivity to support more robust statistical modelling.

Sampling Techniques

A total of 1704 milk samples were subjected to the alcohol stability test at the 'Jeta e Re' milk collection point in the period January - December 2022. This test was performed by mixing 2 mL of milk with 2 mL of 75% ethanol and gently swirling the mixture. Only samples that tested negative (i.e., showed no coagulation or flocculation) were considered stable and were included in the subsequent milk fat analysis. After excluding unstable samples, 1,616 samples were retained for fat percentage determination. Thus, 20 mL of milk was taken, which was placed in the 'glass' for sampling, which was immediately placed in the refrigerator at a temperature of 4 degrees Celsius. The analysis for the % fat in the milk samples was carried out on the same day of collection. Since the 1,616 milk samples analysed for fat% % include sample analyses 2 times/farm/month, in the paper, we will present the average values of fat% % of the sample analyses per farm/month, $n = 808$.

Method for analysing % milk fat - Gerber method

To determine the amount of milk fat in the milk as a raw material, we used the Centrifugal Separation of Fat, otherwise known as the 'Gerber Method'. Using a pipette, we first placed 10 mL of concentrated sulfuric acid (density $\rho_{20} = 1.820 \text{ g mL}^{-1} \pm 0.005 \text{ g mL}^{-1}$) in the butyrometer. Immediately after that, through another pipette, we slowly placed 11 mL of milk, allowing a layer to form on top of the acid. After that, we

placed 1 mL. 98% *amyl alcohol* through the pipette. After closing, we took the butyrometer until the white particles disappeared. The inverted butyrometer was placed in a centrifuge and centrifuged at room temperature for 5 minutes at 350 revolutions. After removing the butyrometer from the centrifuge, we placed it in a water bath at a temperature of 65 °C for 10 minutes. The fat % measurement was performed after removing the butyrometers from the water bath, keeping the butyrometers in a vertical position, and taking the reading point at eye level.

Economic Impact Assessment

To evaluate the economic implications of milk fat variation among farms, a simple economic model was used to estimate relative gain or loss based on deviations from the annual average milk fat percentage (3.75%). Farms producing milk with fat percentages above this benchmark were considered to have economic benefit, while those below were classified as experiencing economic loss. The value of milk fat was calculated using a reference price of €0.075 per 1% fat per liter of milk, based on the Kosovo Administrative Instruction MA-No. 20/2006, which regulates milk prices. For each farm, the deviation from the reference level of 3.75% fat was multiplied by this unit price to determine the approximate economic profit or loss. To reflect the profit or loss every month, we multiplied the fat value per month by 3,000 liters, while for annual calculations, the multiplication was done by 36,000 liters. These values were visualized using a categorical column chart, grouping farms into three categories: Profit (> 3.75%), Break-even (= 3.75%) and Loss (< 3.75%). The analysis was performed using *Microsoft Excel*, and the results are presented as numbers and percentages of farms in each category. A summary of the monthly sample sizes and corresponding temperature data is presented in Table 1

Table 1. Number of Dairy Farms and Milk Samples Analyzed per Month, and Monthly Minimum, Average, and Maximum Air Temperatures (°C) in the Istog Region, Kosovo

Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Farms (no)	70	69	71	75	81	78	60	54	58	60	62	70
Samples (no)	140	138	142	150	162	156	120	108	116	120	124	140
Min Temp (°C)	-3	-2	1	6	10	13	15	15	11	7	2	-2
Avg Temp (°C)	0	2	6	11	16	19	22	22	17	12	6	1
Max Temp (°C)	4	7	11	17	21	25	28	28	23	17	11	5

Statistical Analysis

Statistical analyses were performed to assess monthly, seasonal, and farm-level variations in milk fat percentage and their economic implications. Descriptive statistics, including mean, standard deviation, minimum, maximum, skewness, and kurtosis were calculated for each month to evaluate the distribution and variability of fat content in raw milk. To assess the influence of environmental factors on milk composition, *Spearman’s* rank correlation test was used to examine the relationship between milk fat percentage and temperature parameters (minimum, average, and maximum monthly temperatures), given the non-parametric characteristics of the data.

Comparisons across months and seasons were performed using the *Friedman* test to detect statistically significant differences in milk fat percentage. Where the assumptions of normality and homogeneity of variance were met, the *Bonferroni* post hoc test was applied for multiple pairwise comparisons.

RESULTS AND DISCUSSION

The results of the % milk fat analyses throughout the months of a calendar year are presented in Table 2.

Table 2. Descriptive Statistical Parameters of Monthly Milk Fat Percentage in Raw Milk Samples from Dairy Farms in the Istog Region

Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Valid	70	69	71	75	81	78	60	54	58	60	62	70
Mean	3.716	3.794	3.793	3.793	3.807	3.761	3.793	3.682	3.76	3.697	3.712	3.716
Std. Dev.	0.221	0.169	0.168	0.163	0.133	0.156	0.169	0.22	0.169	0.231	0.234	0.221
Skewness	-1.66	-2.24	-2.22	-2.28	-0.18	0.11	-0.60	-1.50	-0.60	-1.63	-1.65	-1.66
Kurtosis	3.948	7.779	7.724	8.392	-0.66	-0.95	-0.006	2.946	-0.10	3.527	3.508	3.948
Minimum	2.9	3	3	3	3.5	3.4	3.3	3	3.3	3	3	2.9
Maximum	4	4	4	4	4	4	4	4	4	4	4	4

From the analysis of all samples ($n = 1,616$) for % milk fat, the values range from 2.9% as the lowest value to 4% as the highest value. Compared to the results of % milk fat in the research of other authors, it turns out that the minimum values are similar, while the maximum values are somewhat lower than in the results of other authors. Thus, it is reported that milk fat comprises 2.4–5.5% of raw milk, depending on the cow's species and lifestyle (Herold, 2011); the fat content of milk from cattle reared in developed countries is in the range of 3.4–5.1% (Walstra et al., 2006) and that milk contains fats from 3.8 to 5.5%. (Fox et al., 2015).

The *Friedman* test was conducted to determine whether there were statistically significant differences in milk fat percentage across 12 months, and the test yielded statistically significant results ($p < .001$). The significant result of the *Friedman* test justified conducting post hoc analysis using Conover's pairwise comparisons with *Bonferroni* correction. Out of the 66 possible month-to-month comparisons, three were found to be statistically significant ($p_{bonf} < 0.05$). Specifically, May showed significantly higher milk fat percentages compared to January ($p = 0.006$), August ($p = 0.044$), and December ($p = 0.006$). These findings imply that May represents a peak period in fat content among the months evaluated, whereas January, August, and December represent periods of comparatively lower fat levels. The remaining comparisons did not yield statistically significant differences after *Bonferroni* adjustment, suggesting relatively stable fat content during those intervals. The overall effect size, as measured by *Kendall's W*, was low, indicating that while some monthly differences exist, the magnitude of variation is not strong across all months.

The fat percentage gradually increases from January (3.716%) to May, reaching its peak in April and May, the fat content drops in June and reaches its lowest in August (3.67) and increases again in September and stabilizes through to December (Fig. 1).

To assess the relationship between milk fat percentage and environmental temperatures across months, *Spearman's* rank-order correlation was applied. The correlation coefficients were calculated between fat percentage and three temperature parameters: minimum (low), average, and maximum monthly temperatures. The results revealed very weak and statistically non-significant correlations. None of these results reached the threshold for statistical significance ($p < 0.05$), and all coefficients were close to zero. These results imply that milk fat content is likely influenced more by other biological or management-related factors, such as breed, feed quality, and lactation stage, rather than by ambient temperature alone.

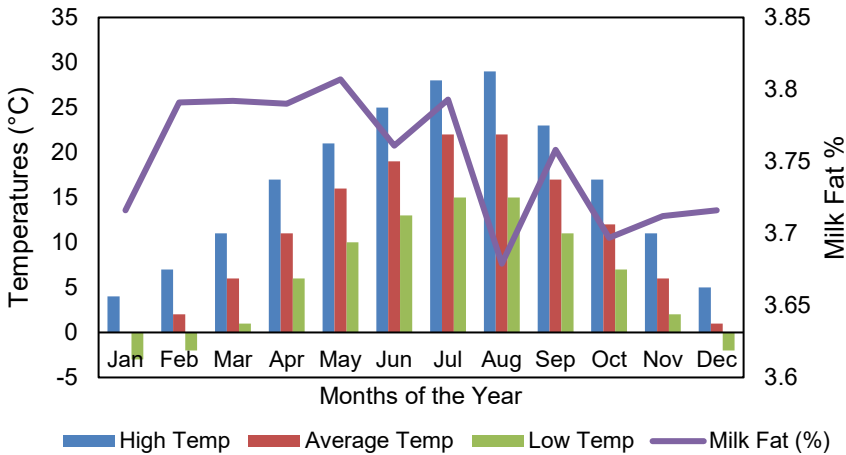


Figure 1. Monthly Variation of Milk Fat Percentage about Minimum, Average, and Maximum Ambient Temperatures.

The observed monthly variation in milk fat percentage aligns with established literature on the influence of seasonal and management-related factors on milk composition. Heck et al. (2009) report that milk fat concentration increased from a minimum of 4.10 g per 100 g in June to a maximum of 4.57 g per 100 g in January, while Cimen M. et al. (2013) reported that in summer months (July and August), the milk fat rates were lower than the test value (3.2%).

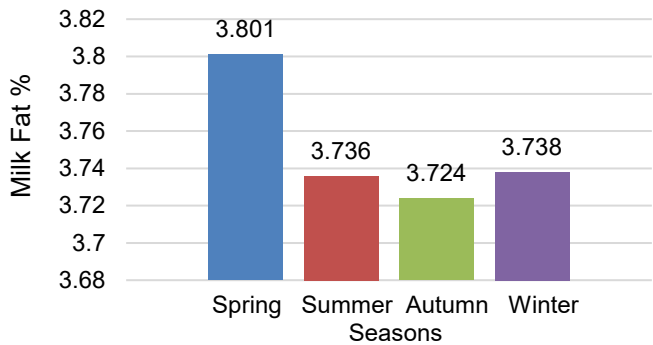


Figure 2. Seasonal Variation in Milk Fat Percentage Across Spring, Summer, Autumn, and Winter.

Descriptive statistics for milk fat percentage were calculated across four seasons: Spring, Summer, Autumn, and Winter. The highest mean fat % was observed in Spring (3.801%), followed by Winter (3.738%), Summer (3.736%), and the lowest in Autumn (3.724%). (Fig. 2). The seasonal distributions varied in dispersion, with the lowest standard deviation in Summer (0.116) and the highest in Winter (0.173). Post hoc analysis confirms that Spring is the only season with a statistically higher milk fat % compared to Winter ($p = 0.009$), even after multiple comparison correction. Although uncorrected p -values suggested differences between Summer and Autumn as well, they were not significant after *Bonferroni* adjustment.

The results obtained during our research can be supported by the works of other authors, both in the general aspect of the role and seasonal impact on the % of milk fat, while some works have presented different results in the specific aspect. Thus several studies have confirmed the negative impact of elevated temperatures on milk fat percentage in dairy cows. For example, Joksimović-Todorović et al., 2011 reported that higher rate of milk fat was recorded in spring in relation to summer period the level of significance being $p < 0.01$ In the *Czech Fleckvieh* and *Holstein* breeds, milk fat content was significantly lower in summer (3.71 and 3.91 g per 100 g, respectively) compared to winter (Hanuš et al., 2016). Results showed the mean value of fat % in four seasons (winter, spring, summer, and autumn) are 3.6 ± 0.055 , 3.27 ± 0.053 , 3.1 ± 0.058 and 3.4 ± 0.049 , respectively. Milk fat level was lower in the summer season compared to any other season, but winter showed the highest amount of milk fat (Kabil et al., 2015); The milk fat were the highest in the winter and the lowest in the summer period (Yildirim & Cimen, 2009); fat and protein percentages of milk samples were significantly ($p < 0.05$) lower during the hot season compared to the cold season. (Bahashwan, 2014), and similar results can be found in many research studies by other authors.

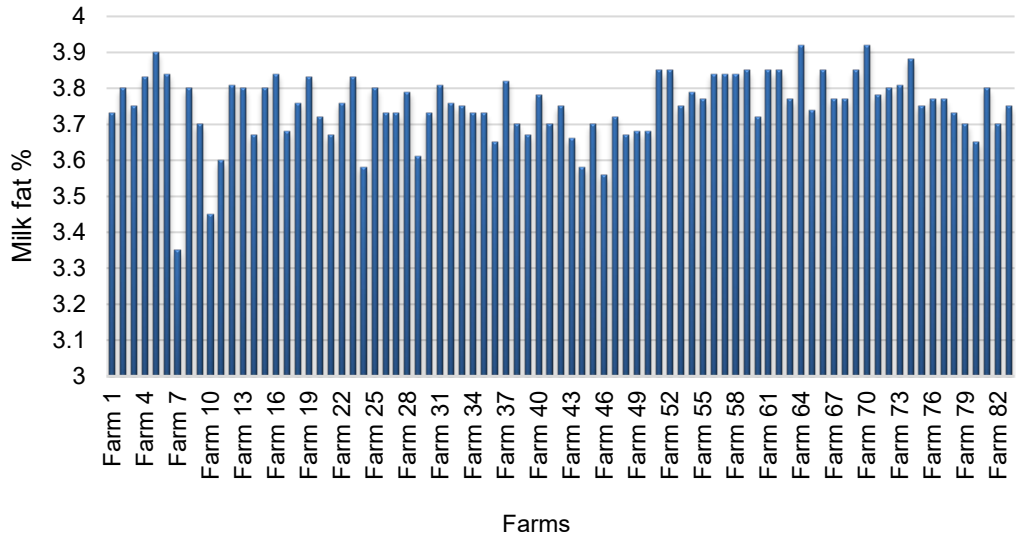
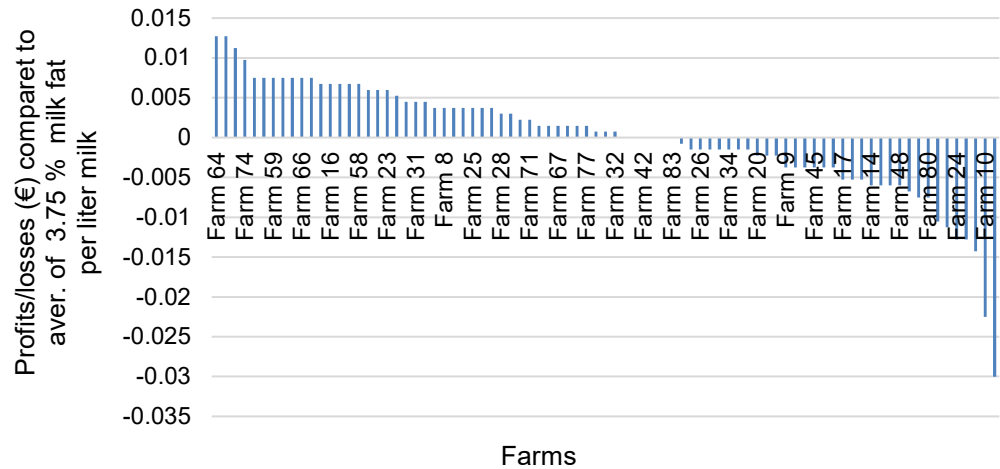


Figure 3. Average Milk Fat Percentage (%) per Farm Across the Studied Dairy Farms.

When it comes to the average % of milk fat per farm, the lowest average value was 3.35% (farm no. 7), while the highest average value was 3.92% (farm no. 70), with an overall average for all farmers of 3.75% (Fig. 3). Through the Kruskal-Wallis test, statistical differences ($p < 0.05$) are found in the distribution of milk fat percentage between the farms. While many farms maintain stable fat percentages in their raw milk, a few experience greater variability, potentially due to farm-specific factors like nutrition, breed, and management practices. Significant differences in mean milk fat percentages across different farms suggest the influence of diverse factors on milk composition. These findings underscore the need for adaptive management practices and further research to identify and mitigate the causes of variability, ensuring consistent and high-quality milk production.

Differences in fat % between months of the year and between different farms reflect on the economic factor of farmers. Thus, farmers with a higher % of fat milk benefit from more income, while farmers with a lower % suffer significant economic losses. Fig. 4 summarizes farmers' economic benefits or losses based on their milk fat percentages. The benchmark is the overall average of 3.75%. Farms producing above the benchmark are assumed to have economic benefits, while those producing below it have economic losses.



36,000 liters per farm, the impact of milk fat percentage on farm income was quantified. The reference fat percentage was set at the average value of 3.75%, resulting in a baseline annual income of €10,125 per farm. Farms producing milk with fat percentages above 3.75% experienced profit gains, while those below this threshold incurred economic losses. The highest profit was recorded by Farm 64 and Farm 70, both with an average fat content of 3.92%, translating into an annual income of €10,584, a gain of €459, or +4.53% compared to the reference. In contrast, Farm 7, with a fat content of 3.35%, recorded the largest economic loss, with an annual income of €9,045 and a deficit of €1,080, equating to a loss of 10.67% below the average baseline. Overall, the relative difference in income between the top-performing and the lowest-performing farms amounted to €1,539 per year, or 15.2% of the reference income. This significant disparity underscores the critical economic importance of optimizing milk fat content through effective breeding, feeding, and farm management strategies.

If we specifically evaluate the economic benefits or losses over the months of the year, it results that the highest average fat percentage was observed in May (3.807%), yielding the highest monthly revenue of €856.5, which is approximately €17.20 more than the annual average income. This reflects a 2.06% increase in fat content compared to the baseline. Other months with positive deviations include February, March, April, and July, all showing elevated fat content and consequently higher profits. In contrast, August exhibited the lowest fat percentage (3.682%), resulting in the lowest income of €828.6, corresponding to a loss of €10.71, or 2.09% below the average. Months like October, January, and November also showed slight losses due to below-average fat values.

Analyzing the impact of seasons on farmers' economic performance, it turns out that spring recorded the highest average fat percentage at 3.801%, followed by winter (3.738%), summer (3.736%) and autumn (3.724%). These changes, although numerically moderate, translate into significant economic impacts when projected over large volumes of milk, especially in pricing systems that reward higher fat content. Although these values may seem modest, when aggregated across many farms and over time, the economic impact is considerable.

CONCLUSIONS

This study investigated monthly and seasonal variations in the fat percentage of raw milk collected from 83 dairy farms in Kosovo, analyzing a total of 1,616 milk samples. The results revealed statistically significant differences in milk fat content across months and seasons. Specifically, milk collected in May exhibited a significantly higher fat percentage compared to January, August, and December. At the seasonal level, spring samples showed a higher milk fat content than winter, as confirmed by post hoc analysis following *Friedman* testing.

Although differences in ambient temperature across the months were documented, a statistically significant correlation between temperature and milk fat percentage was not established based on the current dataset. Therefore, while temporal trends were observed, the specific environmental or management-related causes of fat variation could not be definitively isolated.

Furthermore, the study demonstrated that these variations in milk fat content translate into measurable economic differences for farmers, given that milk pricing in Kosovo is linked to fat percentage. Farms with higher average fat values received correspondingly higher estimated monthly income, highlighting the financial relevance of milk quality monitoring.

Future research should aim to include and control for additional variables such as cow breed, feeding practices, housing conditions, and herd size to better elucidate the factors influencing milk fat content

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Estimation of temporal and spatial characteristics of oat development parameters using Sentinel-1 backscatter data

T. Fedoniuk^{1,*}, P. Pyvovar¹, P. Topolnytskyi¹, I. Bezvershuk¹,
V. Tereshchuk¹ and I. Puleko²

¹Polissia National University, Staryi Blvd., 7, UA10008 Zhytomyr, Ukraine

²Zhytomyr Military Institute named after S.P. Korolyov, Myru Avenue, 22, UA10004 Zhytomyr, Ukraine

*Correspondence: tanyavasiluk2015@gmail.com

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Abstract. The implementation of precision agriculture is an urgent priority for Ukraine's agricultural sector under climate change and restricted use of unmanned aerial vehicles in border regions. This study aims to clearly define and evaluate the potential of Sentinel-1 radar data in identifying temporal and spatial variations in oat crop density and structure during the growing season under field conditions in Ukraine. The technique encompassed the acquisition of Sentinel-1 satellite images in VV and VH polarizations, data processing by SNAP, field assessments of height, plant density, and phenological development, along with statistical analysis of the association between satellite data and land observations. The study demonstrated that the reflectance coefficient values in VV and VH polarizations fluctuate according to the oat development phase: a reduction in backscattering was noted at the onset of the growing season, followed by an increase during the stem formation and earing phases. The VH/VV ratio is responsive to variations in moisture, plant biomass, and stress conditions. The modelling demonstrated a substantial correlation among planting rate, herbicide application, and polarization markers. The findings validate the efficacy of Sentinel-1 for monitoring crop structure irrespective of weather conditions. This method enables farmers to obtain dependable information for making decisions regarding crop management, timely fertilizer application, or harvesting. The regression model demonstrated a consistent association with a $R^2 = 0.61$, suggesting the potential for further research utilizing multi-year data to develop integrated yield forecasting models.

Key words: precision agriculture, remote sensing, herbicide, agriculture, plant density, polarization.

INTRODUCTION

Ukraine is well-known for its agricultural commodity production capacity, which contributes significantly to its export volume. The exportation of agricultural products from Ukraine frequently relies on worldwide price patterns, climatic circumstances, and political influences (Shebanina et al., 2023). Ukraine has recently prioritized the advancement of precision agriculture to enhance food security regulation and forecasting

(Shelestov et al., 2020). Several scientists anticipate that the transition to precision agriculture will lead to enhanced productivity, reduced environmental footprint, reduced pesticide usage, transparent production, and more intelligent production techniques (Liu et al., 2017; Finger et al., 2019; Zou et al., 2021; Fuentes-Peñailillo et al., 2024). The current availability of high-resolution optical data has exceptional prospects for agricultural applications (Weiss et al., 2020). Satellite remote sensing (RS) offers vital data to a wide range of consumers, including individual farmers, large food producers, and national and international government agencies (Kumar et al., 2022). Optical imagery has the capability to forecast crop yield, define areas for specific management practices, facilitate the application of variable rates, and track variations within and between fields over multiple years (Kansakar & Hossain, 2016). Oat (proxy indicator *Avena sativa* L.) is a vital cereal crop in Ukraine, particularly in the Polissia region, due to its resilience to cold climates and importance in both human consumption and livestock feed. It is typically sown in early April and harvested between July and early August (Singh et al., 2024).

The European Union (EU) urges Member States to modify the Integrated Administration and Control System (IACS) and enhance the utilization of Sentinel images to achieve complete surveillance of agricultural regions, taking advantage of the abundant and accessible satellite data provided by the Earth observation program - Copernicus (Sarvia et al., 2021). Currently, there are multiple sources for accessing publicly accessible space images from MODIS, Sentinel-2, and other satellites. Additionally, several organizations in Ukraine acquire satellite images from private suppliers. Nevertheless, the cloud cover in Ukraine significantly diminishes the dependability of optical images. On average, around 20% of the examined multi-time data sets yield a distinct (< 2 Octa) image throughout the plant growth period (Parisi et al., 2021).

While unmanned aerial vehicles (UAVs) have gained significant popularity for agricultural monitoring, the monitoring of broad areas in Ukraine continues to rely on satellite RS. In Ukraine, the main reason for this is the temporary limitation on the use of UAVs due to the military aggression of the Russian Federation in the territory of Ukraine. This restriction particularly applies to border areas and zones near the conflict zone.

Simultaneously, the satellite RS provides many possibilities. Radar operating at frequencies 1–10 GHz can penetrate cloud cover and remains unaffected by sunlight. This makes it very suitable for agricultural applications, as it can offer accurate and timely observations. The Sentinel-1 mission provides distinct advantages for agricultural monitoring through radar observations due to two key factors: (1) its frequent flights enable the generation of extensive and precise forecasts, and (2) the images are accessible without any limitations or constraints (Pasternak & Pawluszek-Filipiak, 2022). Although Sentinel-1 was originally designed as a dual-satellite system (Sentinel-1A and Sentinel-1B), the decommissioning of Sentinel-1B in 2022 has slightly impacted revisit frequency. However, the extensive archive of unique and high-quality Sentinel-1B data remains accessible through the Copernicus Data Ecosystem and continues to support thousands of users worldwide in advancing Earth observation research. The Sentinel-1 mission remains operational and effective with Sentinel-1A, and the upcoming launch of Sentinel-1C aboard the Vega-C rocket, scheduled for late 2024, is

expected to restore the full capabilities of the mission and ensure continuity of data delivery for Sentinel services and applications (The European Space Agency, 2024).

Presently, the mission comprises a pair of satellites that are identical in nature. Specifically, the mission successfully launched two spacecraft, Sentinel-1A and Sentinel-1B, operating in the C-band frequency in 2014 and 2015. They occupy the same orbital plane and guarantee comprehensive and precise worldwide coverage every 12 days. In Europe, the default method for obtaining data over the ground is through interferometric mode, which allows for the collection of both VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive) data. By considering numerous orbits, both ascending and descending, and accounting for the varying geometries of the satellites, it is possible to reach a revisit time of less than two days for most areas in Europe and available for Ukraine every 1–2 days as well (Khabbazan et al., 2019; Kaushik et al., 2021; Beriaux et al., 2021). Sentinel-1 data used to classify the landscape cover of particularly valuable protected areas (Romanchuck et al., 2017; Fedoniuk et al., 2021), for weed detection on maize fields (Skydan et al., 2021; Fedoniuk & Skydan, 2023; Fedoniuk et al., 2025). Previous and ongoing research highlights the potential of Sentinel-1 for crop monitoring throughout the growing season. In their study, Wang et al. (2019) compared Sentinel-1 data with estimates of the Normalized Difference Vegetation Index (NDVI) based on observations of precipitation, temperature, green area index, and fresh biomass made from optical and ground-based data (Wang et al., 2019). They demonstrated that Sentinel-1 data, especially the VH/VV ratio, can provide useful information on crop development. They highlighted the potential for distinguishing cultures based on the temporal variation of backscatter (Liu et al., 2017). The study also showed that for barley and maize, NDVI and VH/VV correlated well with green area index and fresh biomass. Crop temporal and spatial characteristics were analyzed using Sentinel-1 backscatter data by Harfenmeister et al. (2019). Stude highlighted possibilities of Sentinel-1 backscatter and polarization ratio (VH/VV) time series and found that they were related to vegetation water content, height, biomass index, and leaf area, demonstrated the ability to estimate vegetation water content from Sentinel-1 imagery using Random Forest simulations (Harfenmeister et al., 2019; Holtgrave et al., 2020).

The VH/VV polarization ratio can offer valuable insights into crop growth and progress. A high ratio values can indicate increased moisture (Petropoulos et al., 2015). Plant biomass can be accessed using the VH/VV ratio, as it correlates with changes in plant growth and general condition (El Hajj et al., 2017; Greifeneder et al., 2018). Furthermore, VH/VV ratio used to identify stressful conditions such as diseases or pests that impact plant structure, as well as radio wave reflection (Mani et al., 2021). Also, the VH/VV ratio is helpful in assessing structural changes in the vegetation cover, such as plant height and density (López-Granados, 2011).

The current study focuses on continental Ukraine, a highly productive agricultural region, to evaluate the effectiveness of Sentinel-1 in monitoring oats, a crop of regional importance. Although Sentinel-2 provides high-resolution optical imagery and could serve as an alternative to Sentinel-1, its application during the 2023 growing season was hindered by persistent cloud cover in the study region. Therefore, Sentinel-1 radar data, unaffected by atmospheric conditions, was preferred to ensure consistent temporal coverage and data continuity across the crop growth stages.

This study aims to clearly define and evaluate the potential of Sentinel-1 radar data in identifying temporal and spatial variations in oat crop density and structure during the growing season under field conditions in Ukraine. The research objective was to determine if such data could serve as a reliable alternative in precision agriculture where UAV deployment is restricted and optical imagery is hindered by cloud cover.

MATERIALS AND METHODS

Key characteristics of study area

The experimental plot was a part of larger the experimental field of the Polissia National University (N 50°26'; E 28°4). The site has predominantly Gleic Albic Luvisol (Endoclayic, Cutanic, Differentic, Katogleyic, Ochric type of soil according to PrWRB (2022).

Data was collected with a frequency of one week using each source. During field research, the parameters of main crops, cereal weeds, broadleaf, and short-leaved weeds were measured by height and density for oat. We conducted in situ measurements of oat crop vegetation parameters between April 5 and October 7, 2023, to test search schemes based on various satellite sensors, including Sentinel-1. We selected sample points for each field studied. While direct field measurements of soil moisture, salinity, and organic matter were not recorded in this campaign, we assumed relatively homogenous soil properties across the experimental site. Moreover, the VH/VV polarization ratio served as a proxy indicator of crop moisture content and stress. Inclusion of these variables is foreseen in follow-up research.

Weekly measurements of vegetation height, density, and plant phenology assessments were made at each location. Phenological stages were defined using the BBCH scale. Plant height was measured using a ruler; density was determined by stem count within a 1×1 m frame.

Planting density was measured by manually counting the number of stems in a 1×1 m area around each sampling point. Sowing density refers to the total number of stems, plants, and shoots in the accounting area, depending on the stages of culture development. Simultaneously, we determined the number of plants and shoots (pieces per m²) (Fig. 1).

Several variables are defined in this study. We assigned specific codes to each plot, which contained data from multiple variables (Table 1).



Figure 1. Location of study area.

Here and further in the text: DP – double seed rate with subsequent herbicide application; DN – double seed rate without herbicide application; NP – standard seed rate with subsequent herbicide application; NN – standard seed rate without herbicide application.

Table 1. Variant coding principles

1 st code symbol – sowing density	2 st code symbol - protection	Number
D double sowing (440 kg ha ⁻¹ or 12 million seeds ha ⁻¹)	norm P Protection (herbicides application)	1,2,3 – replication
N Normal sowing (220 kg ha ⁻¹ or 6 million seeds ha ⁻¹)	No protection (herbicides-free)	

Preparation of RS data

A space study was performed utilizing data obtained from the Sentinel-1 spacecraft (Copernicus Open Access). The satellite channels were selected for their capacity to deliver photos with superior spatial resolution (10 m) and the frequency of spacecraft traversing the research area, thereby ensuring consistent observation circumstances. Sentinel-1 measurements yielded space images in the radio wave spectrum using IWS mode, featuring a resolution of 5×5 m and a bandwidth of 20×20 km with VV and VH polarization. Data processing determined the average radiation intensity values at the midpoint of each section. Fig. 2 displays the tails (frames) of the relative turns (160, 109, 36) of the Sentinel-1 spacecraft overlapping the territory of Ukraine.



Figure 2. Coverage of Ukraine's territory with the tails (frames) of relative turns (160, 109, 36) of the Sentinel-1 spacecraft.

Sentinel-1 is in a near-polar, sun-synchronous orbit with a 12-day cycle and 175 revolutions per cycle. The Sentinel-1 dataset and its corresponding image properties are summarized in Table 2.

Table 2. The Sentinel-1 dataset and its corresponding image properties

Shooting mode	Product type	Distinction	Polarization	Number and type of relative orbit
Interferometric	Ground Range	High resolution	Dual DV	36 (eastern)
Wide-swath mode	Detected	(HR)	(VV/VH)	109 (eastern)
(IW)	(GRD)			160 (ascending)

Obtaining and preprocessing satellite imagery

Satellite data were acquired using the Copernicus Open Access Hub – an open platform for downloading Sentinel-1 images. Sentinel-1 (radar images) were used because of their ability to penetrate clouds and provide consistent data irrespective of weather conditions. Preprocessing of the satellite images was done in the SNAP (Sentinel Application Platform) environment and included the following steps:

1. Orbit correction – applying orbital files to correct satellite positioning.
2. Speckle filtering – reducing radar noise.
3. Terrain correction – ensuring accurate image geolocation.
4. Image mosaicking or cropping to the boundaries of the study areas.

To effectively conduct the experiment, we formed a panel database that incorporated the results of physical examinations of plants and soil, data from Sentinel-1. Observation took place in the same areas, which do not change over time in terms of size and type of observation. The object of the sample was 2 oat plots, which were formed from one experimental field. The database formation process provides the sample depth, which determines the number of observations for a specific researched field. A revisit time was achieved of 12 days by considering all available Sentinel-1 images for 2023 at the experimental field test site. A total of 78 Sentinel-1 scenes are available throughout the field campaign.

We used vegetation indices and textural characteristics to determine the crop density. The polarization channels VV and VH were present, representing the signal's vertical and horizontal polarizations, respectively. We also analyzed the images using reflectance values to identify areas with varying levels of vegetation density.

Three indicators determine the type of plot cultivation, ten indicators stem from a visual survey, two indicators derive from data from the Sentinel-1, and the remaining indicators come from soil tests at the experimental site.

After all preprocessing steps, the data were resampled to a spatial resolution of 10×10 m. Three different Sentinel-1 tracks, each with its own geometry and parameters regarding incidence angle, azimuth angle, and orbit direction, covered the test site area in 2023.

Statistical instruments

ANOVA and several statistical methods were employed to evaluate the impact of herbicides and sowing density on each spectral channel image. Regression analysis was employed to develop models for forecasting oat development levels.

The regression model used was a multiple linear regression of the form:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n + \varepsilon \quad (1)$$

where Y is the dependent variable (backscatter response), X_i are independent predictors (e.g., VV, orbit geometry); β_i are coefficients, and ε is the error term.

Only factors that retained statistical significance after correction were considered credible.

ANOVA was used to evaluate variance among treatment groups, with p -values adjusted using the False Discovery Rate (FDR) correction.

RESULTS AND DISCUSSION

The results of the search for satellite channels for surveys of the studied area

Weather conditions and the time of day directly affect the image's quality, restricting the utilization of optical data. The data obtained from the radar equipped with the Sentinel-1 spacecraft, which uses synthetic aperture technology, is free and independent of defined conditions. For example, lighting conditions do not affect the shooting process, and the data updates regularly every twelve days with a high spatial resolution of 10 meters. This enables the resolution of a variety of environmental monitoring issues, including those related to agriculture.

Merging different geospatial data allows for the effective use of high-quality time sets of satellite information. The experimental field's region coincides with three tails (frames) of relative turns (160, 109d, 36) of the Sentinel-1 satellite. Each frame measures 260×160 km. A total of 26 Sentinel-1 images were used within the specified time frame, using the shooting settings outlined in Table 1.

The Sentinel-1 satellite orbits the Earth three times a day, with each orbit occurring every 12 days. Each orbit has a designated direction and time. The first orbit of the satellite, known as 36d, takes place at 6 to 7 in the morning, but this time is not ideal for accurate measurements due to the presence of dew on plants. The second orbit, known as 160a, occurs from 6 to 7 p.m. The third orbit, known as 109d, takes place at noon (Fig. 3).

The location of the tiles (frames) in which the experimental field is registered is shown on the layout.

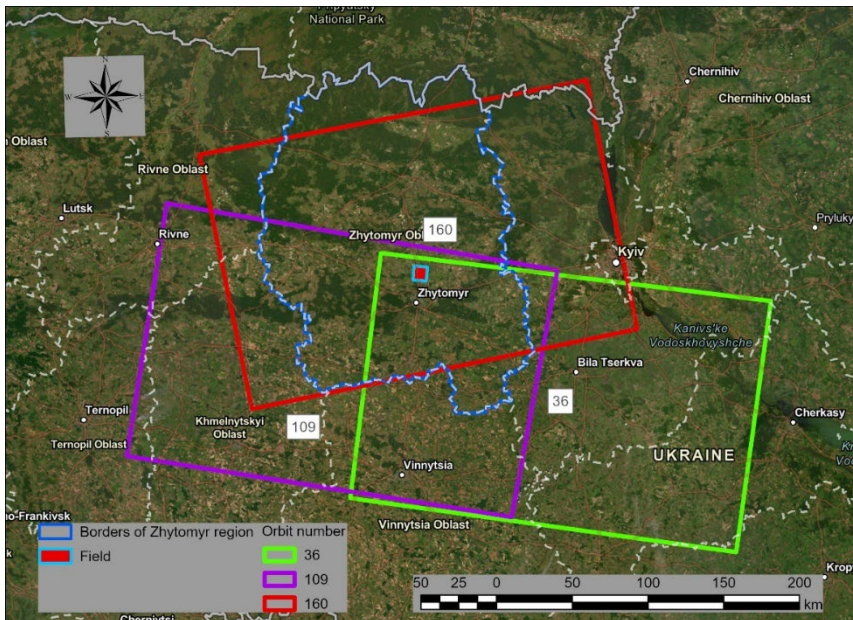


Figure 3. Coverage of the experimental field with tails (frames) of the Sentinel-1 spacecraft's relative turns (160, 109d, 36).

The characteristics of the signals emitted from the spacecraft, the type of land cover, the relative location of the experimental site, and the spacecraft's flight path determine the parameters of the registered image.

Utilization of polarization channels VV and VH for the estimation of oat crop density

To determine crop density, the Sentinel-1 radar polarization channels VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive) were used. Throughout the oat cultivation period, reflected signals were standardised to facilitate the comparison of various images. Recent research (Skydan et al., 2022; Fedoniuk et al., 2025) clearly shows that the VV channel is better for analyzing vertical plant structures, while the VH channel is more sensitive to different leaf orientations and structural differences in crops. The analysis of texture during the examination of crop structure features enabled us to categorize zones based on varying crop densities.

A study established that Sentinel-1 data, particularly the VH/VV ratio, can yield valuable insights on crop development. They specifically emphasised the findings from the time series study of the Sentinel-1 backscatter and ratio (VH/VV), noting their correlation with plant water content, height, and biomass index. The correlation between the observed Sentinel-1 data fluctuated during the growing season, with backscatter variations mostly influenced by structural changes during certain intervals.

The backscatter values VH and VV of oat fields exhibit a little decline until early June, followed by an increase leading up to harvest (Fig. 4). The backscatter signal is often more robust in VV polarization, commencing at approximately -9 dB (option NN - 26 April 2023) and around -11 dB (option NP - 26 April 2023), subsequently diminishing to approximately -15.5 to -18 dB by June 6, 2023. By the end of July, it rose once more to -12 dB (DN) and -18 dB (NN).

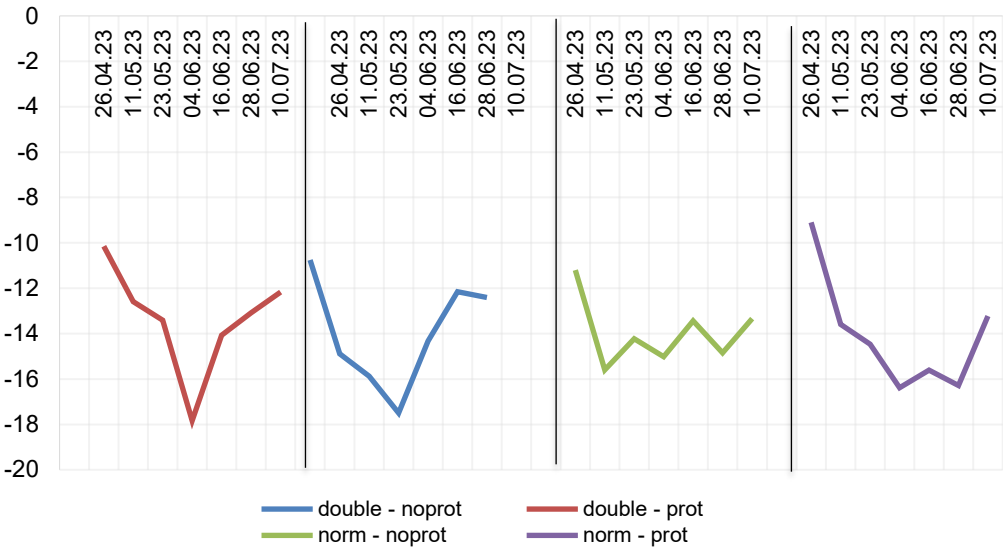


Figure 4. Backscatter VV values of oat fields.

VH backscatter commences approximately -20 dB (DP) and -22.5 dB (NP) on 26 April 2023, then decreasing to its lowest levels of approximately -21.8 to -24.2 dB in June (Fig. 5). The VV polarization backscatter rates demonstrate a more significant yearly fluctuation in comparison to the VH backscatter rates. The reduction in backscatter value till the end of June is particularly pronounced in VV backscatter. In April, preliminary results are significantly lower, exhibiting greater variability due to several cold snaps.

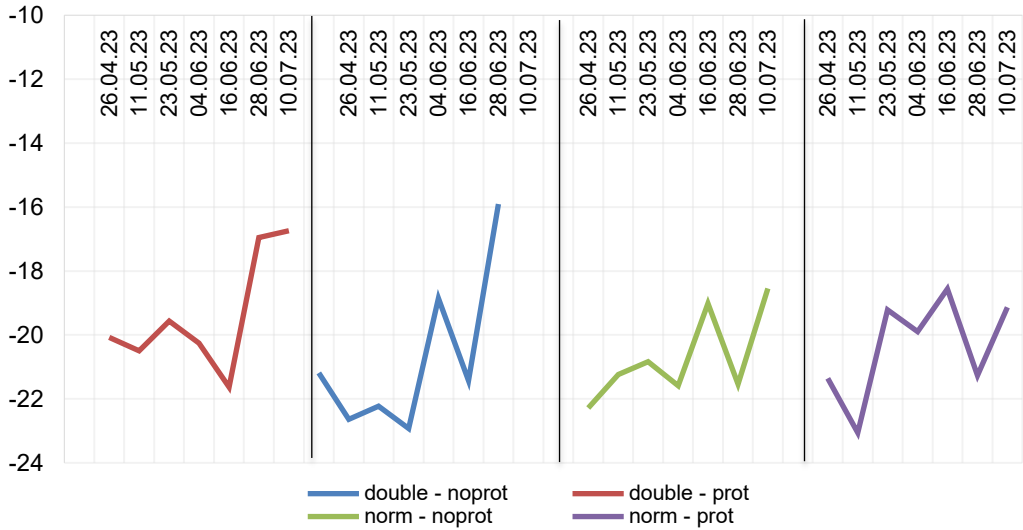


Figure 5. Backscattering value of VH in oat fields.

The VH/VV ratio exhibits an increase from the onset of the growth season until early June, following which it stabilizes or experiences a minor decline. VH/VV values commence at approximately -8 and attain their peak at roughly -2.5 in early June.

Table 3. The model depicting the correlation between the components of expanding oat fields and the polarization indicator

Call: $L_m(\text{Formula} = \text{Value} \sim \text{SowingNorm} + \text{Protection} + \text{VV} + P_{109d} + P_{160a} + P_{36d}, \text{data} = \text{data})$
 Residuals: Min -11.117; 1Q -1.802; Median -0.147; 3Q 2.001; Max 8.475

Indicator	Coefficients:			
	Estimate, S	Std. Error	t-value	Pr(> t)
(Intercept)	-12.435	0.138	-154.924	< 0.001
SowingNorm	-0.256	0.119	-2.145	0.032
Protection	-0.425	0.117	-3.618	< 0.001
VV	7.217	0.114	63.178	< 0.001
P_109d	0.852	0.136	6.239	< 0.001
P_160a	0.279	0.142	1.964	0.050
P_36d	NA	NA	NA	NA

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1; Residual standard error: 2.89 on 2554 degrees of freedom; Multiple R-squared: 0.613; Adjusted R-squared: 0.613; F-statistic 809.9 on 5 and 2554 DF; p -value < 0.001.

The derived model indicates (Table 3) that the sowing rate serves as the indicator for the satellite reaction. The variation in backscatter throughout the growing season can be attributed to the effects of soil and crop density, alongside structural alterations in plants and their moisture levels. In April, oat fields commence vigorous vegetative growth. The regression model used for evaluating the relationship between oat development and satellite indicators is described as follows:

$$Y = -12.435 - 0.256 \cdot \text{Sowing norm} - 0.425 \cdot \text{Protection} + 7.217 \cdot \text{VV} + 0.852 \cdot P_{109d} + 0.279 \cdot P_{160a} + \varepsilon \quad (2)$$

where Y is the predicted backscatter response, and ε is the error term. The model yielded an R^2 of 0.613, indicating a moderate to strong relationship.

A standard p -value was employed to assess statistical significance, with an adjusted p -value. The false discovery rate (FDR) control method was employed to ascertain this. This strategy reduces the likelihood of obtaining false-positive results when numerous hypotheses or variables are concurrently examined.

At this stage, the plant's height typically measures only 12–15 cm, insufficient for generating a discernible reaction in satellite imagery. Consequently, the condition of the soil surface at this moment is the primary factor influencing backscattering. The value of backscatter diminishes as the vegetative portion of plants develops, attributed to increased signal attenuation, a phenomenon documented in various publications (Harfenmeister et al., 2019; Getahun et al., 2024). These circumstances are mostly indicative of VV backscattering and are less prominent in VH backscattering. The VV backscatter is primarily influenced by the direct contributions of soil and vegetation, whereas the presence of vertical plant structures (stems) progressively attenuates the signal. VH backscattering is often more responsive to vegetation volume scattering; nevertheless, for oat plants, soil backscattering remains predominant during early phenological stages. Backscatter oscillations at the onset of 2023 are attributed to snow covering the fields, resulting in alterations to the scattering properties.

During May and June, oats undergo the phenological phases of vigorous growth. During these phases, the plants commence stem development, increase in height, and produce flag leaves. Backscatter values attain a minimum during the development of oat flag leaves, leading to maximum signal attenuation.

When the backscatter rates reach their minimum, the impact of plants on scattering surpasses the impact of the soil, leading to a backscatter rates increase for both polarizations.

Subsequently, the signal is predominantly scattered by vegetation, which increasingly overshadows the influence of the soil, leading to a continuous rise thereafter. In the following growth season, the soil's contribution rises once more as the plants' phytomass dehydrates. This results in a reduction in the increase in backscatter during late phenological phases to stable or diminishing values.

During the latter part of summer, the backscatter signal indicates alterations in vegetation structure and moisture content. The alteration in vegetative structure is particularly evident in oats. Following the decline of backscatter readings to their nadir in June, they commence an upward trajectory once more. However, in early June, the backscatter levels significantly rise by around 8 dB during a brief duration. The plants are currently sufficiently desiccated, with a moisture level below 50%. The backscatter values of oat fields decline once more following their peak during ear bending.

The experiment demonstrates that utilizing polarization channels VV and VH from Sentinel-1 data efficiently estimates oat crop density. This enables farmers to comprehend the status of their crops and make informed judgments regarding crop management. Sentinel-1 data, particularly the VH/VV ratio, can yield valuable insights into crop development. They emphasized the ability to differentiate cultures based on the temporal variation of backscatter. Outcomes of time series study of Sentinel-1 backscatter and polarization ratio (VH/VV) and their observed correlation with plant water content, height, and biomass index. The correlation between observed Sentinel-1 data and plant development fluctuated during the growing season, with backscatter fluctuations mostly influenced by structural changes during certain intervals.

The limitations of the research

A multisensory approach, utilizing satellites, was implemented to alleviate the impact of mistakes in evaluating oat development parameters. However, while collecting data from different sources, several types of errors may occur owing to differing factors. The primary category of errors, associated with meteorological conditions (cloud cover, fog, aerosols), may distort the image and undermine the integrity of the original data.

The influence of weather conditions was alleviated by standardising the shooting parameters for satellite imagery: ensuring a consistent cloud cover percentage (not surpassing 10%) and aligning the date of the satellite's transit over the research site. The insufficient resolution of satellite imaging can impede oat development detection. Thus, the satellite channels were chosen for their ability to provide photos with the highest spatial resolution (10 m) and the frequency of spacecraft passing over the research area, assuring uniform observational circumstances. Spectral offsets may affect the accuracy of vegetation type categorisation; hence, the study incorporated calibrated sensors and multispectral analysis.

The second block of factors may include data collection and processing errors, such as georeferencing inaccuracies (deficiencies in determining coordinates). RTK-GNSS was utilised for precise positioning to reduce errors. Noise and artefacts, such as reflections, shadows, and variable lighting, were corrected by image pre-processing and illumination normalisation. Furthermore, inconsistencies may occur when utilising different formats and procedures for processing data from satellites and other sources. The methodologies and timing of data gathering, processing techniques, and the application of standardised algorithms were synchronised. The identical conditions and observation timeframe were selected; specifically, the drone flyby occurred between 11:00 and 12:00 in the afternoon and the processing level is S2MSI2A.

The third group of errors may pertain to possible misclassifications of plants, arising from the similar spectral characteristics of cultivated plants and weeds. The risk was alleviated by sampling (5–8 pixels per microfield) and doing triplicate experiments, utilising machine learning, deep neural networks, and additional spectral indices (NDVI, GNDVI, MSAVI). Due to persistent cloud cover, it was not possible to derive NDWI or other optical vegetation indices from Sentinel-2 imagery. This limitation constrained our ability to directly assess vegetation water content via optical indices. Future research will consider multi-sensor integration to incorporate NDWI alongside radar-derived metrics. The various stages of oats growth confound identification; hence, multi-temporal data were utilised, conducting the investigation across vegetative periods. Furthermore, the

human factor may affect outcomes, especially through inaccuracies in model training or result interpretation. To prevent this, all data were verified by field validation utilising independent test sets.

CONCLUSION

Utilizing Sentinel-1 data to assess oat crop density is an efficient method owing to its distinctive characteristics. Weather-independent radar imagery yields precise and dependable outcomes for effective agricultural management: polarization channels VV (offers insights into vertical vegetation structures, aiding in the estimation of plant density and height) and VH (responsive to varying leaf orientations and crop structural inhomogeneities, beneficial for identifying density fluctuations).

Graph analysis and regression analysis enable us to infer the mechanisms of dispersal of oat fields at various phenological growth stages. The temporal behavior of oat fields exhibits sensitivity to alterations in plant structure, such as earing, and variations in moisture levels. The temporal patterns reflect the phenological progression of oat plants, evidenced by heightened signal attenuation due to vegetative growth in spring and alterations in scattering upon attaining a specific height and the emergence of flag leaves. This information might assist farmers in identifying the ideal periods for fertilizer application or harvesting. The disparities across fields are typically more pronounced than the variability within a field, attributable to the geometric properties of the images. Moreover, structural alterations in plants are not consistently reflected in the assessed yield indices.

The study confirms that the stated objective of using Sentinel-1 data to evaluate oat crop density and structure was achieved. The model demonstrated sufficient accuracy to warrant future exploration and practical application. The regression analysis results are notably favorable for oat fields during the early phenological stages, from tillering to full maturity. R^2 values about equal to 0.61 were characteristic of VV backscatter.

Nevertheless, regression outcomes exhibited considerable variation between fields attributable to disparities in data quality, incidence angle, planting density, or fertilizer application. A more extensive database encompassing extra years and observational fields is required to derive universally applicable regression equations for estimating yield parameters from backscatter measurements. The regression equations remain highly reliant on the available field data; nonetheless, discernible trends are evident and beneficial for subsequent research.

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Enhancing biogas production predictions using ARIMAX models on mixed silages

M. González-Palacio^{1,*}, L. González-Palacio², S. Villegas-Moncada³,
C. Arrieta-González³, M. Luna-delRisco³ and C. Arroyave-Quiceno⁴

¹Universidad de Medellín, Faculty of Engineering, Department of Information Technology, Carrera 84 # 30-65, CO 050026 Medellín, Colombia

²Universidad EAFIT, Faculty of Engineering, Department of Product Design and Experience, Calle 49 # 7 Sur-50, CO 050022 Medellín, Colombia

³Universidad de Medellín, Faculty of Engineering, Department of Energy, Carrera 84 # 30-65, 050026 Medellín, Colombia

⁴Universidad de Medellín, Faculty of Engineering, Department of Environmental Sciences, Carrera 84 # 30-65, CO 050026 Medellín, Colombia

*Correspondence: magonzalez@udemedellin.edu.co

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Abstract. Biogas production as a renewable energy source is gaining more attention from different actors in the energy sector due to the use of different residual products for its generation. This interest also comes from the agricultural sector. A typical crop used for biogas production is maize, which poses environmental challenges related to soil erosion and nutrient depletion. Furthermore, land use changes can also reduce biodiversity and attract pests. An increasing number of strategies to diminish these issues rely on combining maize with other leguminous plants, improving the nutritional silage profiles, and potentially enhancing biogas production. Nonetheless, adopting these new approaches remains limited since the farmers hesitate to invest in new technologies without clear and quantifiable improvements. In this regard, in this study, we propose time-series-based models to predict biogas and methane production based on the silage features of crops and the time-series data. In particular, we fitted models based on Autoregressive Integrated Moving Average with eXogenous variables (ARIMAX) to capture the temporal dependencies, aiming to characterize the methane volume and methane concentration accurately. We used a previously validated measurement campaign, which included other anaerobic digestion variables like volatile solids, crude protein, cellulose, and hemicellulose, among others, from crops of maize and mixed maize-legume silages, along with the production of biogas and methane, with a sample period in days. The reactor was a 5 L fermenter operated at 40 °C with manual mixing daily. It used inoculum and silage, with a 21-day delay before measurement. Biogas volume was recorded using a measuring cylinder, and composition was analyzed with a Dräger X-am 8000. We tested our ARIMAX-based models regarding their goodness of fit using the determination coefficient R^2 and the Root Mean Square Error (RMSE). In the case of the methane volume, we obtained an R^2 of 0.92 and an RMSE of 0.001 liters, and for the case of methane concentration, our models exhibited an R^2 of 0.908 and an RMSE of 0.85%. Our promising models help farmers, researchers, and policymakers to accurately

characterize and forecast biogas and methane production as promising renewable energy generation technologies.

Key words: anaerobic digestion, biogas production, time series, maize-legume silage, time-series forecasting.

INTRODUCTION

The global demand for energy sources has increased dramatically regarding the growing of production industries, data centers, computing for processing Artificial Intelligence (AI) based solutions, among others (Tiismus et al., 2025). In this regard, different alternative and renewable energy strategies have arisen to diversify the energy matrix, aiming to diminish the dependence on classical generation techniques based on fossil fuels, nuclear, or hydroelectric power plants (Mamidala et al., 2023). Among these approaches, anaerobic digestion has emerged as a suitable and promising option for biogas production to be further employed for thermal energy generation (Liu et al., 2021). This biological process is based on the use of organic materials that are decomposed by microorganisms in an oxygen-free environment, resulting in methane, carbon dioxide, and minimal traces of other gases depending on the chosen feedstocks (Mao et al., 2015). Furthermore, anaerobic digestion offers unique advantages, like the types of feedstocks that can be used to produce biogas, including livestock manure, food wastes, and sewage sludge (Thakur et al., 2023). For instance, pig manure is commonly used since its broad production in dedicated farms, making this feedstock highly available and biodegradable (Ferreira et al., 2024). Nonetheless, animal-based feedstocks can be very variable according to the characteristics of the surrounding environment, as in other processes (González-Palacio et al., 2024). The factors include climate, animal diet, housing systems, and management practices. Recent studies have emphasized that these environmental conditions significantly influence the physicochemical composition of animal-derived materials, such as manure, fat, and by-products, which in turn affect their suitability for bioenergy production or nutrient recovery (Okolie et al., 2023). This variability challenges the prediction of methane production and concentration.

In that way, promising alternatives of feedstocks based on crops started capturing the attention of the productive sector since they offer several advantages over other substrates, like the high level of biomass yield and convenient biochemical composition, among others (Hoang et al., 2022), which refers to the high content of fermentable sugars, cellulose, and hemicellulose, which are ideal for biofuel production due to their ease of conversion and high energy potential (Himmel et al., 2007). In particular, maize offers the advantage of high predictability since it can be produced to be consistent, facilitating a stable Anaerobic Digestion (AD) process. The consistency of maize silage is characterized by a relatively uniform chemical composition, particularly in terms of its carbohydrate content, which includes cellulose and hemicellulose. This uniformity contributes to predictable and stable biogas production rates and yields and stable AD performance (Kaparaju & Rintala, 2005). However, the cultivation of maize poses different environmental challenges, such as soil erosion and nutrient depletion (Ologunde et al., 2025). These issues can be mitigated by intercropping maize with

leguminous plants, enhancing the soil structure, fertility, and nutritional profile, improving the biogas production (Kintl et al., 2024). Nonetheless, the prediction of biogas production to adequately forecast the performance under different configurations is a time-consuming and expensive process that can be threatened by multiple sources, such as weather variations or pests (Pfordt & Paulus, 2025).

For this reason, active research is being conducted to develop reliable methods for predicting biogas production in nonlinear and highly variable AD processes, with the goal of identifying the best operational parameters, such as temperature, retention time, and feedstock mixture ratios, to enhance system efficiency and methane yield. Previous attempts at digester performance prediction employ mostly machine-learning models whose operation may not be traced back directly from the physical processes of the digester. The authors in (Kim et al., 2025) depicted the everyday evolution of a whey-fed lab reactor on a graph-convolutional network. The study used laboratory-scale anaerobic digesters with a 50 mL working volume, operated at 37 °C, and fed with whey-based substrate every three days to maintain a hydraulic retention time of 30 days. Different organic loading rates were applied, including high, medium, and low levels, with fluctuating patterns such as stepwise and abrupt changes to mimic real-world operational variations. Although the network simulated gas-rate dynamics highly accurately ($MSE = 0.01$) and identified shifts in the microbial community abundance with an R^2 of 0.72 and a microbial community composition with an R^2 of 0.87, the large number of latent parameters prevents a straightforward explanation of such associations.

The study conducted in (Zou et al., 2024) proposed a machine learning-based prediction model of biogas production in full-scale dry anaerobic digestion of kitchen food waste. The study employed operational data collected for 1.5 years from four full-scale digesters, including parameters such as biomass amount, addition of centrifuged sludge, liquid level, digester capacity, amount of product, and biochemical parameters such as pH. Eight machine learning algorithms were evaluated, of which CatBoost was the most accurate with R^2 values from 0.604 to 0.915 for biogas prediction. Although the high predictive performance, the complexity of the model, and the many latent parameters complicate a direct understanding of the inter-variable relationships.

The research carried out in (Avinash & Mishra, 2024) investigated the predictive potential of AI-based and kinetic models for AD biogas production. Batch digestion trials under various moisture content, organic load, and operational parameters like temperature, pH, and retention time were carried out to train the models. Different models, like artificial neural network (ANN), adaptive neuro-fuzzy inference systems (ANFIS), were trained and tested based on experimental biogas yield data. ANFIS network produced biogas yield with high precision ($RMSE = 0.670$, $R^2 = 0.999$) compared to traditional kinetic models that also provided good fits. Although the models were able to identify general trends, the dense input variable and biogas output relation within particular AI models had numerous parameters and hence may be hard to interpret as direct underlying biological processes.

The investigation reported in (Farzin et al., 2024) evaluated the efficacy of auto-tuning machine learning models for biogas yield prediction from a municipal wastewater treatment plant on a full scale. Data obtained from operation experiments collected from South-Tehran municipal wastewater treatment plant were utilized for parameters such as

influent and effluent volatile solids, pH, temperature, and organic loading rates. Different combinations of hyperparameter tuning and feature selection were performed using genetic algorithms and particle swarm optimization for enhancing model performance. Support vector regression (SVR) and ANNs were used with the models. The most precise model was formed using SVR with $R^2 = 0.77$ for test and 0.49 for RMSE. Despite this achievement, the complex relationship among the selected parameters discourages simple interpretability of the relationships among operating variables and biogas production.

The approach in (Geng et al., 2024) proposed a prediction model of food waste anaerobic digestion biogas production using an augmented mix-up data augmentation strategy and an improved global attention Long-Short Term Memory (LSTM) network. The data were derived from two AD food waste reactors with actual production data, including parameters such as pH, volatile fatty acids, total solids, volatile suspended solids, ammonia nitrogen, and chemical oxygen demand from a six-month monitoring period. Different feeding regimes and organic loading conditions were mimicked to simulate operational variances. Artificial training samples were generated by the proposed model via mix-up in an attempt to counteract the data sparsity issue, and utilized an improved global attention scheme in the LSTM architecture for better modeling of temporal dependency. Performance in prediction was adequate ($R = 0.988$), and the model strongly predicted the actual daily biogas production ($MSE = 0.002$) and was capable of providing recommendations for feed adjustment to optimal energy output. However, the interpretability of each input feature is lost with added complexity due to the attention mechanism and data augmentation methods.

While these studies show that data-driven models are capable of representing highly variable processes, they are subjected to a key limitation since they are based on non-interpretable architectures, so practitioners lack explicit information about how different predictor variables can affect the prediction. Few recent studies have revisited statistical time-series models. The authors in (Prasad et al., 2023) compared SARIMAX and ARIMA with a variety of machine-learning baselines on 117 days of batch data. The results showed that plain ARIMA had the lowest error of prediction ($RMSE = 3.26 \text{ L day}^{-1}$), indicating that plain parametric models perform similarly to black-box learners when faced with common temporal autocorrelations.

The summary of the reviewed approaches is shown in Table 1. where the following can be noticed. While these efforts demonstrate that data-driven models are able to track highly variable processes, they both possess two limitations that are of particular importance for crop-based digestion: (i) none of them deals with dedicated energy crops or mixtures of forage, though these substrates form a growing fraction of agricultural biogas plants, and (ii) all are based on non-interpretable architectures, thus practitioners have no explicit guidance on how fibre, starch or protein content affects the prediction. In this paper, we present a method based on Autoregressive Integrated Moving Average with exogenous variables (ARIMAX) models to estimate methane volume and content for several silage profiles. We used an extensive measurement campaign in (Kintl et al., 2024) where different silages were prepared for the experiment, including the monocultural

maize silage (MA) and the mixtures of maize with white sweet clover (MA+WSC), white lupin (MA+LU), and fodder vetch (MA+VE) in a wet weight ratio of 70:30.

Table 1. Comparison of techniques used to forecast biogas production in anaerobic digesters

Author	Variables considered to forecast biogas production	Techniques	Black-box?
(Kim et al., 2025)	Temperature (37 °C), hydraulic retention time (30 d), organic loading rate (high/medium/low, stepwise & abrupt changes), feeding frequency (every 3 d), microbial community composition	Graph-Convolutional Network (GCN)	Yes
(Zou et al., 2024)	Biomass amount, addition of centrifuged sludge, liquid level, digester capacity, amount of product removed, pH	CatBoost gradient-boosted decision trees	Yes
(Avinash & Mishra, 2024)	Moisture content, organic load, temperature, pH, retention time	ANFIS / ANN	Yes
(Farzin et al., 2024)	Influent & effluent volatile solids, pH, temperature, organic loading rate	Support Vector Regression (SVR) + GA/PSO tuning	Yes
(Geng et al., 2024)	pH, volatile fatty acids, total solids, volatile suspended solids, ammonia nitrogen, chemical oxygen demand	Global-attention LSTM with mix-up augmentation	Yes

Parameters of measurement considered during the experiments involved the silage chemical composition including measured variables like volatile solids, neutral detergent fiber, acid detergent fiber, crude fiber, starch, cellulose, hemicellulose, crude protein, lipids, and acid detergent lignin (Palacio et al., 2017); while volume and composition of the produced biogas were analyzed for methane yield through fermentation tests. Other physical parameters measured were the density of the silage and some other operational variables, namely, temperature of incubation, period of fermentation, and amount of silage used (Gonzalez-Palacio et al., 2018). Our original contributions are three-fold:

1. A feature extraction process where we analyze how different variables affect the production and concentration of methane using statistical indexes.
2. A modeling stage where we fit a parametric ARIMAX that considers the predictor variables that highly influence the AD process and methane production.
3. We interpret how the different variables affect the process of methane production, providing valuable insights on how to improve anaerobic digestion processes.

The rest of this paper is organized as follows: Section II describes the database we used to determine each variable's statistical features. Section III is divided into two subsections. The first subsection explains the feature analysis and extraction, and the second subsection shows the proposed models. Section IV shows the results after applying the proposed methodology and analyzes their practical implications. Finally, Section V concludes the paper.

EXPERIMENT & DATABASE DESCRIPTION

The experiment in (Kintl et al., 2024) consisted of assessing biogas production from different silage mixtures, namely maize and legumes. The silages were made in mini-silos, with the silage mixtures being monocultural maize silage (designated as MA) and mixtures of maize with white sweet clover (MA+WSC), white lupin (MA+LU), and fodder vetch (MA+VE) in a fresh weight ratio of 70:30. The maize for the silages was cut manually at a stubble height of 18 cm, shredded into pieces of approximately 15–20 mm using a cutter (Deutz-Fahr MH 6505), then mixed with a bacterial inoculant (Silo Solve EF by Chr. Hansen Holding Ltd.) and filled into mini-silos and fermented. After that, the authors subjected the silages to 90 days of incubation in anaerobic conditions. Then, the mini-silos were sampled for subsequent analyses. For the fermentation, 24 batch fermenters of five liters each were used, preserving the anaerobic conditions throughout the experiment. There were three fermentation systems with eight fermenters each, totaling 24 fermenters. In each system, two fermenters were controls, and the remaining six fermenters were dosed with silage samples. Since there were four silage variants, each was tested in three replicate fermenters across all systems. After the incubation period of 90 days, the mini-silos were opened, samples were homogenized, frozen, and transported for chemical analyses and fermentation tests. Regarding sampling frequency, the samples were collected once after the 90-day incubation.

The setup permitted daily measurement of biogas production, with the produced biogas displacing a salt-saturated solution from the measuring cylinder into an expansion tank. The biogas generated was passed through an instrument (Dräger X-am 8000) for its composition, especially methane content. The fermenter conditions were carefully controlled, where the temperature was at $40\text{ }^{\circ}\text{C} \pm 0.2\text{ }^{\circ}\text{C}$ provided by water baths. From the fermentation process, the volume and composition of the produced biogas were determined. Besides, the efficiency and yield of the biogas and methane production were also assessed from the varying silage mixtures. The variables measured in the experiment trials are as follows:

1. **SUBSTRATE:** The type of silage being analyzed (e.g., maize, mixed silage with legumes).
2. **DAY:** The day of sampling during fermentation.
3. **DM:** Dry Matter (%), representing the portion of the silage that remains after water is removed.
4. **VS:** Volatile Solids (%), a measure of the organic matter in the silage that can generate biogas.
5. **NDF:** Neutral Detergent Fiber (%), indicating the structural carbohydrates present in the plant material.
6. **ADF:** Acid Detergent Fiber (%), a measure of the resistant fibrous fraction containing cellulose and lignin.
7. **CF:** Crude Fiber (%), representing the indigestible portion of the feedstuff.
8. **STARCH:** Starch (%), the amount of starch present in the silage, which is a key fermentation substrate.

9. **ASH:** Ash (%), representing the inorganic mineral content remaining after combustion of the organic matter.

10. **CELLULOSIS:** Cellulose (%), the content of cellulose, a major component of the plant cell wall.

11. **HEMI-CELLULOSIS:** Hemicellulose (%), the content of hemicellulose, another digestible structural carbohydrate.

12. **CP:** Crude Protein (%), measuring total protein content available in the silage.

13. **LIPIDS:** Lipids (%), representing the fat content present in the silage.

14. **ADL:** Acid Detergent Lignin (%), measuring the lignin content, which affects digestibility.

15. **BIOGAS:** Biogas Volume (L), the total volume of gas produced during anaerobic digestion.

16. **METHANE:** Methane Volume (L), indicating the volume of methane gas produced as part of the biogas.

17. **METHANE_CONTENT:** Methane Content (%), the concentration of methane in the biogas, highlighting the fermentation efficiency.

Furthermore, Table 2 shows the descriptive statistics regarding the mean, standard deviation, minimum, maximum, and quartiles. These statistics were calculated using the entire dataset, encompassing the maize and the diverse silage mixtures, illustrating the distributions and variability of the key chemical parameters across the experiments.

Table 2. Descriptive statistics of the AD process

	Mean	Std. Dev	Min	Q1	Median	Q3	Max
DAY	11	6.092	1	6	11	16	21
DM	32.222	1.136	30.53	31.783	32.33	32.77	33.7
VS	95.65	0.519	94.78	95.507	95.885	96.028	96.05
NDF	33.825	3.347	30.17	32.03	32.95	34.745	39.23
ADF	22.807	2.332	20.41	21.438	22.1	23.47	26.62
CF	17.44	2.812	15.19	15.73	16.175	17.885	22.22
STARCH	24.782	7.8	15.57	18.322	24.285	30.745	34.99
ASH	4.35	0.519	3.95	3.973	4.115	4.492	5.22
CELLULOSIS	22.727	3.342	19.49	19.97	21.775	24.533	27.87
HEMI-CELLULOSIS	12.375	0.826	11.04	12.037	12.66	12.997	13.14
CP	11.28	1.719	9.03	10.012	11.325	12.593	13.44
LIPIDS	2.81	0.404	2.25	2.625	2.805	2.99	3.38
ADL	0.568	0.268	0.32	0.35	0.48	0.698	0.99
BIOGAS	0.652	0.18	0.145	0.605	0.658	0.713	1.026
METHANE	0.254	0.085	0.022	0.22	0.254	0.304	0.383
METHANE_CONTENT	38.815	10.441	12.22	28.689	37.537	42.601	55.106

This statistical overview can be used to understand and model their influences on biogas production. From this table, the following can be noticed. The DM content did not exhibit high variability, with an average of 32.22% and a standard deviation of 1.136, which denotes homogeneity in the composition of the substrate. Similarly, the VS, which is important for methane production, had little variation, with an average of 95.65% and a small range between 94.78% and 96.05%, which also suggests homogeneity in the organic matter present and favorable to microbial degradation. On the other hand, NDF

and ADF, indicative of carbohydrate substrate structure, were highly varied and ranged between 30.17% and 39.23% for NDF and 20.41% and 26.62% for ADF, thus showing variation in the composition of materials subjected to experiments, especially with respect to fiber contents. The same behavior was exhibited by the CF contents, which varied in the range of 16.175%, with the highest value as high as 22.22%, a fact suggesting variation in digestibility for samples. Besides, starch contents, impacting the immediate availability of fermentable carbohydrates, were very variable, with a mean of 24.78% and a standard deviation of 7.8%, ranging from 15.57% to 34.99%, suggesting variation in silage composition, which might impact fermentation processes. Furthermore, ash contents were also variable, highly uniform, and showed values that cluster around 4.35%, reflecting the incorporation of inorganic matter. The cellulose and hemicellulose contents, contributing to the slow biomass decomposition, were relatively variable in their content. Cellulose ranged between 19.49 and 27.87%, with an average of 22.727%, while hemicellulose ranged between 11.04 and 13.14%, indicating a relatively uniform composition in this portion of the fiber. The crude protein content, which is important for microbial processes, averaged 11.28 and ranged between 9.03 and 13.44%, indicating variable substrate compositions. Even though present in lesser concentrations, the range for lipids extended between 2.25 and 3.38%, with an average of 2.81%, and could impact methane yield through high-energy contents. The lignin of acid detergent, which represents the resistant biomass, was characterized by minimum values, with an average of 0.568 and a high of 0.99%. This indicates that lignin, which is one of the limiting substrates in anaerobic digestion, is at a minimum concentration and might, therefore, encourage higher biodegradability. The yield range for biogas production was from 0.145 to 1.026 liters (l), averaging (l). Similarly, the methane yield ranged between an average of 0.254 L and a high of 0.383 L. Methane in biogas had a high variance between 12.22% and 55.1%, averaging at 38.8%. This suggests that variable substrate compositions impact methanation concentrations notably. Together, the magnitude and spread of biogas, methane, and methane content (bolded in Table 2) provide a realistic, internally consistent dataset that reflects both the transient and the quasi-steady phases of AD, making it well suited for performance analysis and for testing predictive models that must cope with highly dynamic digester conditions.

METHODOLOGY

The modeling process is depicted in Fig. 1 and comprises four stages. The first stage is the Extraction, Transformation, and Load (ETL) step to transform the variables into a set of suitable measurements that can be used for modelling purposes. The second stage analyzes which predictor variables effectively explain the variability of the objective variables and selects the subset of them that is useful for the subsequent models. The third stage deals with the modeling, where ARIMAX-based models are fitted to predict methane volume and methane content. Our modeling framework is built upon the ARIMAX(p, d, q) model, an advanced version of the standard ARIMA model incorporating external predictors. In this context, p refers to the autoregressive terms representing the effect on the target variable at present due to values from the past, d is the number of differentiations necessary to fulfill the stationarity assumption, and q refers to the count of moving-average terms describing serially correlated shocks. The 'X' in ARIMAX indicates that, in addition to its own history and past of error

forecasts, the series is regressed on exogenous covariates (in this case, silage composition measurement) such that the model is able both to capitalize on internal temporal relationships and quantify the direct impact of external predictors on biogas and methane output. The parameters are estimated simultaneously (typically by maximum likelihood), and the selection of p , d , and q is based on standard diagnostic statistics such as the autocorrelation and partial autocorrelation functions. Finally, the fourth stage uses the models' predictions to analyze the results and practical implications. The following subsections detail each stage.

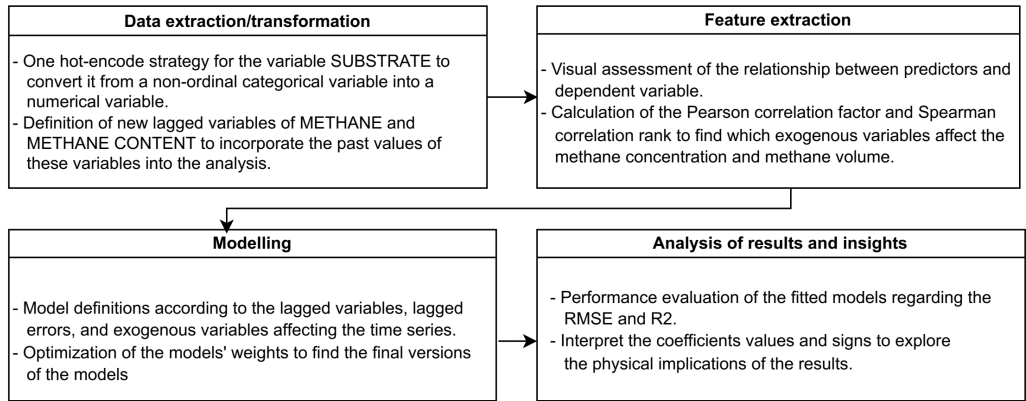


Figure 1. Modeling process that consists of four stages: data extraction and transformation, feature extraction, modeling, and analysis of results.

Data extraction and transformation

The first step we carried out to prepare the database includes two tasks: *i*) a one-hot encoding strategy to convert a non-ordinal categorical variable into a numerical one, like in the case of SUBSTRATE, whose order and values do not exhibit a particular order, and *ii*) a lagging strategy for the variables METHANE and METHANE CONTENT since past values of these variables affect the current and future state of them.

One-Hot encoding

This technique is used to convert categorical variables into numerical representations without inserting a false ordinal relation between categories. If a categorical variable X has k categories, we can transform it into a binary matrix representation where each category represents a binary feature. Mathematically, the variable X can be represented as

$$X = \{\text{MA}, \text{MA} + \text{LU}, \text{MA} + \text{VE}, \text{MA} + \text{WSC}\}, \quad (1)$$

where each element in the set represents a particular combination of the maize and a certain leguminous. We can create a one-hot encoding representation using an indicator function by

$$X_i^{(j)} = \begin{cases} 1, & \text{if the sample } i \text{ belongs to category } j \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where $X_i^{(j)}$ represents the presence (1) or absence (0) of category j in sample i . This transformation is required since the considered models cannot process or analyze

categorical variables directly. It avoids the algorithms assuming a hierarchical or categorical relationship among the categories, which is incorrect in this context.

Lagged variables

Since the methane concentration and methane volume can be modeled using time-series analyses, the incorporation of lagged variables is crucial to enhance the predictability of the fitted models. This dependence can be mathematically modeled as follows. Let Y_t be a time-series variable (e.g., METHANE or METHANE_CONTENT) where t represents time (days in this case). A lagged variable is

$$Y_{t-k} = \text{Value of } Y \text{ at time } t - k, \quad (3)$$

where k represents the lag order (e.g., 1, 2, ..., n days before). In that way, each lag indicates a new variable that can be considered for the time-series analysis for feature extraction purposes.

Features extraction

The second step deals with the relationship between predictor variables with respect to the dependent variable. To this end, we conduct the following steps. First, we plot each independent variable versus the METHANE and METHANE_CONTENT to understand if a predictable pattern can be found from these relationships. After defining these regions, we use the Pearson correlation factor which describes the linearity between the variables within the range of $[-1, 1]$. That is, *i*) a value close to +1 means a strong positive correlation; *ii*) a value close to -1 means a strong negative correlation; and *iii*) a value close to zero means an insignificant correlation.

Besides this, the Spearman correlation coefficient measures whether there is a monotonic nonlinear function that captures the patterns and relationships between two variables. It is performed by ranking data from lowest to highest, assigning sequential ranks across every row in the dataset, calculating a difference d for both the predictor and dependent variables at every rank, and computing the rank correlation coefficient ρ . Our design criterion was to consider the variables whose Pearson and Spearman indices were above 0.5, meaning that the chosen variables can explain more than 50% of the variability of the corresponding dependent variables.

On the other hand, we also have to analyze how the past values of METHANE and METHANE_CONTENT can affect the current values of both variables, that is, how the lagged versions of them can be used to forecast their current and future values. It can be performed using the following analysis: *i*) first, we determine if the time series for both variables are stationary, using the Augmented Dickey-Fuller (ADF) test, *ii*) in case of non-stationarity, differentiate the time series until stationarity, *iii*) obtain the Partial Autocorrelation Function (PACF) and the Autocorrelation Function (ACF), and *iii*) with these results, determine the lagged variables and past errors that affect the current and future predictions. Regarding the ADF test, we can calculate the following expression for p lags by

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^p \alpha_i \Delta Y_{t-1} + \epsilon_t, \quad (4)$$

where $\Delta Y_t = (\rho - 1)Y_{t-1}$ represents the first-order difference, δ is a coefficient obtained using Ordinary Least Squares which represents how the prior value Y_{t-1} affects the

current value Y_t , α_i are the coefficient for p lagged values of Y_t , and ϵ_t is zero-mean independent and identically distributed gaussian noise. Then, we calculate the ADF statistic by

$$\text{ADF statistic} = \frac{\rho}{\text{SE}(\rho)}, \quad (5)$$

where $\text{SE}(\rho)$ is the standard error of ρ . The ADF statistic is then compared with the critical value of 0.05 (95% confidence) and if it is less than the critical value, we conclude that the time series is stationary. In case that the series is not stationary, we compute the first difference as

$$Y_{\text{lag1}} = Y_i - Y_{i-1}, \quad (6)$$

where Y_i is the i^{th} value of the series and Y_{i-1} is the prior value of the series. The same procedure can be implemented for more lags if needed.

Modelling

Once we have selected the features that are essential in the prediction of METHANE and METHANE_CONTENT, we fit a parametric method (ARIMAX). The ARIMAX(p, d, q) model is a time-series model that aims to incorporate the dependence of the dependent variable on their p past values, q past forecasted errors, d differentiations over the dependent variable, and the influence of the exogenous variables. It can be represented by

$$Y_t^* = \beta_0 + \sum_{k=1}^K \beta_k X_{t,k} + \sum_{i=1}^p \phi_i Y_{t-i}^* + \sum_{j=1}^q \theta_j \epsilon_{t-j} + \epsilon_t, \quad (7)$$

where Y_t^* represents the differenced series after applying d levels of differencing to achieve stationarity. The term β_0 is the intercept, β_k represents the coefficients associated with the exogenous variable $X_{t,k}$, considering that there are K exogenous variables. The coefficients ϕ_i correspond to the autoregressive terms that capture the dependence of the series on the past values. The moving average terms are weighted using θ_j , accounting for the past forecast errors on the current observation, and ϵ_t is the error noise. We use the PACF and ACF to determine the values for p and q . We use the Pearson/Spearman indexes to determine the exogenous variables that affect METHANE and METHANE_CONTENT from Table 2. Finally, we differentiate the series until the ADF test indicates stationarity.

RESULTS

This section presents the results of the proposed framework for modeling METHANE and METHANE_CONTENT. We used Anaconda Python for the statistical analysis regarding correlations, stationarity, and ARIMAX modeling. The time series are depicted in Fig. 2. From these trends, it can be noticed that the production and concentration of methane exhibit two stages. First, the variables rapidly increase, and then they tend to stabilize. The changes in the substrates influence the system's capacity to produce methane. In that way, we will provide ARIMAX-based models for both METHANE and METHANE_CONTENT.

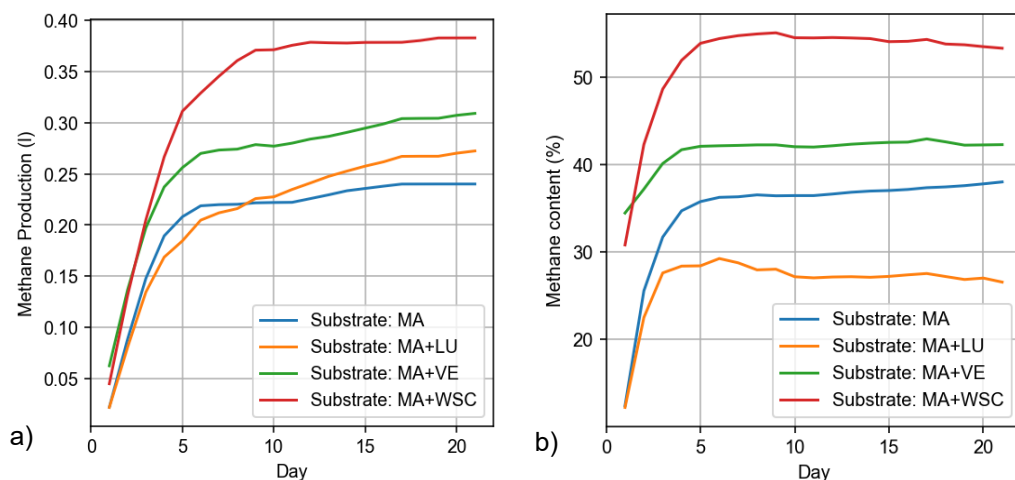


Figure 2. Raw time series from (Kintl et al., 2024) of (a) methane production in liters, and (b) concentration of methane in %.

Features extraction

After applying the one-hot encoding previously discussed in Eqs (1) and (2), we computed the Pearson and Spearman correlation indexes to elucidate which predictor variables can explain the variability of the dependent variables. The results of both tests are depicted in Fig. 3 and Table 3, from which it can be noticed how various parameters of silage composition are related to methane production since the absolute volume of methane (METHANE) and the methane percentage in biogas (METHANE_CONTENT) exhibit high correlations. The strongest positive correlations are between Crude Fiber (CF) and METHANE and METHANE_CONTENT with Pearson correlation coefficients of 0.547 and 0.766, respectively. This would suggest that all of the silages with higher fiber content yield more methane, likely due to these silages having more degradable fibrous material available for microbial degradation. Acid Detergent Fiber (ADF) and Neutral Detergent Fiber (NDF) also show moderately high positive correlations with methane production, once again in agreement with the fact that substrates of fiber lead to greater production of methane.

Furthermore, DAY of sampling has a high correlation with methane formation, i.e., METHANE (0.625 Pearson, 0.634 Spearman). This would be an indication of an increase over time in the formation of methane due to successive degradation of organic matter during fermentation. Its correlation with METHANE_CONTENT is less (0.214 Pearson, 0.194 Spearman), so the amount of methane is rising over time, but its proportion in the gas phase is relatively more stable. Cellulose (CELLULOSIS) and Hemicellulose (HEMI-CELLULOSIS) also correlate positively with methane production at METHANE_CONTENT (0.479 Pearson, 0.471 Pearson for CELLULOSIS and HEMI-CELLULOSIS, respectively). This would imply that these structural carbohydrates are being enriched by methane through their most likely microbial degradation pathways. Conversely, Crude Protein (CP) and Lipids are inversely related to both measures of methane. The crude protein is -0.252 and -0.466

Pearson correlated with METHANE and METHANE_CONTENT, respectively, and lipids have a stronger inhibitory effect on METHANE_CONTENT (-0.324 Pearson, -0.353 Spearman). These patterns suggest that substrates that have greater protein and lipid content may inhibit the production of methane, perhaps due to microbial inhibition or redirection of the metabolic pathways to produce alternative fermentation end products.

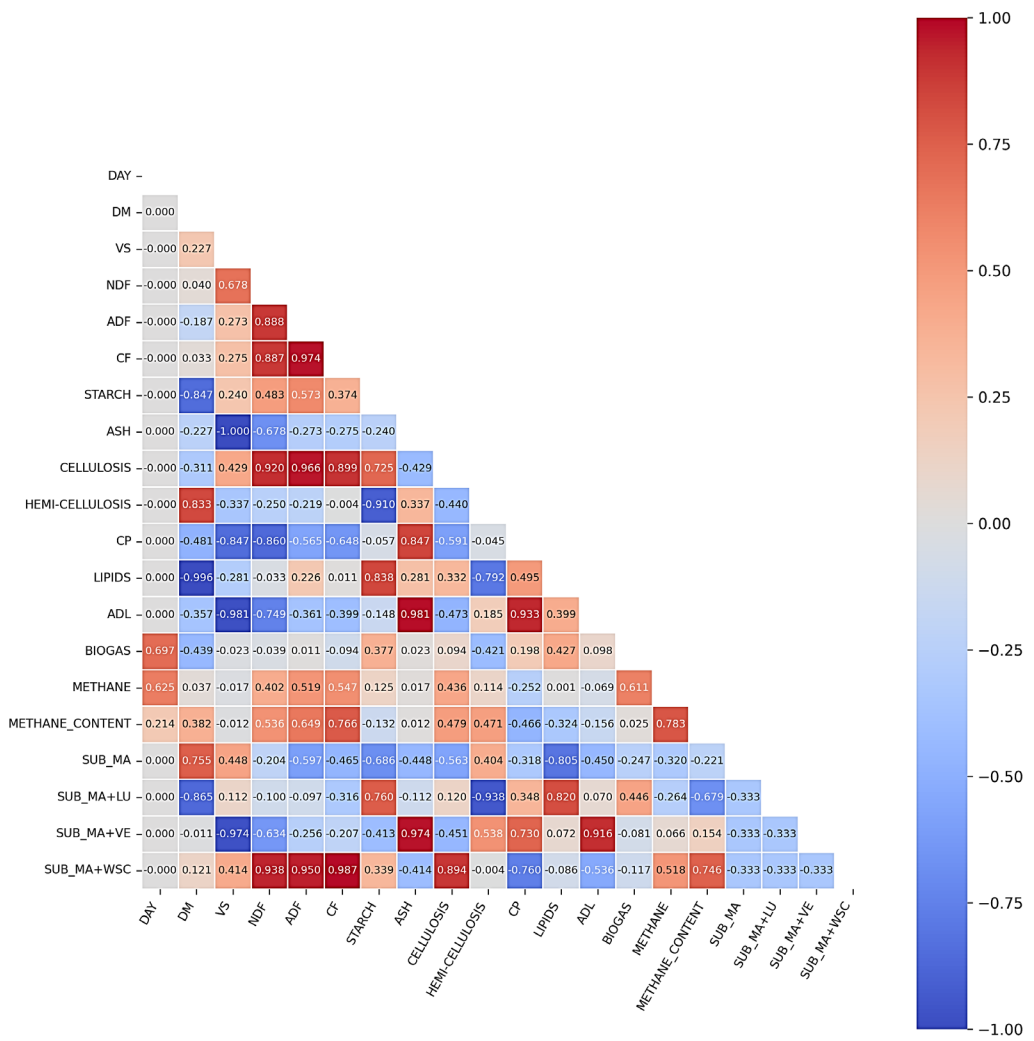


Figure 3. Correlation matrix of the raw data from (Kintl et al., 2024) based on the Pearson index.

Table 3. Pearson and Spearman correlation indexes for METHANE and METHANE_CONTENT versus possible predictor variables of the whole dataset provided by (Kintl et al., 2024). Variables highlighted in bold indicate correlations over 0.5. As a design parameter, we chose these variables since they can explain the variability of the dependent variables over 50%

Predictor variable	Pearson		Spearman	
	METHANE	METHANE CONTENT	METHANE	METHANE CONTENT
DAY	0.625	0.214	0.634	0.194
DM	0.037	0.382	-0.007	0.353
VS	-0.017	-0.012	-0.191	-0.019
NDF	0.402	0.536	0.230	0.169
ADF	0.519	0.649	0.465	0.363
CF	0.547	0.766	0.649	0.735
STARCH	0.125	-0.132	0.144	-0.181
ASH	0.017	0.012	0.191	0.019
CELLULOSIS	0.436	0.479	0.465	0.363
HEMI-CELLULOSIS	0.114	0.471	0.090	0.375
CP	-0.252	-0.466	-0.180	-0.346
LIPIDS	0.001	-0.324	0.007	-0.353
ADL	-0.069	-0.156	-0.180	-0.346
SUB_MA	-0.320	-0.221	-0.424	-0.247
SUB_MA+LU	-0.264	-0.679	-0.293	-0.706
SUB_MA+VE	0.066	0.154	0.182	0.255
SUB_MA+WSC	0.518	0.746	0.535	0.698

The correlations also indicate that silage compositions incorporating white sweet clover (MA+WSC) exhibit the strongest positive correlation with METHANE_CONTENT (0.746 Pearson, 0.698 Spearman), suggesting that this mixture enhances methane enrichment in the produced biogas. This could be attributed to the biochemical composition of white sweet clover, which may provide optimal fermentable substrates for methanogenesis. In contrast, silages containing white lupin (MA+LU) show a strong negative correlation with METHANE_CONTENT (-0.679 Pearson, -0.706 Spearman), indicating that its inclusion may reduce methane concentration in the biogas. The high protein content and potential presence of bioactive compounds in white lupin might inhibit methanogenic activity, leading to lower methane yields. The impact of fodder vetch (MA+VE) appears to be more neutral, with weak positive correlations (0.066 Pearson, 0.255 Spearman), suggesting that while it does not significantly enhance methane concentration, it also does not strongly inhibit it. These findings imply that white sweet clover is the most favorable silage component for maximizing methane content, while white lupin may hinder methane production, potentially making it less desirable for biogas optimization. In summary, the exogenous variables for the ARIMAX models for METHANE are ADF, CF, and SUB_MA+WSC. Regarding the exogenous variables for METHANE_CONTENT, we selected NDF, ADF, CF, SUB_MA+LU, and SUB_MA+WSC.

Regarding the use of ARIMAX models, we have to assess the following conditions: *i*) determine if the METHANE and METHANE_CONTENT series are stationary using the Augmented Dickey-Fuller (ADF) test (Eqs (4) and (5)),

ii) differentiate the series until stationarity (Eq. (6)), and iii) use the ACF and PACF to elucidate which lags and past errors contribute to the predictions. For the first and second steps, we conducted the ADF tests, whose results are depicted in Table 4. From this, it can be noticed that the differentiation of the time series achieved stationarity since the ADF statistics are greater than the critical values and the p -values are less than 0.05, equivalent to a statistical significance of 95%. In that way, we chose $d = 1$ in the ARIMAX model; that is, we will use the first difference instead of the raw time series.

Table 4. Augmented Dickey-Fuller Test for METHANE and METHANE_CONTENT time series without differentiation and with differentiation. If the ADF statistic is greater than the critical value or the p -value is less than 0.05 (95% confidence), the resulting time series is stationary

Differentiation order	METHANE			METHANE_CONTENT			Conclusion
	ADF statistic	Critical value	p -value	ADF statistic	Critical value	p -value	
No differentiation	-2.416	-4.137	0.137	0.757	-3.889	0.99	No stationary
Differentiation 1	-4.58	-3.517	0.0001	-6.862	-3.516	1.59E-09	Stationary

For the third step, we computed the ACF and PACF to elucidate which lags and past errors should be considered for the corresponding models using the differentiated series. The plots of these functions are depicted in Fig. 4. Each vertical line indicates the lag in the case of the ACF and the past error in the case of the PACF. If a line is over the blue-shaded region, it means that the corresponding lag/error should be considered for the regression.

From Fig. 4, (a), it can be noticed that the plot of the ACF of the differenced METHANE series is positive at lag 0 and negative at lag 1, and the remaining values fluctuate within the confidence band (blue-shaded area). It shows that the moving average term has to include error terms at lag 0 and 1 and because the subsequent lags do not show any correlation. Besides, from Fig. 4, (b), it can be noticed that the PACF also shows that the lags 0, 1, and 2 are significant, indicating that an autoregressive term of order 3 would be sufficient to capture dependencies in the data. These patterns indicate that an ARIMAX model for METHANE would consist of three autoregressive terms, two moving average terms, and the exogenous variables ADF, CF, and SUB_MA+WSC, that is, an ARIMAX(3,1,2) expressed as

$$\text{CH}_4_t = \beta_0 + \beta_1 \text{ADF} + \beta_2 \text{CF} + \beta_3 \text{WSC} + \phi_1 \text{CH}_4_{t-1} + \phi_2 \text{CH}_4_{t-2} + \phi_3 \text{CH}_4_{t-3} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2}, \quad (8)$$

where CH_4_t represents the methane volume at the time t , ADF represents the Acid Detergent Fiber content, CF represents the Crude Fiber content, WSC represents the silage with maize and white sweet clover, CH_4_t represents the methane volume in the previous day, CH_4_{t-2} represents the methane volume two days ago, β_0 represents the independent term, β_1 is the weight for the ADF, β_2 is the weight for the CF, β_3 is the weight for the silage prepared with maize and white sweet clover WSC, ϕ_1 is the weight for the lag 1 of CH_4 , ϕ_2 is the weight for the lag 2 of CH_4 , ϕ_3 is the weight for the lag 3 of CH_4 , θ_1 is the weight for the lagged error ϵ_{t-1} , and θ_2 is the weight for the lagged error ϵ_{t-2} .

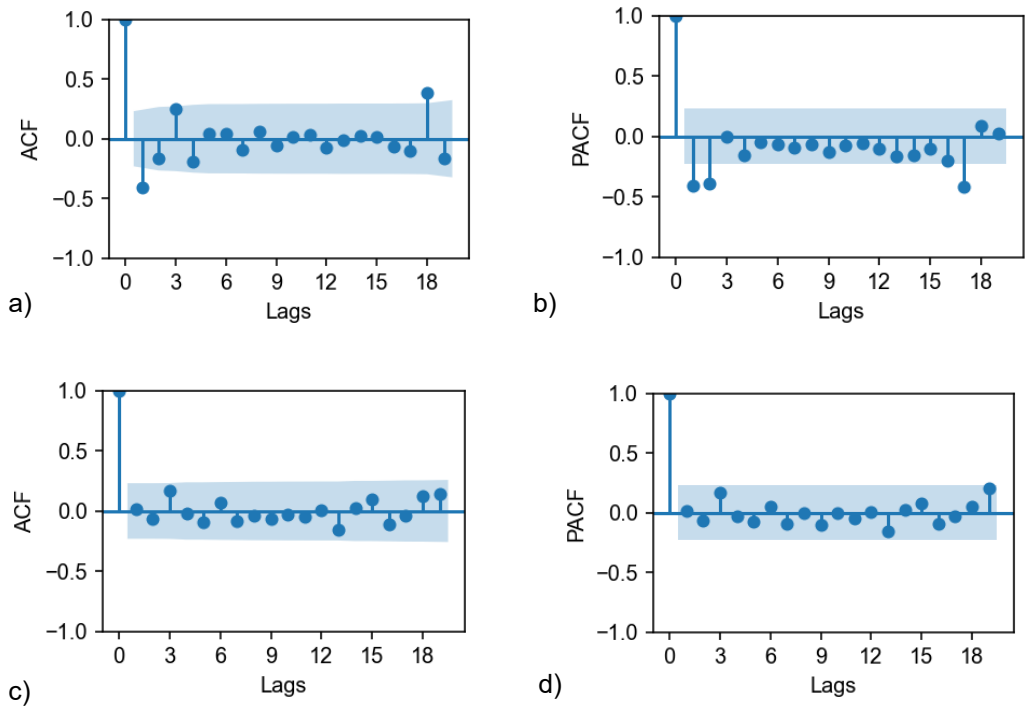


Figure 4. Plots of (a) ACF of METHANE, (b) PACF of METHANE, (c) ACF of METHANE_CONTENT, and (d) PACF of METHANE_CONTENT. The plots are for the differentiated series.

Regarding the METHANE_CONTENT, we analyze Fig. 4, (c), and (d) where the following can be noticed. First, Fig. 4 (c), shows the ACF plot and indicates that only the lag 0 is significant (the first difference), so it suggests that only the first lagged error should be included in the model because the other lags are inside the blue-shaded region. Besides, Fig. 4, (d), shows the PACF, suggesting the same configuration, i.e., only the first lagged difference should be considered. This implies that a single moving average and a single autoregressive term would be appropriate. Since both series required one difference to become stationary, an ARIMAX(1,1,1) specification is a feasible model of the underlying dynamics described by:

$$C\_CH4_t = \beta_0 + \beta_1 ADF + \beta_2 CF + \beta_3 WSC + \beta_4 NDF + \beta_5 LU + \phi_1 C\_CH4_{t-1} + \theta_1 \epsilon_{t-1}, \quad (9)$$

where C_CH4_t represents the methane content at the time t , $CH4_{t-1}$ represents the methane content in the previous day, NDF represents the Neutral Detergent Fiber, LU represents the silage with maize and white lupin, β_0 represents the independent term, β_1 is the weight for the ADF, β_2 is the weight for the CF, β_3 is the weight for the silage prepared with maize and white sweet clover WSC, β_4 is the weight for NDF, β_5 is the weight for the silage prepared with maize and white lupin, ϕ_1 is the weight for the lag 1 of C_CH4 , and θ_1 is the weight for the lagged error ϵ_{t-1} .

Modeling

This subsection shows the fitted models and the corresponding results in predicting METHANE and METHANE_CONTENT. We also provide a goodness-of-fit analysis for each fitted model.

ARIMAX model for METHANE

We fitted the model in Eq. (8), obtaining the coefficients in Table 5. To carry out the fitting process, we used the first 16 days of METHANE values and the values from 17 to 21 to perform the goodness-of-fit analysis. We aim to evaluate how the models perform with unknown data that has not been observed previously in the training phase.

The coefficients in Table 5 help analyze the contribution of different factors to methane production from physical and statistical standpoints. The variables of substrate composition, ADF, CF, and WSC have coefficients expressed as liters per percentage unit or liters and indicate how the methane yield is affected by variation in the feedstock composition. The moving average components (θ_i) and autoregressive components (ϕ_i) are adimensional because they measure the impact of past values of methane and past errors of forecasting on the observed output. Furthermore, we can analyze the magnitudes and signs of the coefficients to draw conclusions about the effects of the different variables.

For instance, the Acid Detergent Fiber coefficient is 0.0697 liters per unit percentage, or a 1% increase in ADF causes an increase of 0.0697 liters of methane. This relatively low value suggests that ADF exerts a very small effect on methane production, most likely because it is composed of cellulose and lignin, which are broken down slowly. For the case of Crude Fiber (CF), the model obtains a more pronounced effect with a coefficient of 0.1327 liters per percentage unit, which implies that substrates with more crude fiber produce more methane. Besides, this suggests that CF is a more effective predictor of methane yield than ADF. Finally, the coefficient for WSC (0.6045 liters) showed the largest contribution, which indicates that the availability of this substrate significantly triggers methane production.

On the other hand, the autoregressive coefficients (ϕ_1, ϕ_2, ϕ_3) capture the impact of past methane values on current methane output. The positive value of ϕ_1 at 0.2016 indicates that an increase in methane production at the time $t-1$ causes an increase in methane at the current time t , indicating some persistence in methane production. However, the negative values for $\phi_2 = -0.0402$ and $\phi_3 = -0.427$ imply a suppression effect with lag, where methane levels two and three times in the past contributed to lowering current methane output. The more negative value of ϕ_3 indicates that this oscillatory effect is stronger after three-time steps, perhaps due to substrate depletion, microbial adaptation, or inhibitory compounds affecting methane production in the long term.

Table 5. Fitted weights for the ARIMAX(3,1,2) model for METHANE

Coefficient	Variable	Value	Units
β_1	ADF	0.0697	liter/%
β_2	CF	0.1327	liter/%
β_3	WSC	0.6045	liter
ϕ_1	$CH4_{t-1}$	0.2016	Adim
ϕ_2	$CH4_{t-2}$	-0.0402	Adim
ϕ_3	$CH4_{t-3}$	-0.427	Adim
θ_1	ϵ_{t-1}	0.6417	Adim
θ_2	ϵ_{t-2}	-0.413	Adim

The parameters of the moving average (θ_1, θ_2) capture the effect of past errors in predicting the current methane production. The positive value of $\theta_1 = 0.6417$ means that higher-than-average methane production in the previous time step increases the current value, and this helps support short-term fluctuations. The negative value of $\theta_2 = -0.413$ means that two periods' past errors work in the opposite way and counter or reduce very large fluctuations.

Regarding the accuracy of the ARIMAX model for METHANE, we obtained an R^2 of 0.92 and an RMSE of 0.001 liters, which demonstrates the ability of the fitted model to forecast the methane volume production when different exogenous and time series-based variables are considered. To show graphically the quality of the forecasts provided by the ARIMAX model, we present Fig. 5 from the following can be noticed.

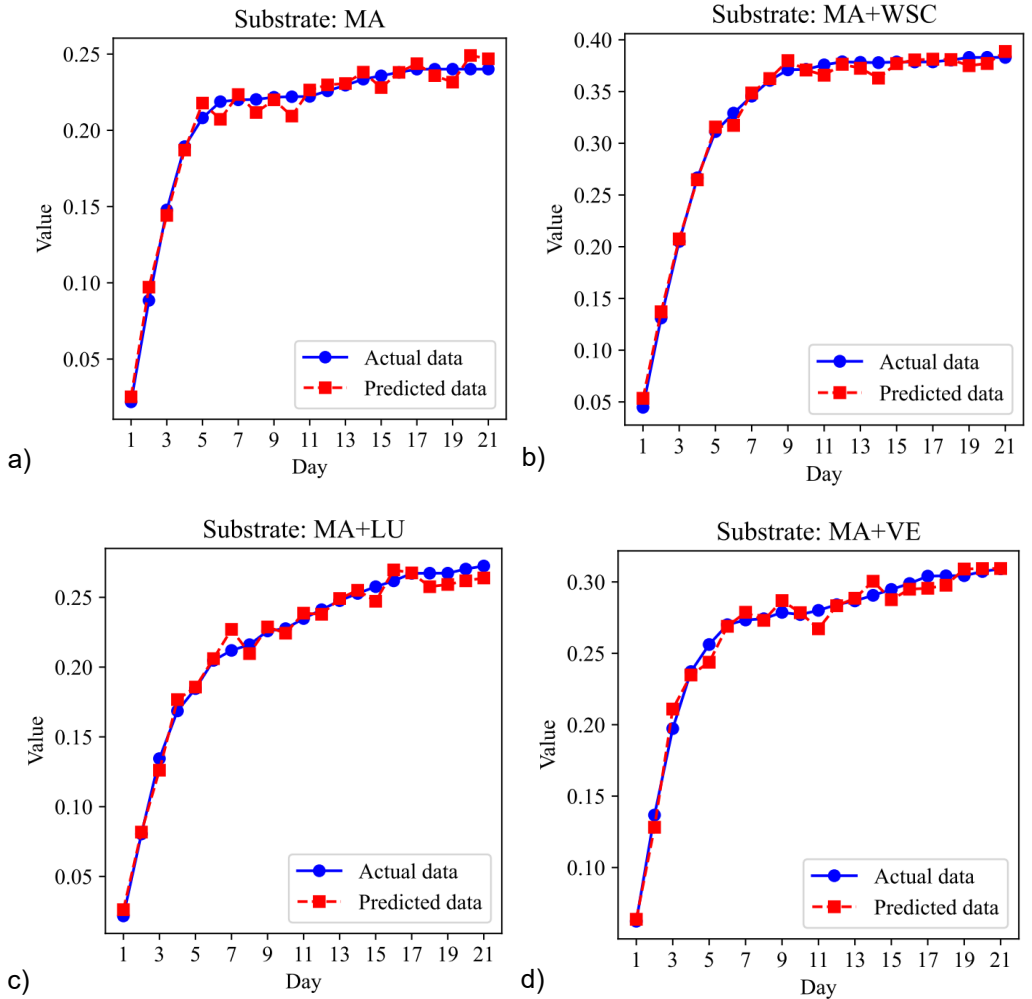


Figure 5. Performance of the ARIMAX model for METHANE for (a) maize, (b) maize plus white sweet clover silage, (c) maize plus white lupin silage, and (d) maize plus fodder vetch silage.

The forecast accuracy (red dashed line with square markers) adequately captures the methane production as time increases. The forecasted values closely follow the real data trend, accurately catching the initial increase as well as the later stabilization phases. The predicted and actual values show low deviations, particularly in the initial and mid-periods of methane production. However, there are some minor deviations at later stages since the calculated values occasionally fall below or above the measured values. Despite these minor differences, the model can create the overall trend and show its high predictive power.

ARIMAX model for METHANE_CONTENT

We fitted the model in Equation (9), obtaining the coefficients in Table 6. . To carry out the fitting process, we used the same process of separating the first 16 days of METHANE_CONTENT values and used the values from 17 to 21 to evaluate how the model performs with unknown data.

Physically, the coefficients in Table 6 define the effect of different factors on methane concentration dynamics. For instance, the coefficient for ADF ($\beta_1 = 0.1823$) shows that acid detergent fiber has a positive effect on methane production at a moderate level. ADF is the least digestible fraction of fiber, primarily cellulose and lignin. Its positive effect shows that although it is not fully degradable,

there is still a portion that is fermented by microbes, producing methane. The coefficient for CF ($\beta_2 = 0.2532$) indicates that crude fiber has a more important positive effect compared to ADF. Crude fiber consists of cellulose and a fraction of the hemicelluloses, which are fermented in part by methanogenic microorganisms. This indicates that the digestibility of the fiber component plays a key role in the methane concentration. With respect to the coefficient for WSC ($\beta_3 = 0.3815$), it can be noticed that the use of a combination of maize and white sweet clover has a significant positive effect on regulating methane. Since WSC includes fermentable sugars, which are readily fermented to volatile fatty acids and, eventually, methane in anaerobic conditions, this is directed towards the key driving role of fermentable substrates in methane emission. Conversely, the coefficient for NDF ($\beta_4 = 0.0824$), which symbolizes neutral detergent fiber, exhibits a significantly smaller positive effect. This small effect means that while some part of its composition is responsible for the generation of methane, the NDF does not allow microbial fermentation to produce high concentrations of methane. Furthermore, the coefficient for LU ($\beta_5 = -0.5245$) is negative, and the suggestion is that the addition of white lupin inhibits the methane concentration increase. This inhibition suggests that white lupin constrains microbial activity, reduces the level of fermentable substrates, or disrupts the anaerobic digestion.

The autoregressive coefficient $\phi_1 = 0.3241$ indicates that a previous methane content significantly affects the current values. This means that the methane concentration has an autoregressive pattern, which holds that environments that are supportive of methane creation in earlier stages are likely to maintain production for

Table 6. Fitted weights for the ARIMAX(1,1,1) model for METHANE

Coefficient	Variable	Value	Units
β_1	ADF	0.1823	Adim
β_2	CF	0.2532	Adim
β_3	WSC	0.3815	%
β_4	NDF	0.0824	Adim
β_5	LU	-0.5245	%
ϕ_1	C_CH4_{t-1}	0.3241	Adim
θ_1	ϵ_{t-1}	0.2841	Adim

longer periods. The coefficient for the moving average $\theta_1 = 0.2841$ explains how past random errors impact the current methane concentration. It indicates that a variation in methane generation is explained in part by omitted variables in the last period.

Regarding the accuracy of the ARIMAX model for METHANE_CONTENT, we obtained an R^2 of 0.908 and an RMSE of 0.85, which demonstrates the fitted model's ability to forecast the methane concentration with the lagged variables, errors, and exogenous variables chosen. We depict the actual and predicted trends in Fig. 6.

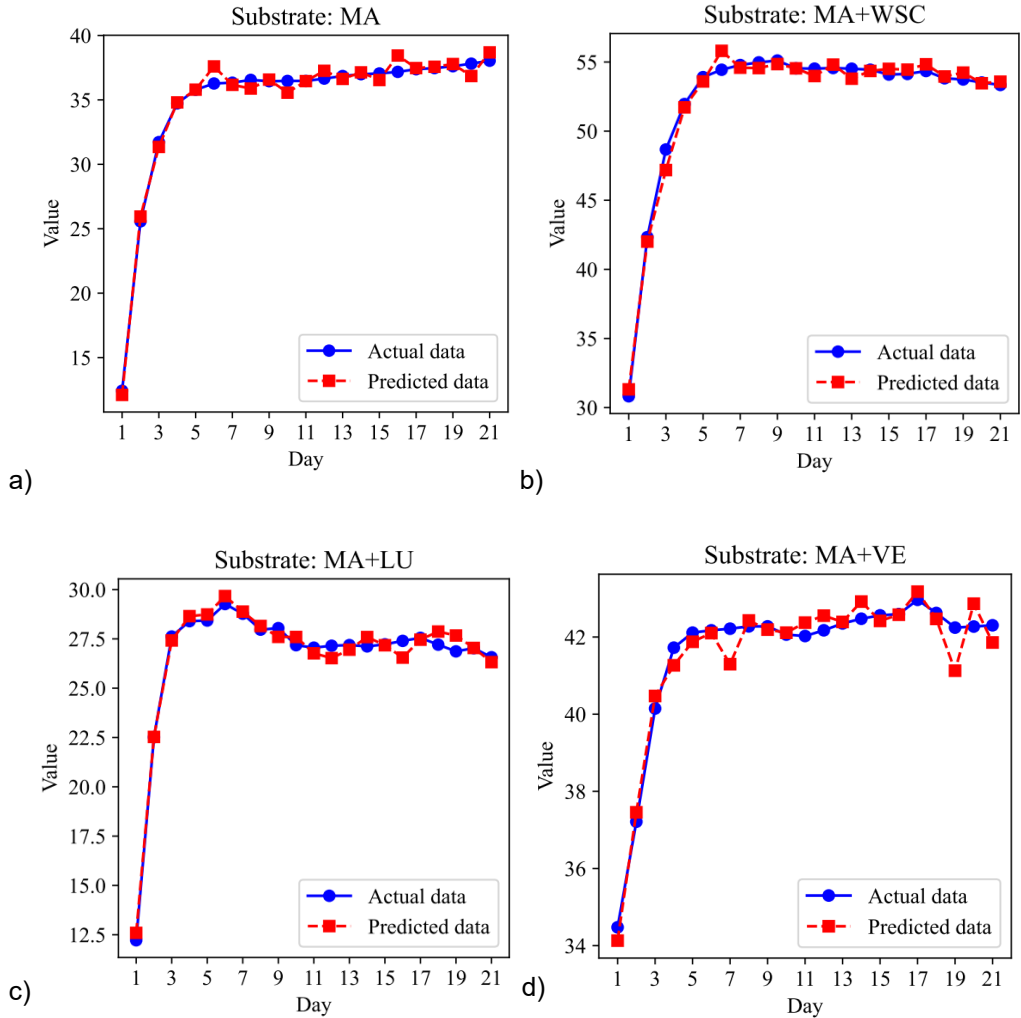


Figure 6. Performance of the ARIMAX model for METHANE_CONTENT for (a) maize, (b) maize plus white sweet clover silage, (c) maize plus white lupin silage, and (d) maize plus fodder vetch silage. The y-axis is in units of % of methane.

From Fig. 6, the following can be observed. First, it can be noticed that the ARIMAX model has a strong predictive power for the considered substrates, as observed from the very close convergence of true and forecasted values. The model captures the

sharp early increase in methane production accurately and also the subsequent stabilization. Based on y-axis values, white sweet clover + maize (MA+WSC) possesses the maximum methane content with values of more than 55%. This verifies the hypothesis that there are readily fermentable substrates present in white sweet clover, through which there can be rapid microbial degradation leading to the generation of methane. For MA only, methane content levels are at about 38-40%, with a slightly lower terminal concentration than MA+WSC. Despite this difference, the model is highly predictive in accuracy, tracking the actual path very closely with little variation. For the case of MA+LU silage, a fluctuating trend can be noticed, a methane peak of approximately 30%, with a subsequent drop, and then a flat line. In all the cases, the prediction accuracy of the ARIMAX model suggests an adequate ability to forecast the methane concentration under different conditions of exogenous variables.

With these results, we show that our ARIMAX models exhibit an adequate predictive ability (an R^2 of 0.92 and an RMSE of 0.001 L for methane volume, and an R^2 of 0.908 with 0.85% RMSE for methane concentration), indicating that silage composition and its time variation can predict gas outputs with confidence. In practice, this means that operators can use these models for real-time process control, adjusting feedstock mix (for example, favoring maize + white sweet clover, which our forecasts show yields maximum methane concentrations above 55%) in an effort to maximize biogas quality and quantity. Most significantly, the coefficients associated with the exogenous variables (e.g., CF's 0.1327 L/% and WSC's 0.6045 L unit change) directly translate to operational recommendations on how most strongly individual silage components affect the creation of methane, allowing decision-making regarding crop mix and settings from evidence to farmers and managers.

CONCLUSIONS

Generation of biogas from mixed maize-legume silages is a renewable-energy source that is sustainable, but its wider adoption may have been prevented by uncertainty about the quantitative value of different mixtures of feeds. To bridge this knowledge gap, we developed a time-series-based forecasting model founded on parametric ARIMAX(p,d,q) techniques that aim to explain a series' internal dynamics and exogenous silage chemistry variables, which can be selected through Pearson and Spearman correlation analyses. By translating categorical types of substrates into one-hot encoded representations and choosing the most effective predictors, our methodology empowers statistical integrity with functional usability.

Our feature-selection analysis showed that acid detergent fiber (ADF) and crude fiber (CF) are the most important positive predictors of methane yields. The CF contributes to biogas volume, confirming the principal role of digestible fiber in facilitating sustained methane production. The ADF contributes a smaller effect, as would be expected because of its lower rates of digestion in the digester. Conversely, a rise in crude protein and lipid levels inhibits methane production, most likely due to ammonia accumulation and long-chain fatty-acid toxicity, directing microbial metabolism towards non-methanogenic products.

The ARIMAX(3,1,2) model for methane volume yielded an R^2 of 0.92 and RMSE of 0.001 L, while the ARIMAX(1,1,1) model for methane concentration achieved an R^2 of 0.908 with RMSE of 0.85%. Unlike black-box regressors such as LSTM networks, which provide minimal insight into the effect of individual feedstock components on performance, our transparent ARIMAX approach offers insightful coefficient estimations. This transparency allows operators to make real-time silage blend adjustments to maximize biogas yield and quality using evidence-based process control.

USE OF GENERATIVE AI DECLARATION: The authors confirm that they used ChatGPT to fix typo errors, improve grammar, translate some excerpts from Spanish, and enhance the readability of the manuscript. However, they declare that the manuscript is original, and the improved texts obtained from the language models have been carefully reviewed.

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Utilizing APSIM model for predicting wheat yield in no-tillage farming systems in Ninawa

M.A. Hussein¹, A.A.A. Luhaib^{1,*} and K.A. Aikins^{2,3}

¹University of Mosul, Center for Arid Farming and Conservation Agriculture Research's (C.AFCAR), Al Majmoaa Street, IQ41002 Mosul, Iraq

²Kwame Nkrumah University of Science and Technology, Department of Agricultural and Biosystems Engineering, MCGM+M8M, Kumasi, Ghana

³University of South Australia, Agricultural Machinery Research and Design Centre, STEM, Mawson Lakes, SA 5095, Australia

*Correspondence Email: adnan.luhaib@uomosul.edu.iq

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Abstract. This research explored how wheat responds agronomically when cultivated under no-tillage and multi-tillage farming scenarios, representing conservational and conventional systems, respectively. Using site-specific soil data, the Agricultural Production Systems sIMulator (APSIM) was calibrated to investigate the long-term (7 winter seasons) influence of tillage-induced soil health on crop yield, and some of the yield components. As a results, wheat yields and yield components were significantly (p -value < 0.05) higher under no-tillage conditions. In years with moderate rainfall ($\approx$ 230 to 400 mm in-season), the predicted values of grain yield and total biomass between no-tillage and multi-tillage systems showed superiority to no-tillage system. Despite the demonstrated superiority of the no-tillage system in providing the best values for the investigated indicators under dry conditions, the differences in grain yield and total biomass between the two farming systems decreased with increasing rainfall. The differences in simulated and observed data were 13% and 8% for grain yield and biomass, respectively, under no-tillage condition, and approximately 6% and 10% for grain yield and total biomass, respectively, under multi-tillage condition. APSIM simulated outcomes showed that increased productivity, and annual yield under no-tillage system, was able to increase total financial incomes of wheat by USD120–396 ha⁻¹ depending on in-season rainfall and the tillage system practiced. Therefore, no-tillage appears to offer a more sustainable and viable approach to boosting nutrition uptake and grain yield compared to the conventional technique in water-limited environments.

Key words: conservation agriculture, multi-tillage, conventional agriculture, wheat crop, yield components.

INTRODUCTION

Modern agricultural systems face unprecedented challenges, including soil degradation, climate variability, and diminishing natural resources, which threaten global food security and ecological stability (Chamen et al., 2003; Botta et al., 2010;

Jørgensen, 2012). In response to these pressing issues, conservation agriculture has emerged as a transformative approach that redefines traditional farming paradigms (Zhu et al., 2025), which concentrate on minimal soil disturbance, permanent soil cover, and diversified crop rotations (Srean et al., 2025). Conservation agriculture seeks to harmonize agricultural productivity with environmental stewardship. Through prioritizing the preservation of soil structure and organic matter, this system enhances water infiltration, reduces erosion, and fosters microbial activity, thereby improving long-term soil health and resilience (AL-Wazzan & Muhammad, 2022; Zhang et al., 2025).

The adoption of conservation agriculture is increasingly recognized as a critical strategy for mitigating the adverse effects of climate change, particularly in regions vulnerable to droughts, extreme temperatures, and erratic rainfall patterns. Studies have demonstrated its capacity to sequester carbon, enhance biodiversity, and optimize water-use efficiency, offering a viable pathway to sustainable intensification. Furthermore, the integration of agroecological practices within conservation agriculture frameworks promotes synergies between crop and livestock systems, reducing reliance on synthetic inputs and lowering production costs for farmers (Hussein et al., 2021a, 2021b; Hassan et al., 2022).

Climate challenges are accelerating the use of predictive models in farm decision-making. These mechanistic tools simulate crop performance by explicitly representing causal processes (Challinor et al., 2009). The Agricultural Production Systems sIMulator (APSIM) is a key model for projecting yield responses to climate shifts and soil factors (Keating et al., 2003). Recognized globally for its sophistication, APSIM is capable of modelling complex agricultural systems through interconnected components covering plants, animals, soil, climate, and management (Akponikpè et al., 2010). As a leading dynamic simulator, APSIM is also capable of predicting water and nitrogen dynamics across different soil fertility scenarios. Over the years, this eco-physiological program has become well-established through comprehensive validation in diverse environments (Asseng et al., 2000; Chenu et al., 2011; Peake et al., 2011; Balwinder-Singh et al., 2011). APSIM stands out for its modular process-based approach, ability to simulate long-term soil-plant-management interactions, and integration with data-driven technologies. Compared to other tools (e.g., DSSAT or AquaCrop), this modelling software offers a unique combination of mechanistic depth, modular flexibility, and proven applicability to complex agricultural systems. Its ability to integrate multi-year climate data, precise soil-plant processes, and emerging technologies makes it especially valuable for studies aiming to optimize irrigation and enhance sustainability.

Improvements in soil structure under no-tillage systems also appear to improve plant uptake of water and nutrients. Despite its documented benefits, the widespread implementation of conservation agriculture in Iraq remains hindered by socio-economic, institutional, and knowledge-based barriers. Smallholder farmers, in particular, often face challenges related to access to appropriate technologies, financial resources, and extension services. This paper explores the multifaceted dimensions of conservation agriculture, examining its agronomic impacts on the performance of wheat crop under this particular farming system.

Despite APSIM's global validation (Carberry et al., 2013), its application to Iraqi agroecosystems, particularly contrasting conservational and conventional practices, represents a novel contribution. Therefore, the main objectives of this study were to (1) assess wheat yield response to soil preparations under different tillage conditions; (2) predict the Long-Term effects of soil health and weather changes on grain yield and biomass using APSIM to simulate 7 years crop productivity and hydrological outcomes, based on measured soil properties; (3) quantify the Long-Term economic returns based on the grain yields derived from APSIM model.

MATERIALS AND METHODS

Field experimental site

The field trial was conducted during the winter season of 2023–2024 at Tel kaif district, about 13 km Northeast of Mosul, within the Ninawa plains, Iraq (coordinates: 36°27'32.2", 43°9'22.5"). Overall, during the field experiment, temperatures remained close to historical norms, though springtime lows were slightly cooler (Fig. 1 left). Rainfall during the season (from the beginning of October to the end of April) was higher than the historical averages by recording more than 800 mm, which was similar to the growing seasons of 2018–2019 (890 mm) (Fig. 1 right).

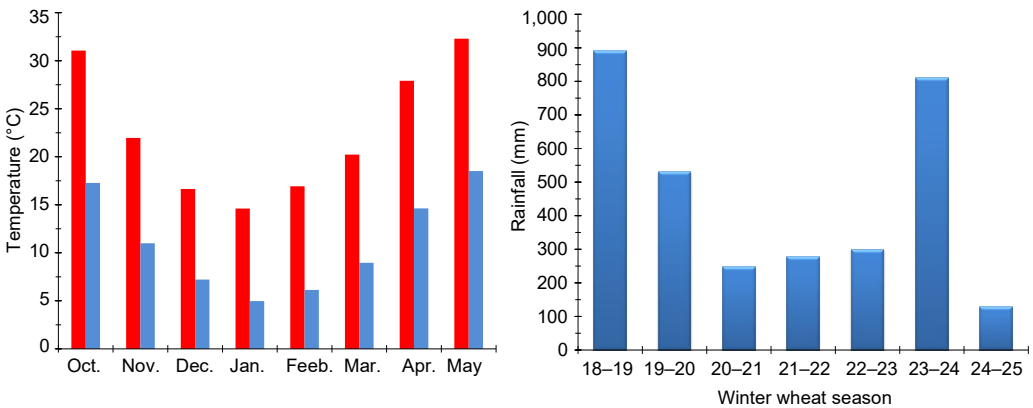


Figure 1. Average monthly maximum and minimum temperatures (left) and total seasonal rainfall (October – May) during the modelled period (right), records for Mosul, Ninawa, Iraq (data sourced from Directorate of Agriculture).

The soil at the site is classified as a Black-Gray soil. It is moderately well-drained with minimal slope ($< 0.5\%$). Particle size analysis revealed a high silt content ($\approx 54\%$ in the top 200 mm), typical of soils used for cereal cropping in this region. The area had a history of at least three years of cereal production prior to the study.

Field study

The trial was conducted on two adjacent farms representing the two farming system treatments (no-tillage and multi-tillage). The adjacent farms were chosen in order to eliminate the effects of environmental and soil differences on results. One of the farmers has been practicing conservation agriculture (no-tillage) since 2008, while the other

farmer still utilizes conventional tillage and seeding system (multi-tillage). During the experiment, primary tillage was done using a mouldboard plough, followed by seedbed preparation with two passes (one across the other) using a tine cultivator on the multi-tillage farm. This is the typical combination of tillage operations employed by farmers in Iraq. Wheat (*Triticum aestivum* L. variety: DİNÇ) was sown on 16 December 2023 at a target density of 300 plants m⁻² using a no-tillage planter with disc openers at 150 mm row spacing with both farming systems. The seeder slightly disturbed the soil to improve seed-to-soil contact without deep loosening. Crop establishment was uniform across all plots. One irrigation event ($\approx$ 25 mm) was applied after planting to ensure emergence. Two nitrogen sources were applied to the crop, namely, Urea (46% N) and Diammonium phosphate DAP (46% N). Each Fertiliser type was applied in two equal doses: first at the time of planting and then during stem elongation. Application rates were 100 kg ha⁻¹ for each fertilisation stage. The experimental plots consisted of stripes of 50 m wide and 100 m long. Three plots (replications) were randomly selected within 5 ha farmland of each of the two farming systems. During crop growth, plant height, spikes per m² and grains per spike were observed and recorded. Yield parameters evaluated in this study included crop biomass yield, grain yield and thousand grain weight (TGW).

Simulation Approach

The Agricultural Production Systems sIMulator (APSIM), a process-based modelling platform (Holzworth et al., 2014), was employed to model dryland wheat production under contrasting soil management practices (conservational vs. conventional systems) over 7 years (2018–2025). Prior to this, the biomass and grain yield outputs of the model were validated against the field experimental results. Economic analysis of wheat production in the Ninawa Governorate based on the 7-year APSIM simulation result comparing the no-tillage and multi-tillage farming systems was also conducted. This included the total income per ha derived from the two farming systems and the difference between them for each simulated years, based on the 2024 Iraqi wheat market price of USD 600 ton⁻¹ (Ministry of Agriculture in Iraq, 2024).

Detailed model specifications, including module descriptions and codebase access, are available in the APSIM documentation repository (<https://www.apsim.info/>). A Black-Gray soil type was simulated, with climate inputs sourced from regional meteorological records. To assess soil compaction effects on crop development, the SoilWat module was selected to model soil-water dynamics, deviating from prior methodologies that utilized alternative modules (e.g., Huth et al., 2012; Antille et al., 2016).

Soil physical and hydraulic properties (Table 1) were measured during the one-year field experiment to calibrate and guide parameterisation and application of APSIM, and to model the long-term impacts of simulated soil conditions of no-tillage and multi-tillage farming systems on crop productivity and biomass. These properties were measured directly from soil samples taken from the study site. Specifically, undisturbed soil cores were collected from the top 300 mm layer at multiple locations within the experimental plots. Bulk density (BD) was determined using the core method. Saturation threshold (SAT) and upper drainage capacity (DUL, often equivalent to field capacity) were subsequently determined in the laboratory using the constant head method

(Klute, 1965). Saturated hydraulic conductivity (KSAT) values were restricted to the upper 150 mm for conventional system, while deeper profiles (300–600 mm) were extrapolated from historical datasets of analogous soils (Dalglish & Foale, 1998; Connolly et al., 2001). For conventional systems, pedotransfer functions based on particle-size distributions (Gee & Bauder, 1986) were applied to estimate lower moisture limits (LL) across all depths and DUL/SAT below 300 mm. Surface runoff coefficients were adjusted to 73 for multi-tillage (Kodur et al., 2017), with a 7-unit increment for multi-tillage scenarios (McCloskey et al., 2014), while evaporation parameters followed default APSOIL database configurations. The simulation was run to cover a continuous period of 7 years (2019–2025), enabling the prediction of multi-year future crop yield based on experimental measurements. The simulation was based on the Continued Wheat template of the APSIM software as this was the mostly closely aligned template to the environmental conditions of this study.

Table 1. Soil physical properties used in the APSIM simulations for conservation agricultural (no-tillage) and conventional farming (multi-tillage) conditions for a Black-Gray soil at Ninawa, Iraq

Depth (mm)	Bulk density (g cm ⁻³)	Porosity (%)	Plant lower limit (m ³ m ⁻³)	Drained upper limit (m ³ m ⁻³)	Saturation (m ³ m ⁻³)	K _{SAT} (mm day ⁻¹)
Multiple-Tillage						
0–100	1.14	0.57	0.22	0.30	0.54	950
100–150	1.16	0.56	0.25	0.30	0.53	501
150–200	1.19	0.55	0.23	0.35	0.47	104
200–300	1.21	0.54	0.23	0.34	0.43	51
300–400	1.23	0.54	0.24	0.35	0.42	52
No-tillage						
0–100	1.36	0.49	0.21	0.25	0.47	52
100–150	1.24	0.53	0.24	0.27	0.48	26
150–200	1.33	0.50	0.23	0.36	0.43	20
200–300	1.29	0.51	0.24	0.34	0.40	21
300–400	1.26	0.52	0.25	0.35	0.40	25

Wheat (*Triticum aestivum* L.) was modelled annually with sowing triggered by cumulative rainfall thresholds (≥ 20 mm within 5 days) between mid-November and mid-December. If the rainfall threshold was unmet, forced planting occurred by the end of December. Seeding density (300 plants m⁻²) and nitrogen application (200 kg ha⁻¹ urea and DAP) aligned with regional practices (Zadoks et al., 1974). Initial soil moisture (95% of maximum capacity) was equilibrated via a 7-year pre-simulation data.

Model outputs were calibrated against empirical yield data, with simulated yield disparities (13% between no - and multi-tillage) closely mirroring field observations (12%). Seasonal water-use efficiency, calculated as grain yield per unit seasonal rainfall (Hochman et al., 2009), served as a key performance metric.

Statistical analysis

Statistical Package for the Social Sciences (SPSS-version 23) software was used to analyse the data derived from the field study (Swan & Sandilands, 1995). Means of yield and yield components were compared for significant differences using independent samples *t-test* at 5% level of probability. Linear regression analyses were applied to examine the relationships between grain yield and rainfall during the simulated seasons.

RESULTS AND DISCUSSIONS

Field Results

The results derived from the field investigation, presented in Table 2, indicate that measured yield components were significantly influenced by the tillage-farming system ($P < 0.05$). Significantly higher grain yield (3,900 kg ha⁻¹), total dry biomass (10,433 kg ha⁻¹), plant height (105.5 cm) and TGW (29.5 g) were obtained where no-tillage technique was used, compared to the conventional tillage system (3,600 kg ha⁻¹, 8,916 kg ha⁻¹, 83.3 cm and 24.43 g for grain yield, biomass, plant height and TGW, respectively). No significant differences were observed in the other parameters (spikes per m² and number of grains per spike).

Table 2. Measured yield components as affected by tillage-farming systems ($n = 3$)

Farming system	Biomass (kg ha ⁻¹)	Spikes per m ²	Plant height (cm)	Grains per spike	TGW (g)	Yield (kg ha ⁻¹)
Multi-tillage	8,916 b	395.67 b	83.30 b	31.12 b	24.43 b	3,600 b
No-tillage	10,433 a	399.50 b	105.50 a	32.50 b	29.50 a	3,900 a

This finding suggests that the excessive use of tillage operations has negative effects across all agricultural domains, particularly impacting environmental sustainability and the economic viability of the agricultural sector. Farmers in Ninawa Governorate invest substantial funds in performing multi-tillage passes prior to planting. This practice, based on traditional farmer knowledge, aims to loosen and invert the soil to increase aeration as a result of increased porosity as evidence in Table 1. However, it overlooks the significant water wastage, as the large pores created between soil particles allow rainwater to percolate rapidly beyond the root zone, from which the crop derives little benefit (Alrijabo, 2014). These outcomes were also confirmed by Ghosh et al. (2015) who investigated the agronomic and economic benefits of adopting conservation farming technique.

Validation of APSIM Results

Fig. 2 displays the differences between observed and predicted grain yields and total biomass for wheat during the growing season of 2023–2024 under both investigated farming systems. These results confirmed that field-model discrepancies remained within the acceptable ranges, showing approximately 13% and 8% differences for yield and biomass, respectively, under no-tillage farming system, versus 6% and 10% under conventional system.

This alignment demonstrates that rainfall patterns and tillage systems influence wheat productivity not only in empirical studies but also under simulated conditions

when environmental parameters are replicated. These predicted outcomes were within the range reported by previous studies (e.g., Radford et al., 2007), and other projects that compared the effects of compacted and non-compacted soils on simulated crop yield and yield components (e.g., Galambošová et al., 2017; Shaheb et al., 2018). The outcomes also confirm that the impacts of compaction due to no-tillage farming system on crop performance depends on the seasonal rainfall, minimum and maximum temperatures (McKyes et al., 1979). Such validation significantly supports pre-planting decision-making by farmers, particularly regarding farming system selection.

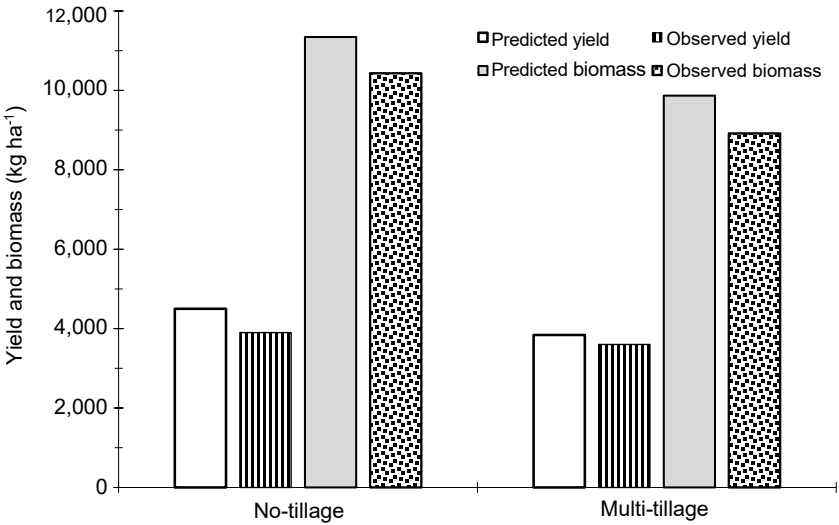


Figure 2. Differences between observed and predicted grain yields and biomass obtained from the field and APSIM model, respectively, during the 2023–2024 season.

Long-Term Predicted Results

Fig. 3 shows the fluctuation in predicted wheat production (grain yield and total biomass) from 1818 to 2024 relative to seasonal rainfall. Peak values for grain yield and total dry weight were recorded during the rainy seasons of 1818–2019 and the 2023–2024 winter season. In contrast, the 2024–2025 season recorded the lowest predicted wheat production in the past seven years, with yields falling below 1,000 kg ha⁻¹ under conventional tillage systems and approximately 1,300 kg ha⁻¹ under no-tillage systems.

Simulated outcomes indicate that agricultural management systems exert sustained influence on crop productivity and biomass accumulation across diverse climatic scenarios, aligning with single-season trial observations. Repeated tillage operations demonstrate particularly adverse impacts on yield parameters and vegetative growth during suboptimal precipitation periods. In arid and semi-arid dryland ecosystems, pre-sowing soil moisture reserves fundamentally govern production viability. Consequently, modelled variations in this critical (water) resource dictate phonological outcomes and inform strategic sowing decisions (Zeng et al., 2021; Yu et al., 2024).

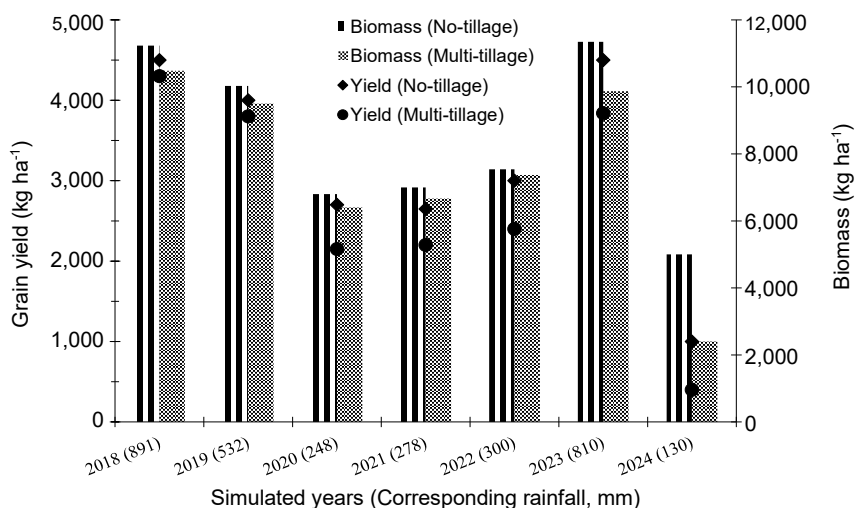


Figure 3. Grain yield and total biomass derived from the two farming systems and their relations with total seasonal rainfall during the simulated period (2018–2024).

Predicted yields and biomass under rainfall variability for no-tillage and multi-tillage conditions are shown in (Fig. 4, a and b), respectively. Conventional farming system represented by multi-tillage reduced grain yield and biomass, by 65% and 48%, respectively, when the rainfall condition fell below average ($< 30^{\text{th}}$ percentile = 230 mm). These differences between the two farming systems decreased within the average seasonal rainfall (2,700, 2,780 and 3,000 kg ha⁻¹ yield under conservational tillage farming system versus 2,500, 2,570 and 2,800 kg ha⁻¹ yield under the conventional farming system). The biomass response followed the same trend, with both farming systems. The differences between the two farming systems decreased in the years that received above average rainfall compared to the dry seasons which reflects similar behavior of crop response during the field studies.

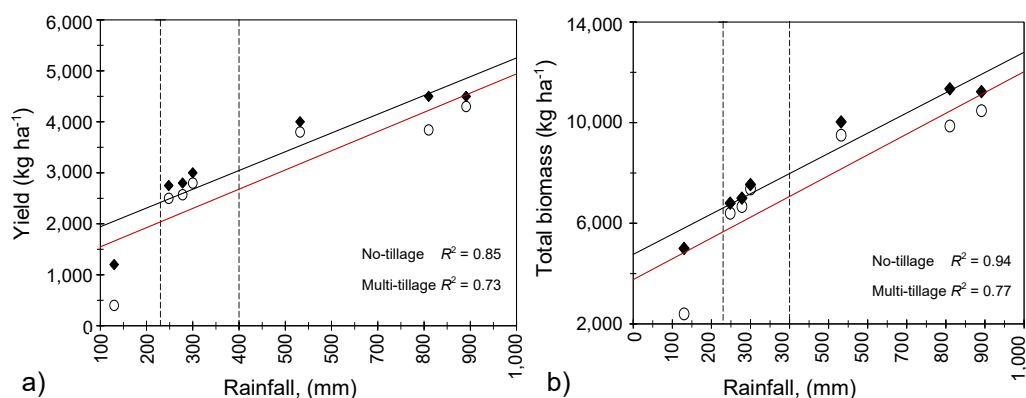


Figure 4. Simulated long-term (2018–2025) wheat (a) Grain yield and (b) Total biomass within a wheat-fallow cropping system on Iraqi Black-Gray soil, comparing no-tillage and multi-tillage farming systems as a function of rainfall. The dashed vertical lines indicate the 30th (left) and 70th (right) rainfall percentiles.

Economic analysis

Table 3 shows the economic analysis results of the two tillage-farming systems derived from APSIM-modelled grain yield during the 7-year simulated period. These outcomes focus exclusively on yield differentials and their resulting financial implications between the no-tillage and multi-tillage farming systems. Although, the operational costs disparities were not accounted, based on several studies (e.g., Loss et al., 2014; Loss et al., 2015; Luhaib et al., 2017; Hasan et al., 2022) conservation farming system have demonstrated superiority in reducing variable costs (e.g., fuel and lubrication, labor, and maintenance) by about USD 100 ha⁻¹ compared with conventional farming system.

Following the yield results presented in Fig. 2, the no-tillage system resulted in higher total income in all simulated seasons compared to the multi-tillage system (Table 3), based on Iraq’s wheat grain price of USD 600 ton⁻¹ (Ministry of Agriculture in Iraq, 2024). The differences in income ranged from USD 120 in the 2018 season to USD 396 ha⁻¹ in the 2023 season, proving the higher profitability of no-tillage farming, especially in seasons with above average rainfall and when cost of production would be factored in.

Table 3. Financial returns from the two tillage systems based on 7-year APSIM outcomes

Season	Rainfall	Total income (USD ha ⁻¹)		
		No-tillage	Multi-tillage	Differences
2018	891	2,700	2,580	120
2019	532	2,400	2,280	120
2020	248	1,620	1,290	330
2021	278	1,589	1,320	269
2022	300	1800	1,440	360
2023	810	2,700	2,304	396
2024	130	600	240	360

CONCLUSIONS

Enhanced wheat grain yield and total biomass in no-tillage farming system were mainly explained by avoidance of multi-tillage and minimized soil disruption in both short and long-term investigations. This was confirmed by differences in all agronomic indicators of crop performance in field experiment findings (number of spikes, plant height, number of grains per spike and thousand grain weight) observed in the two farming systems. Conservation agriculture appears to be a more effective practice to help increase input-use-efficiency (while reducing total farm operations), which in this study resulted in improved economic returns of USD 120 to 396 ha⁻¹. In the long-term modelling investigation, the predicted outcomes revealed that the impact of the implemented farming system on grain yield and biomass is dependent on in-season rainfall with better results in years with rainfall above average and vice versa. Long-term simulations suggested that productivity of wheat in the arid and semi-arid conditions could be improved if the crop was managed under no-tillage system, depending on rainfall.

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Evaluation of agromorphological and grain physical traits in Greek barley accessions

A. Katsileros^{1,*}, M. Giannakoulia¹, T. Fraggatzis¹, E. Tani¹, I. Mandala² and Penelope J. Bebeli¹

¹Agricultural University of Athens, Department of Crop Science, Iera Odos 75, GR11855 Athens, Greece

²Agricultural University of Athens, Department of Food Science and Human Nutrition, Iera Odos 75, GR11855 Athens, Greece

*Correspondence: katsileros@aua.gr

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Abstract. This study assessed the agromorphological and grain physical traits of twelve barley (*Hordeum vulgare* L.) accessions, comprising eight Greek landraces and four cultivars, over two consecutive growing seasons (2022–2024). Significant genotypic effects and accession-by-year interactions were observed for most agromorphological traits, particularly plant height, spike morphology, and grain yield components. Grain physical characteristics, evaluated during one season, also revealed clear genotypic differentiation. Specific landraces, H1 (from Amorgos Island), H8 (from Pyrgos Region), and the old cultivar Athinaida, demonstrated high productivity and adaptability, performing comparable to, or even surpassing, modern cultivars under variable Mediterranean conditions. Accessions originating from the Greek islands produced smaller but firmer grains, traits that likely reflect adaptation to arid environments, whereas those from the mainland and modern cultivars exhibited larger, less firm grains. Principal Component Analysis (PCA) and cluster analysis, integrating both agromorphological and grain physical traits, revealed consistent patterns of differentiation, grouping accessions according to their geographic origin and breeding status. These findings highlight the genetic value and adaptive potential of Greek barley landrace genetic material for breeding programs aiming to improve resilience, quality, and yield stability in low-input agricultural systems.

Key words: genotype-environment interaction, phenotypic variability, grain morphology, traditional germplasm, yield components.

INTRODUCTION

Barley (*Hordeum vulgare* L.) is one of the most important cereal crops globally, particularly in the Mediterranean region, where it has been cultivated for thousands of years. As one of the first crops to be domesticated in the Near East Fertile Crescent (Harlan & Zohary, 1966), barley (*Hordeum vulgare* ssp. *vulgare*) is considered an excellent model for understanding how major crops adapt to climate change (Dawson et al., 2015; Zhou et al., 2024).

In Greece, recognized as an important center of barley evolution and diversification (Jakob et al., 2014), barley plays a significant role in human nutrition, livestock feeding, and the brewing industry. Barley landraces, also referred to as traditional, local, or farmers varieties, or local populations have evolved over centuries of traditional farming practices and under the specific environmental conditions of the Mediterranean (Ceccarelli et al., 1998). They are genetically heterogeneous populations that have been developed through natural and human selection in specific eco-geographical regions (Casañas et al., 2017; Lazaridi et al., 2024) and exhibit high levels of genetic diversity (Brbaklić et al., 2021). This diversity provides resilience against multiple biotic and abiotic stresses, such as drought, low soil fertility, and pathogen infections (Škipars et al., 2021; Vasilaki et al., 2023).

Nevertheless, the intensification of agriculture has led to genetic erosion and the loss of valuable traits critical for long-term agricultural sustainability (Ficiciyan et al., 2018; Robbana et al., 2023). Despite their agronomic and ecological value, many barley landraces have been gradually replaced by commercial cultivars bred for uniformity and high productivity under intensive conditions (Gadissa et al., 2021). In Greece, this trend is particularly evident, with traditional varieties now occupying only a small fraction of cereal cultivation, mostly in remote areas (Thanopoulos et al., 2021). This loss of biodiversity causes genetic erosion and undermines efforts toward sustainable agriculture. Barley landraces, shaped by long-term adaptation, possess traits such as yield stability, efficient resource use, and stress tolerance, making them valuable genetic materials for cultivation in low-input environments and for incorporation into modern breeding programs (Monteagudo et al., 2019; Kumar et al., 2020).

Recent studies underscore the importance of evaluating key agromorphological and grain physical traits in landraces, as these characteristics influence yield potential, end-use quality, and processing performance (Baik & Ullrich, 2008; Assadzadeh et al., 2022; Ghazy et al., 2024). A better understanding of phenotypic diversity can reveal genotypes with improved performance under environmental stresses, contributing to resilient farming systems (Visoni et al., 2023). Systematic classification and phenotypic evaluation methods, like those used in other cereals, provide insights into the agronomic potential of local varieties (Protonotariou et al., 2023; Spanic et al., 2024). These efforts support the identification of promising genotypes for breeding and the development of conservation strategies to safeguard this valuable genetic and cultural heritage.

This study aims to assess the plant agromorphological and grain physical traits of selected Greek barley landraces. By identifying key parameters that contribute to yield, resilience, and quality, it seeks to provide essential information for their conservation and strategic use in modern agriculture, with broader implications for biodiversity and food security.

MATERIALS AND METHODS

Plant material

The plant material comprised twelve *Hordeum vulgare* L. accessions, including three commercial cultivars, one old cultivar, and eight landraces (Table 1). The landraces were collected from geographically and ecologically isolated regions across both insular and mainland Greece (Fig. 1), aiming to capture the country's agroecological diversity.

Table 1. Origin, breeding status, and geographical coordinates of the barley accessions evaluated in the study

Code	Accession name	Breeding status	Location of origin
H1	-	Landrace	Amorgos, Cyclades, Aegean
H2	-	Landrace	Amorgos, Cyclades, Aegean
H3	-	Landrace	Arkadia, Peloponnese
H4	-	Landrace	Karpathos, Dodecanese, Aegean
H5	-	Landrace	Panagia, Limnos, North Aegean
H6	-	Landrace	Dafni, Limnos, North Aegean
H7	-	Landrace	Paros, Cyclades, Aegean
H8	-	Landrace	Prasino, Pyrgos, Peloponnese
H9	Athinaida	Old cultivar (selection from landrace population)	-
H10	Triptolemos	Cultivar	-
H11	Thessaloniki	Cultivar	-
H12	Explora-R2	Cultivar	-

The old cultivar, Athinaida, originated from a selection within a local insular landrace population (Mylonas et al., 2014). All landraces were donated to the Plant Breeding and Biometry Laboratory of the Agricultural University of Athens (AUA) for further evaluation and conservation. The commercial cultivars were provided by the Institute of Plant Breeding and Genetic Resources - Thessaloniki, Greece (IPBGR) and the company Agrogen SA Greece. Among the twelve accessions, eleven were classified as six-row barley and one (Thessaloniki) as two-row. All accessions used in this study were hulled barley, a type typical of barley cultivated in Greece.

Experimental design

The field trials were conducted over two consecutive growing seasons (2022–2024) at the experimental field of the Agricultural University of Athens (37°59'06.8" N, 23°42'24.7" E; altitude 24 m). A randomized complete block design (RCBD) with three replications was used. Each complete block included all twelve barley accessions, resulting in 36 experimental plots. Each plot consisted of four rows (1 m long, 0.25 m row spacing, 0.10 m between plants). Sowing took place in mid-November and harvest at the end of May. Prior to sowing, basic tillage was performed, which included plowing and harrowing to prepare the soil. Basic fertilization was applied according to the nutritional needs of the plants, using a mix of macro- and micronutrients based on

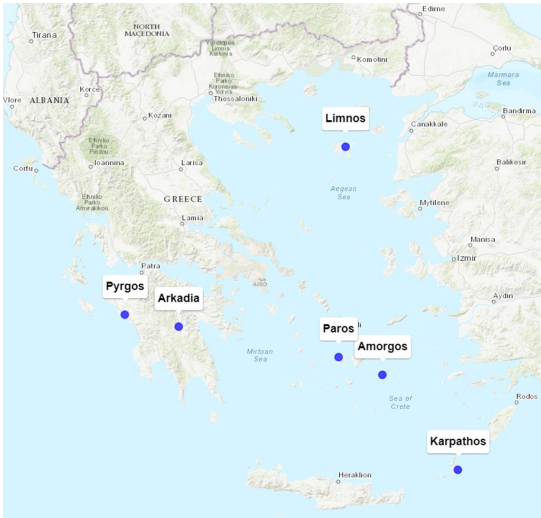


Figure 1. Geographical distribution of the barley accessions collected across mainland and insular Greece.

soil analyses. Weed control was mechanical, while irrigation and plant protection treatments were applied only, when necessary, mainly during flowering and grain filling. The soil was classified as clay loam with neutral pH and moderate organic matter. Meteorological data for the two growing seasons (mean temperature and total precipitation), as well as the average values for the last 30 years (1991–2020), were obtained from the National Observatory of Athens (NOA) and are presented in Fig. 2.

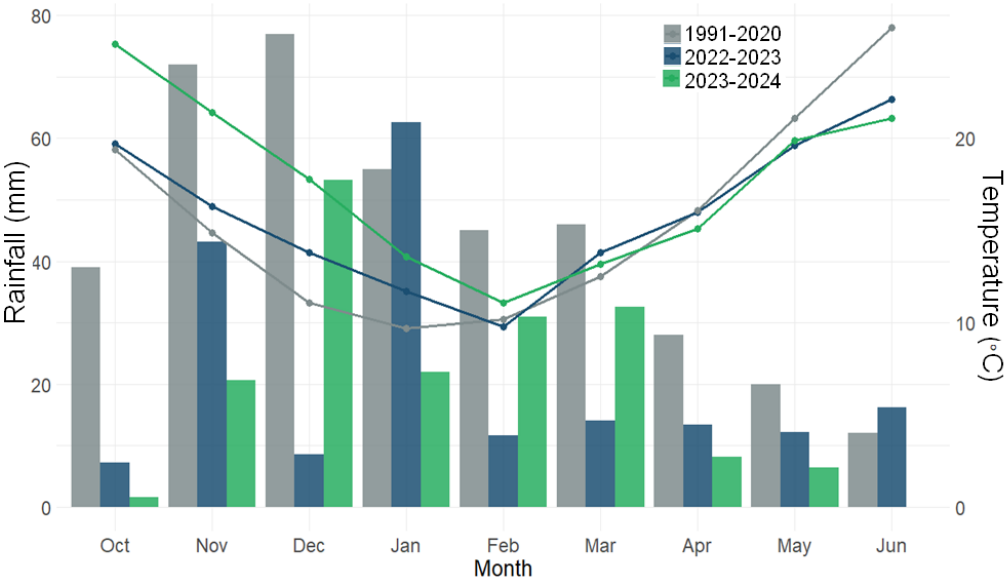


Figure 2. Monthly distribution of total rainfall and mean air temperature during the barley growing seasons of 2022–23 and 2023–24, and the long-term climate means for the period 1991–2020.

Plant agromorphological and grain physical trait measurements

A comprehensive set of agromorphological and grain physical traits was evaluated to characterize plant performance and grain physical properties (Table 2). Among the physical traits, the geometric (e.g., diameter, perimeter, area) and colorimetric characteristics (L, a*, b*, whiteness index) were measured on dehulled grains. Thousand kernel weight (TKW) was determined by weighing 1,000 randomly selected kernels, subsequently used to calculate bulk and tap densities. Bulk density (pb) was defined as grain mass per unit bulk volume, whereas tap density (pt) was measured after applying 100 mechanical taps to reduce void spaces. The Carr Index (CI), calculated as $CI (\%) = [(pt - pb) / pt] \cdot 100$, was used to assess flowability, an important parameter for processing and storage.

Grain firmness was measured using an Instron Universal Testing Machine (Model 3343, Nordwood, MA, USA) equipped with a 1 kN load cell. Fifty intact grains per accession were compressed to 50% of their original width using a 4 cm diameter probe at a speed of 1 mm min⁻¹. Grain color was evaluated with a spectrophotometer (NS800S, Shenzhen 3nh Technology, China) under the CIE-Lab* color space, recording L* (lightness), a* (green–red spectrum), and b* (blue–yellow spectrum) values. The whiteness index (WI) was also calculated to capture variations in grain appearance.

Grain shape and size parameters were analyzed through image processing. One hundred grains per accession were scanned twice using an HP Scanjet 4370 (Hewlett-Packard, USA), and processed with Image Pro Plus 7 software (Media Cybernetics, USA). Geometric traits included grain area (mm²), aspect ratio, average optical density, minimum and maximum diameters (mm), perimeter (mm), roundness, and overall grain dimensions (length and width in mm). All measurements were performed in triplicate to ensure reproducibility and statistical accuracy.

Table 2. Description of Measured Agromorphological and Grain Physical Traits

Trait name (Abbreviation)	Unit	Methodology
Plant height	cm	Measured from soil surface to the tip of the spike
Plant weight	g	Dry weight of total aboveground plant biomass
Number of stems	no.	Number of all stems per plant
Number of spikes	no.	Number of spikes per individual plant
Spike length	cm	Measured from spike base to tip, excluding awns
Number of spikelets	no.	Total number of spikelets per main spike
Weight of main spike	g	Dry weight of the main spike per plant
Weight of main spike grains	g	Dry weight of grains from the main spike
Weight of other spikes' grains	g	Dry weight of grains from the secondary spikes
Number of grains	no.	Total number of grains per plant
Total yield	g	Combined dry grain weight per plant
Thousand kernel weight (TKW)	g	Weight of 1000 grains
Volume	cm ³	Measured grain volume
Tap volume	cm ³	Grain volume after tapping
Bulk density	g cm ⁻³	Grain mass per unit volume (without compaction)
Tap density	g cm ⁻³	Grain density after 100 mechanical taps
Carr Index (CI)	%	Calculated as $[(pt - pb) / pt] \cdot 100$
Grain firmness (SF)	N (Newton)	Force required to compress grain to 50% width
Grain color (lightness) (L*)	CIE-Lab*	L = seed lightness (spectrophotometer)
Grain color (green-red) (a*)	CIE-Lab*	a = green (-) to red (+) (spectrophotometer)
Grain color (blue-yellow) (b*)	CIE-Lab*	b = blue (-) to yellow (+) (spectrophotometer)
Whiteness Index	Index	Calculated index reflecting grain surface whiteness
Seed area (Area)	mm ²	2D projected area of grain (image analysis)
Aspect ratio	Ratio	Ratio of grain length to width
Average density (Density)	Unitless	Mean grain density
Diameter max	mm	Shortest cross-sectional width from image analysis
Diameter min	mm	Longest cross-sectional length from image analysis
Diameter ave	mm	Mean cross-sectional diameter from image analysis
Perimeter	mm	Total boundary length of grain from image analysis
Roundness	Unitless	Shape index ($4\pi \cdot \text{area}/\text{perimeter}^2$); higher = rounder
Grain length	mm	Longest seed axis (image analysis)
Grain width	mm	Width perpendicular to length (image analysis)

Statistical analysis

Statistical analysis was performed using R (R Core Team, 2024). All agromorphological and grain physical traits were measured at the individual plant level. The quantitative variables were subjected to analysis of variance (ANOVA) after verifying the assumptions of normality and homogeneity of variances using the Shapiro-Wilk and Levene's tests, respectively (Fox & Weisberg, 2019). Post hoc

comparisons among means were conducted using Tukey's Honest Significant Difference (HSD) test at a significance level of $\alpha = 0.05$ (de Mendiburu, 2023). Accession $\times$ year interaction analysis was applied only to agromorphological traits, as grain physical traits were evaluated during a single growing season. Pearson's correlation analysis was conducted using accession means. Principal Component Analysis (PCA) was performed to reduce the dimensionality of the agromorphological and grain physical traits, allowing for a clearer visualization of the relationships among the accessions. This analysis helped to identify key patterns in the data and revealed the main sources of variability within the dataset. Cluster analysis was performed on standardized data using hierarchical clustering (Maechler et al., 2025), with the Ward linkage method and Euclidean distance as the dissimilarity metric.

RESULTS AND DISCUSSION

Plant Agromorphological Traits

Mean values of quantitative agromorphological traits for all studied barley accessions are summarized in Table 3. A highly significant genotypic effect was observed across most traits, particularly for plant height, spike morphology, grain number, and total yield. Additionally, year-to-year variation had a significant effect, underscoring the influence of environmental fluctuations between growing seasons. The 2022–2023 season, characterized by more moderate climatic conditions, was associated with enhanced biomass accumulation and increased grain weight. In contrast, the 2023–2024 season, which experienced generally warmer temperatures and lower rainfall (particularly in June), resulted in taller plants and longer spikes, but generally lower grain yields (Bento et al., 2021). This distinction highlights the complex interaction between climatic factors and plant development, where warmer temperatures in the 2023–2024 season, coupled with reduced rainfall, may have led to increased vegetative growth but reduced reproductive success, affecting overall yield (Hossain et al., 2012).

Plant height varied significantly among accessions, with landraces H1 and old barley cultivar Athinaida (H9) producing the tallest plants (> 78 cm), while cultivar Triptolemos exhibited the shortest stature (63.26 cm). This height difference could be attributed to traditional selection for biomass and competitive ability in landrace genetic material, as well as to the absence of dwarfing genes that are commonly introduced in modern cultivars (Richards et al., 2002). Similarly, previous studies have highlighted the genetic diversity of landraces in terms of plant stature, with crop landraces generally showing greater height compared to modern cultivars (Radic et al., 2024). Interestingly, the strong positive correlation between plant height and spike length did not translate into higher productivity, suggesting resource allocation trade-offs typical of Mediterranean environments (Richards et al., 2002; Brunner et al., 2024). These findings are in line with other research that has indicated that, while taller plants may develop longer spikes, they do not necessarily result in higher yields (Mullualem et al., 2024; Hlisenikovsky et al., 2024).

Table 3. Mean values of quantitative agromorphological traits and multiple comparisons among barley accessions using Tukey's *test* ($\alpha = 0.05$)

Treatments	Plant height (cm)	Plant weight (g)	Number of stems	Number of spikes	Spike length (cm)	Weight main spike (g)	Number of grains	Weight of main spike grains (g)	Weight of other spikes' grains (g)	TWK (g)	Total yield (g)
H1	80.59 ^a	24.49	9.51	7.47	11.96	1.61	40.13	1.32	3.87	32.68 ^{ab}	5.19
H2	76.49 ^{abc}	20.54	8.14	6.6	12.15	1.51	39.72	1.27	3.12	32.06 ^{ab}	4.35
H3	69.1 ^{abc}	17.68	7.78	3.92	11.09	4.7	38.56	1.01	1.24	25.51 ^{bc}	2.02
H4	70.45 ^{abc}	17.57	8.37	6.18	12.10	1.45	45.46	1.59	2.56	36.85 ^a	4.15
H5	66.29 ^{bc}	20.49	8.46	5.03	11.49	1.49	40.00	1.17	2.25	28.38 ^{abc}	3.62
H6	71.67 ^{abc}	25.34	8.36	6.08	12.82	4.10	41.55	1.12	2.63	26.77 ^{bc}	3.75
H7	74.98 ^{abc}	20.33	8.47	6.01	12.25	1.51	40.68	1.21	2.68	29.64 ^{abc}	3.59
H8	70.82 ^{abc}	30.21	9.07	7.02	12.26	1.62	40.26	1.37	3.84	33.01 ^{ab}	5.21
H9	78.02 ^{ab}	23.31	7.23	6.38	10.85	1.80	47.08	1.56	4.38	33.09 ^{ab}	5.93
H10	63.26 ^c	23.75	8.30	6.31	10.46	1.52	50.95	1.24	3.28	24.66 ^{bc}	4.50
H11	65.02 ^{bc}	18.60	7.70	6.75	13.77	2.95	26.10	0.84	2.25	32.19 ^{ab}	3.04
H12	67.04 ^{bc}	17.23	7.00	4.75	12.56	1.48	56.27	1.20	2.03	21.19 ^c	3.62
Prob > F ¹	*** ¹	ns	ns	***	***	ns	***	ns	***	*	***
2022–2023	53.94 ^b	27.00 ^a	9.39	7.01	6.21	2.71	43.33	1.45 ^a	3.31	33.76 ^a	4.69
2023–2024	88.35 ^a	16.25 ^b	7.01	5.07	17.75	1.58	41.13	1.04 ^b	2.38	25.58 ^b	3.50
Prob > F	***	***	***	***	***	*	*	***	***	***	***
Accession x Year	ns	ns	*	*	***	*	**	ns	***	ns	***
R ² ²	0.92	0.57	0.57	0.71	0.99	0.49	0.80	0.55	0.78	0.56	0.80
CV% ³	9.45	39.17	23.21	20.84	6.28	61.68	11.75	31.24	26.28	26.89	22.15
G. Mean ⁴	71.14	21.63	8.20	6.04	11.98	2.14	42.23	1.24	2.84	29.67	4.09

¹ Prob > F: Significance level; * / ** / ***: $p < 0.05$ / 0.01 / 0.001; ns: Not significant; ² R²: Coefficient of determination; ³ CV%: Coefficient of variation;

⁴ G. Mean: Grand mean: Different letters indicate significant differences based on Tukey's *test*.

In terms of spike productivity, landrace H1 recorded the highest number of spikes per plant (7.47), closely followed by landrace H8 and old cultivar H9. H8 also exhibited the highest total plant biomass (30.21 g), indicating strong vegetative vigor. This vegetative vigor is a key factor in overall plant productivity, as confirmed by previous findings where higher biomass was positively correlated with greater yield potential (Křen et al., 2014). Main spike length and weight were significantly influenced by both genotype and growing season, with significant accession $\times$ year interactions. The variability in spike characteristics due to environmental factors further supports the importance of genotype $\times$ environment interactions in shaping crop performance (Hlisnikovský et al., 2024).

Yield-related traits further differentiated the accessions. While cultivar Explora-R2 produced the highest number of grains per plant (56.27), this did not translate into a high final yield due to relatively low grain weight. In contrast, landrace H8 and old cultivar H9 (Athinaida) achieved the highest grain yields (5.93 g and 5.21 g per plant, respectively) by combining high grain number with greater grain mass. This aligns with previous studies that highlight the importance of balancing both grain number and grain size for achieving high productivity (Zhang et al., 2021). Additionally, landrace H1 also demonstrated robust productivity. Conversely, landrace H3, despite producing the heaviest main spike (4.70 g), yielded poorly overall (2.02 g), likely due to a limited number of spikes and reduced grain set, further illustrating the complexity of yield formation.

Thousand-kernel weight (TKW), a key component of grain yield, showed significant variation among genotypes and across years. Landraces H4 (36.85 g) and old cultivar H9 (33.09 g) recorded the highest TKW values, indicating superior grain-filling capacity. The importance of TKW for overall yield potential has been well-documented, as higher TKW values are consistently associated with increased grain yield (Zhang et al., 2021). This trait plays a crucial role in determining final productivity and is a key target for breeders looking to improve barley yields.

The interaction between year and accession had a significant effect on barley yield. More specifically, the environmental conditions of the 2023–2024 growing season, characterized by warmer temperatures and lower rainfall compared to the 2022–2023 season and the long-term average (1991–2020), had a marked impact on the productivity of the barley accessions. Among the landraces, H7 exhibited the smallest yield decline (-32%), standing out for its superior adaptability compared to other landraces such as H8 (-36%) and H1 (-38%) (Fig. 3). This differential response to environmental stress is consistent with findings from other studies that emphasize the role of genetic adaptability in mitigating yield losses under adverse conditions (Hlisnikovský et al., 2024). Additionally, H5, although experiencing some yield reduction, maintained higher yields than many other landraces, suggesting potential resistance to environmental stressors, which is a valuable trait for sustainable agriculture. Notably, landrace H4, although not one of the top-performing germplasm, showed relative stability among the landraces, with a yield decline of only -25%, in contrast to the more significant reductions observed in others. This suggests that H4 may possess inherent traits that allow it to better withstand environmental stress (Salimi et al., 2023; Czembor & Czembor, 2025).

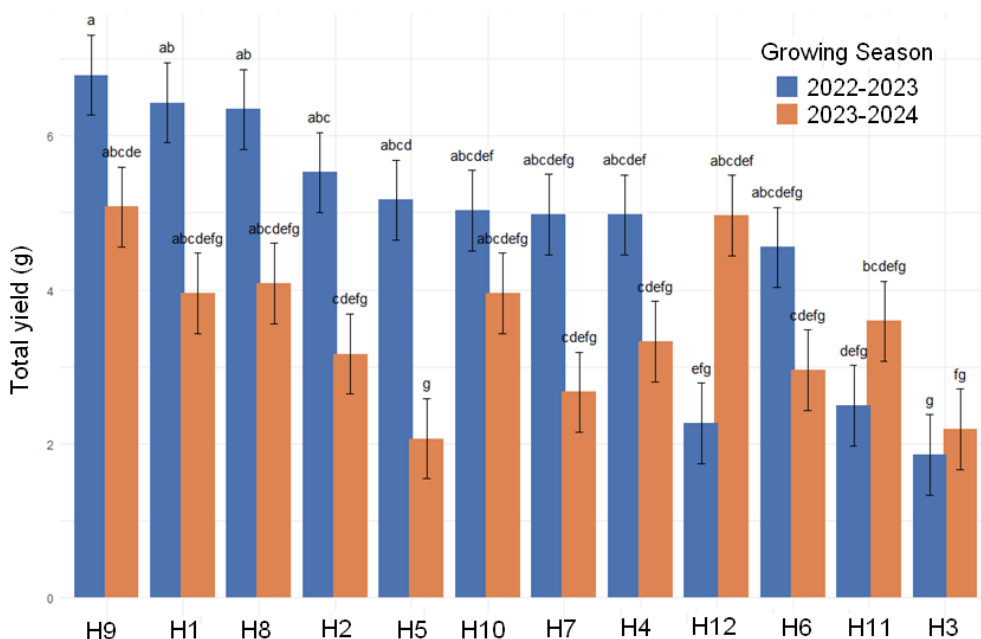


Figure 3. Multiple comparisons of total yield of barley accessions per Growing Season using the Tukey *test*. Different letters indicate significant differences ($\alpha = 0.05$).

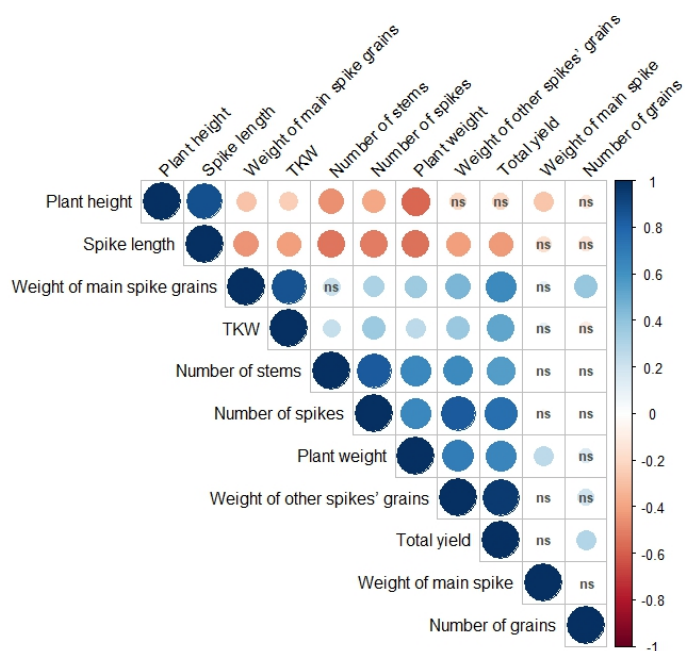


Figure 4. Correlation coefficients between quantitative agromorphological traits of the studied barley accessions ($n = 72$). Circle size shows correlation strength; color indicates direction (red: negative, blue: positive). Non-significant correlations are denoted as 'ns'.

Pearson correlation analysis among the measured traits (Fig. 4) revealed several statistically significant associations. Total grain yield was significantly correlated with 1,000-kernel weight ($r = 0.95$), grain weight from secondary spikes ($r = 0.64$), and grain number from the secondary spikes ($r = 0.65$). This reinforces the importance of both the main and secondary spikes in contributing to the final yield. The number of stems per plant was significantly correlated with both spike count ($r = 0.83$) and spike length ($r = 0.75$), suggesting that genotypes with higher tillering capacity also tend to produce longer and more numerous spikes. Additionally, spike length was significantly positively correlated with 1,000-kernel weight ($r = 0.83$). These correlations support the additive value of both the main and secondary spikes in determining overall productivity (Radic et al., 2024). Plant height was significantly positively correlated with spike length ($r = 0.87$), yet significantly negatively correlated with traits directly associated with seed yield, such as plant weight ($r = -0.57$). This suggests that taller plants with longer spikes may not always achieve greater yield, likely due to biomass allocation constraints under Mediterranean conditions (Richards et al., 2002; Brunner et al., 2024). Furthermore, a significantly positive correlation was observed between the grain weight of the main and the grain weight of the secondary shoots, reinforcing the additive value of both the main and secondary spikes in determining the final yield (Güngör et al., 2024).

Grain Physical Traits

Statistical analysis revealed significant differences among barley accessions across multiple quality parameters (Tables 4, 5). The old cultivar Athinaida (H9) demonstrated higher performance in grain firmness (116.92 N), lightness (52.44), and whiteness index (47.80), closely followed by H5 (firmness: 113.90 N; L: 50.24; WI: 47.11). Both accessions exhibited significantly higher values in these key quality traits compared to the rest of the cultivars, underscoring their potential for food and processing applications. However, it should be noted that no biochemical or nutritional quality assessments were conducted, limiting the extent to which these traits can predict actual food processing suitability (Marshall et al., 1986; Berman et al., 1996).

Moreover, the landraces H1, H7, H8, and old cultivar Athinaida (H9) displayed increased bulk and tap densities ($\geq 0.44 \text{ g cm}^{-3}$ and $\geq 0.48 \text{ g cm}^{-3}$, respectively), reflecting compact and uniform grain structures. These characteristics are particularly favorable for industrial processing, packaging efficiency, and storage stability. Regarding colorimetric traits, Athinaida and Triptolemos showed elevated red-green color balance (a^*), while Explora-R2 exhibited the lowest (b^*) value, indicating reduced yellow pigmentation, an attribute that may influence consumer appeal and visual sorting in processing lines.

Regarding morphometric traits, H1 and H8 stood out for their large average grain diameters (5.89 mm and 5.62 mm, respectively) and long grain lengths (8.41 mm and 8.59 mm), indicating well-developed and full grain. Athinaida (H9) also combined favorable values of roundness (1.37), perimeter (20.43 mm), and density (152.81 g cm^{-3}), further highlighting its robust grain structure. In contrast, cultivar Explora-R2 presented the highest aspect ratio (2.11) and grain density (159.47 g cm^{-3}), yet combined these with lower firmness, brightness, and yellowness, traits that may limit its suitability for specific end uses.

Table 4. Mean values of quantitative physical and colorimetric grain traits and multiple comparisons among barley accessions using Tukey's test ($\alpha = 0.05$)

Treatments	Grain firmness (N)	Volume (cm ³)	Tap volume (cm ³)	Bulk density (g cm ⁻³)	Tap density (g cm ⁻³)	CI	L	a	b	WI
H1	102.91 ^b	101.78	88.22 ^b	0.47 ^a	0.52 ^a	11.66	50.80 ^{ab}	5.27 ^{abc}	19.74 ^{ab}	46.68 ^{ab}
H2	101.25 ^b	126.89	106.67 ^a	0.39 ^{ab}	0.47 ^a	15.79	49.72 ^{ab}	4.16 ^{abc}	18.09 ^{ab}	46.39 ^{ab}
H3	107.32 ^b	94.67	83.56 ^{bc}	0.36 ^{ab}	0.41 ^{ab}	11.36	48.35 ^{ab}	3.86 ^{bc}	16.36 ^{ab}	45.67 ^{ab}
H4	105.26 ^b	108.89	96.44 ^b	0.39 ^{ab}	0.43 ^a	10.86	50.79 ^{ab}	5.32 ^{abc}	19.56 ^a	46.72 ^{ab}
H5	113.90 ^{ab}	95.67	82.22 ^{bc}	0.42 ^{ab}	0.47 ^a	11.56	50.24 ^{ab}	4.03 ^{abc}	17.41 ^{ab}	47.11 ^a
H6	100.54 ^b	100.78	85.89 ^b	0.39 ^{ab}	0.44 ^a	13.10	48.22 ^{ab}	4.84 ^{abc}	16.03 ^{ab}	45.33 ^{ab}
H7	96.96 ^{bc}	102.89	90.00 ^b	0.45 ^a	0.50 ^a	10.54	50.31 ^{ab}	4.45 ^{abc}	18.68 ^{ab}	46.70 ^{ab}
H8	107.85 ^{ab}	102.89	93.11 ^b	0.45 ^a	0.48 ^a	7.21	49.64 ^{ab}	2.93 ^c	16.56 ^{ab}	46.74 ^{ab}
H9	116.92 ^a	99.33	88.22 ^b	0.44 ^a	0.49 ^a	9.99	52.44 ^a	6.02 ^{ab}	20.39 ^a	47.80 ^{ab}
H10	96.69 ^{bc}	87.78	74.89 ^{cd}	0.44 ^a	0.49 ^a	12.17	46.91 ^{ab}	6.79 ^{ab}	10.98 ^{bc}	44.12 ^{ab}
H11	93.99 ^c	76.00	71.33 ^{cd}	0.51 ^a	0.54 ^a	5.16	49.93 ^{ab}	5.94 ^{ab}	19.63 ^{ab}	45.87 ^{ab}
H12	91.65 ^c	89.11	78.67 ^c	0.25 ^b	0.29 ^b	11.31	40.98 ^b	6.27 ^a	5.24 ^c	39.55 ^b
Prob > F ¹	*	ns	*	*	*	ns	*	**	*	*
R ² ²	0.47	0.25	0.47	0.41	0.52	0.19	0.51	0.67	0.57	0.52
CV% ³	14.52	26.14	21.75	27.29	21.25	61.93	8.82	27.26	38.09	6.91
G. Mean ⁴	102.9	98.88	86.60	0.41	0.46	49.03	42.23	4.98	16.55	45.72

¹ Prob > F: Significance level; * / ** / ***: $p < 0.05$ / 0.01 / 0.001 ; ns: Not significant; ² R²: Coefficient of determination; ³ CV%: Coefficient of variation;

⁴ G. Mean: Grand mean; Different letters indicate significant differences based on Tukey's test.

Table 5. Mean values of geometric grain traits and multiple comparisons among barley accessions using Tukey's *test* ($\alpha = 0.05$)

Treatments	Grain area (mm ²)	Aspect ratio	Density	Diameter max (mm)	Diameter min (mm)	Diameter ave (mm)	Perimeter (mm)	Roundness	Grain length (mm)	Grain width (mm)
H1	28.17	1.97 ^{ab}	143.79 ^b	8.38 ^a	4.25	5.89	21.56	1.32 ^{ab}	8.41 ^a	4.37
H2	27.21	2.08 ^{ab}	146.93 ^b	8.42 ^a	4.12	5.67	21.25	1.35 ^{ab}	8.41 ^a	4.17
H3	27.04	1.96 ^{ab}	148.77 ^b	8.19 ^{ab}	4.18	5.67	21.24	1.33 ^{ab}	8.20 ^{ab}	4.34
H4	27.94	1.91 ^{ab}	147.09 ^b	8.23 ^{ab}	4.32	5.78	21.41	1.31 ^{ab}	8.26 ^{ab}	4.45
H5	26.85	2.07 ^{ab}	150.78 ^b	8.49 ^a	4.07	5.61	21.55	1.38 ^{ab}	8.50 ^a	4.22
H6	26.43	1.93 ^{ab}	148.75 ^b	7.88 ^{ab}	4.11	5.55	20.73	1.32 ^{ab}	7.89 ^{ab}	4.26
H7	26.45	2.02 ^{ab}	145.18 ^b	8.16 ^{ab}	4.06	5.59	20.98	1.33 ^{ab}	8.17 ^{ab}	4.2
H8	27.13	2.18 ^a	145.35 ^b	8.58 ^a	3.95	5.62	21.55	1.37 ^{ab}	8.59 ^a	4.07
H9	24.47	2.11 ^{ab}	152.81 ^{ab}	8.17 ^{ab}	3.89	5.4	20.43	1.37 ^{ab}	8.19 ^{ab}	4.01
H10	22.54	1.88 ^b	153.4 ^{ab}	7.30 ^b	3.88	5.19	18.9	1.27 ^b	7.32 ^b	3.99
H11	23.87	1.85 ^b	147.31 ^b	7.55 ^{ab}	4.07	5.43	19.63	1.29 ^{ab}	7.57 ^{ab}	4.18
H12	23.8	2.11 ^{ab}	159.47 ^a	8.04 ^{ab}	3.73	5.24	20.46	1.43 ^a	8.06 ^{ab}	3.91
Prob > F ¹	ns	**	*	*	ns	*	ns	*	**	ns
R ² ²	0.46	0.60	0.69	0.61	0.37	0.43	0.46	0.51	0.61	0.33
CV% ³	8.99	4.83	2.31	4.31	5.92	4.86	5.11	3.68	4.31	6.47
G. Mean ⁴	25.99	2.01	149.13	8.11	4.05	5.55	20.80	1.33	8.13	4.17

¹ Prob > F: Significance level; * / ** / ***: $p < 0.05$ / 0.01 / 0.001; ns: Not significant; ² R²: Coefficient of determination; ³ CV%: Coefficient of variation;

⁴ G. Mean: Grand mean; Different letters indicate significant differences based on Tukey's *test*.

Correlations between various characteristics provided further insights into the relationships among the grain properties (Figs 5, 6). A significantly positive correlation was observed between grain firmness and both bulk density and tap density ($r = 0.33$ and 0.35 respectively), suggesting that firmer grains tend to be denser (Aghajani et al., 2012). This relationship is important for grain processing, as denser grains might affect milling and processing efficiency. Furthermore, a significantly positive correlation between diameter and grain size (both length and width) was found ($r = 0.73$ and 0.92). Roundness and perimeter were also positively correlated ($r = 0.38$), indicating that more rounded grains tend to have a larger perimeter, which is expected given that rounder grains are typically more compact and easier to process. Moreover, increased roundness may also be indicative of grain maturity or the absence of morphological defects, as mature grains tend to develop a more symmetrical shape during ripening.

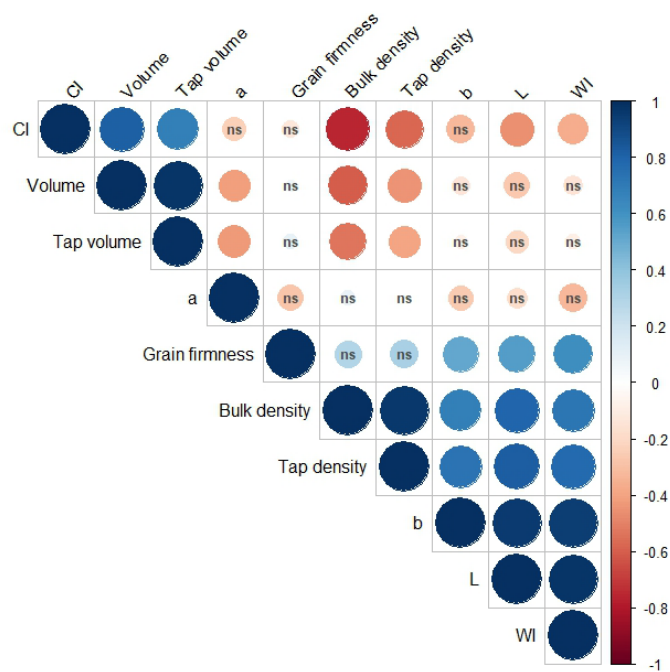


Figure 5. Correlation coefficients between physical and colorimetric grain traits of the studied barley accessions ($n = 36$). Circle size shows correlation strength; color indicates direction (red: negative, blue: positive). Non-significant correlations are denoted as ‘ns’.

Color parameters, such as L (lightness) and b (yellow-blue), were significantly positively correlated with the whiteness index (WI) ($r = 0.97$ and 0.94 respectively), meaning that grains with a higher lightness and more yellow hue tend to have better whiteness quality. This has important implications for applications where color and product quality are critical, such as in flour production or other grain-based products (Novaro et al., 2001). However, in composite flour mixtures where color differences are minimal or not visually perceptible, the impact of these color attributes on overall quality may be reduced, highlighting the need for complementary quality parameters in such

contexts. Lastly, there was a negative correlation between grain firmness and the a (red-green) index ($r = -0.34$), suggesting that firmer grains tend to have a lower ‘red’ intensity.

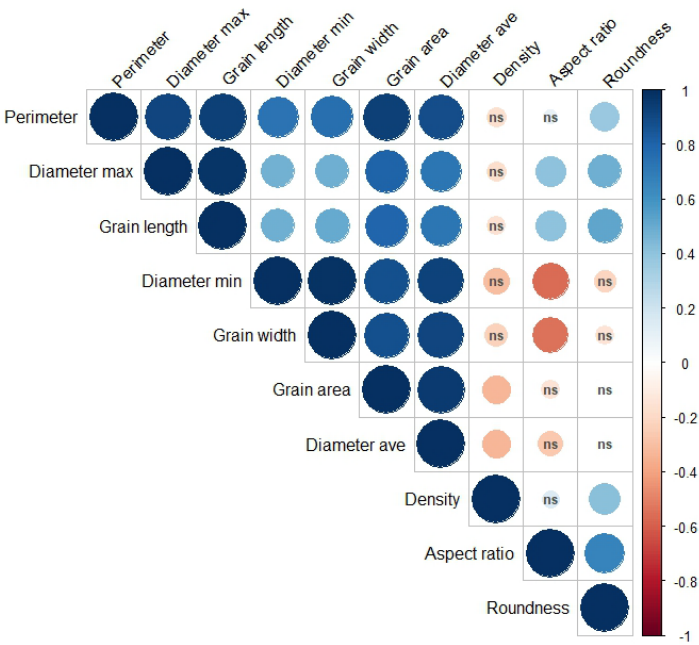


Figure 6. Correlation coefficients between geometric grain traits of the studied barley accessions ($n = 36$). Circle size shows correlation strength; color indicates direction (red: negative, blue: positive). Non-significant correlations are denoted as ‘ns’.

Landrace H6 and old cultivar H9 exhibited the highest grain firmness, making them more suitable for industrial processing applications where durability is required (Marshall et al., 1986; Berman et al., 1996). Larger and more spherical grains, as observed in landraces H6 and H8, were associated with better processing quality and higher commercial preference. This is an important finding for grain processing, as larger tend to yield better results in milling and are generally preferred in certain industrial applications (Marshall et al., 1986; Berman et al., 1996; Novaro et al., 2001). Larger grains also typically have higher market value and are more efficient in processing. Moreover, color parameters such as whiteness and lightness, which were higher in accessions H8 and H9, could enhance consumer acceptance in food industries. These differences in color may influence the consumer acceptance of grains in the market, with brighter and whiter grains generally being preferred.

Grouping of Accessions

Cluster analysis based on agronomic and grain physical traits clearly distinguished the barley accessions according to their geographic origin and breeding status (Fig. 7). The first two principal dimensions explained 55.2% of the total variation (35.5% and 19.7%, respectively), with PC1 mainly associated with grain physical traits (average

diameter, whiteness index, area, thousand kernel weight) and PC2 reflecting variation in bulk density, roundness, spike count, and seed length.

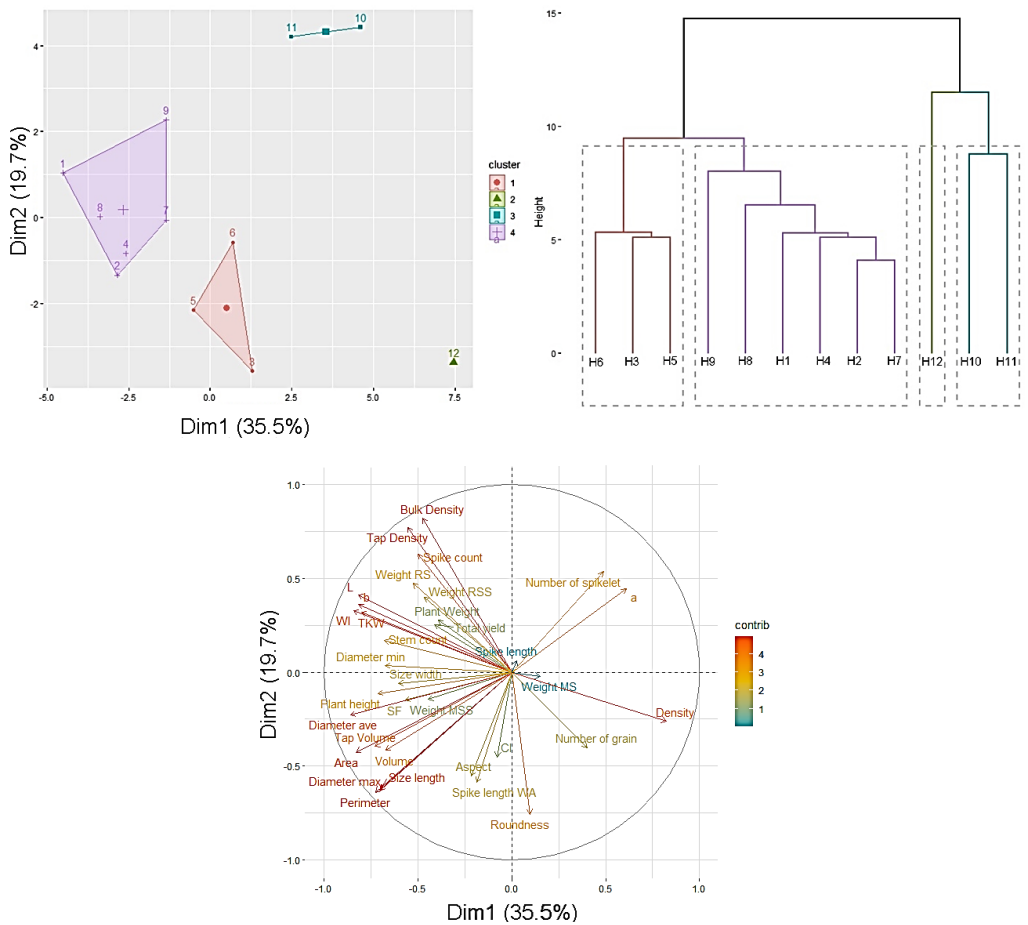


Figure 7. Cluster plot, dendrogram, and PCA biplot of barley accessions based on all recorded traits.

Aegean Island landraces formed a distinct cluster, characterized by smaller, harder seeds and shorter plants, traits that likely reflect adaptation to dry and nutrient-poor island environments. Mainland accessions (e.g., H3, H8) and the old cultivar Athinaida (H9) clustered more closely with other landraces, while modern cultivars (Triptolemos, Thessaloniki, Explora-R2) grouped separately, showing high morphological uniformity as a result of targeted breeding for productivity and agronomic stability. Notably, some traditional accessions (e.g., H8, H9) performed as well as or better than modern cultivars in several agronomic traits, highlighting their potential for use in breeding programs. Despite their morphological diversity, landraces shared structural traits such as spike architecture and seed hardness, indicating parallel adaptation to traditional, low-input farming systems, in agreement with findings reported for other cereal landraces (Korpetis et al., 2023).

CONCLUSIONS

This study highlighted the significant phenotypic variability among cultivar and landrace barley accessions under Mediterranean conditions. Agromorphological trait analyses revealed strong genotype effects and significant accession $\times$ year interactions, while grain physical traits displayed distinct genotypic differences. Landraces, particularly those from the Aegean islands, exhibited unique morphological and physical profiles, such as smaller but firmer grains and reduced plant height, traits that may reflect long-term adaptation to arid and low-input environments. Cluster analysis effectively grouped accessions according to geographic origin and breeding status, highlighting the structural divergence between landraces and modern cultivars. Notably, several accessions (e.g., H1, H4, H8, H9) demonstrated agronomic performance comparable to or exceeding that of modern cultivars, showing promising levels of yield stability and adaptive potential under Mediterranean field conditions. These traits may indicate a degree of resilience; however, further physiological studies and evaluation under targeted abiotic stress conditions are required to substantiate this adaptive potential. While the findings offer valuable insights into the phenotypic diversity and agronomic potential of Greek barley landraces, their broader validation would benefit from additional testing across environments and under defined stress conditions. Such efforts could help consolidate the present conclusions and further support their relevance for breeding and adaptation.

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Analysis of charging capacity for electric vehicles in soviet-era apartment districts from the perspective of substation power availability

J. Lumi* and A. Tooming

Estonian University of Life Sciences, Institute on Forestry and Engineering,
Chair of Energy Application Engineering, F.R. Kreutzwaldi 1, EE51006 Tartu, Estonia
*Correspondence: janek.lumi@emu.ee

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Abstract. This article analyses the potential for electric vehicle (EV) home charging in a Soviet-era apartment district powered by the Lammi substation in Tartu, Estonia. Using one year of hourly electricity consumption data from 360 apartments, the study evaluates three load management scenarios to determine how many EVs can be supported without overloading the existing transformer infrastructure. The analysis is based on a worst-case winter week, reflecting realistic household consumption patterns and typical EV charging behaviour, which does not require daily charging. Three load control strategies are compared: (1) dynamic load management limited by weekly peak load; (2) fixed nighttime charging within a capped substation load; and (3) full dynamic charging for all apartments. The results show that up to 96, 218, and 360 EVs could be supported under these respective scenarios. The findings highlight how the choice of charging strategy significantly affects infrastructure demands and demonstrate that coordinated load management can enable broader EV integration without immediate large-scale investment. The study contributes practical insight for energy planners and housing associations seeking to align smart charging systems with the technical limits of existing substations.

Key words: charging, electric vehicles, load management, residential charging, substation capacity.

INTRODUCTION

The main research question of this article is the following: How many electric vehicles (EVs) can realistically be charged at home in a Soviet-era apartment district under different load management strategies, without overloading the existing substation infrastructure? Specifically, the study evaluates whether the current capacity of the Lammi substation (serving 360 apartments) allows for meaningful EV integration and how this depends on the presence and type of Smart Charging Management Systems (SCMS).

Rather than setting an artificial threshold (such as 50% of households), this research formulates a more practical question: What is the maximum number of EVs that can be charged in a given week under various management scenarios? This approach reflects real-world needs, where energy planners and housing associations must determine what

kind of smart charging setup (if any) can allow the widest possible EV adoption under infrastructure constraints.

A key insight driving this analysis is that EV owners do not typically need to recharge daily. With an average energy consumption of 20 kWh per 100 km and a typical daily driving distance of around 50 km, the average user only needs about 70 kWh of energy per week (EV Database, 2025). In practice, this means most EVs are charged once or twice per week - not every day. Accordingly, this study analyzes charging potential during the worst-case consumption week (8–14 January 2024), not a single day or hourly peak. This better reflects how SCMS systems can balance demand over time rather than being constrained to short peak periods.

Three different EV integration scenarios are analyzed:

1. Dynamic Load Management Based on Weekly Peak Power – showing that up to 96 EVs could be supported;
2. Fixed Nighttime Load Management (23:00–07:00) – allowing up to 218 EVs to be charged;
3. Dynamic Load Management for All Apartments (360 EVs) – requiring a calculated minimum capacity of 242 kVA to meet full weekly charging needs.

It is important to note that the 360 kVA limitation referenced in this study is not an imposed constraint of the analysis, but rather the realistic technical limit of the Lammi substation's transformer (90% of the transformer's rated 400 kVA), selected to reflect engineering safety margins used in practical network planning.

These scenarios illustrate the trade-offs and limits under real-world conditions, helping to define how SCMS should be configured. In essence, this article provides the energy consumption modeling needed to help set up SCMS to manage supply limitations effectively - one of the key challenges in older residential areas.

Greenhouse gas emissions from the transport sector are a key target of the European Union's climate policy (European Commission, 2024). A major element of this strategy is raising the use of electric vehicles (EVs), which decreases dependency on fossil fuels while also improving the environmental quality of urban areas. However, that creates some concerns about whether the electrical grid is up to the task, at least in older residential areas where the infrastructure may not be designed to accommodate today's level of demand.

This issue relates especially to Estonia where up to 70% of the population lives in apartment buildings (Estonian Human Development Report, 2020). Residential areas like Tartu's Annelinn already have considerable electrical grid loads and the integration of new types of intense loads like electric vehicles could have a significant impact on the stability of the network. Lammi substation in Annelinn provides power to several large apartment buildings, including using the first transformer output, 360 apartments.

Estonia has seen rapid growth in electric vehicle numbers. By the beginning of 2025, Estonia had registered nearly 8,400 battery electric vehicles, a significant increase from previous years (Ministry of Climate, 2025). According to a study commissioned by (Elering, 2022), approximately 250,000 electric cars and electric vans are forecasted in Estonia by the year 2040. This growth represents a heavy new demand, especially on residential low-voltage networks where home-based charging is generally favoured (Sica et al., 2025).

Hence, understanding the capacity of the existing grid and exploring how to enable EV adoption without jeopardizing the reliability of the network or requiring urgent, large-scale and expensive investments in infrastructure would need to be a requirement. A number of different studies have been performed in recent years in order to explore the effect that EV charging has on the power distribution system. A study titled 'Impact assessment of electric vehicle charging on distribution networks' analysed the influence of EV loads on low-voltage distribution systems under various charging strategies. It demonstrated that uncoordinated charging may lead to transformer overload and voltage drops, particularly during peak periods. The study also concluded that coordinated or smart charging significantly improves network stability and reduces energy losses (Khan et al., 2024). A different study, titled 'Impact of electric vehicle charging demand on power distribution systems', quantified the impacts of EVs on distribution systems, warning that without heavy investments in infrastructure, an increasing number of EVs could lead to network overloads affecting reliability (Li & Jenn, 2024). These findings underscore the importance of care in design and load management to successfully integrate EVs within existing distribution networks.

Smart charging has become an important strategy for minimising the adverse effects of EV charging on electrical networks. The study 'Impact of public and residential smart EV charging on distribution power grid equipped with storage' analysed if smart charging could be used as a tool for easing the impact of integration of EVs into the distribution systems, concluding that significant reduction in grid load during peak periods and better overall network performance could be observed (Khalid et al., 2024).

Recent studies emphasize the importance of smart charging and centralized Vehicle-to-Grid (V2G) management systems. Secchi et al. (2023) proposed an algorithm enabling smart EV charging integrated with centralized V2G capabilities to minimize grid load variability and enhance grid stability, particularly under conditions of increased penetration of photovoltaic (PV) systems and electric vehicles.

There are a few case studies that have looked at the impact of EV charging in particular areas. For example, the research 'Impact of Electric Vehicle Charging on Power Distribution Systems: A Case Study of the Grid in Western Kentucky' examined the effects of EV charging on the power distribution system in Kentucky (Roy et al., 2023), showing the possibility of overload and providing mitigation measures. This highlights the importance of regional analyses to better understand the effects of EV charging interaction with specific distribution systems.

The key takeaway is that the last five years of research shows charging electric vehicles has a big impact on electrical grids, but smart charging and new technologies can help meet the needs. It highlights the importance of continued research and investment to facilitate a smooth transition to electric transportation without compromising the reliability and efficiency of the power grid.

MATERIALS AND METHODS

The dataset of this study consists of hourly electricity consumption data from the first transformer output (T1) of Lammi substation from 9 December 2023 to 8 December 2024. The data are from control measurements of the distribution company with estimated values of active power (kW) and apparent power (kVA). To guarantee data quality, measurement errors were identified and excluded according to the Z-score

method (± 3 standard deviations). Also, outliers, had to be removed - since values below 20 kW(0.025 pu previously) and 20 kVA(0.025 pu from the max. apparent power) were considered unreliable. Thus, 90 data points were discarded from analysis out of a total of 8,784, and the final number of data points for analysis was 8,694.

Simulation Assumptions:

- The research based on the transformer output T1 load in the Lammi substation: The Lammi substation serves 360 apartments. This study was conducted on the Lammi substation, because it supplies only residential apartment buildings and no other consumers like commercial or educational buildings. This will enable the examination of EV charging effects on electricity consumption in an apartment building context without the influence of alternative patterns of consumption.

- In simulations, the apparent power (kVA) sent for electric vehicle charging is equal to the active power (kW). In reality, EV charging has also a certain reactive power component, however, this simplification is used in the present work in order to concentrate on the analysis of the active energy consumption impacts and avoid excessive complexity in the simulation model. Future studies should pay attention to reactive power in detail.

- The simulation assumes up to one electric vehicle for each apartment.

- Conventional daily energy consumption for electric vehicles is assumed to be 20 kWh per 100 km (EV Database, 2025), and average daily driving distance is 50 km (Solar On EV, 2024). That means around 10 kWh of charging needs per day or 70 kWh a week. These averages are consistent with numerous European studies and official data sources. In the real world, energy consumption and daily driving distance can differ greatly depending on the season, with energy consumption usually on the high side in winter and daily distance varying for holiday or work and school changes. Needless to say, such seasonal and usage-related variations merit distinct detailed scrutiny, which is not the focus of this article.

- The rated power for the transformer output is 400 kVA, but for ensuring grid reliability and safety, the maximum load used in simulations is limited to 90% of the rated power, namely a maximum of 360 kVA.

- Dynamic load management is used to manage electric vehicle charging:

- Charging power is evenly distributed among chargers according to the maximum allowed total load (known as power sharing).
- The maximum load can be limited either according to the weekly peak load or according to the substation's specified load limit (360 kVA).

Analysis of Electricity Consumption Data and Derivation of Models

To analyze electricity consumption, three separate trend functions were derived based on corrected measurement data.

Daily Load Profile (hourly-based)

The average hourly apparent power consumption per apartment, characterizing daily energy use, was modelled using a sixth-degree polynomial function (Eq. 1), fitted to the measured hourly data over the full year. This function allows approximation of typical daily load profiles in the absence of direct measurements:

$$f_{hour} = 1.64 \cdot 10^{-7} \cdot x^6 - 1.13 \cdot 10^{-5} \cdot x^5 + 2.89 \cdot 10^{-4} \cdot x^4 - 3.43 \cdot 10^{-3} \cdot x^3 + 1.90 \cdot 10^{-2} \cdot x^2 - 3.52 \cdot 10^{-2} \cdot x + 1.27 \cdot 10^{-1} \quad (1)$$

where x represents the hour of the day (0–23).

Fig. 1 shows the average hourly apparent power (kVA) consumption pattern per apartment derived from the hourly measurement data of Lammi substation. The solid line is the average hourly values, which illuminate the typical residential energy usage cycle over 24 hours. Nighttime has a particularly low consumption time frame, who start coming back on around 6:00 or so. Peak usage is between 16:00 and 20:00, which is in line with the average household schedule and evening energy-consuming activities. The dotted line shows the trendline of a 6-order polynomial fitted to the measured data points. The close match between the average consumption values and the polynomial trendline demonstrates a good mathematical fit for modeling purposes. However, this does not imply that each individual day follows this exact profile.

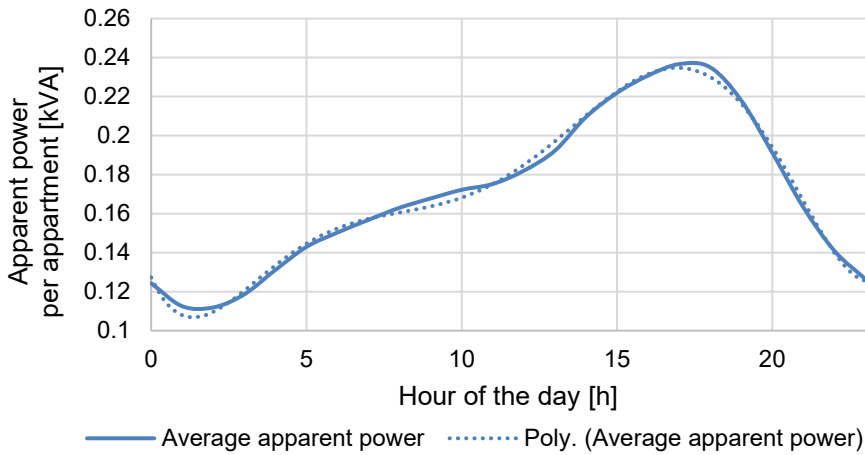


Figure 1. Average hourly apparent power consumption (kVA) per apartment over a typical day, based on one-year measurement data from Lammi substation. The solid line represents measured averages; the dotted line shows a 6th-degree polynomial approximation.

Note: The hourly, daily, and weekly trend functions presented here are not used directly in the simulation scenarios. Rather, they are developed to provide generalized approximations of residential consumption behavior. These trendlines can assist readers in future analyses or planning activities where measured data is unavailable, allowing them to simulate consumption with comparable accuracy based on fitted equations.

Weekly Load Profile (daily-based)

Weekly variations in average daily apparent power consumption per apartment were approximated using a sixth-degree polynomial regression function (Eq. 2). This captures general load patterns across weekdays and weekends, which can assist in week-based charging strategy planning:

$$f_{day} = -2.44 \cdot 10^{-5} \cdot y^6 + 3.45 \cdot 10^{-4} \cdot y^5 - 1.63 \cdot 10^{-3} \cdot y^4 + 2.72 \cdot 10^{-3} \cdot y^3 + 2.15 \cdot 10^{-4} \cdot y^2 - 3.85 \cdot 10^{-3} \cdot y + 1.68 \cdot 10^{-1} \quad (2)$$

where y denotes the day of the week (0 = Monday, ..., 6 = Sunday).

Fig. 2 presents the average weekly pattern of apparent power (kVA) consumption per apartment, calculated by aggregating daily measurement data over the entire week. The solid line shows the typical daily consumption from Monday (marked as day 0) through Sunday (day 6), illustrating how electricity usage varies throughout the weekdays. Consumption remains fairly consistent from Monday to Thursday but clearly rises beginning on Friday, reaching its highest point on Sunday, probably reflecting more household activities occurring during weekends. The dotted line shows a sixth-order polynomial trendline, which effectively summarizes the overall weekly pattern. While the polynomial provides a good fit to the average weekly consumption pattern, it should be interpreted strictly as a modeling tool. No statistical analysis was performed to confirm periodicity across all weeks, and further work is needed to determine the consistency of weekly load cycles.

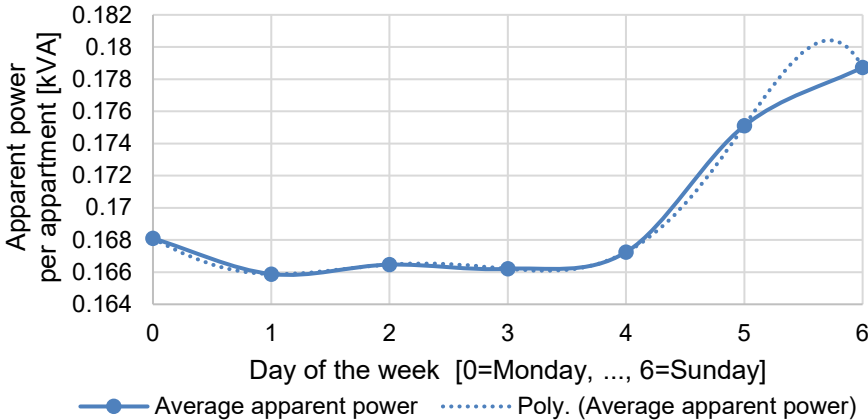


Figure 2. Average daily apparent power consumption (kVA) per apartment across days of the week. Values are based on aggregated yearly data. A 6th-degree polynomial approximation is shown as a dotted trendline.

Annual Load Profile (weekly-based)

Seasonal variation in apartment load was modelled using a sinusoidal approximation (Eq. 3), reflecting the impact of heating and lighting needs across different weeks of the year:

$$f_{week} = 2.586 \cdot 10^{-2} \cdot \sin(8.855 \cdot 10^{-2} \cdot z + 2.280) + 1.779 \cdot 10^{-1} \quad (3)$$

where z represents the week number of the year (1–52).

Fig. 3 depicts the average weekly apparent power (kVA) consumption per apartment throughout a year, calculated from weekly aggregated measurement data. The figure clearly reveals seasonal patterns, showing higher electricity consumption in the colder winter months at the start and end of the year, while consumption noticeably drops during summertime. The lowest electricity usage appears roughly between weeks 20 and 30, corresponding to the summer period, when daylight hours are longest, and less energy is typically needed for heating and lighting. In contrast, the highest electricity consumption happens in winter, driven mainly by greater use of heating systems, lighting, and home appliances. These observations confirm how significantly weather and seasonal changes impact residential electricity usage.



Figure 3. Average weekly apparent power consumption (kVA) per apartment by week number (1–52), reflecting seasonal variations. The curve includes a sinusoidal approximation based on fitted historical data.

Charging scenarios

In this chapter, we discuss electric vehicle charging options available at the Lammi substation by applying different load management techniques and scenarios to assess the ability of the existing substation to meet EV charging demand. Note: The analysis is developed on the week of minimum yearly capacity reserve (08.01.2024–14.01.2024).

Scenario 1: Dynamic load management based on weekly peak power

In this case, dynamic load management was applied, since avoiding exceeding the maximum load of the substation when charging EVs during the week was needed, accounting for the peak power in the week of EV consumption. It was estimated that in this solution approx. 6,756 kWh can be used weekly to charge electric vehicles.

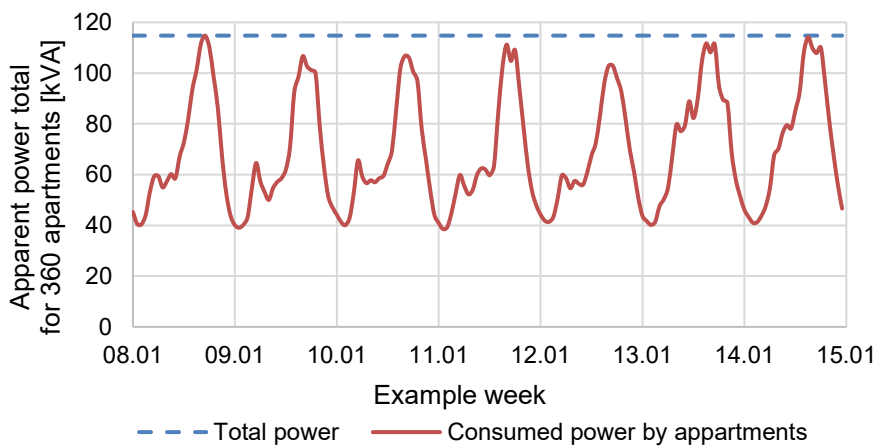


Figure 4. Hourly total apparent power consumption (kVA) for 360 apartments during the week of 8–14 January 2024. The dashed line represents the maximum available transformer capacity based on dynamic load management constrained by weekly peak consumption.

For reference, each electric vehicle needs about 70 kWh of energy per week on average, which means this solution would potentially accommodate the charging of nearly 96 electric vehicles. Fig. 4 illustrates the actual hourly apartment power consumption during the example week (8–14 January 2024), along with the maximum allowable load set according to the weekly peak power. The difference between the maximum allowed load and actual consumption clearly indicates the available power capacity for EV charging.

Scenario 2: Fixed nighttime load management

The second scenario used fixed load control at night (23:00–07:00). In this implementation, the substation load was constrained to 360 kVA, representing 90% of the rated capacity of the substation (400 kVA). Under this scenario, calculations showed that approximately 15,291 kWh of energy would be available weekly for electric vehicle charging. Assuming an average weekly energy requirement from the aforementioned source (70 kWh per vehicle per week), this method can sufficiently service for up to 218 electric vehicles per week. Fig. 5 illustrates hourly apartment consumption for the example week (8–14 January 2024), the total power capacity (blue dashed line), and the fixed maximum allowable load set at 360 kVA (green dashed line). The graph clearly shows the substantial available capacity during nighttime hours allocated for EV charging, highlighting the effectiveness of this load management approach.

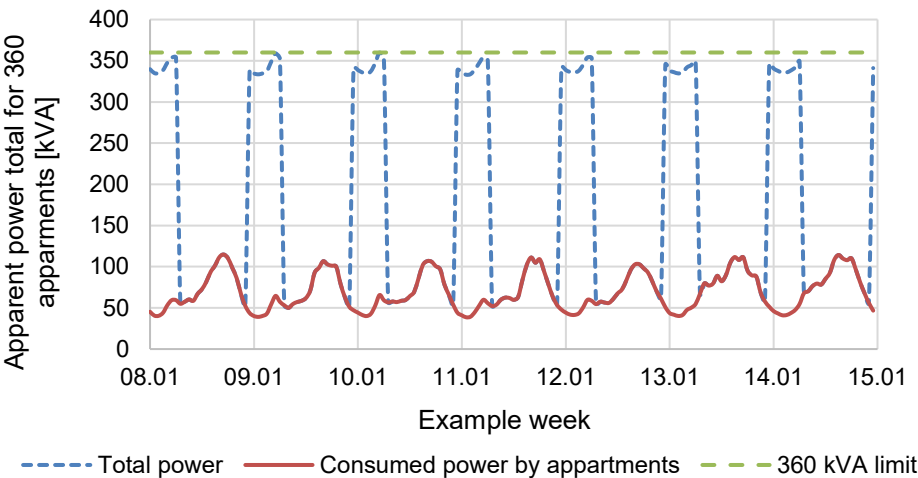


Figure 5. Hourly total apparent power consumption (kVA) for 360 apartments during 8–14 January 2024. The blue dashed line shows the total transformer capacity (400 kVA), and the green dashed line represents the 360 kVA limit applied during nighttime charging (23:00–07:00).

Scenario 3: Dynamic load management for 360 electric vehicles

The third case assumed the presence of one electric vehicle per apartment (360 vehicles in total). The analysis was conducted in order to find out the necessary required substation capacity to satisfy the weekly energy demand of all these EVs with respect to dynamic load management policy. The minimum total capacity of substation should be approximately 242 kVA, according to collected data and calculations.

With this capacity, enough charging could be provided for all of the 360 electric vehicles while considering the current energy consumption of the building as well. Fig. 6 presents hourly apartment apparent power consumption during the example week (8–14 January 2024), with the calculated total power capacity required to serve all apartments and associated EV charging.

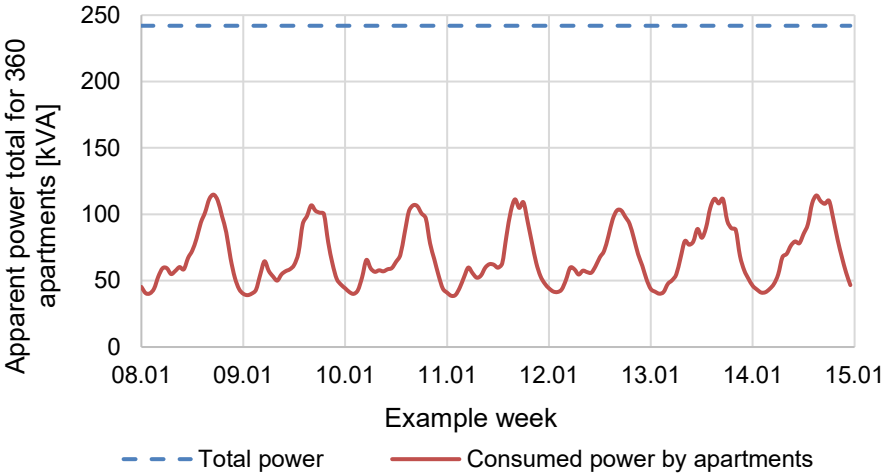


Figure 6. Hourly total apparent power consumption (kVA) during 8–14 January 2024. The dashed line shows the calculated minimum substation capacity (242 kVA) required to support charging for all 360 EVs through dynamic load management across the full week.

These three scenarios help evaluate the utility and capacity of the existing electrical grid and substation with widespread electric vehicle deployment. All scenarios give clues about the investments needed, allowing for grid operators and housing associations to better plan the rollout of electric infrastructure.

RESULTS AND DISCUSSION

In this chapter, we discuss how the scenarios presented in Chapter Materials and Methods could be used in practice for solutions for electric vehicle charging problems. This provides different opportunities and limitations for the usability of all scenarios in different contexts.

Scenario 1: Dynamic load management based on weekly peak power – provides a suitable approach for housing associations wanting to autonomously manage the EV charging requirements of individual households. The main reason for this scenario is the flexibility of the system and the tight regulation of the load of the electrical grid in time and volume to avoid exceeding provided electrical infrastructure. However, this solution presupposes the availability of smart chargers combined with dynamic load management software from day one, which may involve higher up-front capital costs and increased technical complexity.

The second scenario: Fixed nighttime load management – is applicable in cases where EV penetration is low, and grid load can be unambiguously defined. Because charging restrictions are made in fixed time periods at a set maximum load level, the primary benefit to this methodology is that it eliminates the need to set up a complex dynamic load management scheme from the outset. However, this method is problematic: if there are many electric vehicles in a region, load ramps may happen heavily at the beginning and/or end of the charging times when using this method, which may lead to instability in the grid and the need for even more investments in the electricity networks.

The third scenario: Dynamic load management across the entire residential area, and it's an answer for local governments in the case of massive electric vehicle usage. The benefit to this scenario is that it has the potential to be deployed across broad regions all at once vs. each building or housing association having to spend on its own separate charging infrastructure. It also has the benefits of creating load levelling on the electrical grid and reducing the need for additional power investments. In this case, though, a full-fledged load management system would need to be developed and implemented, alongside coordination between network operators, local governments, and residents.

Comparable findings have been observed in related literature on residential grid capacity under EV charging scenarios. For instance, (Li & Jenn, 2024) found that uncontrolled EV charging could lead to transformer overload when EV penetration exceeded 30–40%, even in well-maintained U.S. suburban networks. In the present study, a dynamic load management approach accommodated up to 96 EVs (27% of households), while a fixed nighttime load window supported 218 EVs (over 60%). These results suggest that smart, time-based load shaping strategies can allow for significantly higher EV integration without overloading substations. Similarly, Khan et al. (2024) emphasized that coordinated charging can reduce transformer stress by up to 40% compared to unmanaged scenarios – aligning well with the substation efficiency improvements demonstrated here. These comparative insights reinforce that with proper load management, legacy infrastructure can reliably support a transition to widespread EV adoption.

In summary, the above examples highlight different solutions, and the choice of approach depends primarily on the existing load conditions and the potential for smart charging deployment. This study does not assess cost, pricing models, or detailed investment requirements. However, cost-benefit analysis and infrastructure upgrade cost modeling would be a valuable direction for future research to support implementation planning.

CONCLUSIONS

The affordability of electric vehicles (EVs) plays a critical role in the review of the Lammi substation and analysing the load management techniques. We analysed hourly electricity consumption data from 2023, employing a Z-score threshold to make sure that the data quality was high by removing insignificant errors in measurement.

The scenarios contemplated showed that the potential charging load of the existing substation can vary significantly depending on the selected load management strategy:

Dynamic load management – whereby power for charging EVs was limited to weekly peak power – allowed for the charging of up to 96 electric vehicles per week.

With applying fixed nighttime load management, limiting the charging load to 360 kVA (90% of the substation's rated capacity), the number of electric vehicles that could be charged weekly increased to about 218.

In the case of dynamic load management for all 360 apartments (one EV per apartment), the minimum required substation capacity was calculated at approximately 242 kVA, sufficient to ensure all electric vehicles were charged adequately.

It assists distribution network operators and housing associations to understand the interventions that need to be made in order to allow electric vehicles more widespread adoption and helps drive infrastructure developments in line with realistic load profiles and technical constraints of substations.

The findings provide useful insights into the number of EVs that can be supported under specific transformer capacity constraints and load management strategies. These results can serve as input for future planning and simulation studies by network operators and building associations considering smart charging adoption. While this study does not include a cost or infrastructure investment analysis, it establishes a foundational understanding of the technical conditions under which EV charging can be introduced in older residential grids.

It is important to emphasize that this study focuses on typical operating conditions based on realistic weekly consumption data. The modeling does not address rare boundary conditions or system failure scenarios, which would require a broader simulation scope and contingency analysis. Investigating such edge cases – including extreme peaks, system faults, or coinciding high-load events – would be a valuable extension for future research to complement the present findings.

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The cow reproductive perspective in relation to the colostrum quality and udder health in early lactation

I. Lūsis^{1*}, I. Sematovica² and M. Ostrovskā²

¹Latvia University of Life Sciences and Technologies, Faculty of Veterinary Medicine, Institute of Food and Environmental Hygiene, Str. K. Helmana 8, LV3004 Jelgava, Latvia

²Latvia University of Life Sciences and Technologies, Faculty of Veterinary Medicine, Clinical Institute, Str. K. Helmana 8, LV3004 Jelgava, Latvia

*Correspondence: ivars.lusis@lbtu.lv

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Abstract. The study aimed to evaluate cow reproductive performance in relation to colostrum quality measured using a digital Brix refractometer and udder health in early lactation. A dataset of 676 cows was collected from one commercial dairy farm in Latvia over 36 months in 2022–2024. Colostrum Brix% was associated with the year and season of the year. The colostrum quality, as measured by the Digital Brix refractometer, was acceptably high, ranging from 23 to 30 in all cows during the study. The main individual factors associated with colostrum Brix% were the number of lactations, the sex of the calf, and lactose content in the first milk recording after calving. No association was detected between colostrum Brix% and the length of the dry period or the last milk recording data. Neither somatic cell count nor colostrum Brix% was associated with reproductive performance, service period, or the number of inseminations.

Key words: Brix, immunoglobulins, milk lactose, somatic cell count.

INTRODUCTION

Colostrum quality is a crucial prerequisite for ensuring passive immunity in a calf during the postnatal period and the first weeks of life. Measurements of colostrum quality by a refractometer can be easily applied at any farm. The obtained results can guide immediate decisions about the suitability of colostrum for the calf, either by direct use or by freezing and storing it in a freezing chamber for later use. If the refractive index of colostrum or Brix% is less than 21, the colostrum is suboptimal for the rise in passive immunity in a new-born calf because it might contain insufficient level of immunoglobulins ($\text{IgG} < 50 \text{ g L}^{-1}$) (Quigley et al., 2013). Feeding of good-quality colostrum with Brix% > 22 from another cow or using thawed colostrum from a storage might serve as a preferable option.

The amount and composition of colostrum produced vary depending on multiple individual-level, herd-level, and seasonal factors (Westhoff et al., 2024).

A recent study highlighted the importance of metabolic status, nutrient utilisation, and the increasing availability of antioxidants during the last six weeks of gestation for volume of colostrum and immunoglobulin content of the colostrum (Rossi et al., 2023). The hypothesis proposed in this context is that colostrum quality measurement data might serve not only as a parameter for immediate action in favour of optimal building up of strong passive immunity in calves, but also as an indicative measure of cow preparedness for entering a new lactation with a successful reproductive and udder health perspective. However, there are no studies on evaluating hypotheses about possible associations of colostrum quality data and cow further reproductive performance in the new-started lactation. Therefore, the aim of the current study was to assess cow reproductive performance in relation to colostrum Brix percentage and udder health during early lactation. To achieve the aim, the objectives were as follows: evaluate yearly and seasonal fluctuations of the colostrum Brix% over a whole two-year period of time; compare colostrum Brix% values between cows in 1st and 2nd lactation with older cows; evaluate associations between colostrum Brix% and the number and sex of calves born to the cow; check for the possible impact of the length of the dry period on the colostrum quality; check for associations between colostrum quality and somatic cell count before and after the dry period; check the associations between colostrum quality, length of service period, and the number of inseminations.

MATERIALS AND METHODS

The study was conducted on a commercial dairy farm located 100 meters above sea level in Latvia in a moderate climate zone (56°28'10"N; 22°53'27"E) over 36 months in 2022–2024. Cows were included in this study if colostrum was visually acceptable (free of blood and debris) and the amount was more than one litre. Cows were excluded from the study due to a lack of colostrum, mastitis at calving, or trauma to the udder or teats. Cows after colostrum investigation were followed up throughout the entire service period (from parturition to conception) until pregnancy was confirmed. Infertile cows were followed up until they were removed from the herd, but no longer than 400 days of the lactation.

Colostrum quality was measured using a digital Brix refractometer (MA871, Milwaukee Electronics Kft, Hungary), within the first calf feeding process (within 2 hours after calving), and the values were recorded for each calving as Brix%.

For each cow included in the study, milk recording data were obtained from the cow pedigree cards of the Agricultural Data Centre. The dataset was supplemented by the cow's milk yield, somatic cell count, fat percentage, protein percentage, and lactose percentage recorded during the first milk recording after calving. For multiparous cows, the dataset was supplemented by the cow's milk yield, somatic cell count, fat percentage, protein percentage, and lactose percentage recorded during the last milk recording before drying off at the end of the previous lactation. For all cows with a full lactation, the dataset was supplemented with the cow's total milk yield, average somatic cell count, average fat percentage, average protein percentage, and average lactose percentage for a standard 305-day lactation. The length of the dry period preceding the calving was also registered for all multiparous cows.

The number of calves (single or twins) was registered and included as a covariate when building a regression model. The gender of the calf (female or male) was also recorded.

Reproductive performance of individual cows was evaluated by the calving intervals, length of the service period, and the number of inseminations required to get the cow pregnant.

Cows with somatic cell count higher than 200,000 cells mL⁻¹ were assumed to be suffering from some udder inflammation or any other problems of milk secretion. For the somatic cell count results to match the data normality assumption, the absolute value was converted to a somatic cell count score (SCS) standardised log₂ units using formula (1), or in cows with a low somatic cell count of less than 12,000 cells mL⁻¹, to SCS = 0. After the conversion, the somatic cell count threshold value of 200,000 cells mL⁻¹ corresponds to SCS = 4.0 log₂ units (Shook, 1993).

$$SCS = \log_2(SCC \cdot 10^{-5}) + 3 \tag{1}$$

where SCS – somatic cell count score, log₂ units; SCC – somatic cell count, cells mL⁻¹.

Statistically, proportions were compared using the Pearson Chi-square test and Fisher's exact test. The length of the dry period, calving interval, and service period were compared between cow groups using the Student t-test; however, associations were evaluated by multiple linear regression.

Linear regression coefficients and all differences between groups were considered statistically significant if $P < 0.05$.

RESULTS AND DISCUSSION

During a thirty-six-month period of the study, $n = 676$ calving were followed up, and colostrum samples were obtained at each calving. The proportion of primiparous cows among all cows was 36.9%, 33.3%, and 34.3% in the first, second, and third years of the study. The proportion of second-parity cows was 26.2%, 23.9%, and 28.7%, respectively (Table 1). There were no significant differences in the parity distribution between the three years of the current study. This should be noted because the volume of colostrum in older cows increases, and a recent study (Rossi et al., 2023) showed a negative low correlation between colostrum volume and IgG ($r = -0.28$), IgA ($r = -0.15$), but not with IgM.

Table 1. The number (proportion) of heifers and second-parity cows among all cows during the three-year study (year 2022, 2023, and 2024)¹

Parity	Year 1	Year 2	Year 3	TOTAL
1 st lactation	100 (36.9%)	99 (33.3%)	37 (34.3%)	236 (34.9)
2 nd lactation	71 (26.2%)	71 (23.9%)	31 (28.7%)	173 (25.6%)
3 rd lactation	52 (19.2%)	56 (18.9%)	20 (18.5%)	128 (18.9%)
4 th lactation	30 (11.1%)	51 (17.2%)	10 (9.3%)	91 (13.5%)
5 th lactation	6 (2.2%)	16 (5.4%)	6 (5.6%)	28 (4.1%)
6 th lactation	7 (2.6%)	3 (1.0%)	4 (3.7%)	14 (2.1%)
7 th lactation	4 (1.5%)	1 (0.3%)	0 (0.0%)	5 (0.7%)
8 th lactation	1 (0.4%)	0 (0.0%)	0 (0.0%)	1 (0.2%)
TOTAL	271 (100.0%)	297 (100.0%)	108 (100.0%)	676 (100.0%)

¹The difference between years was not significant ($p > 0.05$).

The colostrum quality, as measured by the Digital Brix refractometer, was acceptably high in all cows during the study. The minimum value of colostrum Brix% was 23 but the maximum was up to 30. However, there was higher proportion ($p < 0.05$) of Brix% values of 25–26 in Year 2 and Year 3 if compared to the Year 1 of study (Table 2).

The seasonal fluctuations of the average Brix% values were less expressed during the first year of study (Fig. 1). There were no significant differences ($P > 0.05$). During the second year of the study, the highest average value of colostrum Brix% (25.5 ± 0.1) was reached in spring (March, April, May). A significantly lower average value of 25.1 ± 0.1 was detected in summer (June, July, August). Colostrum quality stayed at a similar level also in the next season (September, October, November). Although the dynamics of colostrum Brix% by season are unclear, the decrease in colostrum quality towards summer and fall can likely be attributed to the higher likelihood of thermal distress in late-stage pregnant cows. A research study showed decreased rumination, higher rectal temperatures, and reduced milk yield in cows during acute heat stress (Penev et al., 2021). Other researchers have found lower colostrum Brix% values in calving around August and September; therefore, banking high-quality colostrum might be one option to address fluctuations (Borchardt et al., 2022).

Table 2. The number (proportion) of cows in three Brix% categories during the three-year study¹

Brix%	Year 1	Year 2	Year 3	TOTAL
23–24	104 (38.4%)	42 (14.1%)	15 (13.9%)	161 (23.8%)
25–26	148 (54.6%)	231 (77.8%)	83 (76.9%)	462 (68.3%)
27–30	19 (7.0%)	24 (8.1%)	10 (9.3%)	53 (7.8%)
TOTAL	271 (100.0%)	297 (100.0%)	108 (100.0%)	676 (100.0%)

¹The difference between years is statistically significant ($p < 0.05$).

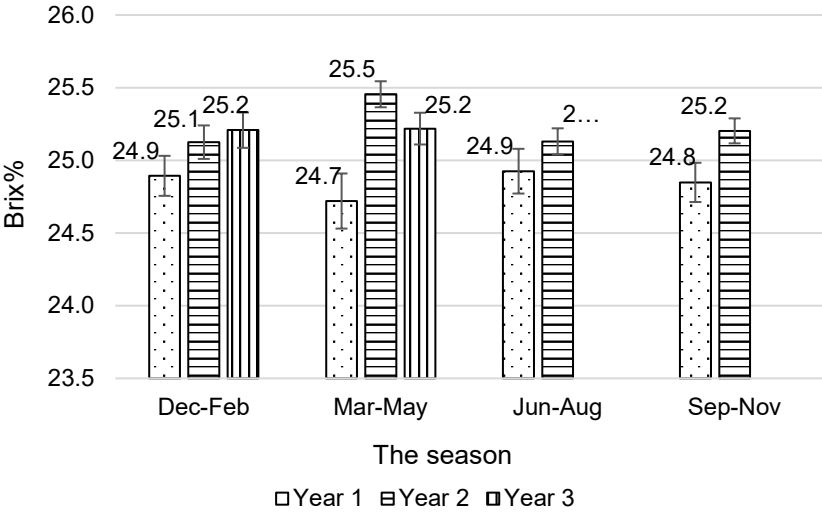


Figure 1. The seasonal fluctuations in the average colostrum Brix percentage.

The effect of cow lactation number or parity was displayed in the table to show a significant association (Table 3). In first parity cows, the Brix% was the lowest. Out of all primiparous cow calvings, 30.5% showed Brix% values in the lower category. Whereas in older cows, only 18.0% of all cows belonged to this category. The second-parity cows were in the middle position. The highest of all colostrum Brix% results were more often in the group of older cows (10.9%) in comparison to first parity cows (5.9%). The tendency for older cows to produce colostrum with considerably higher Brix% is primarily explained by the prolonged stimulation of the cow's immune system by various antigens (Borchardt et al., 2022). However, other explanations could also be accurate, such as the fact that second-lactation cows have a higher mammary secretory ability or that the hormonal and metabolic milieu differs between the first and second lactation, even for the same cow (Cattaneo et al., 2023). In the present study, comparison did not reveal a significant difference in colostrum Brix% between the second lactation and the first lactation in the same cow (25.1 ± 0.1 and 24.8 ± 0.2 , $P > 0.05$). On the contrary, the third lactation Brix% and second lactation Brix% in the same cows were different (25.2 ± 0.2 and 24.5 ± 0.2 , $P < 0.05$).

There was no difference in colostrum Brix% between calving where single calves or twins were born. But there was a significant difference depending on the value of sex. The cows with male calves had higher Brix% than cows with female calves (Fig. 2).

There was no significant association between colostrum Brix% and the milk recording data (milk yield (L), fat %, protein %, lactose %, somatic cell score (SCS in points)) at the last milk control test-day of the previous lactation. There was no significant association with the length of the dry period for multi-parity cows, even though this is often found to be a factor affecting colostrum quality (Dunn et al., 2017; Borchardt et al., 2022). Average milk recording data from the new standard lactation were not associated with colostrum Brix%. Out of data obtained at the first milk control test-day after calving, only lactose % was associated with colostrum Brix%

Table 3. The number (proportion) of cows in three Brix% categories depending on the cow parity¹

Brix%	1 st lactation	2 nd lactation	3 rd + lactation	TOTAL
23–24	72 (30.5%)	41 (23.7%)	48 (18.0%)	161 (23.8%)
25–26	150 (63.6%)	122 (70.5%)	190 (71.2%)	462 (68.3%)
27–30	14 (5.9%)	10 (5.8%)	29 (10.9%)	53 (7.8%)
TOTAL	236 (100.0%)	173 (100.0%)	267 (100.0%)	676 (100.0%)

¹The difference between years is statistically significant ($p < 0.05$).

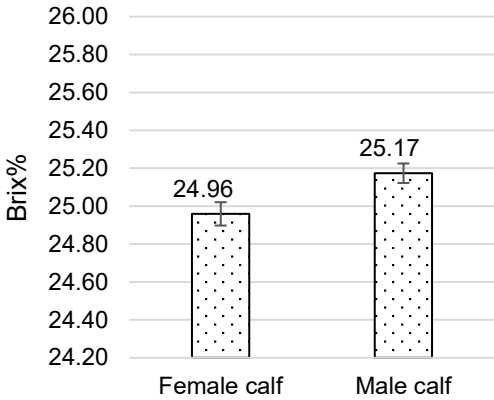


Figure 2. The difference in average colostrum Brix% for cows with male or female calves born.

(Table 4). This probably reflects a mechanism in the udder that is necessary for the transfer of immunoglobulins from blood into milk, but has been overlooked until now. This association is related to the age of the cow, as older cows had milk with lactose percentages above 5.0 and Brix percentages above 26. A negative correlation between the colostrum lactose percentage and the level of IgG has been found in studies by other authors, as colostrum has a lactose percentage as low as the mean $\pm$ SD = 2.7 ± 0.55 (Dunn et al., 2017) or even lower (Soufleri et al., 2021). The highest immunoglobulin levels can be found in the colostrum of cows that are in the 3rd–5th lactation, and the lowest in the primiparous cows (Puppel et al., 2019).

Table 4. Linear multivariable association of colostrum quality with cow-related factors from 1 commercial dairy farm; colostrum quality was assessed using a digital Brix refractometer

Variable	Estimate (% Brix)	SE ¹	Lower 95% CI	Upper 95% CI	P-value
Intercept	22.31	1.10	20.15	24.47	< 0.001
Lactose % at the first milk recording test	0.46	0.22	0.02	0.89	0.039
1 st year of study	Referent				
2 nd year of study	0.31	0.09	0.13	0.48	0.001
3 rd year of study	0.29	0.12	0.04	0.53	0.021
Lactation number	0.10	0.03	0.04	0.16	0.001
Female calf	Referent				
Male calf	0.20	0.08	0.04	0.36	0.001

¹Standard error.

Essential factors for the cow reproductive performance, namely, the service period (days to pregnancy) interval, along with evaluation of Brix% at the start of new lactation are displayed (Table 5).

Table 5. Potential predictors for the cow service period were tested along with colostrum Brix%; colostrum quality was assessed using a digital Brix refractometer

Variable	Estimate (days)	SE ¹	Lower 95% CI	Upper 95% CI	P-value
Intercept	13.6	41.1	-67.3	94.5	0.741
305-day lactation milk yield, 1,000 kg	4.2	0.7	2.7	5.7	< 0.001
Number of artificial inseminations	34.0	1.5	31.1	36.8	< 0.001
Brix% of colostrum	-0.8	1.6	-4.0	2.3	0.608

¹Standard error.

The reproductive perspective of an individual cow in the dairy herd is strongly associated with milk productivity and successful insemination. No significant role was found for colostrum Brix% at the start of new lactation.

CONCLUSIONS

The Brix% of colostrum on a dairy farm is different from year to year. Lower and more variable Brix% values were observed in the summer and autumn seasons, possibly due to higher environmental temperatures and/or high air humidity, which may have

caused thermal discomfort for cows during the last weeks of gestation. Colostrum quality measured by digital Brix refractometer increases from first to second parity and from second to third parity. Some association was detected between Brix% and milk lactose% at the first milk control test-day. Brix% was higher in cows with male calves than in cows with female calves. No significant role was found for colostrum Brix% at the start of new lactation in predicting the reproductive performance of individual cows.

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Using machine learning techniques to assess the technology adoption readiness levels of livestock producers

K. Mallinger^{1,2,*}, L. Corpaci², G. Goldenits², T. Neubauer³, I.E. Tikász⁴ and T. Banhazi^{5,6}

¹SBA Research, Complexity and Resilience Research Group, Floragasse 7/5, AT1040 Vienna, Austria

²University of Vienna, Kolingasse 14–16, AT1090 Vienna, Austria

³TU Wien, Data Science Unit, Floragasse 9-11, AT1040 Vienna, Austria

⁴Institute of Agricultural Economics, Nonprofit Kft., Zsil u. 3–5, HU1093 Budapest, Hungary

⁵AgHiTech Kft, Kisbacom utca 1, Budapest, Hungary, 110, Budapest, Hungary

⁶Wroclaw University of Environmental and Life Sciences, Norwida Str. 25, PL50-375 Wroclaw, Poland

*Correspondence: kmallinger@sba-research.org

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Abstract. Technology adoption in agriculture, particularly in precision livestock farming (PLF), is often hindered by a range of barriers such as high investment costs, limited infrastructure, and uncertainty regarding the reliability and integration of new systems. Understanding these barriers is crucial for promoting the uptake of innovations that enhance sustainability and productivity. This study investigates technology adoption barriers in precision livestock farming to support sustainable agricultural development. A survey of 266 farms across several European countries and Israel was conducted to assess existing infrastructure and farmers' attitudes toward smart farming technologies. Using machine learning techniques, farmers were grouped into two clusters representing different levels of technological readiness. The study identified the most prominent factors influencing technology adoption, including the presence of smart technologies on-site, market accessibility, cost efficiency, and the ability to manage labor shortages. A Logistic Regression model further demonstrated high predictive accuracy for farmers' technological readiness based on these characteristics. These findings provide valuable insights into the main drivers and barriers of PLF adoption and highlight the relevance of data-driven approaches for requirement analysis and targeted policy interventions. By uncovering critical user traits and adoption barriers, this study offers structured guidance for policymakers, industry stakeholders, and researchers to foster the broader adoption of precision livestock technologies.

Key words: cluster analysis, machine learning, precision livestock farming, survey design, technological barriers.

INTRODUCTION

Precision livestock farming (PLF) refers to the use of advanced technologies - such as sensors, automated monitoring systems, and data analytics - to continuously observe and manage livestock production at the individual animal level. By providing real-time insights into animal health, welfare, and performance, PLF enables more efficient resource use, early detection of health issues, and targeted interventions. These capabilities support agricultural activities by enhancing productivity, improving animal welfare, and reducing environmental impacts (Wathes et al., 2008; Banhazi & Black, 2009; Banhazi et al., 2012; Banhazi et al., 2022). As global food demand grows, adopting PLF becomes vital for ensuring sustainable practices and meeting population needs (Araújo et al., 2021). However, successful implementation depends heavily on farmers' willingness to adopt these technologies and on the development of strategies to address existing barriers and concerns (Scown et al., 2019).

While PLF technologies offer significant advantages (Banhazi & Black 2009; Banhazi et al., 2022), their potential can be undermined if technology development and integration fail to align with the specific needs of farmers (Mallinger et al., 2022; Mallinger & Baeza-Yates, 2024). Understanding which farm characteristics and user traits distinguish technologically ready farmers from those less prepared is therefore essential for conducting targeted requirement analyses and designing sustainable, user-centered technologies. Hereby, technological readiness refers to the willingness and ability of farmers to adopt and effectively implement new technologies within their farming operations. However, existing research predominantly relies on traditional statistical (e.g., distributions) or qualitative (e.g., interviews) approaches to characterize PLF user groups and identify adoption drivers (Mallinger et al., 2023). These methods often oversimplify complex relationships between user traits and technology adoption behavior, limiting the ability to uncover distinct adoption patterns and hidden barriers. Furthermore, these approaches are not able to either systematically group farmers based on shared characteristics or investigate how the significance of adoption barriers varies among different types of users.

This study addresses this knowledge gap by applying machine learning techniques, specifically K-means clustering and a Logistic Regression classifier, to analyze survey data from 266 farms and investigate user attitudes toward technological readiness in PLF. The main objectives are to:

- Identify farm characteristics and user traits that differentiate farmers by their technological readiness for PLF adoption.
- Uncover adoption barriers specific to different user groups to support targeted interventions.
- Apply machine learning techniques to reveal latent patterns in survey data and validate user groupings.
- Assess the predictive value of survey variables to identify key barriers to technology adoption.

By uncovering user attitude clusters and understanding factors influencing technological readiness, this study provides structured information for policymakers, industry stakeholders, businesses, and researchers to support the adoption of precision livestock farming technologies.

STATE OF THE ART

The research field of user attitudes toward precision livestock farming is well-established. It is primarily relying on surveys and statistical analysis (Ugochukwu & Phillips, 2018; Abeni et al., 2019; Pathak et al., 2019; Groher et al., 2020; Makinde, 2020; Boothby & White, 2021; Schukat & Heise, 2021b; Akinyemi et al., 2025). Research in this field has identified a range of factors influencing farmers' technology adoption, including economic, socio-demographic, ethical, legal, technological, and institutional aspects, all of which play a role in ensuring broad acceptance (Dhraief et al., 2018; Drewry et al., 2019; Makinde, 2020).

Currently, machine learning has yet to be fully leveraged to detect distinct clusters of user attitudes in precision livestock farming. Some studies (Schukat & Heise, 2021a; Mallinger et al., 2023) have previously explored clusters of farmer characteristics. Schukat & Heise, 2021a adopted a hierarchical cluster analysis to understand the attitudes of German livestock farmers towards smart products. However, the study did not provide any validation of the cluster results and also did not analyze the complex relationship between the questions associated with a cluster. Similar approaches have been used in analyzing user characteristics and behaviors in water resource management (Obringer & White, 2023), social media studies (Kaushik & Bhatia, 2022), and customer segmentation (Tabianan et al., 2022).

This research builds on a prior publication that used clustering for the evaluation of technological adoption barriers (Mallinger et al., 2023). The experiment design for this study is kept the same for comparison. However, the prior study used different distance metrics for the cluster creation of the k-mean algorithm as well as different algorithms to assess the importance of farm characteristics for technological readiness (logistic regression instead of decision tree). By following and extending the conceptual design, the current study uses refined distance metrics to create improved cluster affiliations (up to 97% accuracy) while providing statistical evidence for the significance of the farm characteristics on technological readiness identified by the supervised machine learning algorithm. Thereby, this study provides novel results while contrasting existing literature.

MATERIALS AND METHODS

Fig. 1 illustrates the evaluation and validation of cluster characteristics reflecting user attitudes and farm infrastructure about PLF adoption readiness. This encompasses the entire data processing pipeline, from data aggregation and cleaning to validating applied clustering methods. As depicted in Fig. 1, the experimental design steps will be presented sequentially.

This study is part of the LivestockSense project¹, aiming to develop a functional prototype to assess and predict farmers' technological readiness. The machine learning approach focuses on defining cluster boundaries representing this readiness and creating a model capable of accurately classifying new user questionnaires, as was primarily done in the form of a web-based prototype to identify the technological readiness of precision livestock farmers (Mallinger et al., 2023).

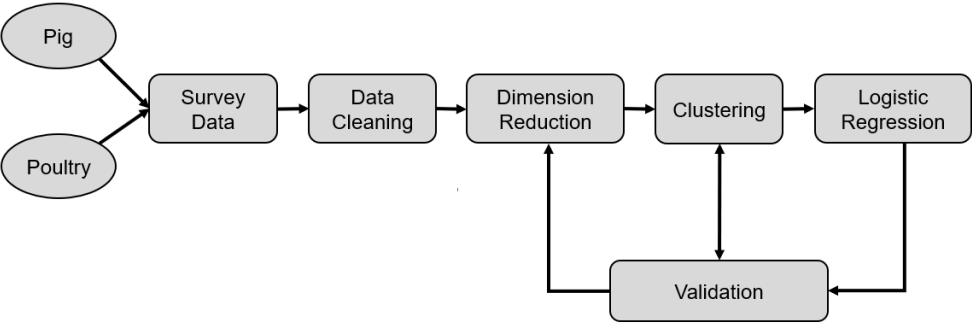


Figure 1. Experiment design and processing pipeline chosen for this study (see also Mallinger et al., 2023).

Survey and Data

This study builds on survey data collected by the LivestockSense research team. Based on self-reported questionnaires, the survey gathered responses from 266 farms across five European countries and one Middle Eastern country, covering the pig (121 samples) and poultry (145 samples) sectors. The questionnaire was designed to capture insights into existing infrastructure and farmers' attitudes toward smart farming technologies.

To assess technological readiness, the survey incorporated multiple perspectives. It examined infrastructure availability (question blocks 1, 2, and 6), the presence of expert knowledge and market access to PLF technologies (question block 4), and farmers' mental attitudes toward PLF adoption (question blocks 3 and 5). In total, 20 key questions were selected to represent farmers' readiness for precision livestock farming. Sub-questions were consolidated into single features, with responses rated on 5-point, 4-point, or 3-point scales to indicate levels of agreement, where 1 represented ‘Strongly disagree’ and 5 indicated ‘Strongly agree,’ for example. The complete list of survey questions used in the analysis is in the Appendix.

Clustering

This study uses the k-means approach to cluster the results. The algorithm takes a set of measurements, where each observation is an n-dimensional vector, and partitions them into k clusters (where $k \leq n$, n representing the total farms contained in the survey) based on their similarity (Jain, 2010). K-means clustering aims to minimize the within-cluster sum of squares, the sum of the squared distance between each data point and its assigned cluster centre. In other words, the algorithm aims to find the number of (k)

¹ <https://livestocksense.eu/>.

centres that minimize the distance between each point and its assigned centre, resulting in clusters that are as compact and distinct as possible. Mathematically, the objective function of k-means is:

$$\arg \min S \sum_{i=1}^k \sum_{x \in S_i} \|x_i - c_i\|^2 \quad (1)$$

where c_i is the centroid of the points in S_i , and x_i is the individual data point that belongs to the cluster S_i . Therefore, $\|x_i - c_i\|^2$ represents the squared Euclidean distance between a given data point x_i and the centroid c_i of the cluster S_i that x_i belongs to.

This study used the Gower's distance to determine the pairwise similarities between observations and create equidistant categories when applying the k-means algorithm. Gower's distance is defined as:

$$s_{ijk} = |x_i - x_j| / R_k \quad (2)$$

where x_i and x_j are two observations, and R_k is the range of the k -th variable. This means that for two answer patterns, the absolute difference will be computed for each question and then divided by the range of possible answer categories. This is particularly useful in our case, as it normalizes the differences between each pair of observations and, therefore, between different scales.

Validation

The validation process consisted of a multi-step mixed-method approach including quantitative (UMAP, Internal Validation Metrics, Supervised Machine Learning) and qualitative evaluation phases (Focus Group). This approach was chosen to ensure that the cluster quality is not only measured based on a mathematical basis that usually includes distance-based metrics but also represents qualities of user attitudes that are not directly measurable. The validation process was iteratively conducted to ensure that the survey questions and cluster results convey user attitudes and technological readiness characteristics.

Firstly, Cluster quality was assessed using three internal validation metrics:

- **Davies-Bouldin Index:** Evaluates cluster similarity by comparing within-cluster and between-cluster distances. Lower values indicate better clustering (Davies & Bouldin, 1979).
- **Calinski-Harabasz Index:** Measures the ratio of the sum of between-cluster to the sum of within-cluster dispersion, with higher values indicating well-defined clusters (Caliński & Harabasz, 1974).
- **Silhouette Score:** This score assesses how well data points fit within their clusters by comparing intra-cluster and nearest-cluster distances. Scores range from -1 (misclassified) to 1 (well-clustered), with values near 0 indicating overlap (Rousseeuw, 1987).

The validation process also includes the UMAP embedding (McInnes et al., 2018) of the data into a two-dimensional space to assess the clustering results visually. UMAP is a non-linear dimensionality reduction technique based on the widely used t-SNE method that embeds the datapoint distribution from a high dimensional space into lower dimensions. We chose UMAP, particularly for its ability to preserve structures, like clusters, in high-dimension and lower-dimension representations. Another advantage of UMAP is that it works with custom distance metrics such as Gower's distance and does not assume continuous variables or normal data distribution. In dimensionality reduction, each explanatory variable represents a dimension, and each observation is a

point in this multi-dimensional space. For example, if height and weight are collected for individuals, they can be plotted on a two-dimensional scatterplot with one variable on each axis. However, with more variables - such as age, education, or family size - the data exist in a higher-dimensional space that cannot be easily visualized. Dimensionality reduction techniques like UMAP project this complex, high-dimensional structure into a lower-dimensional space (typically two dimensions) while preserving essential relationships, such as clustering patterns.

Finally, a Focus Group was assigned to assess outcomes throughout the experiment pipeline continuously. This group included five specialists from four different countries, covering areas such as livestock farming, PLF technology development, and survey design. The evaluation process was carried out iteratively after each significant processing stage, guaranteeing the logical consistency of the selected features and clustering outcomes.

Logistic Regression

This study utilizes a Logistic Regression Model to (1) assess how well the survey questions predict farmers' technological readiness, indicated by the cluster labels derived from the k-means model, (2) develop a model for predicting farmer attitudes, and (3) create an explainable framework that allows for assessing feature importance according to the odds ratio, providing insight into predictions based on the contributions from each feature. Logistic Regression models the probability that a given input belongs to a particular class by applying the logistic function to a weighted sum of the features (survey responses). This probability is expressed as:

$$P(y = 1|x) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^n \beta_i x_i)}} \quad (3)$$

where β_0 is the intercept, β_i are the feature weights, and x_i are the input features. The model is trained by finding β values that maximize the likelihood of the observed labels. In most software solutions, the optimization process is done by gradient descent or iterative methods like the Newton-Raphson Method.

Regarding output interpretation, each β_i represents the effect of a one-unit change in the corresponding feature on the log odds of the outcome occurring. Because interpreting log odds directly can be unintuitive, using the odds ratio, given by e^{β_i} , is common. The odds ratio indicates how much the odds of the outcome change for a one-unit increase in the feature. In the case of predicting only two groups, odds ratios greater than 1 suggest a positive association with group 1, while values less than 1 suggest an association with group 0.

Using a Logistic Regression Model to predict clusters with varying technological readiness, we have two main goals:

1. To see if a supervised modelling method can summarise the correlation between clusters (target variable) and input variables (survey questions).
2. To identify which survey questions provide the most significant insights for distinguishing cluster associations.

For calculating all evaluation metrics, coefficients, p -values, and odds ratios, we took the mean values of a 10-fold stratified cross-validation with a random state set to 42. We assessed feature significance by calculating the p -value for each feature and ranking the significant features according to their significance in descending order.

Predictions were evaluated using the following metrics:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (4)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (5)$$

$$\text{Recall} = \frac{\text{TP}}{\text{P}} \quad (6)$$

$$\text{F1 Score} = 2 * \frac{\text{TP}}{2 * \text{TP} + \text{FP} + \text{FN}} \quad (7)$$

TP represents the True Positive, TN the True Negative, FP the False Positive, and FN the False Negative result.

RESULTS AND VALIDATION

As a first step, we deploy the K-means clustering described in Section 3.2. We use three internal validation metrics: the Davies Bouldin Score, the Calinski Harabasz Score, and the Silhouette Score, to estimate a suitable number of clusters.

Comparison of internal validation metrics and number of Clusters

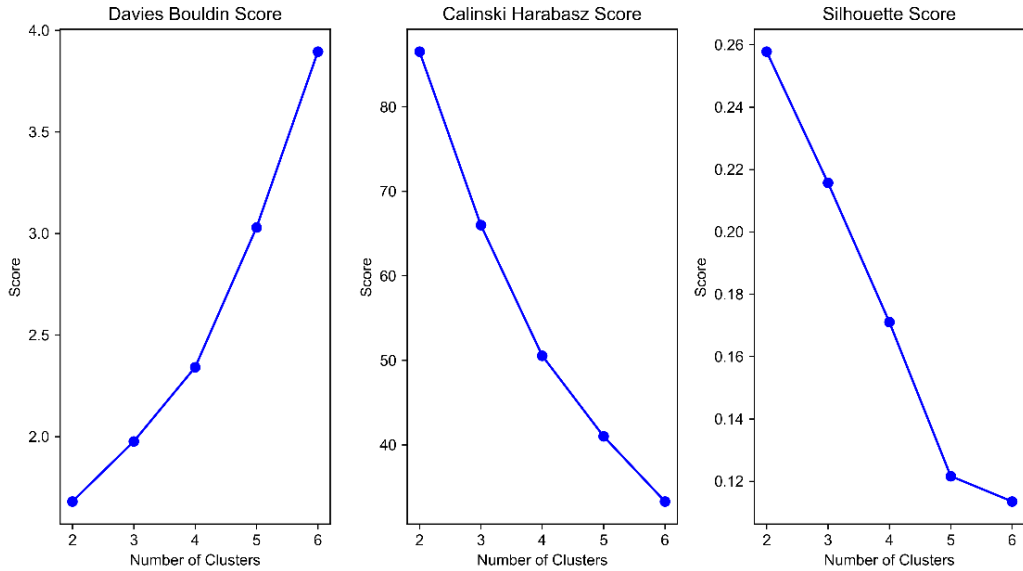


Figure 2. Davies-Bouldin Score on the left (lower is better), Calinski Harabasz Score in the middle (higher is better), and the Silhouette Score on the right (higher is better).

The score development for each number of clusters and each metric is shown in Fig. 2, which depicts the Davies-Bouldin Score in the left diagram, the Calinski Harabasz Score in the centre, and the Silhouette Score to the right. All internal validation metrics indicate that the best separation can be achieved for choosing two clusters, as the Davies Bouldin Score is the lowest at 1.68, and the other two scores are the highest at 86.51 and 0.258, respectively, for all compared clusters.

Of the 266 survey results, 118 belong to Cluster 0 (later defined as technologically not ready), and 148 to Cluster 1 (later defined as technologically ready). To evaluate if the two clusters are distinct from each other and form logical opposites, we used a UMAP embedding. This embedding represents the 20-dimensional farm characteristics in two-dimensional space, enabling a visual inspection of the data distribution. Fig. 3 shows this representation, with the clusters each lying in different regions of the plot, highlighting the differences between the two clusters. Some overlap exists between the clusters, which is to be expected, as some farmers' answers indicate behaviour belonging to the other cluster compared to the one they were assigned to. However, these clusters do not bear any semantic meanings yet, as the separation is currently based on mathematical evaluations. To overcome this, we analyse the distribution of given answers for each cluster.

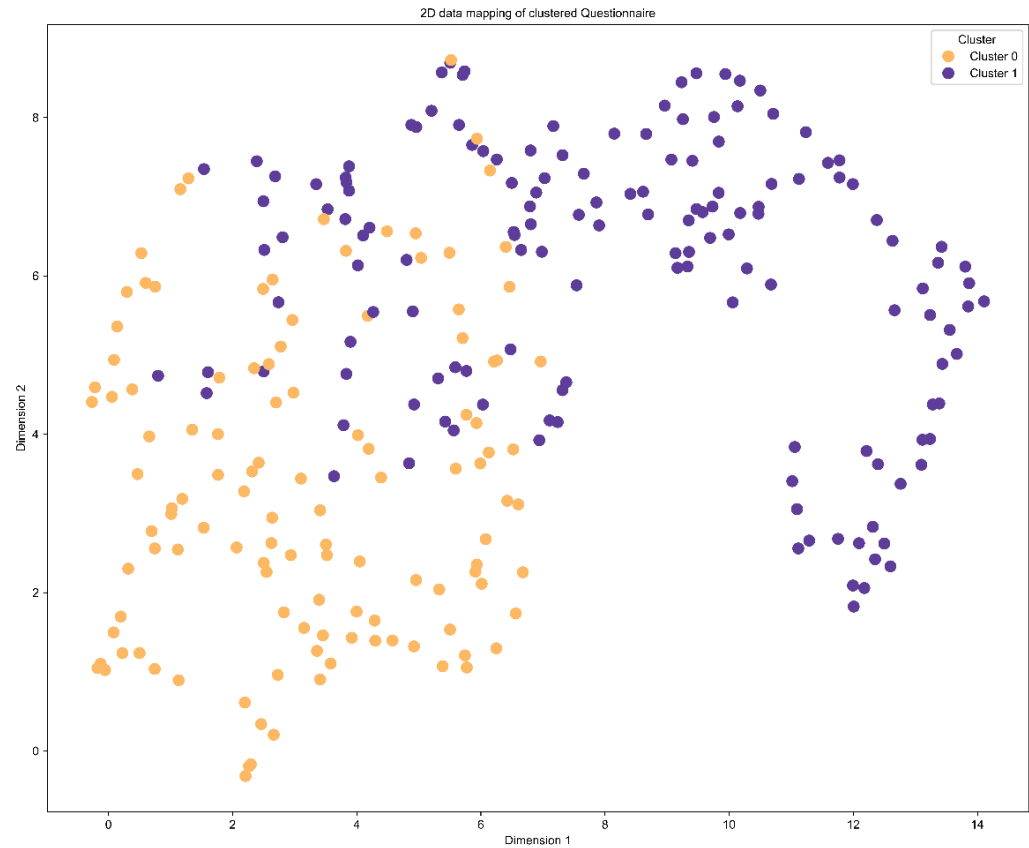


Figure 3. UMAP representation of the two clusters for the visual evaluation of cluster distribution. On the left (orange) are the data points later considered as technologically not ready, whereas on the right (purple) the datapoints defined as technologically ready. The x- and y-axes correspond to the two reduced dimensions obtained through UMAP, capturing the main structure of the high-dimensional data.

Farmer characteristics per cluster

We first analyse the distribution of cluster and survey question characteristics using grouped bar charts, such as those depicted in Fig. 4. We chose these figures in particular because we have six questions, some of which have subquestions. For Questions 3, 4, and 5, each containing multiple subquestions, the response patterns within each cluster are somewhat comparable across the subquestions. Consequently, we selected one subquestion from each as a representative. The plots for the remaining questions can be found in the appendix section.

Cluster composition for representative Questions

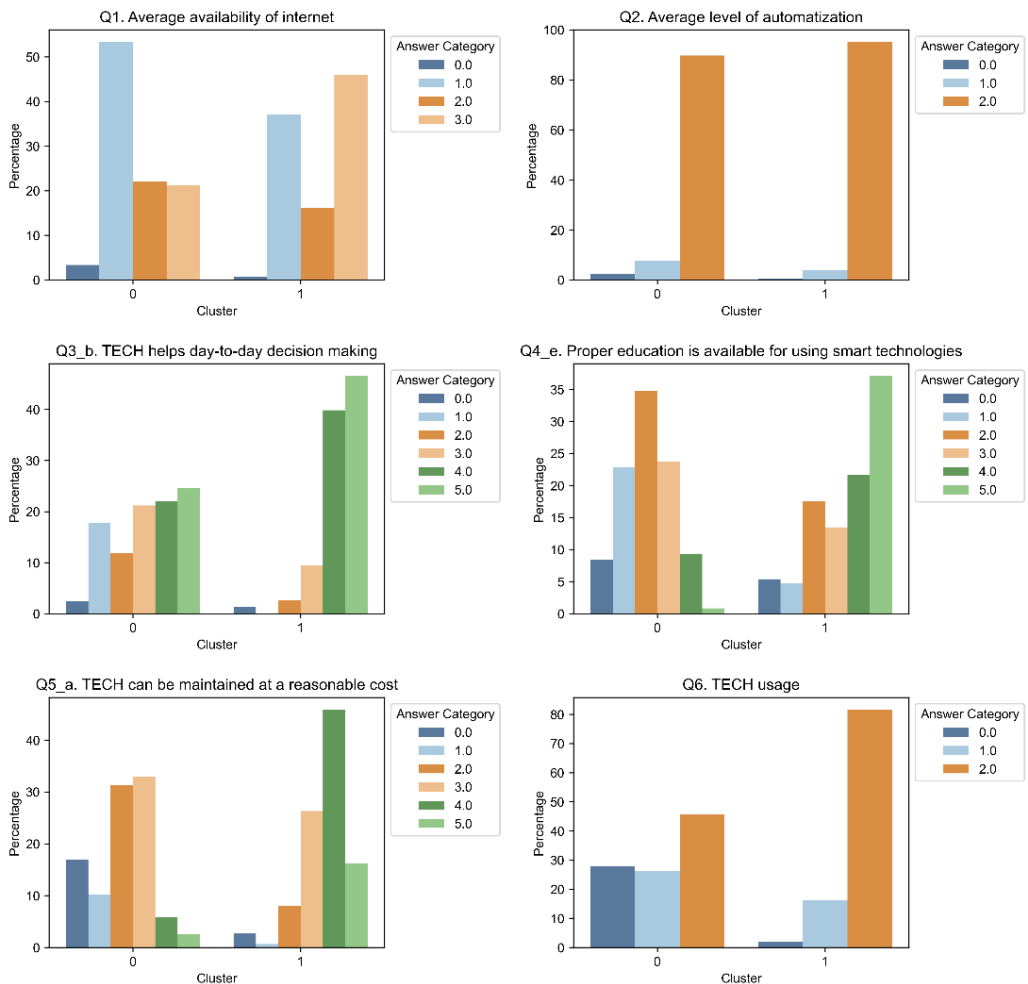


Figure 4. Distribution of answer results as a comparison for Cluster 0 (Technologically not ready) vs. Cluster 1 (Technologically Ready). The number of bars represents the amount of possible answer options. The height of the bars represents the share of an answer category compared to the other categories. In every question, the sum for each cluster, therefore, results in 100.

In each diagram, the answers to one of the survey questions are shown so that the clusters are drawn on the x-axis, and for each cluster, there are as many bars as possible answer categories. As the clusters vary in size, we cannot just represent the absolute values per answer category per cluster to ensure comparability, as it would capture too much cluster size information. Instead, the bar heights represent the fraction of each answer category per cluster.

Fig. 4 compares responses to six questions related to technological readiness across two clusters (Cluster 0 and Cluster 1). Notably, five of these questions (Q1, Q3, Q4, Q5, and Q6) show pronounced differences in how each cluster responded, whereas Q2 (average level of automation) appears more similar between the two groups.

For Q1 (average availability of internet), Cluster 1 shows a substantially higher proportion of respondents in the upper rating categories (e.g., 4 and 5), while Cluster 0 leans toward lower or moderate ratings. A similar pattern emerges in Q3 (technology helps day-to-day decision-making), where Cluster 1 overwhelmingly endorses strong agreement, contrasting with the more moderate or disagreeing responses in Cluster 0.

Likewise, Q4 (proper education is available for using smart technologies) and Q5 (technology can be maintained at a reasonable cost) reveal that Cluster 1 is more likely to perceive educational support and affordability favourably, whereas Cluster 0 exhibits relatively lower levels of agreement. Finally, Q6 (overall technology usage) follows this trend: Cluster 1 reports higher usage, whereas Cluster 0 indicates less frequent or more constrained use. Similar patterns can be found in the other questions presented in the Annex.

Based on the intended focus of the questions that highlight certain barriers to technology adoption, these findings suggest that Cluster 1 is characterized by a high degree of technological readiness - reflected in stronger internet availability, more positive attitudes toward technology's utility, better access to education, perceived affordability, and higher overall usage. In contrast, Cluster 0 consistently reports lower levels of agreement or usage across these dimensions, indicating limited technological readiness. As a result, we define users in Cluster 0 as ‘not technologically ready,’ while Cluster 1 represents farm characteristics who are generally perceived as ‘technologically ready’ to deploy PLF technologies at their farms.

Feature Importance Analysis

As an additional means of result validation, we used a Logistic Regression model to test whether the survey questions are a reliable predictor for each respondent’s cluster membership. Table 1 presents the average accuracy, precision, recall, and F1 score value for a stratified five-fold cross-validation and demonstrates that predictions using the questions allow for high scores in each computed metric. With a total of 97% accuracy and F1-Score, the model provides almost no false, negatives or false positives and can therefore, be used as a robust model to distinguish technological-ready from less technology-ready farmers.

Table 1. This table depicts the result of the logistic regression model, which was used to predict the technological ready and not ready cluster based on the survey questions

Classifier	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.97	0.96	0.98	0.97

In addition to the results presented in Section 4.1, we chose Logistic Regression as an interpretable means to analyse the farm characteristics that separate the technologically ready from less-ready farmers. If the model accurately classifies respondents, it confirms that the survey items capture meaningful differences in technology adoption. Furthermore, we can pinpoint the key factors that distinguish the clusters by computing the p -value and the log odds for each question's estimator. The odds ratio thereby shows the difference in the odds of the outcome occurring for a one-unit increase in the predictor variable, holding all other variables constant. We deemed features corresponding to estimators that are significant on a 0.05 significance level and have a high odds ratio as the most influential questions for predicting cluster association.

Table 2. The table shows the features used in the Logistic Regression model. The features are sorted based on the coefficient. Higher coefficients represent a higher degree of importance or influence on the modelling output. Statistical significance for the importance is tested and represented in the column p -value

Feature	Description	Co-efficient	p -value	Odds ratio
Q6	TECH usage	1.554	0.03	4.731
Q4_a	It is easy to access TECH on the market	1.258	0.024	3.520
Q5_a	TECH can be maintained at a reasonable cost	1.057	0.025	2.876
Q3_a	TECH helps labour shortage	0.952	0.011	2.592
Q5_e	TECH is secure in terms of data management	0.854	0.031	2.348
-	Intercept	-44.888	< 0.01	0
Q3_d	TECH helps meet environmental pollution reduction obligations	0.790	0.060	2.204
Q4_c	It is easy to get information on TECH and distributors	0.991	0.075	2.693
Q3_b	TECH helps day-to-day decision making	0.865	0.093	2.375
Q4_b	TECH can be purchased at an affordable price	0.805	0.105	2.236
Q5_d	TECH operates in a reliable manner	0.918	0.134	2.505
Q4_d	It is easy to get technical assistance to smart technologies	0.917	0.161	2.501
Q5_b	TECH is easy to operate	0.789	0.188	2.201
Q1	Average availability of internet	0.647	0.190	1.911
Q3_c	TECH helps enterprise, marketing and investment decisions	0.471	0.237	1.602
Q3_e	TECH enables the increase production effectiveness	0.552	0.461	1.736
Q4_e	Proper education is available for using smart technologies	0.348	0.468	1.416
Q3_g	TECH provides reliable information	0.538	0.526	1.712
Q5_c	TECH can be connected well with other equipment/software	0.236	0.610	1.266
Q3_h	TECH provides information in a real-time manner	0.469	0.637	1.598
Q2	Average level of automatization	0.104	0.911	1.110

Table 2 shows the features, corresponding estimator, p -value, and odds ratio. The non-significant entries in the table are ranked according to their p -value, and the remaining five variables (and the intercept term) are ranked according to their odds ratio to uncover their importance in separating respondents into ‘technologically ready’ and

‘less ready’ clusters. Q6, ‘TECH usage’, has the highest odds ratio, followed by Q4_a, ‘It is easy to access TECH on the market’, Q5_a, ‘TECH can be maintained at a reasonable cost’, Q3_a, ‘TECH helps labour shortage’, and Q5_e, ‘TECH is secure in terms of data management’. These questions highlight economic considerations and affinity towards technical solutions as the most influential factors for predicting technological readiness. Interestingly, data security is a strong predictor for technological readiness, which indicates that technologically ready farmers value privacy more than non-ready groups.

An intercept term was added to the regression model to ensure unbiased coefficient estimators and accounts for the base case, where all other variables are 0. The intercept is also statistically significant at a p -value close to 0, but the odds ratio is almost 0, thus removing its importance in predicting cluster associations. This means it is very unlikely that a respondent answered with ‘0’ on each question.

While most features do not have statistical significance, this does not mean these questions are irrelevant. Instead, their influence on the prediction is not high enough to rule out a random connection to the prediction outcome.

DISCUSSION

This research explores farmers' attitudes and technological readiness toward PLF technologies. Rather than directly assessing technology adoption, it examines general perceptions of farmers, calculates clusters of similar characteristics and identifies critical farm characteristic and personal perceptions on technology that distinguish technologically ready from non-ready farmers. Methodologically, it highlights the value of machine learning techniques for survey and requirement analysis.

The two primary clusters labelled ‘Ready’ (technologically ready) and ‘Not Ready,’ (barriers to technology adoption) exhibit distinct and consistent attitudes toward PLF technologies. The ‘Ready’ group (148 farms) shows strong agreement with the benefits of these technologies, indicating a high level of acceptance and readiness for adoption. In contrast, the ‘Not Ready’ group (118 farms) demonstrates lower agreement, suggesting a lower preparedness for technological adoption. The distinction between these clusters was further confirmed using UMAP, which revealed a clear separation in the reduced-dimensional space. This separation was also validated by a supervised machine learning model, which could successfully predict the cluster affiliation based on survey responses.

A prior study about barriers to technological readiness (Mallinger et al., 2023) highlighted the ‘ease of access to smart technologies’, ‘the interoperability’ ‘the ability to cope with a labour shortage’, and the ‘ease of operability’ as four distinct characteristics that distinguish technologically ready from non-ready farmers. The current study partially supports these results, as the ‘access to smart technologies’ as well as the ‘ability to cope with labour shortage’ are also highlighted as significant variables. However, this study also highlighted the prior existence of smart technologies as a primary factor used to distinguish the two clusters. This is not particularly surprising and supports the findings of (Mallinger et al., 2024), in which the distribution of said

characteristic was used to validate the usefulness of the cluster results. As the tree-based mechanisms in the study of Mallinger et al., 2023 use the concept of diminishing entropy-values as a factor for identifying important features, it is possible that some farm characteristics were not highlighted adequately if a high degree of predictions are already successful with a small subset of survey questions. As a logistic regression approach automatically uses all questions, the differences between the characteristics are less pronounced compared to a decision-tree algorithm. This highlights that logistic regression might provide a more suitable approach to identifying important characteristics for cluster differentiation. However, more research is necessary to better understand the usability of different machine learning classifiers and regressors in this context.

Prior studies have reported high investment costs as a major barrier (Ugochukwu & Phillips, 2018; Abeni et al., 2019; Pathak et al., 2019; Groher et al., 2020; Makinde, 2020; Boothby & White, 2021). Our study shows a clear separation of farmers' answers between the two clusters regarding the affordability of precision livestock technology. The trained algorithm for predicting technological readiness exhibited stronger links to maintenance costs (coefficient 1.057) than to the initial purchase price (coefficient 0.805), with the prior links also supported by stronger *p*-values. Robustness and reliability are also frequently cited barriers (Drewry et al., 2019; Makinde, 2020; Boothby & White, 2021). We also observe a visible divergence of opinions between the clusters on this point, as shown in Fig. 7, and record a high coefficient of 0.918, although the feature-importance score (coefficient) was not statistically significant. Persistent apprehension about data security was further analysed in this study, again supporting earlier findings (Drewry et al., 2019). Finally, accessibility to the market emerged as one of the most prominent factors separating the clusters, with a high feature-importance coefficient of 1.258 and statistical significance (*p*-value 0.024). As this factor is rarely highlighted in previous work, it should be considered more closely in future research on technological barriers.

More generally, the cluster analysis showed that farmers were nearly evenly divided between those classified as technologically ready and those not ready. This suggests substantial potential for intervention strategies targeting the less-ready group. Notably, the average level of farm automatization did not differentiate between the two groups, suggesting that general mechanization alone is not a sufficient indicator of readiness. In contrast, prior use of smart devices emerged as one of the strongest predictors of technological readiness. Furthermore, the analysis highlights that barriers to technology adoption in livestock farming are not singular but multivariate in nature. Multiple factors must be considered simultaneously to accurately capture the diversity of farmer needs and the complexity of the adoption process.

A limitation of this study is the potential variability of the machine learning techniques. K-means clustering involves randomness in initialization, which can lead to slight differences in cluster assignments across runs. Consequently, small distances between clusters with high standard deviations should be interpreted cautiously, as some data points may shift clusters in different iterations. Similarly, the feature importance analysis from the Logistic Regression should be interpreted carefully. Changes in the distribution of answers could potentially change the order of highlighted questions. To

give a more complete picture, these results should be combined with other tools to evaluate importance, such as the principal component analysis or explainable AI techniques like Partial Dependence Plots or SHAP values. A framework to apply this can be found in (Mallinger et al., 2024).

A key limitation of this quantitative machine learning approach is its data-driven nature. Unlike theory-driven qualitative studies, machine learning identifies patterns without considering the broader context. As a result, it may highlight correlations that do not imply causation. Careful research design, including survey questions, expert analysis, focus groups, or interpretable models, is essential for meaningful interpretation. Additionally, this approach cannot capture nuanced human behaviours during data collection, such as emotions, response delays, or non-verbal communication.

Finally, this research evaluated the predictive power of survey questions in determining farmers' technology readiness. Some questions demonstrated strong predictive value for cluster affiliation, making them particularly useful for identifying the readiness levels of user groups. These insights support the development of more targeted and efficient survey instruments, enhancing data collection strategies for future research. Furthermore, this process can be utilized as a data-driven approach to inform requirements and market analysis, facilitating the development of precision livestock farming technology by aligning it with targeted consumer needs. For example, companies can focus on special offers that keep maintenance and service costs at a minimum. By doing so, it enhances ease of operation and promotes the effective use of economic and environmental opportunities. As a result, the likelihood that these technologies improve production efficiency or animal well-being is significantly increased. Companies can also provide targeted market strategies based on these results. By recognizing that farmers highly value the support of precision livestock equipment in combating labour shortages, they can effectively highlight this aspect in their marketing activities.

This study aimed to demonstrate the benefits of supervised and unsupervised machine learning in this domain, particularly using interpretable models like Logistic Regression. More research is needed to explore the full potential of machine learning for technology adoption studies and to apply different algorithms to specific survey analysis tasks. A comparison to other machine learning approaches can be found here (Mallinger et al., 2023; Mallinger et al., 2024). For an in-depth statistical analysis of the survey data, we refer the interested reader to (Tikász et al., 2023a; Tikász et al., 2023b). Primary factors that distinguished these two groups included prior adoption of smart technologies, market accessibility, cost efficiency, and the ability to cope with labour shortages. The study showed that a Logistic Regression model could successfully predict 97% of farmers' technological readiness while highlighting statistically significant farm characteristics. Depending on the goal of one's work, further research could include a more detailed examination of farm characteristics (e.g., farm age, geography, farm type) and assess farmers' willingness to adopt technologies.

CONCLUSIONS

In this study, the authors identified and analysed two distinct clusters of farmers based on their attitudes toward technology adoption using unsupervised and supervised machine learning approaches. Our findings demonstrated the effectiveness of K-means clustering in revealing overarching similarities in user attitudes and technological readiness, highlighting inherent characteristics within each group and the prominent factors distinguishing them. The cluster analysis showed a balanced split between farmers classified as technologically ready and those not ready, thereby indicating substantial potential for targeted intervention strategies. The less-ready group expressed particular concern about the ability of PLF technology to address labour shortages and support day-to-day decision-making, as well as a lack of available education. Comparatively, the factors that most strongly distinguished the two groups include market accessibility, available education, cost efficiency, and the ability to cope with labour shortages. Notably, the average level of automatization did not differ between groups, suggesting that general mechanization is not a sufficient indicator of readiness. However, prior use of smart devices showed clear differences and was among the strongest predictors in the applied Logistic Regression model, along with market accessibility, maintenance costs, and data management security. The model successfully predicted 97% of farmers' technological readiness while highlighting statistically significant farm characteristics. The analysis further confirms that barriers to technology adoption are multivariate in nature and must be considered in combination to capture the diversity of farmer needs and the complexity of the adoption process.

Therefore, the integration of unsupervised and supervised machine learning methods facilitated the identification of survey questions that play a crucial role in differentiating cluster affiliations based on user attitudes. The authors highlighted the need to investigate the potential of machine learning in this field and its ability to analyse user attitudes. The results can be used to unveil targeted information for survey design, requirement analysis, and policy intervention strategies.

Author Contributions:

Kevin Mallinger: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Luiza Corpaci: Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation.

Georg Goldenits: Writing – review & editing, Writing – original draft, Visualization, Validation.

Thomas Neubauer: Supervision, Funding acquisition.

Ildikó E. Tikász: Data curation.

Thomas Banhazi: Writing – review & editing, Validation, Funding acquisition.

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APPENDIX

APPENDIX A1 – Remaining Distribution of Survey Answers that haven’t been displayed in the result section

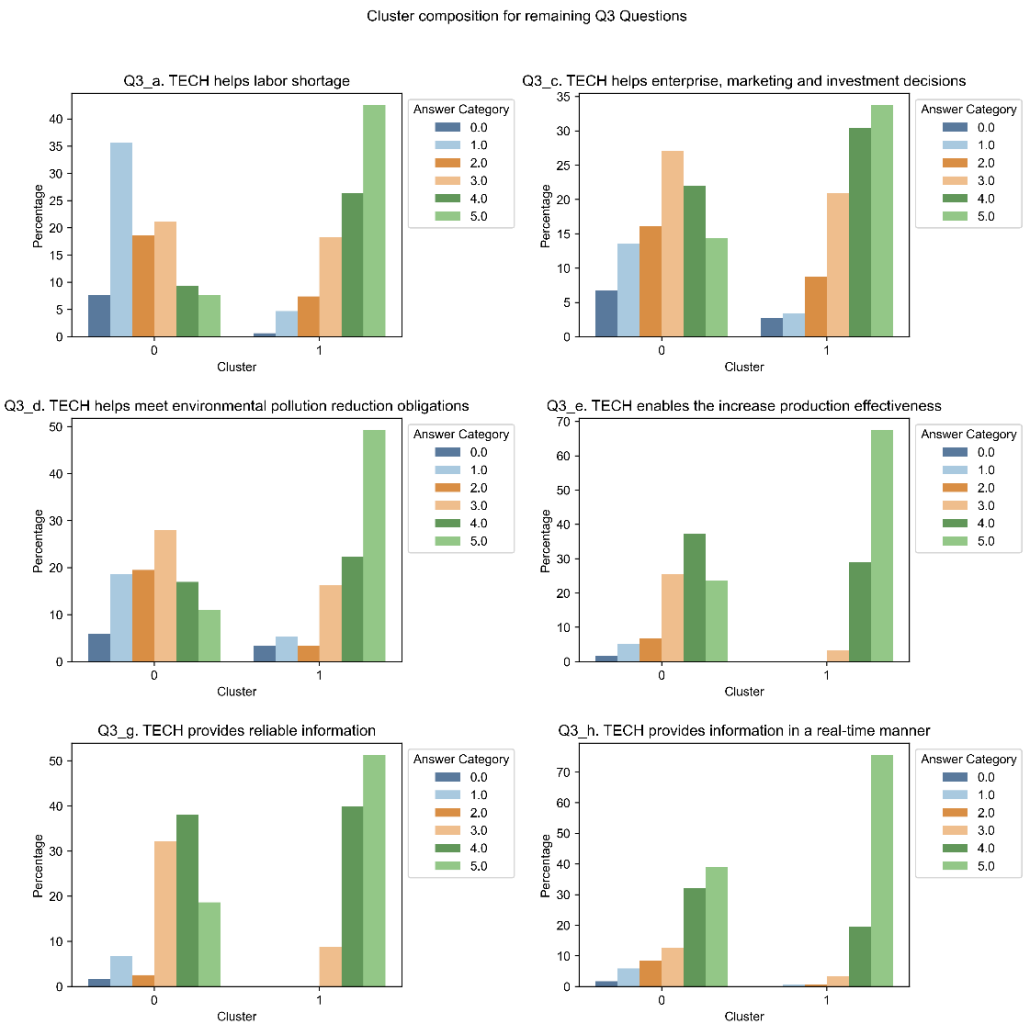


Figure 5. The figure shows the distribution of survey questions in the third category that haven't been shown in the result section. Cluster 0 represents technologically non-ready and Cluster 1 technologically ready farmers.

Cluster composition for remaining Q4 Questions

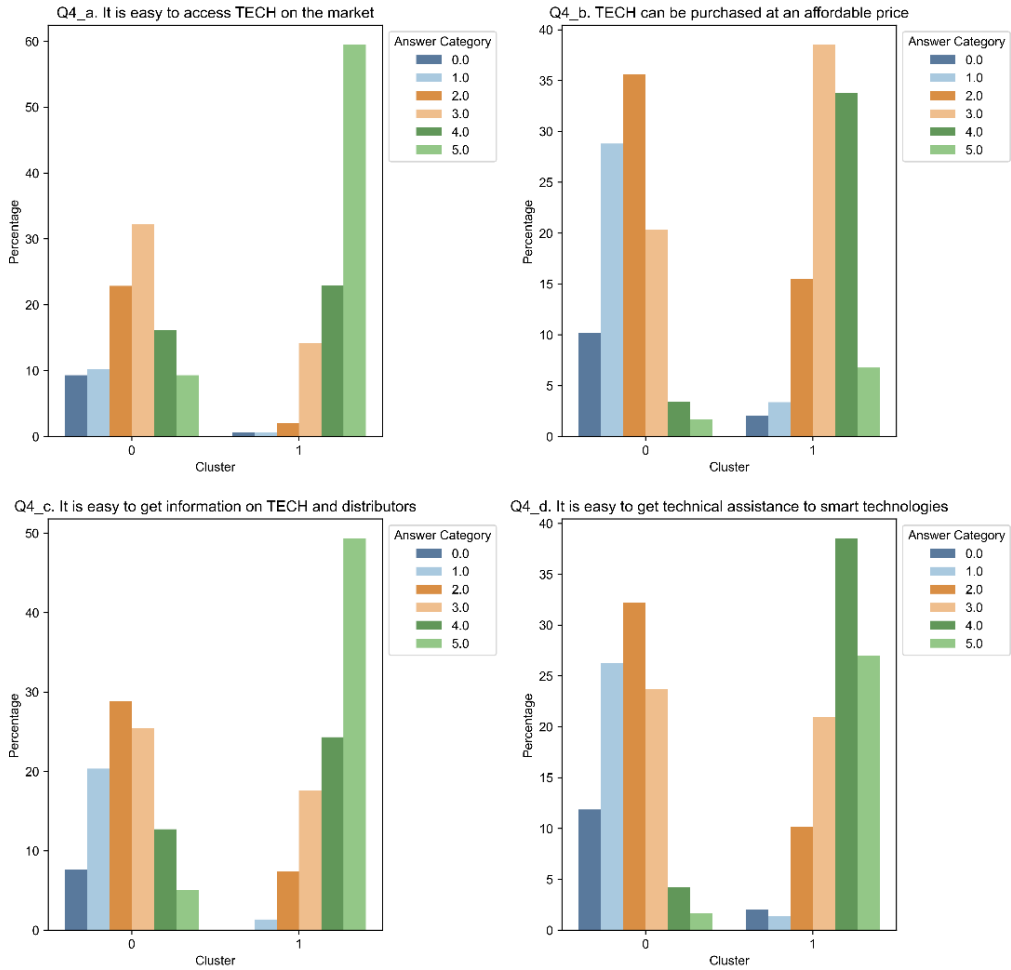


Figure 6. The figure shows the distribution of survey questions in the fourth category that haven't been shown in the result section. Cluster 0 represents technologically non-ready and Cluster 1 technologically ready farmers

Cluster composition for remaining Q5 Questions

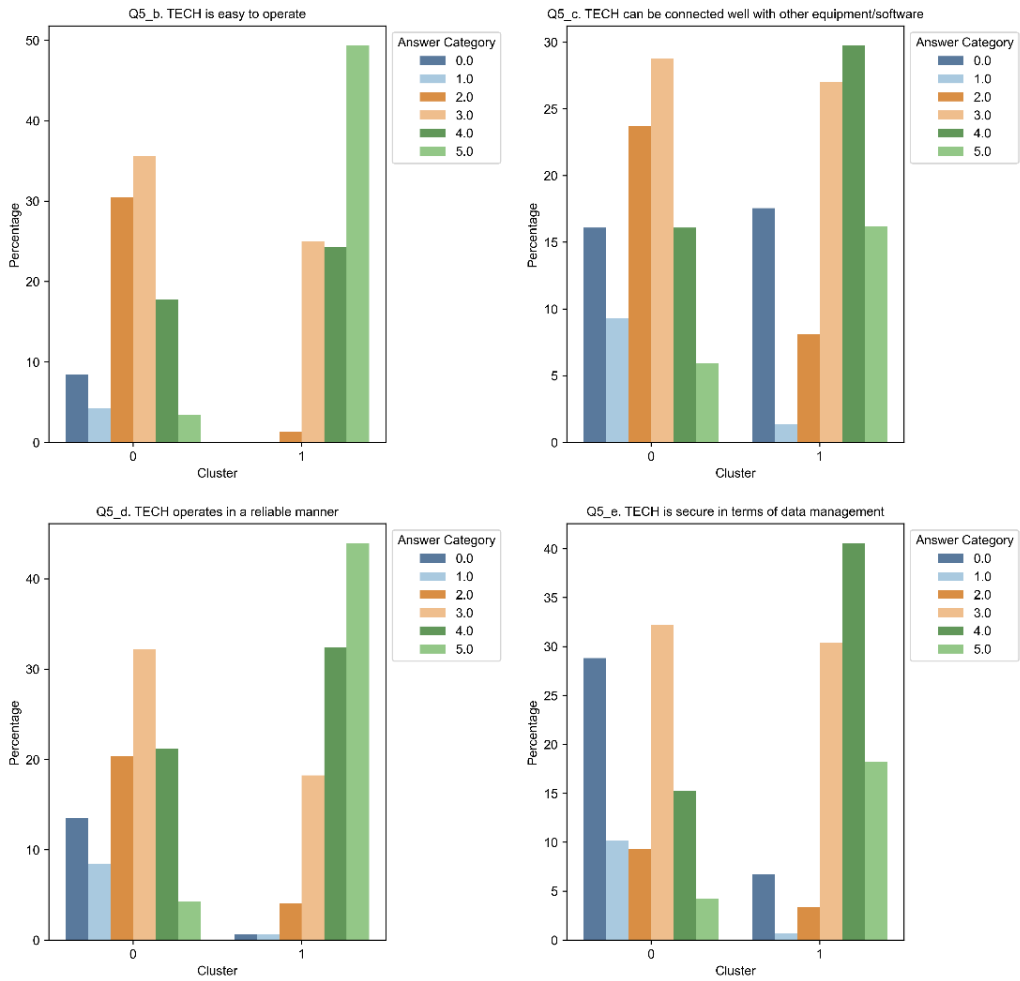


Figure 7. The figure shows the distribution of survey questions in the fifth category that haven't been shown in the result section. Cluster 0 represents technologically non-ready and Cluster 1 technologically ready farmers.

APPENDIX A2 – Survey questions used in this study

Table 6. All survey questions and subquestions that have been used in this study are represented here as well as their range of answer categories

Feature	Question
	1. Please state the average availability of internet access at your farm (0: I don't know, 1: No availability... 4: High availability)
	2. Please state the average level of automatization at your production farm (0: I don't know, 1: Less than 10 y/o, 2: 10-20 y/o, 3: diverse, 4: Over 20 y/o)
	3. Please indicate how much you agree with the statements on smart devices/technologies (sensors, cameras, robots, farm management information system etc.), regardless of whether you use them or not on your farm. (0: I don't know, 1: Strongly disagree... 5: Strongly agree)
Q3_a	help/support to cope with labour shortage.
Q3_b	help/support day-to-day decision-making in the livestock buildings.
Q3_c	help/support enterprise, marketing, and investment decisions.
Q3_d	help/support to meet environmental pollution reduction obligations.
Q3_e	enable an increase in the effectiveness of production.
Q3_f	provide reliable information.
Q3_g	provide information in real-time.
	4. Regarding the availability of smart technologies, please indicate how much you agree with the following statements. (0: I don't know, 1: Strongly disagree... 5: Strongly agree)
Q4_a	It is easy to access smart technologies on the market.
Q4_b	Smart technologies can be purchased at an affordable price.
Q4_c	It is easy to get information on smart technologies and distributors.
Q4_d	It is easy to get technical assistance for smart technologies.
Q4_e	Proper education is available for using smart technologies.
	5. Regarding the operation of smart technologies, please indicate how much you agree with each of the statements. (0: I don't know, 1: Strongly disagree... 5: Strongly agree)
Q5_a	can be maintained at a reasonable cost.
Q5_b	are easy to operate.
Q5_c	can be connected well with other equipment/software.
Q5_d	operate in a reliable manner.
Q5_e	are secure in terms of data management.
	6. Do you use smart devices (sensors, cameras, robots, etc.) at the farm you represent? (0: I don't know, 1: Yes, 2: No.)

The influence of irrigation and seeding rates on the yield of female components lines of corn in conditions of unstable moisture in Ukraine

M.M. Marenych¹, K.V. Koba³, V.V. Hanhur², S.O. Yurchenko¹,
S.M. Shakalii^{2,*}, A.V. Bahan¹, O.O. Chetveryk¹ and A.M. Rybalchenko¹

¹Poltava State Agrarian University, Educational and Research Institute of Agrotechnology, Breeding and Ecology, Department of Breeding, Seed Science and Genetics, 1/3, Skovorody Str., UA36003 Poltava, Ukraine

²Poltava State Agrarian University, Educational and Research Institute of Agrotechnology, Breeding and Ecology, Department of Plant Science, 1/3, Skovorody Str., UA36003 Poltava, Ukraine

³LLC Poltava Sad, village of Rozsoshentsi, UA36000 Poltava, Ukraine

*Correspondence: shakaliysveta@gmail.com

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Abstract. In regions with insufficient rainfall or different climates, the use of irrigation systems is an important element of corn growing technology. The variation in corn yield on non-irrigated lands is 533% and 200% greater than on irrigated lands. Corn yield also depends heavily on sowing density. The optimal plant density is an unstable value. Field studies were conducted in conditions of unstable moisture in the central part of the Forest-Steppe of Ukraine, which according to agro-climatic zoning belongs to the zone of unstable moisture. The experimental design included: assessment of the characteristics of weather conditions during the years of research (2021–2023) and their impact on seed yield (factor A); determination of seed productivity of female components lines of hybrids of different maturity groups P4/440, P5/320, P6/240 (factor B); the impact of growing hybrids with and without irrigation (factor C); the effect of different seeding rates on seed yield (60, 70, 80, 90 thousand seeds per ha⁻¹) (factor D). The test results show that during the change in corn productivity depending on genetic properties, seeding rate and irrigation, the late-ripening hybrid P4/440 was characterized by the highest grain yield when grown under irrigation, with a seeding rate of 90 thousand similar seeds per ha⁻¹ a decrease in the seeding rate from 90 to 80, 70, 60 seeding rate thousand seeds ha⁻¹ was accompanied by a decrease in the yield of seeds of female components lines: in the early-ripening hybrid P6/240 - by 0.31, 0.63 and 1.10 t ha⁻¹ or 5.7, 11.5 and 20.1%, in the mid-ripening hybrid P5/320 - by 0.59, 1.08 and 1.42 t ha⁻¹ or 9.8, 17.9 and 23.5%, in the late-ripening hybrid P4/440 - by 0.39, 0.74 and 1.28 t ha⁻¹ or 6.0, 11.4, 19.8%. The greatest influence on the formation of yield is the irrigation factor - 53%. Genetic properties influenced 28%. gradual increase in the yield of seeds of female components lines of culture when increasing the seeding rate from 60 to 70 thousand seeds ha⁻¹ (by 0.01 t ha⁻¹) and reaching a maximum at a rate of 80 thousand seeds ha⁻¹ (by 0.05 t ha⁻¹). But with an increase in the seeding rate to 90 thousand ha⁻¹, the seed yield sharply decreased by 0.13 t ha⁻¹. The highest yield in variants without irrigation was observed when using the minimum seeding rate - 60 thousand seeds ha⁻¹. A gradual increase in the seeding rate without irrigation

led to a negative result, in particular, a decrease in the average yield for corn hybrids by 0.07–0.31 t ha⁻¹ or 1.8–7.9%. Hybrids reacted differently to the seeding rate and cultivation on rainfed and irrigated land. Early ripening hybrid P6/240, mid-ripening P5/320 and late-ripening P4/440 hybrids formed the highest seed yield when grown under irrigation with a seeding rate of 90 thousand seeds ha⁻¹. When grown without irrigation, the best conditions for the formation of plant components and high yield were noted at the lowest seeding rate of 60 thousand seeds ha⁻¹. The minimum seeding rate ensured the production of seeds with a high mass of 1,000 seeds.

Key words: corn, hybrid, female components lines, irrigation, seeding rate.

INTRODUCTION

Due to climate change in Ukraine, irrigation systems are being widely developed and implemented at the state and regional levels with the participation of international foundations, which is especially important for seed production.

The problem of food security has become critical. Trends in global climate change are increasing the need to find new suppliers of food. Therefore, the development of corn production for grain, along with other crops, is a strategic component of solving the global food problem and a guarantee of financial stability of supplier countries (Vasylishyn et al., 2022).

Military operations in Ukraine have negatively affected the functioning of food systems. Integrated supply chains for agricultural products and food products have been disrupted. Active hostilities are currently taking place in those regions where most grain crops are grown. This has led to a decrease in yields, harvests and grain exports. The export of Ukrainian products to foreign markets has been significantly complicated due to the blockade of Ukrainian ports, which has negatively affected countries that depend on food imports. The consequences have led to serious threats to global food security, namely: a further increase in world food prices; a global jump in inflation, which will primarily affect countries with underdeveloped unstable economies in the Middle East and North Africa (Onegina & Antoshchenkova, 2022).

Corn cultivation is one of the most important aspects of agricultural production, ensuring not only the food security of the state, but also used in animal husbandry and for the production of biofuels. Thanks to technological and scientific achievements in recent years, corn cultivation has become more productive and resistant to various stress factors. A scientifically sound approach to the development and implementation of corn cultivation technology can increase crop yield, ensure its stability, and reduce the impact of negative factors on plant growth and development. In regions with insufficient rainfall or different climates, the use of irrigation systems is an important element of corn cultivation technology (Juraev et al., 2021; Zhu & Burney, 2022). Many years of research have shown that a 30% decrease in precipitation can reduce average yields by 10% (Rohit et al., 2021). Maize yield variability in dryland is 533% and 200% greater than in irrigated areas (Irmak et al., 2022). Severe water stress can significantly limit the growth and development of maize in the field and has a potentially negative impact on its yield (Libing et al., 2019; Bharathi et al., 2021).

Careful monitoring and management of water supply can help reduce the effects of water stress on maize (Zhu & Burney, 2022). Irrigation allows plants to be provided with

the necessary amount of moisture during critical phases for maize and ensure optimal growth and development (Grafton et al., 2018; Lubajo & Karuku, 2022).

Maize yield can vary depending on the level of irrigation at different stages of its development. Studies indicate that insufficient irrigation during the initial stages of growth can lead to underdevelopment of the root system and low yield. During this period, roots and leaves are actively formed, so plants need sufficient moisture to optimally ensure the passage of these important stages in the organogenesis of the crop (Huihui et al., 2019).

It is important to ensure sufficient moisture levels during reproductive development, since during this period plants form generative organs (panicle, ear). Pollination of stamen filaments occurs, the formation and filling of the grain. Insufficient irrigation at this stage can lead to uneven placement of grains on the ear and a decrease in the number of grains per plant (Comas et al., 2019).

During grain ripening, plants require less moisture, but it is necessary to ensure a sufficient level of irrigation to form high-quality grain. Insufficient irrigation at this stage can lead to a low amount of moisture in the grain, which can worsen its quality indicators (1000-grain weight, protein and starch content) and reduce yield (Zou et al., 2021).

In general, corn requires different irrigation at different stages of its growth and development, which contributes to the optimal provision of physiological needs of plants for moisture during the growing season and the formation of stable yields (Afshin et al., 2019; Marilyn & Victor, 2022). The maximum realization of the genetic potential of corn hybrids productivity, improvement of biometric and economic characteristics of cobs and quality indicators of grain is achieved by timely irrigation and providing the plant with the necessary amount of moisture (Huifang et al., 2019; Yue-e et al., 2021).

Corn yield is highly dependent on planting density. The optimal plant density is an unstable value. It can vary depending on various factors, including: climatic conditions, soil type and fertility level, maturity group, and biological characteristics of corn hybrids (Ronald et al., 2021). Increasing corn density in irrigated areas can be an important way to increase the efficiency of plant nutrition, which affects the increase in yield and improve the economic performance of crop cultivation (Hernández et al., 2020; Ning et al., 2019). Some corn hybrids may be more adapted to high plant density and are able to compensate for yield losses due to increased intraspecific competition (Gonzalez et al., 2018; Li et al., 2018; Kamara et al., 2021). In such cases, increasing plant density may not affect yield (Abd El-Aty et al., 2019).

In arid regions, the impact of planting density on maize yield can be important, as water availability is limited and the level of water use efficiency can have critical consequences (Dhaliwal & Williams, 2019; Mylonas et al., 2020). Increased planting density can cause competition for water between plants. If water resources are limited, this can lead to stress for each plant and reduce its yield (Winans et al., 2021; Jiang et al., 2018). Therefore, some scientists believe that in arid conditions with insufficient water, it would be advisable to reduce planting density (Haarhoff & Swanepoel, 2018; Fernando et al., 2020). This will help improve crop moisture supply, their optimal growth and development, and reduce plant competition for water (Anna et al., 2019).

So far, domestic breeders have created a number of corn hybrids that differ among themselves in morphological features, biological features, indicators of yield and grain quality, and have a high level of adaptive potential to adverse environmental conditions (Tryhub et al., 2020).

Studies show that growing corn with optimal plant density is an important aspect for achieving maximum yield and crop quality (He et al., 2022; Ye et al., 2023). The optimal plant density is established taking into account the bioclimatic potential the purpose of growing corn.

The purpose of our research was to determine the components of seed yield formation of female components linesof corn hybrids at different sowing rates and growing crops with and without irrigation.

Research objectives: to investigate the influence of irrigation and different seeding rates on the yield of female components linesof corn hybrids.

MATERIALS AND METHODS

Field studies were conducted in the central part of the Forest-Steppe of Ukraine. According to agroclimatic zoning, the territory of the research plots belongs to the zone of unstable moisture. The climate is continental, with cold winters and hot summers. The number of active temperatures is 2,250 °C. The average annual air temperature in this area is 9 °C. The coldest period during the years of research is observed in January and is -2.6 °C, and the warmest is in August (23.3 °C). The onset of frosts was noted in the first decade of October. The duration of the frost-free period is 175–180 days.

In conditions of unstable moisture, the amount and distribution of precipitation are the main factors that determine the level of efficiency of growing agricultural crops, including corn. Abnormal weather conditions, in particular, a deficit of precipitation and their uneven distribution, can significantly affect the growth and development of plants (Fig. 1).

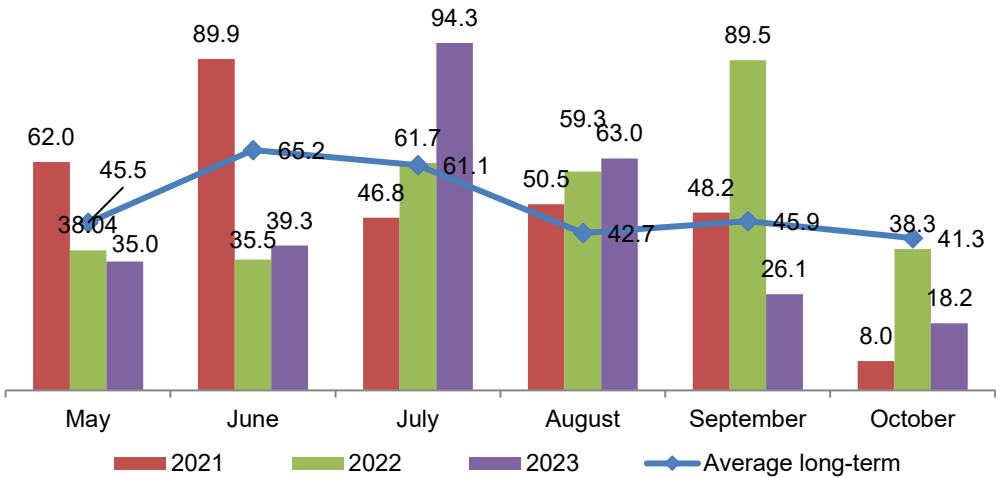


Figure 1. Distribution of precipitation during the corn growing season (average for 2021–2023).

In 2021, the total amount of precipitation in May and June exceeded the multi-year average by 41.2 mm or 37.2%. However, in July, there was a decrease in the amount of precipitation, compared to the multi-year average, by 14.3 mm or 23.4%. In the

following months, the amount of precipitation was close to the multi-year average. In October, the amount of precipitation was 8 mm or 19.3% of the multi-year average, but this did not significantly affect the formation of yields at the final stage of the corn growing season. The amount of precipitation for May–October 2022 was 322.3 mm, which is 20.6 mm or 6.8% more than the multi-year average. This indicates sufficient moisture supply for corn crops during the growing season. But the uneven distribution of precipitation caused a moisture deficit in May and especially in June, which caused a temporary slowdown in the growth processes of the crop.

During the 2023 growing season, the total amount of atmospheric precipitation was lower than the long-term average by 25.8 mm or 8.6%. Their uneven distribution was noted, during which a precipitation deficit of 79.3 mm or 40.1% was observed in May–October, and an excess of 53.5 mm or 51.5% was observed in July–August.

The results obtained indicate significant fluctuations in the distribution of precipitation between years. Such variations can affect the growth of corn, which requires the adaptation of growing technologies to specific weather conditions each year, the use of different approaches to managing agrotechnical measures, taking into account the variability of climatic conditions.

Temperature is one of the key factors affecting the processes of plant growth and development. Optimal temperature conditions ensure efficient corn growth, while deviations from the norm can lead to stressful conditions and reduced yields. Analysis of the temperature regime indicates the presence of significant temperature fluctuations during the growing season of corn in different years, compared with the average multi-year indicators (Fig. 2).

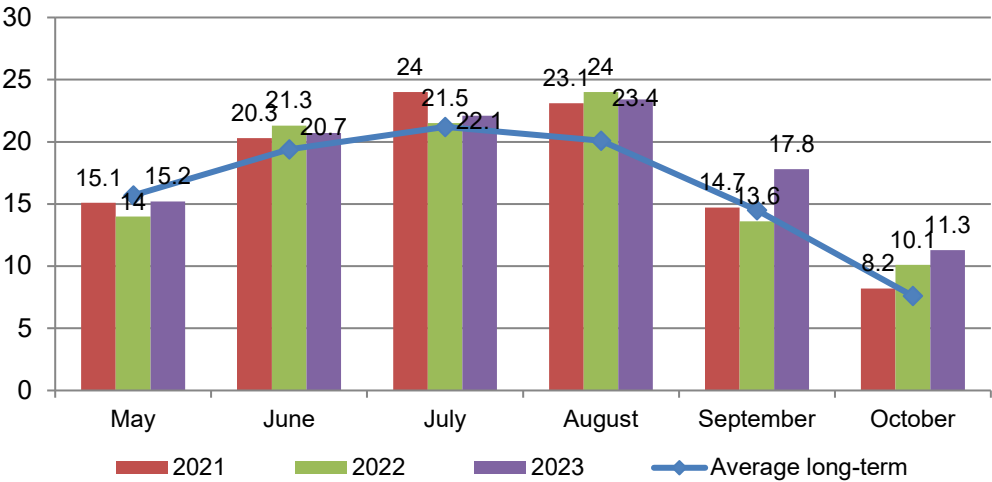


Figure 2. Temperature distribution during the corn growing season (average for 2021–2023).

A stable excess of the average monthly air temperature, compared to the average multi-year values, was observed during June–July in all years of research. But the largest deviations were observed in August–September 2023 and August 2022, when the average monthly temperature exceeded the average values, respectively, by 3.3 °C and

3.9 °C. The air temperature in many months was close to the average multi-year. The data obtained indicate the importance of taking into account the temperature regime for optimizing agrotechnical measures in corn cultivation and adapting to changing climatic conditions.

The main type of soil in the experimental area is typical low-humus chernozem, which by mechanical composition belongs to heavy loams. It is characterized by the following agrochemical indicators: in the arable soil layer (0–20 cm) the humus content is 3.8–4.2%; nitrate nitrogen contains 9.8–10.2 mg, mobile phosphorus – 24.3 mg, exchangeable potassium – 264 mg kg⁻¹ of soil. The content of nutrients in the arable soil layer is equal to low nitrogen supply and medium – phosphorus and potassium. The reserves of available moisture in the meter layer of soil at the time of sowing were within the average long-term value and amounted to 135–140 mm.

The arable soil layer of the experimental plot is characterized by a high absorption capacity (40 mg. equiv./100 g of soil), which is due to the high content of highly dispersed silty particles. The soil density varies from 1.15 g cm⁻³ at the time of sowing to 1.36 g cm⁻³ before harvesting. The reaction of the soil solution is close to neutral – pH 5.9–6.1.

The experimental plan included: conducting an assessment of weather and climatic conditions over the years of research (2021–2023) and their impact on seed yield (factor A) - irrigation was carried out by sprinkling. The irrigation source was a well with water mineralization of 0.78–1.12 g dm⁻³. Water consumption rate – 450 m³ ha.; determination of seed productivity of female components lines of hybrids of different maturity groups P4/440, P5/320, P6/240 (factor B); the impact of growing hybrids with and without irrigation (factor C); the impact of different seeding rates on seed yield (60, 70, 80, 90 thousand seeds ha⁻¹) (factor D). The plot area for each corn hybrid was 120 m². The repetition of the experimental variants was threefold. The placement of variants was randomized according to the seed sowing rate. Corn was sown in the first decade of May. Corn in the experiment was placed after corn. Sowing was carried out using the Precision Planting system. As the seeder moves to a zone with higher or lower density, the system automatically adjusts the seeding rate according to the set scheme.

Irrigation was carried out in critical phases of corn development: V4 (phase 4 leaves) – 20 mm, V8 (phase 8 leaves) – 20 mm, VT (phase of panicle ejection) – 45 mm.

The harvest and moisture content were recorded in the phase of full grain maturity using an OXBO 2460 combine harvester from each experimental site. The yield of corn grain was converted to a standard moisture content of 14%. The mass of 1,000 grains was determined using generally accepted methods (Yeshchenko et al., 2005).

Data analysis was performed using descriptive statistics, regression, and analysis of variance (ANOVA) in the STATISTICA 10.0 software. Experimental data were evaluated using analysis of variance (ANOVA) to calculate the least significant difference (*LSD*₀₅).

RESULTS AND DISCUSSION

The results of the research indicate a significant influence of all the studied factors and their interaction on the formation of the yield of female components lines of corn.

The results of the tests indicate that during the change in corn productivity depending on genetic properties, seed sowing rate and irrigation, the late-ripening hybrid P4/440 was characterized by the highest grain yield when grown under irrigation, with a sowing rate of 90 thousand seeds per hectare (Table 1).

The same seeding rate is the most effective for hybrids P6/240 and P5/320 when grown under irrigation. Studies show that reducing the seeding rate from 90 to 80, 70, 60 thousand seeds per 1 ha was accompanied by a decrease in the yield of seeds of the female components lines: in the early-ripening hybrid P6/240 - by 0.31, 0.63 and 1.10 t ha⁻¹ or 5.7, 11.5 and 20.1%, in the mid-ripening hybrid P5/320 - by 0.59, 1.08 and 1.42 t ha⁻¹ or 9.8, 17.9 and 23.5%, in the late-ripening hybrid P4/440 - by 0.39, 0.74 and 1.28 t ha⁻¹ or 6.0, 11.4, 19.8%. Despite the fact that most modern hybrids have a wide range of optimum plant density due to good compensatory ability (formation of a larger number of grains in a row, a greater mass of 1,000 grains, formation of a second ear). But under irrigation conditions, this biological feature of corn does not compensate for the crop failure caused by insufficient plant density per unit area.

The reaction of corn hybrids to different seed sowing rates when grown without irrigation was the opposite. Studies show that hybrids P6/240, P5/320 and P4/440 formed the maximum seed yield when sowing at the lowest rate - 60 thousand seeds ha⁻¹. At the same time, the seed yield exceeded the experimental variants with a seeding rate of 70, 80 and 90 thousand seeds ha⁻¹ in the hybrid P6/240 – by 0.22, 0.62 and 1.0 t ha⁻¹ or 5.6, 15.7 and 25.3%, in the hybrid P5/320 – by 0.28, 0.63 and 1.07 t ha⁻¹ or 6.3 14.2 and 24.1%, in the hybrid P4/440 – by 0.30, 0.76, 1.87 t ha⁻¹ or 6.0, 15.1 and 37.3%. This indicates that in the conditions of the unstable moisture zone of Ukraine, the main limiting factor for high crop productivity is the reserves of available moisture in the soil during the crop growing period.

Table 1. Yield of female components lines (♀) of hybrids depending on irrigation and sowing rate (average for 2021–2023)

♀ hybrid	Seeding rate, thousand seeds ha ⁻¹	Average productivity, t ha ⁻¹		
		control (no irrigation)	irrigation growth	growth
P4/440	60	5.02	5.20	0.18
	70	4.72	5.74	1.02
	80	4.26	6.09	1.83
	90	3.15	6.48	3.33
P5/320	60	4.44	4.62	0.18
	70	4.16	4.96	0.8
	80	3.81	5.45	1.64
	90	3.37	6.04	2.67
P6/240	60	3.96	4.37	0.41
	70	3.74	4.84	1.1
	80	3.34	5.16	1.82
	90	2.96	5.47	2.51
<i>LSD₀₅</i>				
Year (A)		0.33		
♀ hybrid (B)		0.36		
Irrigation (C)		0.27		
Seeding rate, ha ⁻¹ (D)		0.37		
AB		0.57		
AC		0.46		
BC		0.49		
AD		0.66		
BD		0.72		
CD		0.54		
ABC		0.8		
ABD		1.14		
ACD		0.93		
BCD		0.98		
ABCD		1.61		

It should be noted that corn hybrids reacted differently to an increase or decrease in the seeding rate against the background of irrigation or without irrigation. Experimental data show that with an increase in the seeding rate from 60 to 70 and 80 thousand seeds ha^{-1} in the variant without irrigation, the numerical value of the decrease in the seed yield of the mother forms of corn hybrids was almost the same. But with an increase in the seeding rate to 90 thousand seeds ha^{-1} , the late-ripening hybrid P4/440 stood out with the most negative reaction to the thickening of the sowing and the maximum decrease in yield. This indicates a deficit of available moisture in the soil to meet the physiological needs of hybrids with a longer vegetation period.

When growing corn in the variant with irrigation, with a decrease in the seeding rate from 90 to 80, 70, 60 thousand seeds ha^{-1} in the experiment, the value of the seed yield shortfall was close to the early-ripening hybrid P6/240 and the late-ripening P4/440. In the mid-ripening hybrid P5/320, the yield reduction was significantly greater compared to the early-ripening and late-ripening hybrids, respectively, at the sowing rate of 80 thousand seeds ha^{-1} - by 0.20 and 0.28 t ha^{-1} , 70 thousand seeds ha^{-1} - by 0.34 and 0.45 t ha^{-1} , 60 thousand seeds ha^{-1} - by 0.14 and 0.32 t ha^{-1} .

The grouping of the factors showed that the P4/440 hybrid with irrigation formed a yield of 0.8 t ha^{-1} more than without irrigation (Fig. 3). The difference between the irrigation and non-irrigation options with the P5/320 hybrid was 1.44 t ha^{-1} , and P6/240 - 1.58 t ha^{-1} .

Grouping of the effects of factors showed that the increase in yield under irrigation compared to the control was: in the hybrid P4/440 – 37.1%, P5/320 – 33.4%, P6/240 – 41.7% (Fig. 3).

Thus, for effective management of the yield of female components lines, it is first necessary to take into account their genetic properties, that is, the ability of hybrids to maximize the bioclimatic potential of the region, the resource content of technologies and their transformation into a crop yield. It is genetic features that should become the basic element in determining the strategy for the formation of yield. Irrigation of crops with a value of 95 mm turned out to be effective for the formation of the yield of seeds of female components lines and has prospects for further research in order to clarify irrigation norms.

According to the results of variance analysis, it was found that the irrigation factor has the greatest influence on the formation of yield - 53%. Genetic properties influenced 28%. It was characteristic that the conditions of the growing years, which have a dominant influence when growing corn without irrigation, in this experiment influenced only 12%. This indicates a significant possibility of managing the production processes

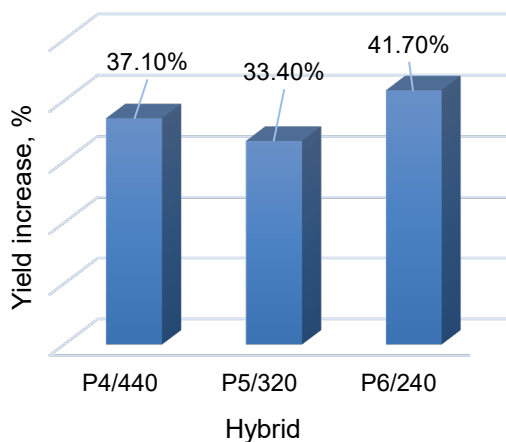


Figure 3. Increase in seed yield of the studied hybrids under irrigation, average for 2021–2023.

of agrocenoses of seed crops. It should be noted that the interaction of the factors studied in the experiment, although it had a less pronounced effect, was statistically significant at a high level of significance ($p \leq 0.01$).

Therefore, in conditions of moisture deficiency, this indicator requires clarification to develop methods for effective management of the yield of female components lines of corn hybrids. For this, it is advisable to also determine reliable indicators - economically valuable traits that are directly related to yield.

Studies show that seed sowing rates also have a significant impact on the formation of the yield of female components lines. The use of irrigation has a noticeable and visual effect, this was also confirmed by the results of mathematical processing of the experimental results.

A steady trend towards an increase in yield is observed in the variants with irrigation (Fig. 4).

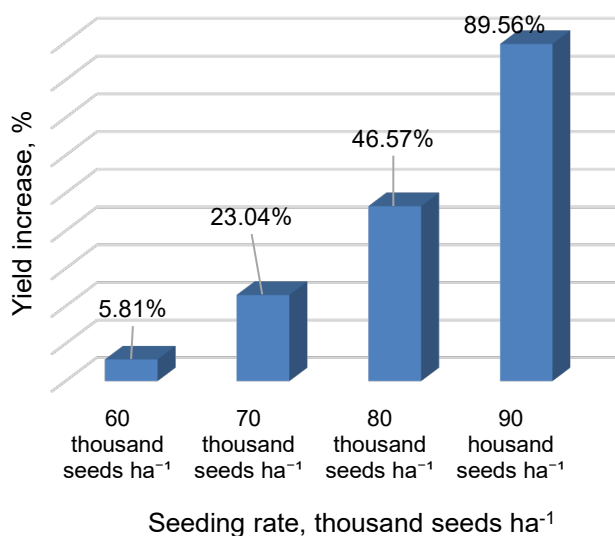


Figure 4. Increase in corn seed yield depending on irrigation at different seeding rates, average for 2021–2023.

The increase in corn seed yield under irrigation compared to the control depending on the seeding rate was: 60 thousand ha⁻¹ - 5.81%, 70 thousand ha⁻¹ - 23.04%, 80 thousand ha⁻¹ - 46.57%, 90 thousand ha⁻¹ - 89.56%.

Thus, on average, for the tested corn hybrids, when grown under irrigation, a gradual increase in the yield of seeds of the mother crop forms was noted when the seeding rate was increased from 60 to 70 thousand seeds ha⁻¹ (by 0.01 t ha⁻¹) and reached a maximum at a rate of 80 thousand seeds ha⁻¹ (by 0.05 t ha⁻¹). But when the seeding rate was increased to 90 thousand ha⁻¹, the seed yield sharply decreased by 0.13 t ha⁻¹.

The highest yield on variants without irrigation was observed when using the minimum seeding rate of 60 thousand seeds ha⁻¹. A gradual increase in the seeding rate without irrigation led to a negative result, in particular, a decrease in the yield on average

for corn hybrids by 0.07–0.31 t ha⁻¹ or 1.8–7.9%. This indicates that in the conditions of unstable moisture in the central part of the Forest-Steppe of Ukraine, effective cultivation of corn seed crops requires optimization of the plant life factor, which is at a minimum (available moisture reserves).

One of the most important indicators of the formation of the yield of corn seed crops is the mass of 1,000 seeds. This indicator characterizes the fullness of the seed, nutrient reserves and significantly determines its sowing qualities and the value of the seed batch as a whole. The obtained research results indicate similar patterns of influence of the studied factors on the mass of 1,000 seeds, as on seed yield (Table 2).

The results of the studies show that the mass of 1,000 seeds was significantly higher in the variants where irrigation was used. In the late-ripening hybrid P4/440, the mass of 1,000 seeds against the background of irrigation was, depending on the seeding rate, from 299.8 to 318.2 g or was higher, compared to growing without irrigation, by 34.3–38.2 g. In the mid-ripening hybrid P5/320, the difference in this indicator was in the range of 35.0–40.4 g, which confirms the importance of irrigation for obtaining high-quality seeds with a large mass, and, therefore, a fairly high potential. A similar pattern was also observed in the early-ripening hybrid P6/240.

The importance of the mass of 1,000 seeds as an indicator is confirmed by its close direct relationship with seed yield – $r = 0.80$ (Fig. 5).

But this indicator is, albeit weakly, but statistically significantly inversely correlated with the seeding rate ($r = -0.24$). It is obvious that the mass of 1,000 seeds turned out to be an important indicator for determining the yield of female components lines and requires further research into its influence on the formation of seed yield of first-generation hybrids.

Table 2. Weight of 1,000 grains of female components lines (♀) depending on irrigation and seeding rate (average for 2021–2023)

♀ hybrid	Seeding rate, thousand seeds ha ⁻¹	Weight of 1,000 seeds, g		
		control (no irrigation)	irrigation growth	growt
P4/440	60	283.9	318.2	34.3
	70	276.7	314.9	38.2
	80	270.1	307.0	36.9
	90	265.2	299.8	34.6
P5/320	60	242.7	277.7	35.0
	70	234.8	272.6	37.8
	80	223.9	264.3	40.4
	90	216.9	258.0	41.1
P6/240	60	249.0	280.9	31.9
	70	240.1	275.1	35.0
	80	229.6	271.2	41.6
	90	224.5	267.3	42.8
<i>LSD</i> ₀₅				
Year (A)		0.03		
♀ hybrid (B)		0.04		
Irrigation (C)		0.03		
Seeding rate, thousand ha ⁻¹ (D)		0.04		
AB		0.06		
AC		0.05		
BC		0.05		
AD		0.07		
BD		0.08		
CD		0.06		
ABC		0.08		
ABD		0.12		
ACD		0.1		
BCD		0.11		
ABCD		0.17		

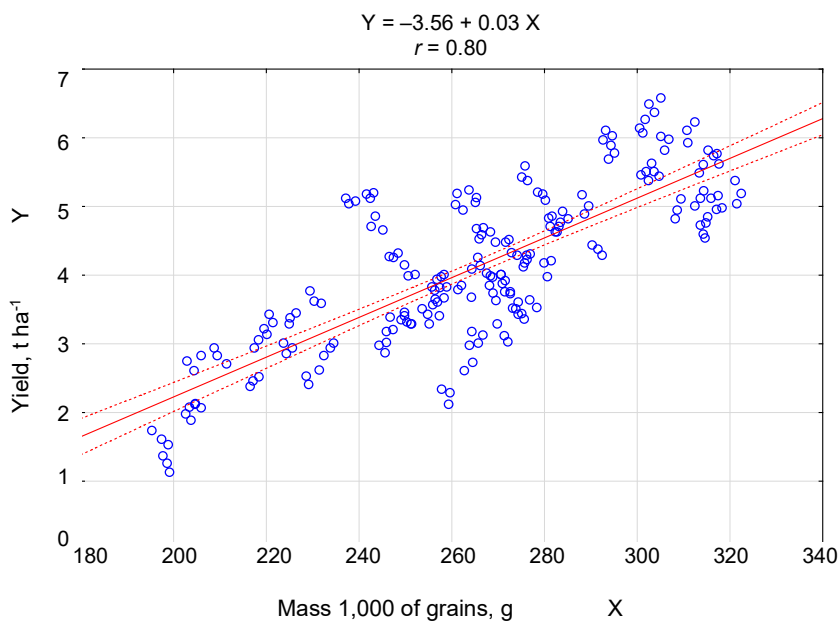


Figure 5. Dependence of seed yield on the mass of 1,000 grains.

But this indicator is in a weak, but statistically significant inverse correlation with the seeding rate ($r = -0.24$) (Fig. 6).

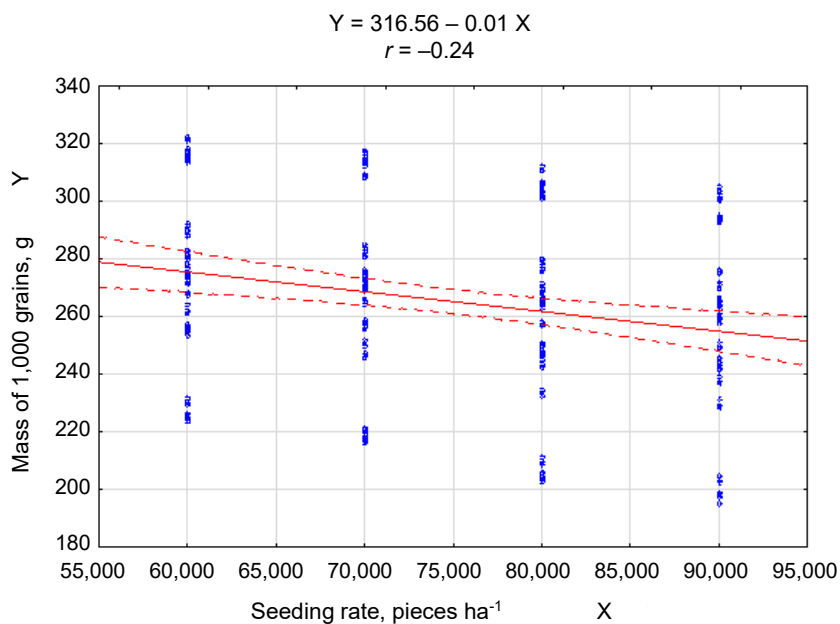


Figure 6. Dependence of seed yield on the mass of 1,000 grains.

Data analysis by the multiple regression method made it possible to establish an equation of the quadratic dependence of the yield of seed crops of female components lines of hybrids on the seeding rate and the mass of 1,000 seeds.

DISCUSSION

Water is one of the important natural resources necessary for plant life, and the increase in its scarcity prompts the search for ways to effectively use moisture and manage the water regime (Brar et al., 2016; Djaman et al., 2022). Maize plants are quite sensitive to water shortages, since their root system is not sufficiently branched and does not penetrate deeply into the soil. It was found that in the panicle ejection phase (VT), 94% of the total root length was located from the soil surface to a depth of 60 cm and 85% in the soil layer up to 30 cm. This distribution of the bulk of corn roots can lead to sharp fluctuations in corn yield in years with a deficit of soil moisture due to frequent drought. The results of our research also indicate the dominant influence of weather conditions, in particular the deficit of precipitation moisture in the panicle ejection phase (VT) and stigma yield (R1) on the level of seed yield when growing corn without irrigation.

According to the experiment, it was found that on average for 2021–2023, both the early-ripening hybrid P6/240, and the mid-ripening P5/320 and late-ripening P4/440 hybrids formed the highest seed yield when grown under irrigation with a sowing rate of 90 thousand seeds ha^{-1} . Sowing corn hybrids with a rate of 60, 70, 80 thousand seeds ha^{-1} against the background of irrigation turned out to be ineffective. Increasing plant density is accompanied by an increase in grain yield of corn hybrids by achieving the optimal number of plants per unit area (Assefa et al., 2016). It has been studied that higher corn plant density contributes to higher grain yield. When testing corn hybrids ZP 500, NS 5010 and AS 534 in Serbia at densities from 50,125, to 59,523, 69,686 and 79,365 plants ha^{-1} during three consecutive growing seasons (2016–2018), it was found that they formed the highest grain yield at the maximum plant density (79,365 plants ha^{-1}) (Mandić et al., 2024).

Studies show that when growing female components lines of corn hybrids without irrigation, high plant density per unit area led to a decrease in seed yield. The highest seed yield of corn hybrids was formed at the lowest seeding rate, in particular 60 thousand seeds ha^{-1} . Increasing the crop density also has its limitations, since exceeding the optimal plant density leads to increased competition for water, nutrients and light, worsening conditions for pollination and the formation of crop structure elements, in particular, a decrease in the number of grains per ear, the weight of 1,000 grains (Berzsenyi & Tokatlidis, 2012; Cerrudo et al., 2020). Therefore, to obtain high corn yields, the plant density must be optimal, since thinned and thickened crops reduce this indicator (Shakalii et al., 2024). One of the most important factors in the quality of seed material is the weight of 1,000 seeds, because well-filled seeds have greater germination energy, a higher percentage of germination and, accordingly, give a good start to plants from the very beginning. In field crops, the dependence of the level of plant yield on the mass of 1,000 seeds was noted (Bahan et al., 2024). The conducted studies revealed that when growing corn hybrids both against the background of

irrigation and in the variant without irrigation, the mass of 1,000 seeds increased from the maximum to the minimum seeding rate. A similar pattern is evidenced by the results of the studies of Zhang et al. (2015) and Jia et al. (2018). Correlation analysis indicates a direct close relationship between the yield of corn hybrid seeds and the mass of 1,000 seeds. This indicates a direct positive effect of the thousand-seed weight indicator on grain yield. The results of the studies of Chen et al. (2017) and Jahangirlou et al. (2021) also showed that these traits determine grain yield.

According to the research conducted by Shatkovsky (Shatkovsky et al., 2020), it was found that irrigation in combination with other agrotechnical measures is a determining factor in the activation of growth processes and the formation of corn yield. The highest yield indicators were achieved when irrigation was used. The lowest corn yield indicators were recorded with natural moisture, which indicates high risks and limited feasibility of growing this crop without additional irrigation.

Fomichev (2019) considers modern irrigation methods as a key factor in the intensification of grain corn growing technologies. The obtained research results confirm that the method of irrigation significantly affects the formation of the main biometric indicators, crop structure and productivity of this crop.

CONCLUSION

Determination of the optimal seeding rate for female components lines of corn hybrids of different maturity groups should be carried out comprehensively, taking into account the bioclimatic potential of the growing area, genetic characteristics and agrotechnical factors. According to the results of the research, it was found that in conditions of unstable moisture in the central part of the Forest-Steppe of Ukraine, one of the decisive factors in the formation of elements of the crop structure and a prerequisite for high corn grain yield is the level of plant provision with available moisture during the growing season. Moisture deficiency limits the formation of high seed yield and 1,000-seed weight.

Hybrids reacted differently to the seeding rate and cultivation under rainfed and irrigation. Early-ripening hybrid P6/240, mid-ripening P5/320 and late-ripening P4/440 hybrids formed the highest seed yield when grown under irrigation with a seeding rate of 90 thousand seeds ha^{-1} . When grown without irrigation, the best conditions for the formation of plant components and high yield were noted at the lowest seeding rate - 60 thousand seeds ha^{-1} . The minimum seeding rate ensured the production of seeds with a high mass of 1,000 seeds.

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Assessment of the spatiotemporal changes of saline-alkaline soils using GIS and, geospatial technologies methods: a community case study

A.O. Markosyan¹, M.H. Zadayan^{2,*}, G. Azgaldyan³, S.K. Baghdasaryan¹, S.Z. Kroyan⁴
and S.A. Markosyan⁵

¹Armenian National Agrarian University, Scientific Center of Soil Science, Agrochemistry and Melioration named after H. Petrosyan, Department of Soil Science, Agrochemistry and Geography of Soils, 24 Admiral Isakov Ave, AM0004 Yerevan, Armenia

²Center for Agricultural Research and Certification, State Non-Commercial Organization of the Ministry of Economy of the Republic of Armenia, Yerevanyan highway 2nd deadlock, building 4, Armavir Marz, v. Merdzavan, AM1139, Armenia

³Hydrometeorology and Monitoring Center of the Ministry of Environment of the Republic of Armenia, State Non-Commercial Organization, GIS and Remote Sensing Service, 46 Charenc, AM0025 Yerevan, Armenia

⁴National University of Architecture and Construction of Armenia, Department of Engineering Geodesy, Teryan St. 105, AM0009, Yerevan, Armenia

⁵Yerevan State University, Faculty of Biology, Department of Biology, 1 Alex Manoogian, AM0025 Yerevan, Armenia

*Correspondence: mhzadayan@gmail.com

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Abstract. Currently, in many countries, soil salinization is recognized as one of the primary land degradation processes, particularly in arid regions, where it significantly limits soil fertility and worsens ecological conditions.

The widespread occurrence of solonchaks soils, including soda-type saline-alkaline soils, along with the intensification of salinization under changing climatic conditions and anthropogenic pressure, highlights the urgent need to update data on their distribution and expansion trends.

This study, conducted between 2020 and 2022, presents the results of a survey of 600 hectares of saline soils in the Mrgashat settlement, Armavir Region, Republic of Armenia (center coordinates: 44° 5' 14.36" E, 40° 7' 14.57" N). A quantitative and qualitative assessment of the current state was carried out using GIS and remote sensing data, alongside soil sampling from six designated points.

Newly salinized areas over the past 10 years were mapped, and the dynamics and direction of salinization were analyzed. The validity of the findings was corroborated by field survey data and relevant statistical indicators.

The results indicate a clear trend of spatial and temporal expansion of salinized soils. Over the last two decades, the total salinized area has increased by 54 hectares, representing a 10.1% growth.

Key words: satellite imagery, vegetation indices, soil salinity, salinity mapping, spectral analysis, salinity index, remote sensing.

INTRODUCTION

Salinity is a spatiotemporally dynamic process of land degradation in semi-arid regions that reduces both the productivity and extent of agricultural land (Periasamy & Ravi, 2020; Xiang et al., 2022). Although the salinization of drylands poses a significant threat to land and water resources in many countries, its importance has only recently gained broader recognition (FAO, 2005).

According to the Food and Agriculture Organization of the United Nations (FAO), the total global area of saline soils amounts to 397 million hectares (FAO, 2005). These soils are prevalent in Africa, Asia, Australia, Europe, Latin America, the Middle East, and North America (Koohafkan & Stewart, 2008; Tong et al., 2023; Calderon Pincay & Pincay Cantos, 2024). For instance, McFarlane et al. (2004) estimated that in Western Australia alone, 14,000 hectares of land have been annually affected by secondary salinization since 1996, and approximately 3.54 million hectares are currently at risk – potentially doubling to 6.5 million hectares (33%) by 2050.

The Republic of Armenia is no exception. Various studies report that 40–45% of the Ararat Plain (about 40,000 ha) has been withdrawn from agricultural use due to varying degrees of salinization and alkalization (Khojoyan, 2013; Yeghiazaryan, 2017).

Salinization is a gradual and often imperceptible process. By the time visible signs emerge, substantial salt accumulation may have already occurred in the soil's active layer, impairing plant growth and development (Melkonyan et al., 2004). Therefore, early-stage monitoring and mapping of salinized areas and severity levels are critical for effective land management and mitigation (Koohafkan & Stewart, 2008; Yeghiazaryan & Yeghiazaryan, 2018).

Traditional salinity assessment methods are often time-consuming, labor-intensive, and costly. Consequently, the application of remote sensing (RS) techniques has become increasingly recommended (Yeghiazaryan, 2017; Smanov et al., 2023).

Modern satellite platforms offer diverse spectral and spatial datasets that support vegetation monitoring, climate assessments, and modeling of future scenarios (Abreu et al., 2024). These technologies allow efficient detection, mapping, and monitoring of salinization with acceptable accuracy (Dwivedi et al., 2008; Zhang et al., 2021).

However, RS accuracy peaks (approximately 83%) when visible surface salt deposits are present (Howari, 2003). In areas where halophytes are dominant or visible salt is absent, detection accuracy decreases (Howari et al., 2002; Shoba et al., 2016). In such cases, integrating satellite imagery with field survey data enhances reliability (Douaoui et al., 2006; Eldeiry & Garcia, 2008). For example, a study in Thailand using Landsat-7 ETM+ in combination with topographic and groundwater data achieved an overall mapping accuracy of 83.6% (Katawatin & Kotrapat, 2005).

In addition to visible and infrared bands, satellites such as Landsat 8 and 9 provide surface temperature and humidity data, which are essential for interpreting solonchic soils (Baldina & Nikolaev, 2024). These thermal indicators are particularly useful in identifying saline soils in bare or sparsely vegetated regions (Koohafkan & Stewart, 2008).

Nevertheless, medium or low spatial resolution can limit RS accuracy when affected zones are smaller than one pixel. Therefore, high-resolution multispectral sensors (< 5 m) are critical for detecting small-scale salinization (Dwivedi et al., 2008).

Although satellite technology is rapidly advancing, historical data remains crucial for long-term land degradation modeling (Burke et al., 2021). Vegetation indices provide valuable insights into both soil salinity and its effects on crop productivity (Wang et al., 2021; Silva, 2024). Halophytic vegetation, in particular, serves as a reliable remote indicator for salinity detection and mapping (Koochafkan & Stewart, 2008; FAO Guidelines, 2017).

Certain salt-tolerant crops, such as alfalfa, barley, and cotton, are also used as indirect indicators of soil salinity in research (Metternicht & Zinck, 2008).

Numerous spectral indices have been employed to classify and monitor salinized land, including NDVI, SAVI, RVI, Tasseled Cap Transformation, SBI, GVI, WI, NDSI, and various salinity indices (Eldeiry & Garcia, 2008; Matinfar et al., 2013; Nguyen et al., 2020). Each is suitable for specific land cover types and salinity conditions. For example, NDVI effectively maps halophyte presence (Elnaggar & Noller, 2009), while SAVI has been applied in the UAE for salinity detection via plant vigor analysis (Huete, 1988; Alhammadi & Glenn, 2008). NDSI helps distinguish saline from non-saline soils based on spectral differences (Nguyen et al., 2020).

Despite extensive international research, no unified methodology for monitoring soil salinity using GIS and RS currently exists. In Armenia, earlier studies have been limited in scale and lack practical application for broad salinity assessments.

Therefore, the aim of this study was to evaluate the effectiveness of combining GIS, remote sensing methods, and field-based soil sampling for assessing the distribution and spatiotemporal dynamics of saline-alkaline soils. These assessments are crucial for designing sustainable management strategies, promoting crop diversification, and developing preventive measures to mitigate salinization.

MATERIALS AND METHODS

Study area

The research was conducted on saline-alkaline soils across a 600-hectare area within the Mrgashat settlement, Armavir Region, Republic of Armenia (Fig. 10. Sentinel-2 classification map showing reclaimed lands).

The soil profile is distinctly stratified and lacks the gradual transitions of genetic horizons typically found in soils developed on alluvial deposits (Hayrapetyan, 2000).

These soils are characterized by high salinity (total salt content: 1–3%), substantial carbonate content (15–20%), low humus levels (0.4–0.6%), and high alkalinity (pH 9–11). The soils also exhibit high exchangeable sodium concentrations (25–30 mEq per 100 g of soil, accounting for 60–80% of total exchangeable cations), and a medium to heavy loamy to clayey texture. Their hydrophysical properties are generally poor (Khojoyan, 2013).

The climate in the study area is classified as sharply arid, with hot, dry summers and snowy winters. The average annual air temperature ranges between 11.0 and 12.3 °C. Precipitation averages 200–235 mm annually, whereas evaporation is significantly higher, ranging from 1,160 to 1,480 mm (Hayrapetyan, 2000).

Remote sensing and GIS analysis

To evaluate the effectiveness of remote sensing (RS) and geographic information systems (GIS) for mapping saline soils, Landsat 8 satellite images were utilized in conjunction with salinity and vegetation indices, including the Normalized Difference Salinity Index (NDSI) and Normalized Difference Vegetation Index (NDVI). These datasets were processed using the ArcMap module of the ArcGIS software package. Field data collection and laboratory analysis were carried out to verify and enhance the reliability of the remote sensing results.

Software and image processing

The study employed both remote sensing and ground-truthing techniques to perform qualitative and quantitative assessments of saline soil distribution. A time-series analysis of satellite images was used to track salinity dynamics over a 20-year interval. Image classification was performed using both automated, computer-assisted techniques and visual interpretation. Input datasets included multi-temporal satellite imagery, scientific and thematic literature, statistical data, and official government sources. The following software platforms were used: ArcGIS 10.5, ENVI 5.3, and SNAP.

Satellite image acquisition and preprocessing

Satellite imagery was retrieved from the Land Viewer platform (EOS). Image selection was based on the following criteria:

- Cloud-free conditions
- Seasonal consistency (summer)
- A 20-year time interval
- Availability of complete pixel information.

Based on visual inspection and data quality, the following images were selected for analysis:

- Landsat 7 (acquired on 13 August 2000)
- Landsat 8 (acquired on 20 August 2020).

The selected images underwent geometric and radiometric correction using ENVI 5.3. FLASH atmospheric correction was applied as part of the preprocessing workflow.

Summer-season imagery was prioritized due to enhanced spectral contrast between salt deposits and halophytic vegetation, which is particularly pronounced during the dry season.

Salinity and vegetation indices

Saline landscapes are typically characterized by sparse or stressed vegetation. Therefore, specific spectral indices were used to identify and map salt-affected soils (Table 1). These include:

- Brightness Index (BI)
- Normalized Difference Salinity Index (NDSI)
- Salinity Indices (SI1, SI2, SI3, SI4, SI5)
- Normalized Difference Vegetation Index (NDVI)
- Normalized Difference Moisture Index (NDMI).

Table 1. Various spectral indices and class formulas were used in the present study

Index	Formula	Reference
NDVI	$(\text{NIR} - \text{R}) / (\text{NIR} + \text{R})$	Tucker, 1979
NDMI	$(\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR})$	Gao, 1996; Wilson & Sader, 2002
NDWI	$(\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$	Gao, 1996; McFeeters, 1996
NDSI	$(\text{R} - \text{NIR}) / (\text{R} + \text{NIR})$	Khan et al., 2005
BI	$\sqrt{(\text{R}^2 + \text{NIR}^2)}$	Khan et al., 2005
SI1	$\sqrt{(\text{B} \times \text{R})}$	Douaoui et al., 2006
SI2	$\sqrt{(\text{G}^2 + \text{R}^2 + \text{NIR}^2)}$	Douaoui et al., 2006
SI3	$(\text{SWIR1} \cdot \text{SWIR2} - \text{SWIR2}^2) / \text{SWIR1}$	Bannari et al., 2008
SI4	$(\text{R} \cdot \text{NIR}) / \text{G}$	Abbas & Khan, 2007
SI5	$(\text{G} \cdot \text{R}) / \text{B}$	Bannari et al., 2008

Note: B = Blue; G = Green; R = Red; NIR = Near-Infrared; SWIR1, SWIR2 = Shortwave Infrared bands.

Field sampling and soil analysis

While remote sensing provides valuable information for identifying salt-affected areas, field validation is essential for ensuring accuracy and model calibration.

Based on the interpretation of satellite images, the most salt-affected zones were identified in the eastern part of the Mrgashat settlement. This zone, covering approximately 600 hectares, was selected for detailed investigation.

Soil samples were collected from the topsoil layer (0–40 cm) at six representative points. The GPS coordinates of each sampling location were recorded using a handheld positioning device with a spatial resolution of 1.5 meters (Table 2).

Table 2. Soil sampling locations and coordinates

No	Sampling site	Longitude (E)	Latitude (N)
1	Train line	44° 5' 28.235"	40° 7' 46.709"
2	Cultivated field	44° 5' 51.633"	40° 7' 30.714"
3	Saline-cultivated field	44° 4' 46.094"	40° 7' 12.730"
4	Halophyte area	44° 5' 28.194"	40° 7' 6.815"
5	Severely saline zone	44° 4' 51.296"	40° 6' 55.230"
6	Salt crust zone	44° 5' 32.057"	40° 7' 21.439"

To align the field data with satellite imagery (on a pixel-based scale), soil samples were collected directly from visible salt crusts identified through remote sensing. Pixels with similar spectral characteristics were grouped, and pseudo-sampling points were introduced to enhance representativeness and improve the reliability of interpolation results.

Five key indicators derived from laboratory analysis were selected for interpolation:

- pH
- Sodium (Na)
- Magnesium (Mg)
- Calcium (Ca)
- Salinity (total dissolved salts in aqueous extract).

Laboratory analyses were performed at the Hydrometeorology and Monitoring Center SNCO using standard methods and advanced instrumentation, including:

- X-ray fluorescence (XRF)
- Inductively coupled plasma mass spectrometry (ICP-MS)
- Ion chromatography (IC).

The results are summarized in Tables 3–6.

RESULTS AND DISCUSSION

Remote sensing indicators and image interpretation

Experimental results demonstrated that no individual spectral index alone provided a complete and accurate representation of soil salinity. Reliance on a single indicator often resulted in substantial misinterpretations and classification errors (Fig. 1).

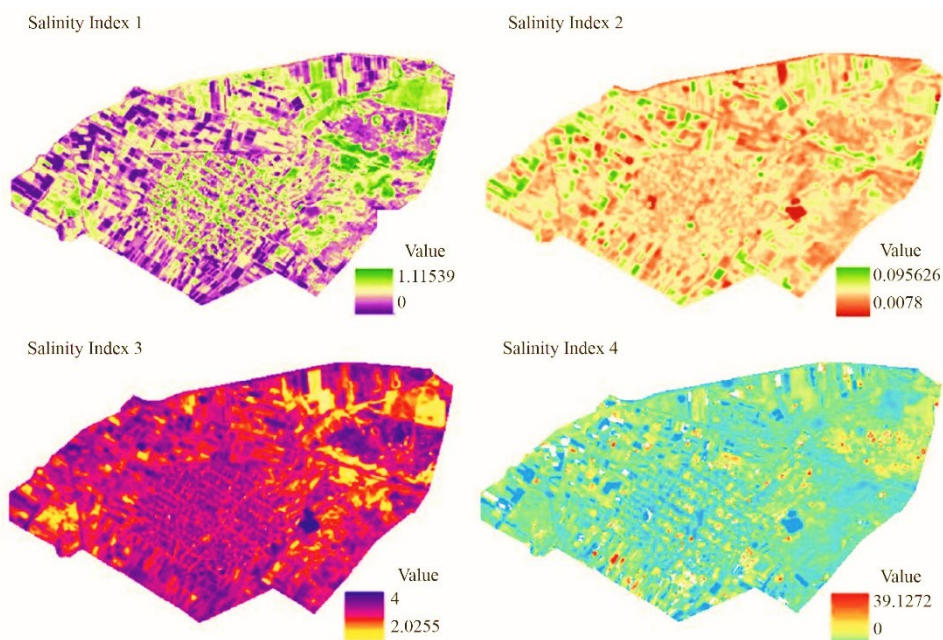


Figure 1. Soil salinity classification in the Mrgashat area based on individual salinity indices.

Given that certain areas were covered with halophytic vegetation, several vegetation indices were also evaluated alongside the salinity indices to enhance classification accuracy (Fig. 2).

Among the indices evaluated, the Normalized Difference Salinity Index (NDSI) most accurately represented actual salinity conditions observed during field validation. However, certain factors reduced detection accuracy:

- Metal roofs and other reflective surfaces produced spectral signatures similar to salt crusts, leading to false positives
- Bare or recently ploughed fields also exhibited high reflectance values, mimicking saline features due to their brightness.

Integration of auxiliary indices

To enhance mapping precision, two additional spectral indicators were integrated into the analysis:

- Land Surface Temperature (LST)
- Normalized Difference Moisture Index (NDMI).

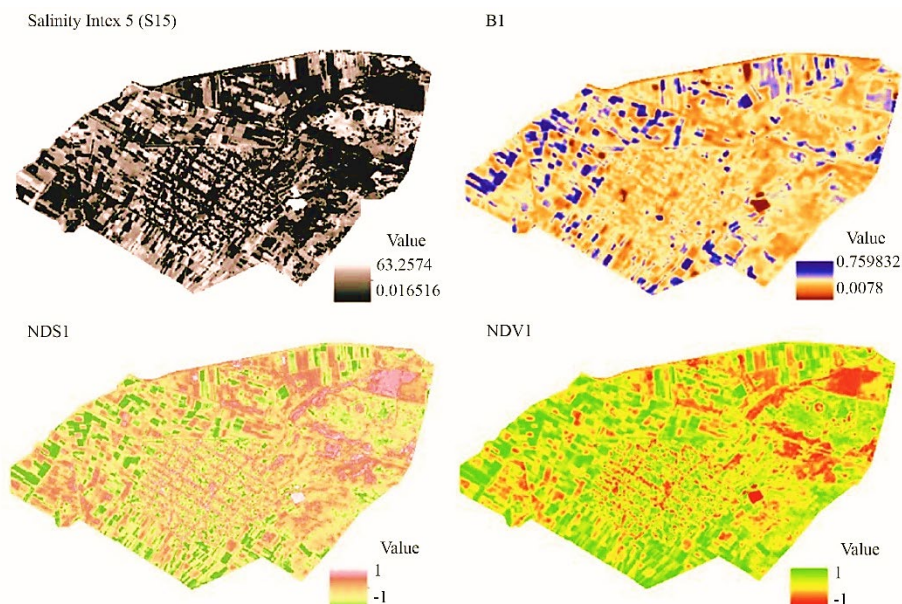


Figure 2. Soil salinity and vegetation classification of the Mrgashat area based on spectral indicators.

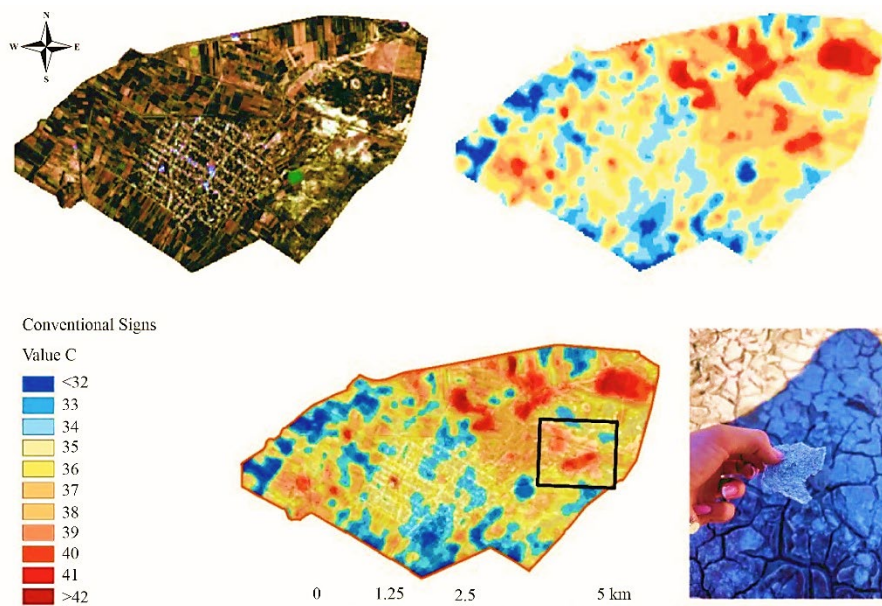


Figure 3. LST raster image of the Mrgashat area (Landsat 8, 28 August 2020).

LST values were derived from the thermal bands of Landsat 8 (acquired on August 28, 2020) using ENVI 5.3, and subsequently calibrated to degrees Celsius (Fig. 3). Surface temperatures in the study area ranged between 32 °C and 42 °C, and were classified into 11 discrete levels.

The Normalized Difference Moisture Index (NDMI) integrates near-infrared (NIR) and shortwave infrared (SWIR) bands to serve as an effective indicator of crop water stress. Severe drought conditions can not only stress crops but also lead to complete crop failure. NDMI is particularly valuable for early detection of water stress, often identifying problems before they become visually apparent.

Our analysis indicates that moisture levels near the boundaries of saline surfaces offer useful contrast. These levels help distinguish saline soils from non-saline reflective surfaces such as rooftops, which exhibit low moisture and appear as hotspots in the LST raster due to their elevated surface temperatures (Fig. 4).

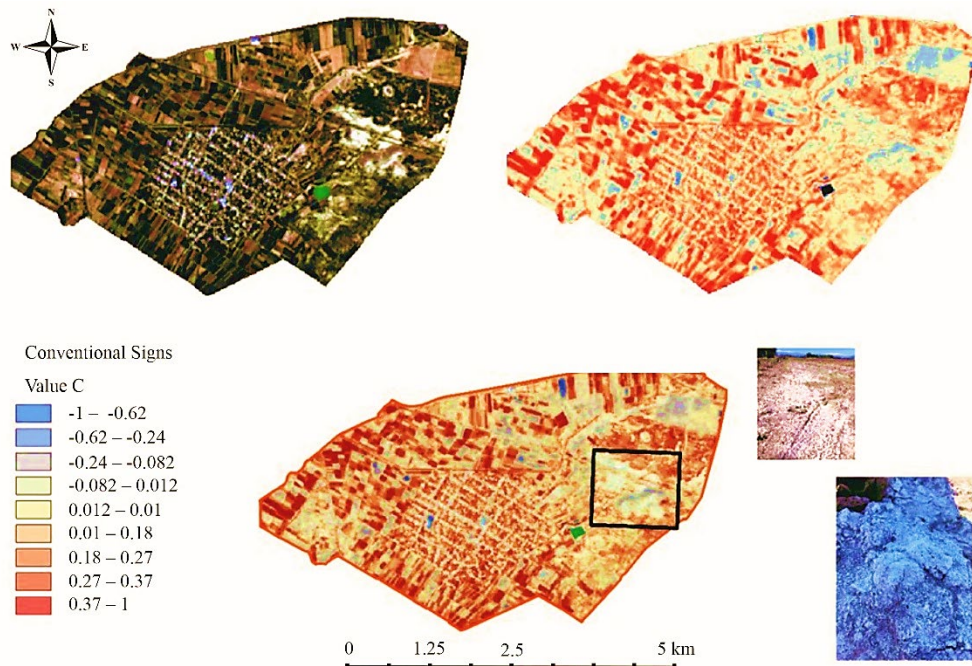


Figure 4. NDMI image of the Mrgashat area (Landsat 8, 28 August 2020).

To enhance classification accuracy, five key indices were integrated into composite raster layers:

- NDVI – Vegetation health
- NDSI – Soil salinity
- NDMI – Surface moisture
- BI – Brightness Index
- LST – Land surface temperature.

Each of these indices provided a distinct representation of salt-affected zones and their surrounding areas. To obtain the most accurate classification, various combinations of these indices were tested, resulting in new composite raster datasets. The spectral components of these composites were derived from the previously calculated indices: NDVI, NDSI, NDMI, BI (Khan et al., 2005), and LST (Fig. 5).

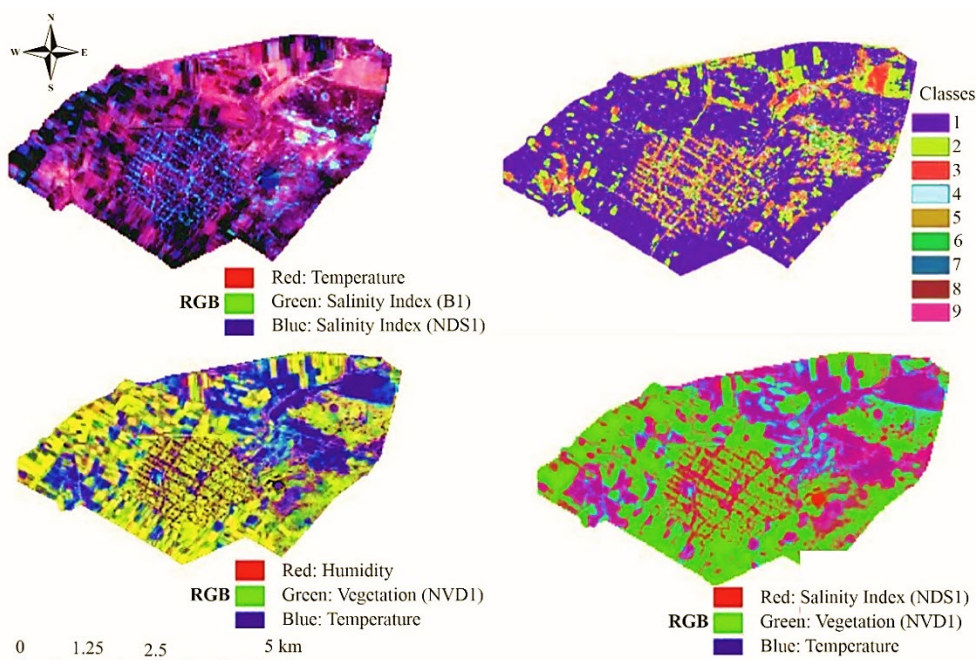


Figure 5. Composite image of Mrgashat lands based on integrated spectral indices.

Classification and Salinity Mapping

Using the Normalized Difference Salinity Index (NDSI) along with the previously derived raster datasets, pixel-based classification was performed. Classification intervals were determined based on the statistical distribution of pixel values for each index.

To validate and refine classification accuracy, vector layers of saline areas - recorded with GPS during field visits (2020–2022) - were overlaid. The *Raster to Polygon* tool in ArcGIS was used to convert classified raster layers into vector shapefiles.

Composite overlays and cross-validation among indices minimized false positives and improved salinity detection accuracy:

- BI (Brightness Index): Identified areas with strong reflectance, primarily surface salt crusts. Filtered using NDMI to exclude high-reflectance non-saline features (e.g., rooftops)
- NDVI: Mapped halophytic vegetation; filtered using LST (Land Surface Temperature) to exclude thermal anomalies
- NDSI: Highlighted areas with minimal visible salt deposits; further refined through combination with other indices.

These filtering steps allowed for precise delineation of actual saline areas from built-up or vegetated land. Final salinity maps were developed for the years 2000 and 2020, classifying affected land into three severity levels (Fig. 6):

1. Severely saline: Surfaces with visible salt crust accumulation.
2. Moderately saline: Transitional areas between crusted zones and vegetated regions.
3. Halophytic vegetation zones: Dominated by salt-tolerant plant species.

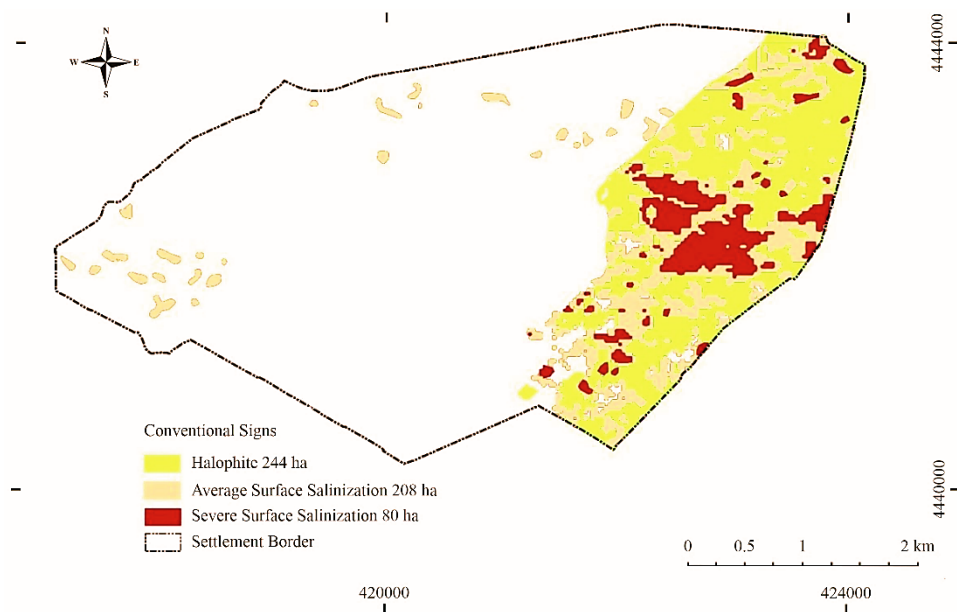


Figure 6. Map of salinity classification in Mrgashat (2000 satellite image).

The total salinized area in 2000 was estimated at 532 hectares, with the following classification:

- Halophytes: 244 ha
- Moderately saline: 208 ha
- Severely saline: 80 ha.

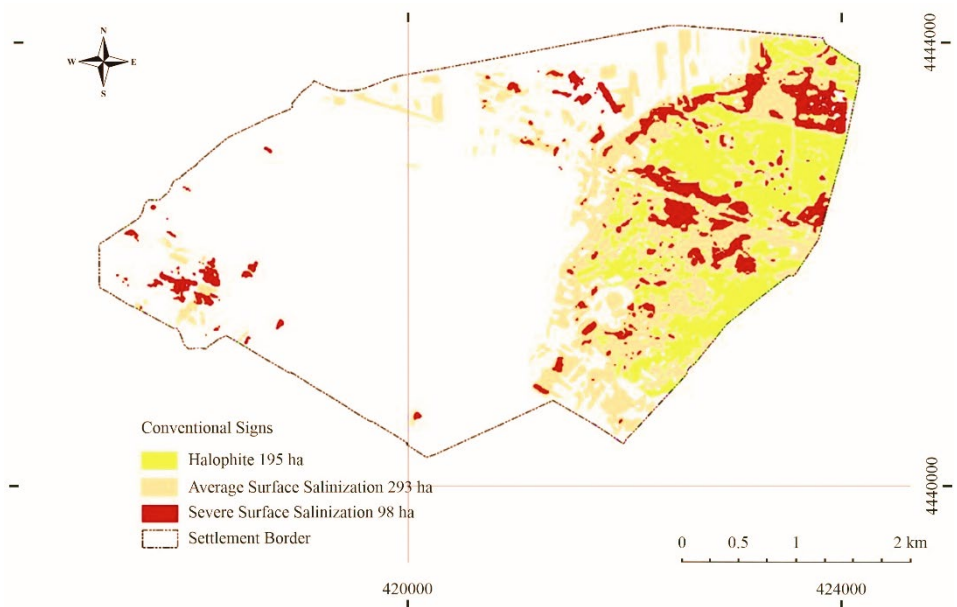


Figure 7. Salinity classification map of Mrgashat (2020 satellite image).

In 2020, the total affected area increased to 586 hectares (Fig. 7), with the following distribution:

- Halophytes: 195 ha
- Moderately saline: 293 ha
- Severely saline: 98 ha.

The net increase in salinized area was 54 hectares between 2000 and 2020. While some inaccuracies are possible - primarily due to the lower spatial resolution (30 meters) of the 2000 satellite imagery - overall trends remain consistent and reliable. Despite the limitations of the imagery, notable changes were detected across salinity classes.

Time-series image analysis revealed the following trends:

- Reduction in halophytic vegetation in areas subjected to plowing and cultivation
- Emergence of surface salt accumulations in nearby uncultivated areas over time.

These findings underscore the dynamic interplay between land use practices and salinization patterns (Fig. 8).

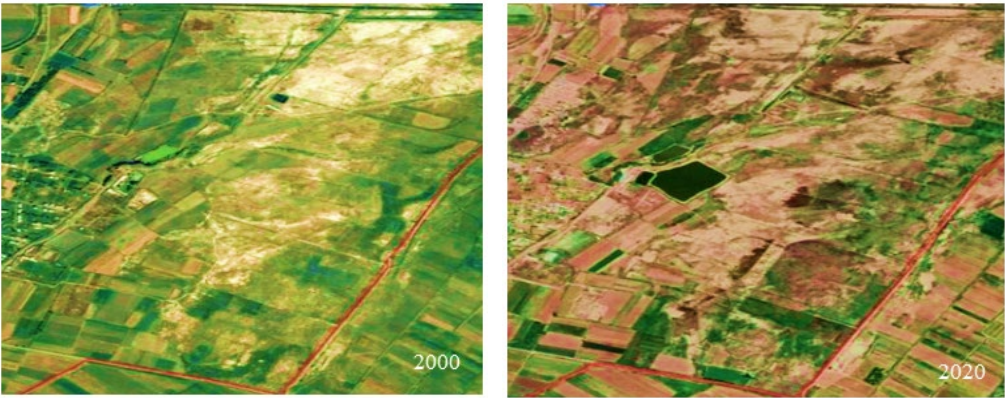


Figure 8. Changes in salinized surfaces due to land-use alterations.

This figure was derived by comparing the classified salinity layers from 2000 and 2020 with the current land surface temperature (LST) raster. The comparison highlights spatial dynamics in salinization patterns related to land-use changes over the past two decades.

Table 3 summarizes soil surface temperatures (in °C) across the classified salinity zones, based on satellite-derived thermal bands. These data provide additional insight

into the correlation between surface temperature and salinity severity, supporting the identification of active versus passive salinization processes.

Table 3. Soil surface temperature (°C) based on satellite thermal bands

Class	2000			2020		
	Min	Max	Average	Min	Max	Average
Halophyte	33.8	46.9	39.7	29.2	40.4	35.2
Medium	33.3	49.3	42.5	33.3	42.2	36.8
Severe	35.2	46.9	44.2	32.2	41.7	38.2

The lowest temperatures consistently corresponded to halophyte-covered areas.

Soil sampling results and land use comparison

Field investigations confirmed significant soil salinization in the study area, as shown in Table 4. The following ranges were observed:

- Electrical conductivity (EC): 18.18–67.68 mS cm⁻¹
- Soluble salt content: 8.2–36.4 g L⁻¹
- pH: 9.57–10.39.

Table 4. Soil Electrical Conductivity (EC) and salt content (field and aqueous extract measurements)

N	pH	Directly in the soil		In the water column	
		EC (soil) mS	Salt (soil) g kg ⁻¹	EC (solution) mS	Salt (solution) g kg ⁻¹
1	9.57	12.07	> 2.99	27.24	12.72
2	10.07	5.33	1.91	18.18	8.2
3	10.07	5.33	1.91	18.18	8.2
4	9.58	21.73	> 2.99	35.42	16.8
5	10.37	7.34	2.6	21.44	9.8
6	10.09	24.69	> 2.99	67.68	36.4

These measurements indicate that the soils are strongly to very strongly saline, which significantly impairs plant growth and agricultural productivity. The high alkalinity (pH above 9.5) further exacerbates limitations for crop development. The dominant salts in the soil include sodium, magnesium, and calcium sulfates, chlorides, carbonates, and bicarbonates. Among them, sodium bicarbonate has the most toxic and detrimental effect on plant health, followed by sodium chloride.

Ionic composition analysis (IC) revealed high concentrations of SO₄²⁻ (2.3–10.0 mg kg⁻¹) and Cl⁻ (1.3–3.2 mg kg⁻¹). These two ions alone accounted for approximately 93.6% of total anions, a chemical environment that is unfavorable for crop development (Table 5).

XRF and ICP-MS analyses revealed significant variations in macroelement concentrations and elevated levels of soluble salts across the study area.

The qualitative composition of salts influences soil appearance and behavior. In soils with high sodium bicarbonate concentrations, organic matter solubility increases, often giving the soil a darker color. Such characteristics were observed in certain locations within the study area.

A key diagnostic trait of saline soils is the uniform distribution of silt-sized particles – notably silicon, iron, and aluminum oxides – throughout the soil profile. Despite visual uniformity, saline soils are typically low in organic matter, nitrogen, and essential mineral nutrients.

Overall, the soils examined were highly saline, heterogeneous, and spatially variable, as detailed in Tables 6 and 7.

Table 5. Ion chromatography (IC) results – anions (mg kg⁻¹)

N	F	Cl ⁻	Br ⁻	NO ₃ ⁻	SO ₄ ²⁻	PO ₄ ³⁻
1	0.063	1.393	< 0.03	0.196	5.806	0.212
2	0.062	1.321	< 0.03	0.167	2.354	0.101
3	0.063	3.222	< 0.03	0.082	5.748	0.197
4	0.063	1.727	< 0.03	0.110	2.799	0.063
5	0.062	2.012	< 0.03	0.174	4.477	0.128
6	0.083	3.036	< 0.03	0.294	9.890	0.157

Table 6. XRF results – major elements (mg kg⁻¹)

N	Al	Si	P	S	Cl	K	Ca	Fe
1	25,140	58,250	< 50	2053	1479	9,248	51,047	39,740
2	27,898	73,404	< 50	1153	1333	8,733	51,942	42,896
3	34,075	10,8957	< 50	3800	5692	10,051	53,920	41,368
4	24,425	56,222	< 50	1269	2756	7,751	49,693	39,724
5	26,719	64,847	< 50	1982	2867	7,837	49,356	39,916
6	25,070	67,269	< 50	4299	4809	8,209	54,469	38,584

High-resolution salinity maps were generated using Inverse Distance Weighting (IDW) interpolation of laboratory-derived soil parameters within ArcMap software. These spatial models revealed that the central zone of the study area exhibited the highest degree of salinization (Fig. 9).

To avoid misclassification, non-agricultural features (e.g., water bodies, ponds) were excluded using a masking technique. The interpolated salinity distribution clearly shows that the central zone of the study area remains the most severely affected. This pattern corresponds with the high-density salt crusts observed in satellite imagery.

Table 7. ICP-MS results – cations (g kg⁻¹)

N	Na	Mg	Al	P	K	Ca
1	2.48	1.59	1.90	1.04	11.03	7.99
2	3.04	2.57	3.66	0.75	10.23	9.97
3	2.02	1.19	1.07	0.92	9.73	6.51
4	2.34	1.58	1.53	0.63	8.25	7.24
5	3.52	2.48	2.96	0.74	9.33	9.89
6	7.21	7.32	10.43	0.75	9.19	19.66

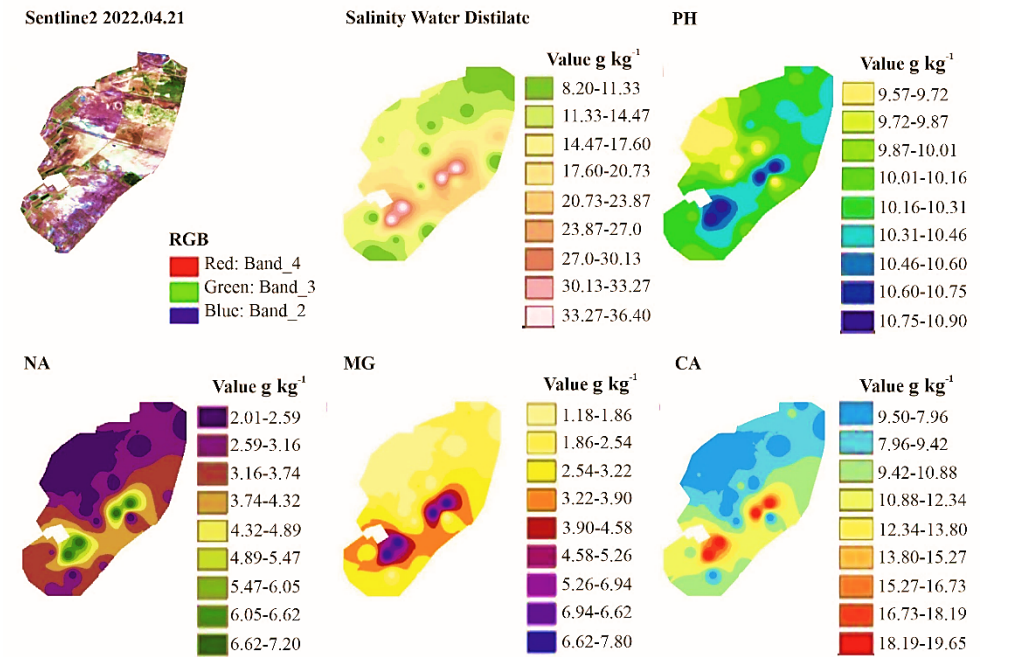


Figure 9. Interpolated salinity map (based on lab data).

Zonal statistics and accuracy assessment

Comparison of classified vector layers with the interpolation raster showed general consistency across salinity classes (severe, moderate, halophyte) regarding minimum and average values. Notable findings include:

- Minimum salinity (all classes): $\sim 8.2 \text{ g kg}^{-1}$
 - Maximum salinity: 36.4 g kg^{-1} in severely saline areas
 - Average salinity: 15.52 g kg^{-1} (severe), 16.53 g kg^{-1} (moderate), 16.3 g kg^{-1} (halophyte)
 - Na content peaks: up to 6.5 g kg^{-1} in halophyte zones; $\sim 7.2 \text{ g kg}^{-1}$ in others.
- Interestingly, despite their bright surface crusts, the most visibly saline zones showed the lowest average water-extract salinity values.

Temporal mismatch limitation

A minor limitation stems from the temporal discrepancy between datasets. Field sampling was conducted in April 2022, whereas the classified satellite imagery is based on 2020 data. Cloud cover and low vegetation activity during spring 2022 limited satellite usability. Sentinel-2 imagery from April 21, 2022, revealed notable land-use changes, including:

- 135 ha of salinized land reclaimed:
 - ✓ 75 ha in 2021
 - ✓ 60 ha in 2022 (Fig. 10).

Agricultural interventions - particularly tillage near the railroad-adjacent zones - have altered the distribution of saline vegetation by 2022.

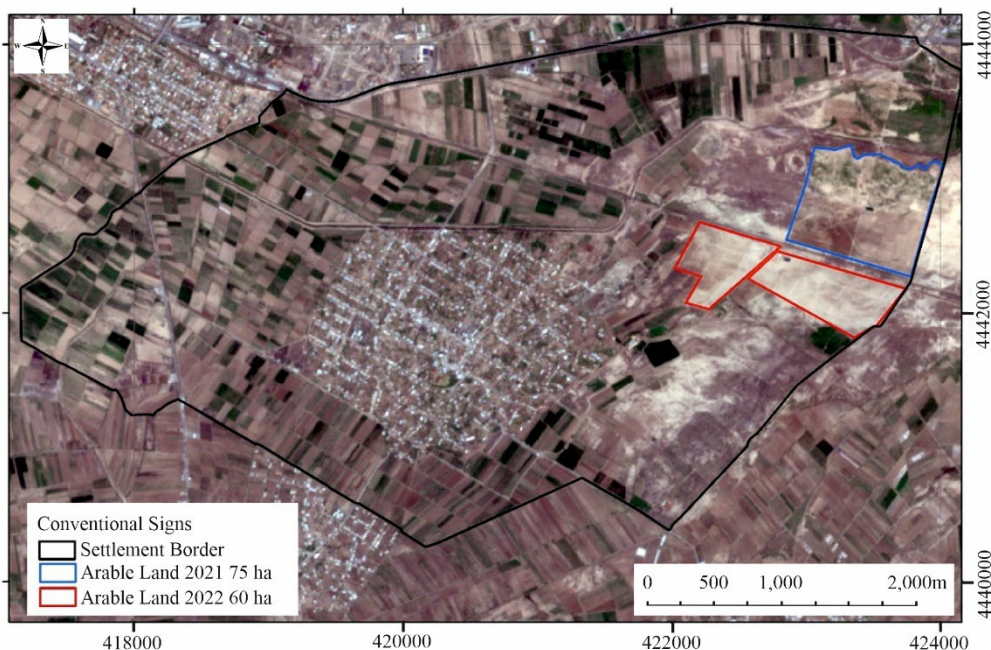


Figure 10. Sentinel-2 classification map showing reclaimed lands (April 2022).

CONCLUSION

This study demonstrates that remote sensing technologies, when integrated with GIS tools and field-based soil sampling, offer a reliable and efficient methodology for assessing and monitoring soil salinization dynamics. The use of multi-year satellite imagery, combined with vegetation and salinity indices, enabled the accurate identification and spatial classification of saline-alkaline soils in the Mrgashat settlement of the Armavir region.

Field and laboratory analyses confirmed the presence of strongly to very strongly saline soils. Water-soluble salt concentrations ranged from 8.2 to 36.4 g L⁻¹, and electrical conductivity (EC) values varied between 18.18 and 67.68 mS cm⁻¹ – well above agronomic thresholds (2–16 mS cm⁻¹). Soils also exhibited high alkalinity, with pH values from 9.57 to 10.39, characteristic of soda-type saline-alkaline conditions.

Remote sensing–based land cover classification revealed a progressive increase in salinized areas over a 20-year period. In 2000, 532 hectares were affected, including:

- 244 ha with halophytic vegetation
- 208 ha of moderately saline soils
- 80 ha of highly saline soils

By 2020, the affected area had increased to 586 hectares, including:

- 195 ha with halophytic vegetation
- 293 ha of moderately saline soils
- 98 ha of highly saline soils.

This represents a net increase of 54 hectares (10.1%), with a notable expansion of moderately saline zones, indicating intensification of salinization processes.

These findings underscore the importance of integrated remote sensing and ground-truthing approaches for effective monitoring of soil degradation. Such methods are crucial for supporting sustainable land management and guiding reclamation efforts in arid and semi-arid agricultural regions.

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Construction, calibration and evaluation of mini-lysimeters in the management of irrigation in a protected environment

M.L. Matos¹, G.B. Lyra², D. Cecchin^{3,*}, C.M. Hüther³, J.P. Francisco⁴,
M.F. Jorge², C.R. Pereira³, L.S. Hamacher³ and L.D.B. da Silva²

¹Rio de Janeiro Botanical Garden Research Institute (JBRJ), 915 Pacheco Leão street, Jardim Botânico, ZIP Code: 22460-030, Rio de Janeiro, RJ, Brazil

²Federal Rural University of Rio de Janeiro (UFRRJ), Engineering Department, Seropédica Campus, Highway BR 465, Km 7, ZIP Code BR23890000, Seropédica, RJ, Brazil

³Federal Fluminense University (UFF), Department of Agricultural and Environmental Engineering, Praia Vermelha Campus, Rua Passo da Pátria, 156, ZIP Code 24210-240, Niterói, RJ, Brazil

⁴State University of Maringá, (UEM) –Ângelo Moreira da Fonseca Avenue, n. 1800, Parque Danielle, Umuarama Campus, ZIP Code 87506-370, Umuarama - PR, Brazil

*Correspondence: daianececchin@id.uff.br

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Abstract. The production of forest seedlings requires controlled environments and specific practices, highlighting the need for rational irrigation management. Historically, excessive irrigation has compromised seedling quality, underscoring the importance of developing technologies and research focused on water use efficiency in nurseries. Thus, technologies that are more financially accessible to producers contribute not only to cultivation but also to the social inclusion of these producers in broader markets. Mini-lysimeters can be effectively used to monitor the water balance in potted and tray-grown plant production, thereby reducing water waste in forest nurseries. In this study, portable electronic weighing mini-lysimeters were constructed for greenhouse evapotranspiration research using load cells (capacity: 20 kg), as sensor elements, and dataloggers for data acquisition. Calibration curves were established by correlating standard weights and voltage readings, and were analyzed using regression analysis. The coefficient of determination (r^2) and the standard error of estimation (SEE) were used to evaluate model accuracy. Under field conditions, the lysimeters' performance was assessed using the correlation coefficient (r); Willmott's index (d); performance index (c) and SEE , with pine and eucalyptus seedlings. The calibration curves were well described by linear models, with r^2 values exceeding 0.994. The highest SEE (2.44 g), observed in mini-lysimeter III, remained below the 4 g detection threshold of the load cell. All performance indicators (r , d , and c) were above 0.999, with SEE values ranging from 6.2 to 36.2 g (less than 1 g per tube), demonstrating that the mini-lysimeters are suitable for monitoring daily evapotranspiration.

Key words: Lysimetry, forest seedlings, load cells, evapotranspiration, irrigation management.

INTRODUCTION

For proper irrigation management it is necessary to know the crop's rate of evapotranspiration (ET_c), and the daily water demands can be obtained directly and accurately using lysimeters. Different lysimeter models are described in the literature, and the size and mounting design of each are based on the specific requirements of the study and the construction conditions and costs involved.

The main advantages of its use are related to calibration, which can be validated mechanically. The smaller fetch requirement when compared to micrometeorological methods, such as the eddy covariance or Bowen ratio, which facilitates its application in protected environments where large homogeneous areas are not always available. the possibility of complete automation and the ease of inspections, as the system is almost fully visible (Allen et al., 2011).

According to Kirnak et al. (2017), under water deficit conditions, applying irrigation at strategic stages of the crop growth cycle can significantly increase yields, even in semi-arid regions. This management highlights the importance of precise technologies, such as mini-lysimeters, to monitor water needs and optimize available resources.

The costs involved in the construction of lysimeters are considered high (Santos et al., 2008; Allen et al., 2011), but the cost savings from using load cell mechanism for measurements make the construction of weighing lysimeters viable (Faria et al., 2006; Santos et al., 2008; Vilela et al., 2015); and they are considered more modern, as they allows automation when coupled with a data acquisition system, thus providing reliable results on the hourly scale, and therefore standing out from the other types of lysimeters (Carvalho & Oliveira, 2012). However, its use has limitations related to operational difficulties due to the sensitivity of load cells, observed on days of heavy rain, following days with intermittent rain, and also on days with intermittent winds (Carvalho et al., 2007).

Given the limitations of using conventional lysimeters in ET studies in protected environments, due to their dimensions, several authors (Grimmond et al., 1992; Misra et al., 2011, Oliveira, 2012, Vilela et al., 2015) developed lysimeters for weighing with smaller structures, also called 'mini-lysimeters', which aim to measure the ET of plants grown in pots or trays. In the literature, there are uses of mini-lysimeters in plants of the species of the family Heliconiaceae (Gervásio & Melo Júnior, 2014); cultivation of vines (*Vitis Vinifera* L.) in pots (Canales et al., 2013; Ruiz-Peñalver et al., 2015); French hydrangea (*Hydrangea macrophylla*) (McCauley & Nackley, 2022); lawns (Wherley et al., 2009); tree species seedlings (Carvalho et al., 2024); eucalyptus seedlings (Oliveira, 2012); wheat (*Triticum aestivum* L., cv. Lang.) (Misra et al., 2011), among others. However, volume limitation of root growth containers is considered to be the biggest problem in the use of mini-lysimeters (Grimmond et al., 1992). However, the main advantages of using mini-lysimeters described in the literature are related to the accuracy of measurements (Grimmond et al., 1992; Misra et al., 2011; Gervásio & Melo Júnior, 2014; Ruiz-Peñalver et al., 2015), and low manufacturing costs (Wherley et al., 2009; Misra et al., 2011; Canales et al., 2013), also emphasizing the greater versatility due to the dimensions (Grimmond et al., 1992; Gervásio & Melo Júnior, 2014); possibility of a greater number of field repetitions and greater operator autonomy (Wherley et al., 2009),

besides the possibility of its use in irrigation system automation (Canales et al., 2013). Additionally, Svoboda et al. (2020) emphasized that root system density and its distribution within the soil profile are directly influenced by irrigation, reinforcing the need to adjust the maximum irrigation depth according to the specific demands of the plants. Tools like mini-lysimeters play a crucial role in this detailed monitoring. Load cell robustness is a feature highlighted by Misra et al. (2011) highlighting that variables such as hysteresis, room temperature and signal response time do not significantly influence the performance of the mini-lysimeter, which has a measurement capacity below 100 kg, being commonly used load cells with a capacity of 20 or 30 kg.

Considering the importance of irrigation management in the preservation of water resources and the advantages of using lysimeters in the measurement of ET by crops, enabling irrigation system automation, the objective of this work was to develop a model of a portable electronic weighing mini-lysimeter for operation in greenhouses; to perform calibration; to evaluate the performance under field conditions, in the irrigation management of eucalyptus (*Eucalyptus urograndis*) clone seedlings cultivated in a protected environment, and to compare the ET values obtained by a mini-lysimeter in contrast to the values calculated according to the UN FAO (the Food and Agriculture Organization of the United Nations) methodology.

MATERIALS AND METHODS

Experiment Location

The experiment was conducted at the Forest Garden of the Rio de Janeiro Botanical Garden Research Institute (JBRJ) – Latitude 22°58'05" S, Longitude 43°14'20" W, altitude 92 m – located in Rio de Janeiro, Brazil. The local climate is classified as Köppen Aw, characterized by a rainy season with high precipitation in summer and a dry winter season (Peel et al., 2007). The average annual precipitation is approximately 2,000 mm, and the mean annual air temperature is 23.8 °C, with a maximum of 30.3 °C recorded in February and a minimum of 16 °C in July (INMET, 2014).

The tests were carried out in a greenhouse aligned in the east-west direction, measuring 12 m in length and 4 m in width, with side walls 1.70 m high, covered with 50% shade cloth. The arched roof was covered with 100-micron plastic film, and the same shade cloth used on the sides was installed above the plastic roof. The greenhouse ends were covered with shade mesh, maintaining the same height as the sides, and the remaining area coated with the same plastic film used for the roof. The maximum ceiling height at the central span the greenhouse was 3 m. The floor, both inside and around the structure, was covered with ground cover mesh (ground raffia).

Determination of ET_c by FAO method

Based on data obtained from an automated weather station (model 2550, WATCHDOG brand, USA), equipped with indoor sensors for temperature, relative humidity, and photosynthetically active radiation (PAR), and an outdoor wind speed sensor, of air installed outside, reference evapotranspiration (ET_o) was calculated using the Penman-Monteith equation as parameterized in FAO-56 (Allen et al., 1998), as shown in Eq. 1:

$$ET_o = \frac{0.408 \cdot \Delta \cdot (Rn - G) + \gamma \cdot \frac{900}{T_m + 273} \cdot U_2 \cdot (e_s - e_a)}{\Delta + \gamma \cdot (1 + 0.34 \cdot U_2)} \quad (1)$$

where ET_o is the reference evapotranspiration (mm d^{-1}); Δ is the slope of the vapor pressure curve at the mean air temperature point ($\text{kPa } ^\circ\text{C}^{-1}$); Rn is the net radiation ($\text{MJ m}^{-2} \text{d}^{-1}$); G is the soil heat flux ($\text{MJ m}^{-2} \text{d}^{-1}$), assumed to be zero, for daily times steps; γ is the psychrometric constant, equal to $0.0725 \text{ kPa } ^\circ\text{C}^{-1}$; U_2 is the wind speed at 2 m high (m s^{-1}); e_s is the saturation vapor pressure (kPa); e_a is the actual vapor pressure (kPa), and T_m is the daily mean air temperature ($^\circ\text{C}$).

To determine e_s , e_a , Δ and T_m , the equations described by Allen et al. (1998) were used. Wind speed (U_2) was estimated as 5% of the outdoor values to reflect indoor conditions, following the methodology adopted by Blanco & Folegatti (2004), Farias et al. (1994).

The net radiation (Rn) was estimated from the measured PAR values. For the conversion of PAR ($\mu\text{mol m}^{-2} \text{s}^{-1}$) to radiation in $\text{MJ m}^{-2} \text{d}^{-1}$, the factor of 4.57 mol MJ^{-1} was used, proposed by McCree (1972), cited by Steidle Neto et al. (2008) for conditions of both direct and diffuse radiation. A PAR/Rs ratio of 45% was adopted, and albedo (α) was set to 0.23, as proposed by Allen et al. (1998). The radiation balance was then calculated using equations provided in FAO-56. To compare the evapotranspiration values measured by the mini-lysimeter with those estimated using the FAO-56 methodology, the daily crop evapotranspiration (ET_c) values were obtained by the product between the daily ET_o values (Eq. 1) and the value of crop coefficients (Kc), as shown in Eq. 2. A Kc value of 0.82 as suggested by Alves et al. (2013), was used:

$$ET_c = ET_o \cdot Kc \quad (2)$$

Mini-lysimeter Construction

Three mini-lysimeters (I, II, III) were constructed, each with a support base made from a metal container (0.35 m high and 0.24 m in diameter) similar to those commonly used in paint. The containers were filled with concrete up to two-thirds of their volume to increase weight and, consequently, stability, allowing for the central installation of a galvanized steel pole. The pole had a square cross-section of 0.06 m and a height of 1.9 m. At its upper end, a metal support arm (0.4 m in length and with a $0.05 \text{ m} \times 0.03 \text{ m}$ rectangular profile), was attached using screws, where the load cell was mounted.

At the end of the support arm, an 'S' type load cell (model BTS-20, Berman Load Cells, Brazil) was installed and powered by a 12 V direct current source. The load cell was made of aluminum, with dimensions of 0.051 m width and 0.076 m height, a maximum capacity of 20 kg, accuracy of 0.02% of full scale (4 g), and sensitivity of $2 \pm 0.2 \text{ mV/V}$. According to the manufacturer, the load cell has an IP65 protection rating, offering complete protection against dust and resistance to low-pressure water jets, which was consistent with the environmental conditions observed during the experiment. The nominal temperature operating range is from $-10 ^\circ\text{C}$ to $+40 ^\circ\text{C}$, with a recommended excitation voltage of 10 VDC and a maximum of 15 VDC. The temperature compensation factor (span) is $\pm 0.03\%$ of the full scale per $10 ^\circ\text{C}$. The load cells supported the seedling trays via plastic-coated steel wires (diameter of 0.00165 m), secured with ties (Fig. 1).

The acquisition and storage of data from the mini-lysimeters, collected via load cells, were carried out using an electronic datalogger (Fieldlogger 512K model, NOVUS, Brazil). Each load cell was connected to an analog input port of the datalogger, where built-in a 24-bit A/D (analog-to-digital) converter processed the signal. Using the FieldloggerConfig V 1.6.0 software, each channel has been individually configured. Data logging was programmed to run continuously, recording values every minute throughout the day. A specific feature in the software, known as a 'Virtual Channel', allowed the insertion of mathematical operations (equations) that converted the sensor readings. This enabled a direct relationship to be established between the load cell output voltage (mV) and the recorded mass (g) according to the calibration equations determined after the final calibration of the mini-lysimeters.

A cost analysis was also performed to evaluate the economic feasibility of the system. The approximate costs of the main components were as follows: S-type load cell (20 kg) – R\$ 440.00 to R\$ 605.00 (US\$ 80 to US\$ 110); datalogger (Fieldlogger NOVUS) – R\$ 3,245.00 to R\$ 4,235.00 (US\$ 590 to US\$ 770); irrigation controller (4 stations) – R\$ 451.00 to R\$ 660.00 (US\$ 82 to US\$ 120); solenoid valves (1 inch) – R\$ 159.50 to R\$ 181.50 (US\$ 29 to US\$ 33); and electrical materials (wiring and power supplies) – R\$ 154.00 to R\$ 165.00 (US\$ 28 to US\$ 30). This total cost is considered low when compared to conventional weighing lysimeters and demonstrates the potential for implementation in small-scale or low-budget agricultural systems.

Mini-lysimeter calibration

For the calibration procedure, standard masses were used, plastic bags filled with sand, of 50, 100, 150, 500, 1,000, 2,000, 2,500, 5,000 g. These masses, either individually or in combination were placed on the trays (without seedling tubes), totaling 20 observations per mini-lysimeter. During the loading phase, the standard masses were gradually applied, and the datalogger readings (in mV) were recorded after stabilization, typically occurring within 1 to 2 minutes. Subsequently, the masses were removed in

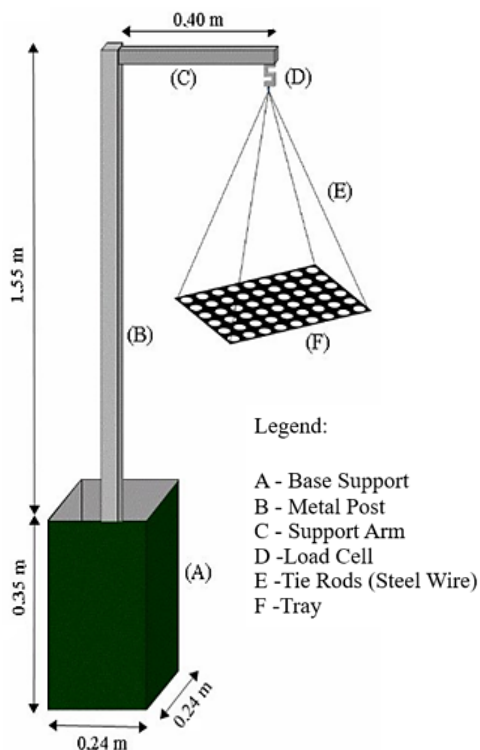


Figure 1. Illustration with the structural components and mounting form of the mini-lysimeter. The wall thickness of the cultivation tubes (tubetes) was 1 mm (0.001 m). The load cells were installed following the manufacturer's guidelines (BERMAN, model BTS-20), positioned so that the axis of the load cells was perpendicular to the support arms.

reverse order, following the methodology described by Vilela et al. (2015). For each applied mass (in g), the average of voltage readings (in mV) from both the loading and unloading phases was calculated, establishing the relationship between voltage and mass values. Calibration curves correlating output voltage (mV) with mass (g), along with their respective equations, were generated using a spreadsheet. These equations were later inserted into the datalogger via the ‘Virtual Channel’ feature of the configuration software, enabling real-time mass readings on each mini-lysimeter.

According to the load cell manufacturer, the temperature compensation factor (span) is approximately 0.03% of full scale per 10 °C. Considering the 20 kg capacity and the average temperature during calibration (~25 °C), a correction of 0.01 mV was applied to the recorded values.

The results of the relationship between masses (applied) and measured values (readings) were subjected to statistical regression analysis. The coefficients of the regression equations were evaluated using the Student's t-test p at a significance level of $p < 0.01$. The coefficients of determination (r^2), was used to assess to proportion of the total variation in the measured values that could be explained by the variation in the applied standard masses (Eq. 3). In addition, the standard error of estimation (SEE), was calculated to verify the influence of other factors on the values recorded by the datalogger (Eq. 4), serving as an indicator of the quality of the fitted models (equations).

$$r^2 = \frac{\sum (V_L - V_{MP})^2}{\sum (V_P - V_{MP})^2} \quad (3)$$

$$SEE = \frac{\sum \sqrt{(V_P - V_L)^2}}{n - 2} \quad (4)$$

where V_L are the measured values (readings); PMV are the means of the default values; VP are the default values (real), and n is the number of observations made.

Performance under field conditions

In order to evaluate whether the performance of the mini-lysimeters was influenced by field conditions, including exposure to high temperatures, humidity, and dust, it was verified whether the mass values recorded by the datalogger, derived from the initial calibration models, remained consistent with the actual mass values applied to the mini-lysimeter after two weeks of use. To confirm the consistency of the results across the load cell measurement range (0 to 20 kg), data analysis was carried out using mini-lysimeters I and III, with applied loads near upper limit (20 kg), and in lysimeter II, with loads near the lower limit (0 kg).

For mini-lysimeters I and III, the initial condition included trays containing 54 tubes, and three tubes were removed at a time until only 27 tubes remained, totaling 10 observations. For mini-lysimeter II, the same initial condition (54 tubes), was used, but six tubes removed at a time until none remained, also resulting in 10 observations.

To evaluate whether the mass values estimated by the regression models were correlated with the applied mass values, the following indicators were used: precision, assessed through the correlation coefficient (r); accuracy, evaluated using Willmott index (d); and the standard error of estimation (SEE).

The correlation coefficient (Eq. 5) was used to determine the accuracy of the calibration equation - indicating the repeatability and stability of the measurement, since it indicates the degree of dispersion of the data obtained (estimated by the equation) in relation to the mean, that is, the random error.

$$r = \frac{n \sum_{i=1}^n V_P \cdot V_E - \sum_{i=1}^n V_P \cdot \sum_{i=1}^n V_E}{\sqrt{n \sum_{i=1}^n V_P^2 - \left(\sum_{i=1}^n V_P \right)^2} \times \sqrt{\sum_{i=1}^n V_E^2 - \left(\sum_{i=1}^n V_E \right)^2}} \quad (5)$$

where VP is the applied value; VE is the value obtained by the model; and ‘ n ’ is the number of observed values (equal to 10).

To determine accuracy, the Willmott index was used, as it reflects the deviation of the mass values estimated by the model from the actual applied mass values. The index ranges from zero, indicating no agreement, to one, indicating perfect agreement. It is calculated using Eq. 6. To assessed reliability, the method proposed by Camargo and Sentelhas (1997) was adopted, which combines the precision index (r) and the accuracy index (d) into a single metric to evaluate overall model performance, as shown in Eq. 7.

$$d = 1 - \frac{\sum_{i=1}^n (V_E - V_P)^2}{\sum_{i=1}^n [(V_E - V_M) + (V_P - V_M)]^2} \quad (6)$$

$$c = r \cdot d \quad (7)$$

where VM is the average value applied (default).

Standard error of estimation (SEE) values were also used to evaluate the influence of other factors on the readings obtained by the datalogger (Eq. 4).

Determination of ideal weight

To evaluate the performance of the mini-lysimeter in irrigation management under field conditions, trials were conducted using trays containing 54 tubes with a volumetric capacity of 280 cm³, planted with eucalyptus (*Eucalyptus urograndis*) seedlings. In order to maintain optimum conditions regarding water availability in the substrates, an ‘ideal weight’ was determined, corresponding to substrate moisture near field capacity. The sets (tray + tubes + seedlings), with the bottom of the tubes protected by foam to prevent substrate loss, were partially immersed plastic reservoirs (water tanks) for 12 hours to promote substrate saturation. After the saturation process, the trays were placed in the shaded, and after 30–40 minutes (a period sufficient for water drainage to cease, as verified in tests using the mini-lysimeter), the sets were weighed using a MICHELETTI model MIC P15 digital scale, with a capacity of 15 kg and a resolution of 0.005 kg. After weighing a total of 24 sets, the value of 10,600 g was defined as the ideal mass of the set, i.e., the mass at which sufficient water is available for optimal seedling growth.

Irrigation management

The trays containing the eucalyptus seedlings were irrigated with Rain Bird model X360 Mister micro-sprinklers, with an approximate flow rate of $0.65 \text{ m}^3 \text{ h}^{-1}$, positioned 0.60 m above each tray. Irrigation was started daily at 7:30 a.m. by a Rain Bird STP6L controller (powered at 100V). The control board activated a $\frac{3}{4}$ " solenoid valve (model DVF-75M Rain Bird), allowing water flow to the seedling stands. However, between the controller and the valve, the electrical circuit was connected to the alarm relay terminal of the data acquisition module (datalogger). This relay, which is normally closed (NC), allowed the passage of electric current and the opening of the valve at the preset time.

In the analog terminals of the data acquisition module were connected to the mini-lysimeter load cells, which monitored the mass variation of the trays containing the eucalyptus seedlings. The configuration, performed using the FieldloggerConfig software, defined the alarm triggering parameter, namely, whenever the set weight of one of the mini-lysimeters was equal to or greater than that ideal value for seedling growth (10.600 g), the relay was activated. This caused it to operate in the normally open (NO) mode, interrupting the electric current, closing the valve, and consequently stopping the irrigation.

RESULTS AND DISCUSSION

Calibration

After recording the voltage readings (mV) during the standard mass loading and unloading processes, the mean voltage values (in mV) were calculated. The observed hysteresis effect was considered negligible, consistent with findings reported by Carvalho et al. (2013); Faria et al. (2006); Gervásio & Melo Junior (2014); Oliveira (2012) and Silva et al. (1999) who also worked with weighing lysimeters equipped with load cells.

Fig. 2 presents the calibration equations obtained through linear regression using the mean values from both loading and unloading cycles, which relate the mass variation to the voltage output of the mini-lysimeters load cells. The linear model adequately represented the mass-to-voltage relationship across all treatments, with coefficient of determination (r^2) exceeding 0.994.

According to the results, the voltage values ranged from 0.24 to 22.93 mV in mini-lysimeters I and II. However, mini-lysimeter III exhibited higher voltage values, ranging from 9.86 to 114.25 mV. This difference is associated with the gauge of the wires used. Due to the distance between the mini-lysimeters and the data logger, thicker wires (1.5 mm diameter) were used for mini-lysimeter III, while 1.0 mm diameter wires were used for mini-lysimeters I and II. These variations altered the input and/or output impedance but did not compromise the final results due to proper calibration.

The variation in the wire length also influenced the voltage readings. Because the lysimeters were installed in different locations within the greenhouse, the lengths of the power supply and data transmission wires varied, leading to differences in the voltages recorded by the datalogger, attributed to wire resistance in addition to connection resistance.

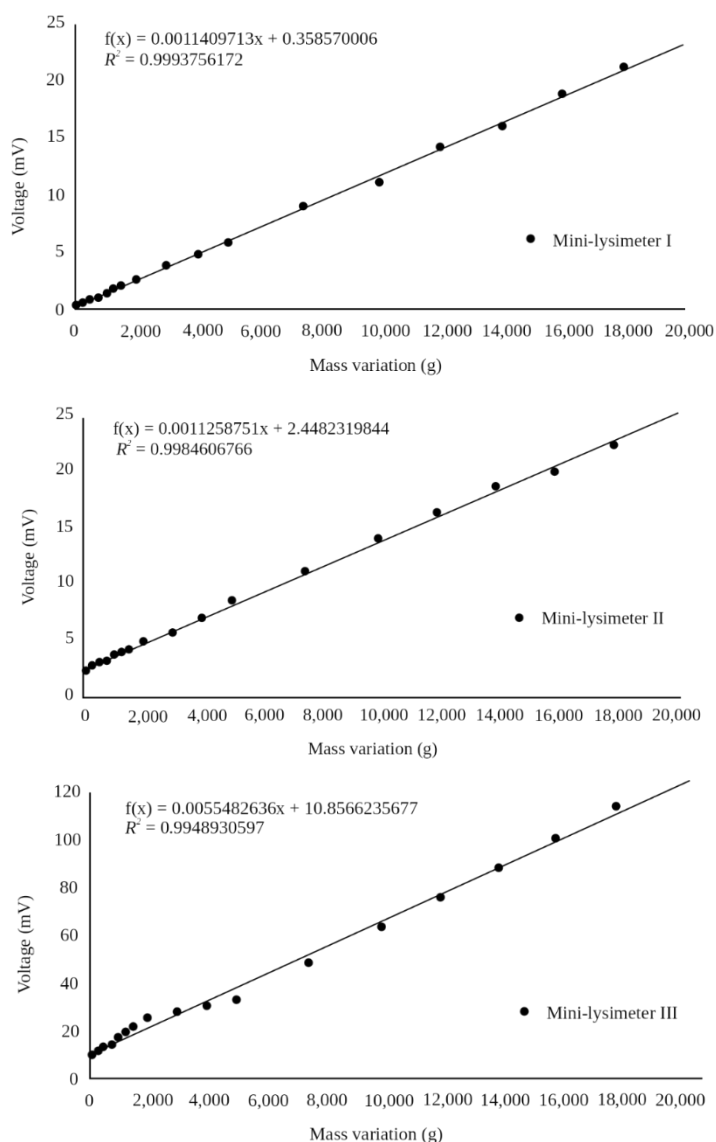


Figure 2. Relationship between mass variation (g) and voltages (mV), with the respective calibration curves of the three mini-lysimeters.

All regression equation coefficients were statistically significant according to the Student's *t*-test at the 1% probability level (Table 1).

Regarding the *SEE* values presented in Table 1, the highest value observed for mini-lysimeter III was 2.44 g; which is below the maximum permissible error of the load cell, specified as 4 g accuracy. Considering the surface area of the tray (0.2204 m²), a mass variation of 2.44 g corresponded to an equivalent water depth of approximately 0.011 mm (or 0.015 mm when considering only the area of the tubes). This value is substantially lower than those reported by other authors during the calibration of 'conventional' lysimeters, such as Carvalho et al. (2011) (0.2 mm); Carvalho et al. (2007)

(0.278 mm), Carvalho et al. (2013) (0.66 mm). These differences are attributed to the capacity and full-scale range of the load cells used in each respective study.

Performance under field conditions

According to the results of the field condition tests, graphs were generated to represent the relationship between the applied masses and the masses recorded by mini-lysimeters I, II and III (Fig. 3); the mean relative error percentages observed were 0.73, 2.67 and 3.84%, respectively.

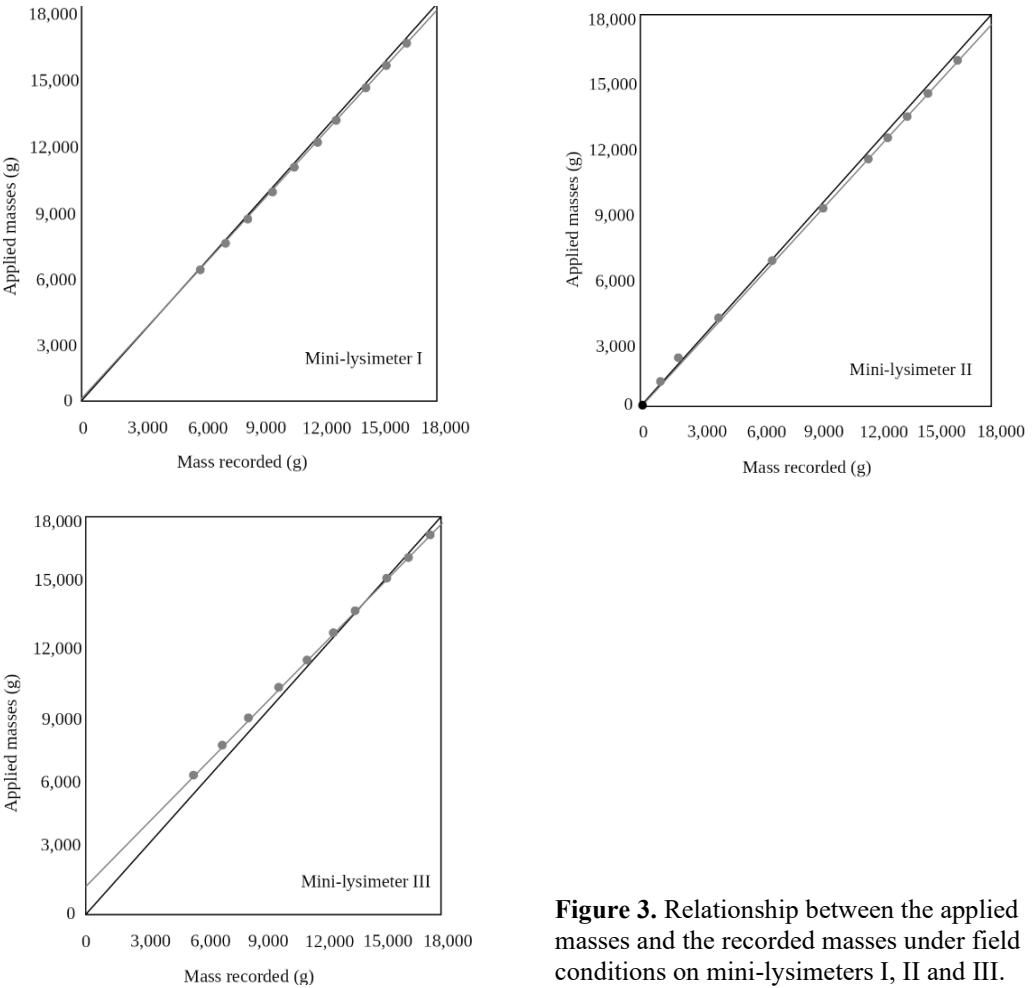


Figure 3. Relationship between the applied masses and the recorded masses under field conditions on mini-lysimeters I, II and III.

The standard errors of estimation (*SEE*) observed between the applied and registered (modeled) masses were 8.49 g, 31.91 g and 6.20 g, for mini-lysimeter I, II and

Table 1. Coefficients of the regression equation (angular coefficient x_1 and intercept - constant) and estimated standard error values, obtained for mini-lysimeters, L_I , L_{II} e L_{III}

Coefficients	Mini-lysimeters		
	L_I	L_{II}	L_{III}
Constant	0.35850*	2.44820*	10.85660*
x_1	0.00114*	0.00113*	0.00555*
SEE	0.175160	0.271508	2.44142
N	19	19	19

*Significance at $p < 0.01$; x_1 – angular coefficient; N – number of samples.

III, respectively. The higher *SEE* value observed in mini-lysimeter II highlights the challenge of calibrating under low-load conditions, where system instability may lead to inaccuracies at the time of measurement. In contrast, mini-lysimeters I and III, which were calibrated under more stable (higher load) conditions, exhibited significantly lower errors. It is important to note that each mini-lysimeter unit contained 54 tubes, meaning the observed errors correspond to less than 1 g per tube, thereby supporting the conclusion that the regression equations provided a good fit to the sample data.

The highest value of EPE (2.44 g) was obtained for the calibration curve for the Eucalyptus 400% treatment, which is below the detectable limit of the cell, which is 4 g. In the field condition evaluation, all treatments had values of correlation coefficient, Willmott index and performance index above 0.999, with EPE ranging from 6.2 to 36.2 g (less than 1 g per tube).

Table 2 presents the correlation coefficients (*r*) and Willmott indices (*d*), obtained for the mini-lysimeters equipped with trays cultivated with eucalyptus seedlings.

Based of the correlation coefficients (*r*), it can be inferred that all mini-lysimeters exhibited a very strong correlation ($r > 0.9$), indicating that the calibration equations presented in Table 2 demonstrated satisfactory accuracy. Furthermore, according to the Willmott index (*d*) values ($d > 0.9$), there was a strong agreement between the reference (observed) values and those estimated by the regression models.

Table 2. Statistical indicators of correlation coefficient (*r*) and Willmott index (*d*) for the relationships established between the models and the patterns observed in mini-lysimeters (*L_I*, *L_{II}* e *L_{III}*)

Mini-lysimeters	Parameters			
	<i>r</i>	<i>d</i>	<i>C</i>	<i>SEE</i>
<i>L_I</i>	0.99999	0.99974	0.99974	8.64
<i>L_{II}</i>	0.99998	0.99985	0.99984	31.91
<i>L_{III}</i>)	0.99999	0.99972	0.99972	6.21

Irrigation monitoring

Considering the superior performance of mini-lysimeter I, this was selected and configured to monitor the irrigation system in the eucalyptus seedling cultivation. The goal was to replace 100% of the evapotranspiration that occurred over a 24-hour period (Eucalyptus 100), restoring the system daily to the predefined reference weight (= 10.600 g) throughout the experiment. Fig. 4 displays the graph generated by the FieldloggerConfig software using the ‘Records graph’ feature, which shows the mass variation recorded at one-minute intervals between July 7, 2015, and July 17, 2015.

The graph illustrates the water replacement through irrigation (‘a’), which increasing the system’s weight up to the predefined reference value of 10,600 g; the rapid drainage of applied water (‘b’) immediately following irrigation, attributed to the combined effects of factors such as the intensity of application from the micro-sprinklers, the water-holding capacity of the substrate, the ease of water drainage from the containers (tubes), evaporation of water retained in tray surfaces, and losses due to evapotranspiration (‘c’).

The most pronounced fluctuations observed in the graphs are associated with operational activities carried out in the cultivation environment, including: movement of personnel near the trays; removal of weeds from the tubes; cleaning of fallen leaves from

the trays; temporary removal of tubes for monitoring seedling morphophysiological traits; and replacement of tubes containing dead plants. These actions caused disturbances that were recorded by the datalogger.

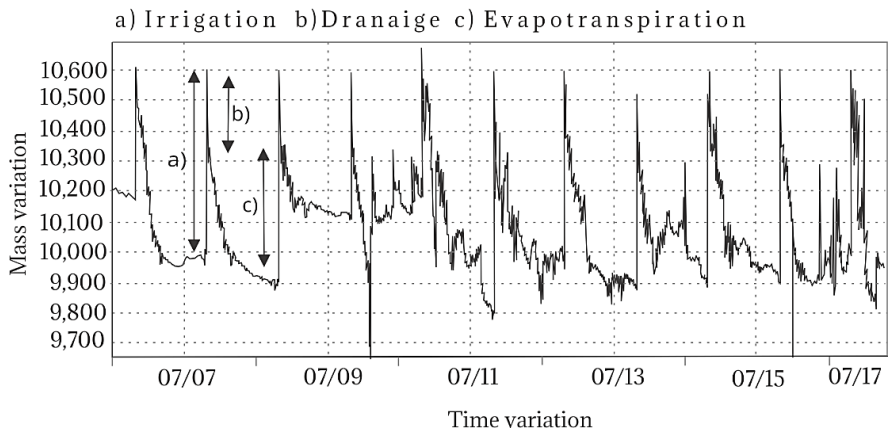


Figure 4. Mass variation recorded at one-minute intervals between 07/07/2015 and 17/07/2015, as generated by the FieldloggerConfig software.

Considering the masses measurements taken at three different times during the experiment, i.e., prior to the start of irrigation (7:30 h), immediately after the end of irrigation (approximately 10–20 minutes after initiation), and at the end of the day (18:00 h) the graph in Fig. 5 was generated, illustrating the mass variations recorded throughout July. During the first three days, improper configuration of hysteresis parameters in the datalogger resulted in multiple activations of the irrigation system. This led to the system mass exceeding the predefined target value due to oscillations around the set point (10,600 g), a problem that was corrected from the third day onward.

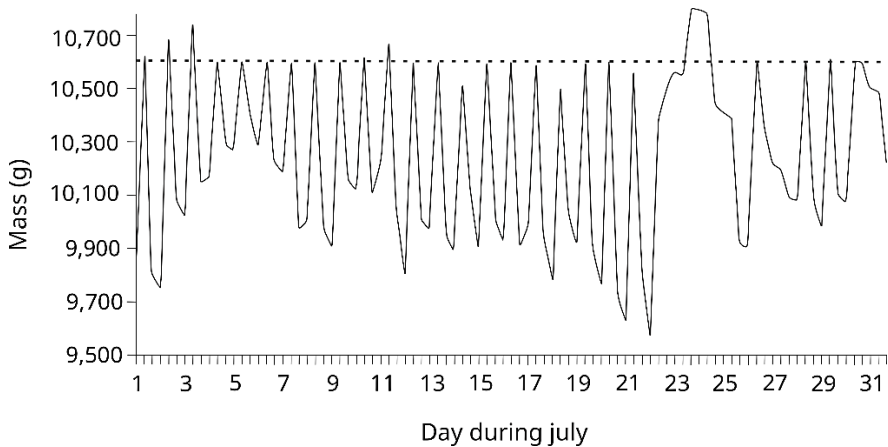


Figure 5. Mass variation recorded before irrigation, immediately after irrigation, and at the end of the day throughout the month of July.

Values exceeding the predefined threshold were also observed on July 11 and 24. On the 11th, a more detailed analysis of the ‘Record Chart’ suggests that some management activity may have occurred simultaneously with irrigation, as indicated by the strong oscillations recorded at that time. On the 24th, the excess water applied manually using watering cans, intended to compensate for the lack of water in the irrigation reservoirs, resulted in values above the predefined limit. Water supply issues also affected irrigation on the 14th and 18th, during which the applied volumes did not reach the target value due to the limited availability of water in the reservoirs. Between July 21 and 25, the lack of water required manual application using watering cans, a procedure that was repeated on the 27th.

Comparison between *ETc* values

Fig. 6 shows the graph containing the *ETc* values obtained by the mini-lysimeter (*ETc* Mini-lysimeter) and calculated by the Penman-Monteith method (Calculated *ETc*), during 31 days of the experiment (July).

According to the Fig. 6, the evapotranspiration (*ETc*) measured by the mini-lysimeter exhibited greater amplitude, ranging from 0.38 to 2.71 mm day⁻¹, whereas the calculated values ranged from 1.23 to 1.88 mm day⁻¹. Although the measured values showed greater variability - likely influenced by specific cultivation conditions that go beyond purely climatic variables – the average *ETc* obtained by the mini-lysimeter was consistent with the calculated value.

The mean *ETc* recorded by the mini-lysimeter during the experimental period was 1.59 ± 0.63 mm day⁻¹, which was only 1.3% higher than the mean *ETc* estimated by the Penman-Monteith method (1.57 ± 0.17 mm day⁻¹). This result demonstrates good agreement, particularly regarding the crop coefficient (*Kc*) used, and resulted in a correlation considered high ($r = 0.59$), according to the classification proposed by Hopkins (2008), between the measured and estimated values.

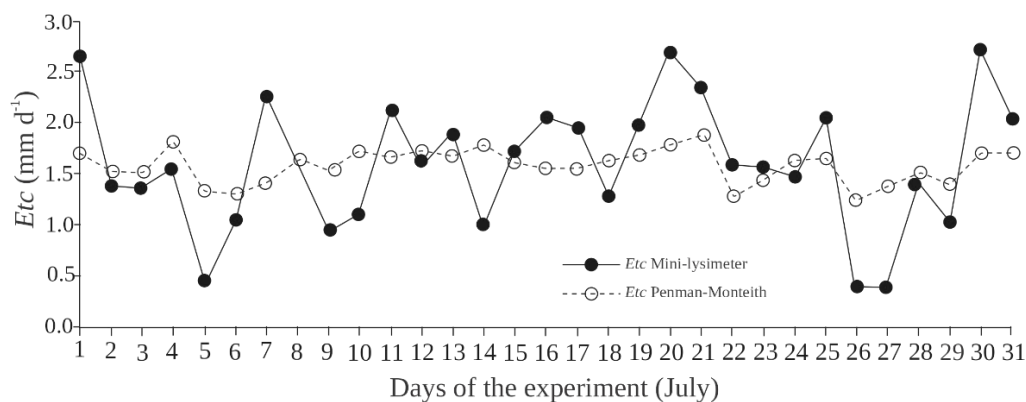


Figure 6. *ETc* values obtained by the mini-lysimeter (*ETc* Mini-lysimeter) and calculated by the Penman-Monteith method (Calculated *ETc*), during period experiment.

CONCLUSIONS

Considering the high accuracy of mini-lysimeters in monitoring the water balance of crops grown in pots or trays, as well as their benefits for irrigation control, it can be concluded that the developed mini-lysimeter model is viable for use in greenhouse environments. Its compact dimensions allow for easy relocation within the growing area. The calibration process yielded equations that were well fitted to the sample data. The performance of the mini-lysimeters was satisfactory for determining evapotranspiration at sub-daily scales, with errors lower than 1 g per tube, confirming their effectiveness as a tool for monitoring water application through irrigation systems.

The performance of the mini-lysimeters proved to be satisfactory for determining evapotranspiration at sub-daily scales, with the calibration of the mini-lysimeter yielding equations that were well adjusted to the sample data. The evapotranspiration of eucalyptus seedlings, obtained through the mini-lysimeters, showed an average of 1.66 mm d⁻¹. The crop coefficient (*K_c*) values calculated for eucalyptus cultivation averaged 1.48. The use of the mini-lysimeter was found to be viable in greenhouse vegetation, as its reduced dimensions allow for free movement within the growing environment.

The growth variables studied indicated that different irrigation levels (equivalent to 100%, 200%, 300%, and 400% of evapotranspiration) did not influence the growth of eucalyptus seedlings. However, the results of water use efficiency (WUE) showed that excess water applied in treatments above 100% of evapotranspiration did not result in effective benefits (biomass gain) for the eucalyptus seedlings, representing water waste and reinforcing the importance of proper irrigation management.

The mini-lysimeter model developed proved to be an excellent tool for monitoring water application through irrigation systems, as it enables effective and efficient water use. This contributes to increasingly crucial decision-making in crop water supply, allowing irrigation scheduling to deliver the right amount of water at the right time for a specific crop. Therefore, further testing on different crops is necessary, as well as efforts to expand such technologies for commercial use.

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Assessment of CO₂ emission rate from extended area sources with WindTrax model in a dairy cattle farm

A. Mattia, M. Merlini, F. Squillace, G. Rossi, L. Conti and V. Becciolini*

University of Florence, Department of Agriculture, Food, Environment and Forestry, via San Bonaventura 13, IT 50145 Firenze, Italy

*Correspondence: valentina.becciolini@unifi.it

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Abstract. This paper aimed to evaluate the WindTrax model to quantify CO₂ (carbon dioxide) emissions in a commercial dairy cattle farm in Central Italy with a low-cost measurement system. A field trial of 20 minutes was conducted in February 2023, using two G-eko 2.0 MSPs (multi-sensor platforms), an anemometer, and a GNSS receiver, in unstable atmospheric conditions. Then, 5-minute averaged data were used as input in the WindTrax software for applying the backward Lagrangian Stochastic model. The model was used for calculating four mean CO₂ emission rates ($0.20212 \pm 0.04994 \text{ g m}^{-2} \text{ s}^{-1}$) with 50,000 particles and the horizontal dispersion of CO₂ concentrations around the sources using different numbers of particles (5,000, 10,000, 30,000, and 50,000). Atmospheric dispersion maps, confidence interval concentration maps, and vertical profile plots were obtained by increasing the number of particles. The model shows better performances, in terms of confidence intervals, with a high number of particles with a stabilization of modeled median values between 30,000 and 50,000 particles. Horizontally, the lowest confidence intervals (near to zero) were obtained at 100–150 m from the sources along the wind direction, suggesting that the downwind sensor could be placed at a greater distance. Similarly, a better-defined vertical trend in modeled concentrations is observed as the number of particles increases. Wind gusts could have a great effect on emission rate calculation with limited sampling periods, as in this case, but simultaneously unstable atmospheric conditions affect the increased dispersion and dilution of CO₂.

Key words: greenhouse gases, livestock farming, low-cost sensors, pollutants dispersion.

INTRODUCTION

In recent decades, the exponential increase in human activities has significantly intensified the anthropogenic greenhouse effect, resulting in rising global temperatures and, consequently, climate change. This has increased public awareness of pollution and environmental issues (Tagliaferri et al., 2020). According to the IPCC (2022) report on global emission data from 2015, the livestock sector accounted for 12–17% of total greenhouse gases (GHGs) emissions, with cattle farming contributing 62% of the sector's total emissions (Global Livestock Environmental Assessment Model 3

dashboard, 2022). Within livestock farms, the primary sources of emissions are enteric fermentation in ruminants (67–68%), manure and slurry storage (23–26%), and feed production (Ripple et al., 2014; Grossi et al., 2019).

Environmental chemical monitoring is essential in bottom-up approaches for emissions inventories and for identifying critical processes that could benefit from targeted mitigation strategies. Various gas sensor technologies are available for this purpose, including amperometric gas sensors (AGS), metal oxide semiconductor sensors (MOX or MOS), nondispersive infrared sensors (NDIR), and photoionization detectors (PIDs) (Cambra-López et al., 2010; Burgués & Marco, 2020). To improve monitoring efficiency, multi-sensor platforms (MSPs) have been developed, enabling the simultaneous operation of multiple sensors. These platforms facilitate the collection of gas concentration data alongside meteorological parameters, providing a comprehensive assessment of emissions (Burgués et al., 2018).

Currently, monitoring GHG emissions is expensive due to the cost of accurate sensors in the market, but the ongoing technological development provides low-cost sensors. The objective of this study was to assess CO₂ emissions obtained with self-engineered multi-sensor platforms on a dairy farm, through the estimation of emission fluxes and the graphical representation of gas concentrations and concentration confidence intervals across the farm area. By employing the WindTrax model to simulate the horizontal and vertical dispersion of the target gas, farmers could adopt an accurate low-cost measurement system that works autonomously, aiming to provide management insights. WindTrax is widely used in agrometeorological studies to estimate emission rates, particularly for GHGs and ammonia (Lin et al., 2015; Yang et al., 2016; Hrad et al., 2021; Genedy & Ogejo, 2022). Existing research primarily evaluates its accuracy in modeling pollutant emissions from area sources, highlighting its relevance as a tool for emission assessment and atmospheric dispersion analysis. Thus, an affordable and accurate emission measurement system that can be easily implemented on commercial farms is needed by farmers to identify critical emission sources, adopting appropriate mitigation strategies.

This study investigated the impact of livestock-related activities on GHG emissions, with a focus on data analysis through specialized simulation methodologies. Specifically, CO₂ (carbon dioxide) emissions were examined using low-cost sensing platforms and atmospheric dispersion modeling as tools for rapid on-farm assessment. This study represented the first application of low-cost sensing platforms combined with dispersion modelling to assess gas emissions and dispersion from livestock buildings in the study area. The study was conducted as part of a research project aiming at assessing greenhouse gases emissions from dairy cattle and swine farming systems across Northern, Central, and Southern Italy using innovative measurement techniques. In Central Italy, the Tuscany region ranks second in terms of dairy cattle population (data provided by the National Zootechnical Registry -BDN- of the Italian Ministry of Health, managed by the 'G. Caporale' Institute in Teramo through the National Services Centre -CSN-). One of the two main dairy production districts in Tuscany is located in the Province of Florence, specifically in the Mugello area, which hosts both larger farms (over 200 lactating cows) and medium-sized farms.

MATERIALS AND METHODS

Study site

The experiment was conducted on a commercial dairy farm in the Mugello area, Province of Florence (Central Italy). The selected farm is representative of the medium-sized dairy farms commonly found in this region. The farm primarily focused on dairy cattle breeding but also operated as an educational farm and agritourism. The cattle housing facility was open on all four sides, and it was situated on relatively flat terrain. At the time of the experiment, the farm housed 123 Holstein Friesian dairy cows in the main building for milk production. Of these, 65 lactating cows were kept in a free-stall pen with cubicles in the resting area and straw bedding, while the remaining 58 cows and heifers were housed in deep-litter pens with permanent straw bedding. All pens had concrete-floored feeding alleys and were equipped with water troughs. A Total Mixed Ration (TMR) was distributed once daily at h 18 00, and a robotic feed pusher regularly repositioned the feed along the self-locking headlocks.

Additionally, 12 calves were kept in individual pens adjacent to the stable, and 12 Belgian Blue White fattening cattle were also present in a pen in the south-east part of the stable. The farm also accommodated a chicken coop and a few donkeys. Contributions to the total emissions were considered negligible.

The slurry from the two rows of pens inside the livestock building, one with permanent litter and the other in cubicles with straw bedding, was collected by automatic scrapers into two underground concrete tanks. The solid fraction, separated from the liquid, was stockpiled in a rectangular uncovered pit. In contrast, the liquid fraction was transferred to an open-air, circular underground concrete tank located north of the stable (Fig. 1).

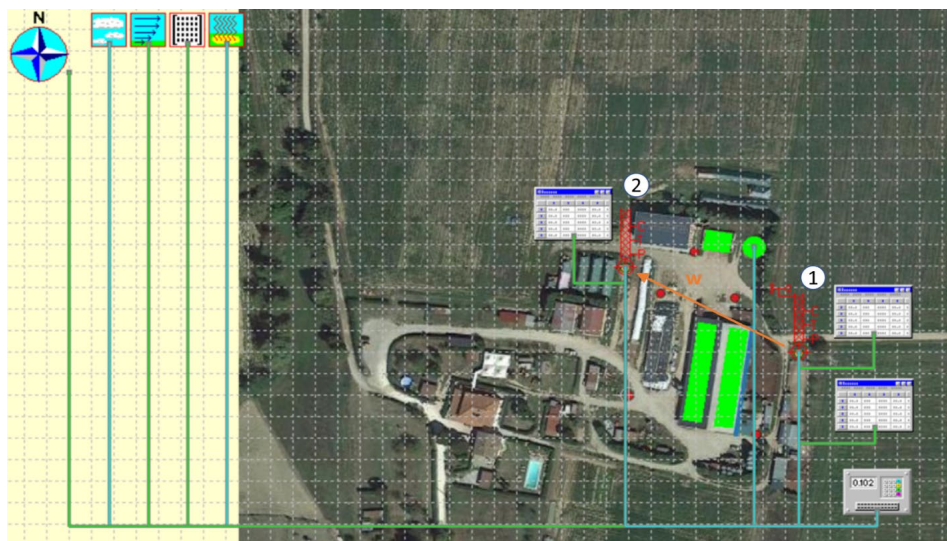


Figure 1. View of the commercial dairy farm (latitude 43.963270°, longitude 11.418885°) and inside the project of the WindTrax software environment. Point 1: upwind G-eko 2.0 multi-sensor unit. Point 2: downwind G-eko 2.0 multi-sensor unit.

Instrumentation

A dual-frequency GNSS receiver (GCX2, Sokkia, Netherlands) with centimetric accuracy was used to georeference the measurement points. Gas concentrations and microclimate parameters were measured using the G-eko 2.0, a self-engineered multi-sensor prototype described in Becciolini et al. (2023). The module, measuring 120×100×67 mm and weighing 0.75 kg, was designed for environmental monitoring. G-eko 2.0 included sensors for measuring CO₂, NH₃, CH₄, PM_{2.5} and PM₁₀ together with atmospheric pressure, temperature, and humidity.

CO₂ was measured using a Non-Dispersive InfraRed (NDIR) sensor, which also integrated temperature and humidity sensors within the same module. The CO₂/T/RH module had dimensions of 23×35×7 mm and a weight of 3.4 g. The technical specifications of the sensing module are detailed in Table 1.

Table 1. Specifications of the cmOSens sensing module

Target parameter	Measurement unit	Measuring range	Accuracy
CO ₂	ppm	0 ÷ 5,000	± 30
Temperature	Celsius degree	−40 ÷ +70	± (0.4 + 0.023 (T − 25))
Relative humidity	%	0 ÷ 100	± 2

The NDIR sensor was selected due to its documented suitability for CO₂ measurements, attributed to its strong and distinct absorption peak in the mid-infrared region, and the absence of common limitations associated with low-cost electrochemical sensors, such as inter-device variability and susceptibility to poisoning by silicone vapours (Burgués & Marco, 2020). Given the documented influence of temperature on the accuracy of NDIR sensors (Martin et al., 2017), the sensor integrated into the first prototype of the multi-sensor system (G-eko 1.0) was calibrated by an independent laboratory under controlled temperature and humidity conditions (Becciolini et al., 2024a). To improve environments, an additional calibration was conducted on the G-eko 2.0 prototype under different temperature and humidity regimes, enabling the development of correction equations applicable to diverse environmental conditions (Becciolini et al., 2024b).

The anemometer (WT87B, Shenzhen Wintact Electronics Co., Ltd., China) used in this study is shown in Fig. 2. This device measured wind speed, temperature and humidity.

Through a dedicated mobile application, the sensor can connect to a smartphone, enabling real-time data recording and storage. The technical specifications of the sensor are provided in Table 2.



Figure 2. Anemometer (WT87B, Shenzhen Wintact Electronics Co., Ltd., China).

Table 2. Specifications of the WT87B anemometer

Target parameter	Measurement unit	Measuring range	Accuracy	Resolution
Wind speed	m s ^{−1}	0 ÷ 30	± 5% ±0.1	0.01
Temperature	Celsius degree	−10 ÷ +45	± 2	0.1
Relative humidity	%	10 ÷ 90	± 5	0.1

Software

Two software packages were used for the analyses: WindTrax (version 2.0.9.7, Thunder Beach Scientific) and QGIS (3.22.5 version, QGIS.org, 2023, QGIS Geographic Information System. QGIS Association. <http://www.qgis.org>).

WindTrax incorporates the WindTrax atmospheric dispersion model (Flesh & Wilson, 2005) and is designed to simulate the dispersion of target gases from both point and extended area emission sources. It includes three modeling approaches: the Atmospheric Surface Layer model, the forward Lagrangian Stochastic (fLS) model, and the backward Lagrangian Stochastic (bLS) model. The bLS model is suited for extended area sources and was used in this study to estimate the CO₂ emission rate (Q , g m⁻² s⁻¹) from various sources, including two rows of pens in the main building, the manure storage, and the slurry storage tank located north of the livestock building (Fig. 1). To run the bLS model, WindTrax requires four parameters describing the surface layer wind model: surface roughness length (z_0 , cm), friction velocity (u^* , m s⁻¹), atmospheric stability or Monin-Obukhov length (L , m), and mean horizontal wind direction (θ , degrees) (Crenna, 2006a). Additionally, at least one gas concentration measurement per source is needed to estimate the unknown emission rates (Flesch et al., 1995). The model also requires a background concentration (C_{BG}), which can be entered directly if known or derived from an upwind concentration measurement. The software then solves a system of equations to calculate coefficients that relate emission rates to measured concentrations and vice versa (Crenna 2006a; Crenna 2006b).

QGIS, an open-source geographic information system (GIS) software, was used both before and after WindTrax simulations. Initially, it was employed to georeference the two sampling points and generate a scaled map for exporting into WindTrax (Fig. 1), ensuring accurate distance proportions within the software. After the simulations, QGIS was used to create raster images visualizing the atmospheric dispersion of CO₂ as modelled by WindTrax.

Experimental setup

The experiment was conducted during a single day in February 2023. First, the prevailing wind direction was determined. Two G-eko 2.0 units were then positioned at the height of 1 m from the ground, one upwind (sampling point 1) and one downwind (sampling point 2) of the emission sources (Fig. 1), aligned with the wind direction. The units were positioned away from obstacles (Flesch & Wilson, 2005; Crenna et al., 2008). The anemometer was placed upwind, near the G-eko 2.0 unit, at a height of 2 m above the ground. Both G-eko 2.0 units recorded CO₂ concentrations (ppm), atmospheric pressure (Pa), and temperature (°C) at a sampling rate of 5 seconds. Wind speed (m s⁻¹) was measured at a sampling rate of 1 second, while wind direction was estimated. Data collection was conducted continuously for 20 minutes. The choice of the sampling period is due to the fact that the 15-minute averaging period is the most commonly used to include homogeneous weather conditions in the analysis, as suggested by the software author (Crenna, 2006b) for capturing representative atmospheric conditions. Furthermore, this work was part of a larger field trial involving measurements at different heights above the ground, so only this data on a 20-minute sampling period was available. Another reason to choose a 20-minute sampling period is the variability of the wind direction, estimated during the field trial and considered with a constant value during the field trial.

Data processing

After the field trial, data were exported in .csv format. A verification process was conducted to ensure data quality, which included assessing whether the recorded values fell within expected ranges and evaluating the consistency between measurements obtained from the two G-eko 2.0 units.

All collected data were processed using Microsoft Excel to generate input files for WindTrax simulations. The following data processing description has not previously been applied, primarily due to the short duration of the field trial, which imposed specific methodological constraints. Other authors (Lin et al., 2015; Pedone et al., 2017) used data obtained by field trials of longer duration, so the sampling period suggested by the author of the software (Crenna, 2006b) was used. Measurements from the G-eko 2.0 units were averaged at 1-minute intervals, resulting in two datasets of 20 values. The same procedure was applied to wind data yielding, in total, three datasets of 20 measurements each. The scaled map of the farm, created in QGIS, was imported into WindTrax to design the extended area sources and accurately locate the sampling points used during the field trial (Fig. 1). The area sources are represented in lime green and the orange arrow represents wind direction. WindTrax requires the specification of sampling points locations and corresponding datasets; therefore, each point was linked to the corresponding dataset (Fig. 1).

Each set of paired measurements of CO₂ concentration collected upwind (C1, N 20) and downwind (C2, N = 20), along with wind data (N = 20) was entered into the model to generate 20 simulations, each estimating an emission rate (Q , g m⁻² s⁻¹). Regarding model specifications, the surface roughness length (z_0) was set to 2.3 to represent the short grass surrounding the livestock farm, which is bordered by arable land. The friction velocity u_* was calculated by the model based on wind speed measurements recorded by the anemometer during the field trial. Atmospheric stability was classified as B according to the Pasquill-Gifford stability classes considering wind speeds below 2 m s⁻¹ and weak daytime solar radiation. The mean horizontal wind direction (θ) was determined using topographic methods based on GPS coordinates of the two sampling points aligned with the wind direction during the field trial, yielding a value of approximately 119.3°. The number of particles in the simulation was set to 50,000.

The 20 calculated Q values were converted into a dataset obtained by averaging the collected data over 5-minute intervals. These data were used to run additional 16 simulations to model CO₂ dispersion over a 270 m × 230 m area. The area was defined based on emission sources and wind direction to represent CO₂ concentrations at a height of 2 m above the ground. The simulation parameters remained the same as previously stated, and the number of particles was set to 5,000 (N = 4 simulations), 10,000 (N = 4), 30,000 (N = 4), and 50,000 (N = 4). Each simulation generated a raster image consisting of 10,000 pixels, with each pixel representing an estimated CO₂ concentration (ppm). These raster images were georeferenced in QGIS by constructing a rectangle of matching dimensions. This kind of analysis was not used by any of the authors of the analysed literature, but it helps to make the measuring system reliable. The method of implementation for obtaining atmospheric dispersions was, however, in accordance with the software manual (Crenna 2006a; Crenna 2006b).

A similar approach was applied to the calculation of vertical profile plots at the sampling point 2. Using the calculated Q values, 16 vertical profile plots of estimated

CO₂ concentrations were modelled. The simulation parameters were the same as those used for the CO₂ dispersion model. Each vertical profile plot provided estimated CO₂ concentrations at heights ranging from 1 to 10 m above the ground, at an interval of 1 m. Both the CO₂ horizontal dispersion and vertical profile estimates were generated along with their respective confidence intervals. R (R Core Team, 2024, version 4.4.0) and Rstudio (Rstudio Team, 2024, version 2024.4.1.748) were used for data analysis by selecting the library function ggplot2 (Wickham, 2016) for creating the vertical profile plots.

RESULTS AND DISCUSSION

The input data were averaged over five minutes and subsequently used for the WindTrax simulations. This averaging period was selected because of the short sampling period adopted during the field trial, despite WindTrax’s potential sensitivity to short-term wind speed and direction variability. Table 3 shows measurements obtained from the G-eko 2.0 units at sampling point 1 (upwind) and 2 (downwind), and the anemometer, which were employed to calculate CO₂ emission rates (Table 4). The highest CO₂ emission rate was obtained for the fourth step, which corresponds to the period with the maximum detected wind speeds.

Table 3. Input data averaged over five minutes detected by the two G-eko 2.0 units and the anemometer at the sampling point 1 (upwind) and 2 (downwind)

Step (run nr.)	Time (CET)	Upwind sampling point					Downwind sampling point		
		temp. (°C)	atm. pressure (Pa)	CO ₂ (ppm)	wind speed (m s ⁻¹)	wind direction (°)	temp. (°C)	atm. pressure (Pa)	CO ₂ (ppm)
1	10:40	10.47	99,568	450.14	0.73	119.3	9.59	99,636	637.68
2	10:45	10.55	99,561	453.98	0.72	119.3	9.47	99,630	635.83
3	10:50	10.39	99,555	448.51	0.57	119.3	9.43	99,627	629.10
4	10:55	10.43	99,557	442.26	1.04	119.3	9.58	99,624	621.08

It should be considered that for all the four steps the atmospheric stability was considered class B (unstable), hence the simulations calculating emission rates are influenced by the wind gusts. For example, observing Tables 3 and 4, step 4 is characterised by maximum wind speed and a consequent calculation of a notable peak in CO₂ emission rate, compared to the other steps. In order to understand the influence of the wind on measured concentrations, i.e. whether the values of detected concentration depends on a real increase of emission rates or on increased particle transport due to increased wind speed, a recent study (Mousavi et al., 2025) assessed the influence of meteorological variables on measured CO₂ concentrations in the Middle East. The correlation between wind speed and CO₂ concentrations is inverse significantly in colder months. The paper explains that higher wind speeds lead to a

Table 4. CO₂ emission rates averaged over five minutes calculated using the WindTrax model (50,000 particles)

Step (run nr.)	Time (CET)	Q (g m ⁻² s ⁻¹)
1	10:40	0.19902
2	10:45	0.19054
3	10:50	0.14932
4	10:55	0.26958

reduction in detected concentrations through the dispersion and dilution processes. Consistently, in this case, the maximum detected concentrations are not reached upwind and downwind with the maximum wind speed (Table 4), thus it is possible to state a greater dispersion of CO₂ at higher wind speeds. In this study, input data were averaged over 5 minutes and not over an interval of 15–30, as recommended by the author of the software. Shorter averaging periods are more subject to wind gusts and in conditions of atmospheric instability, indeed some studies (Carozzi et al., 2013; Tagliaferri et al., 2023) have highlighted a worse level of accuracy in the calculation of emission rates, underestimating them.

Simulations were conducted for all the four steps, covering the entire sampling period. Different numbers of particles (5,000, 10,000, 30,000, and 50,000) were tested, yielding various outputs including concentration maps, confidence interval maps, and vertical profile plots.

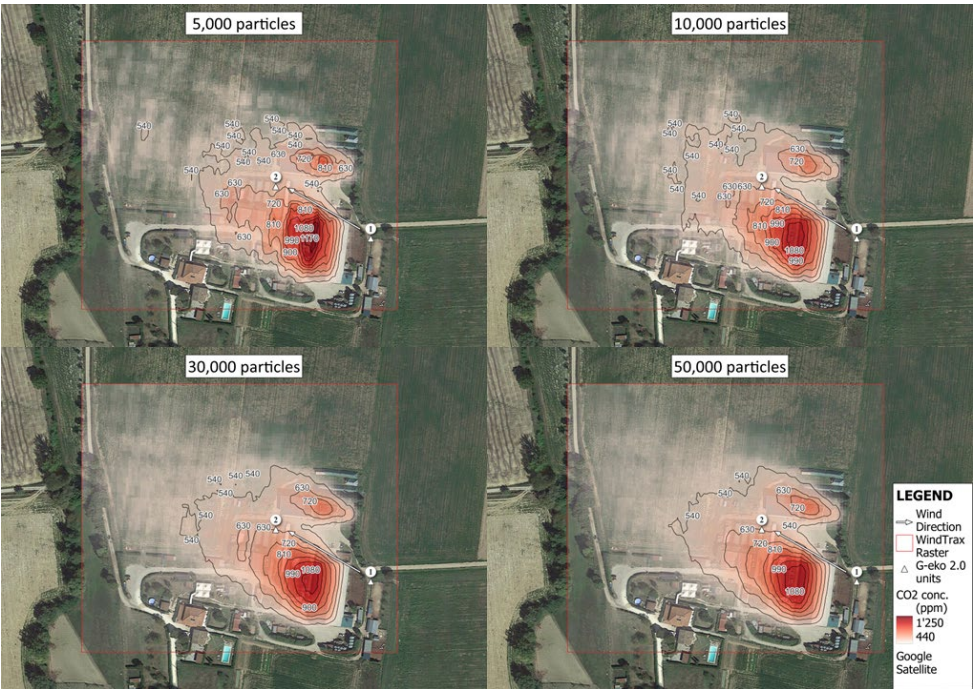


Figure 3. Concentration maps for estimated CO₂ horizontal dispersion at 2 m above ground level modeled with WindTrax simulations using CO₂ measurements averaged at 5-minute intervals. From top left, horizontal contour plots (10 classes separated by 90-ppm intervals) for models computed with 5,000, 10,000, 30,000, and 50,000 particles.

The concentration maps in Fig. 3 were generated for step nr. 1 using different numbers of particles, and indicate the simulated CO₂ concentrations at the height of 2 m above the ground. A uniform colour scale was applied to all four concentration maps, using ten value classes ranging from a minimum of 440 ppm to a maximum of 1,250 ppm, with intervals of 90 ppm, to create horizontal contour plots. Additionally, Fig. 4 shows the concentration map generated for step nr. 1 using 50,000 particles at the height of 2 m above the ground, also representing the emission sources.

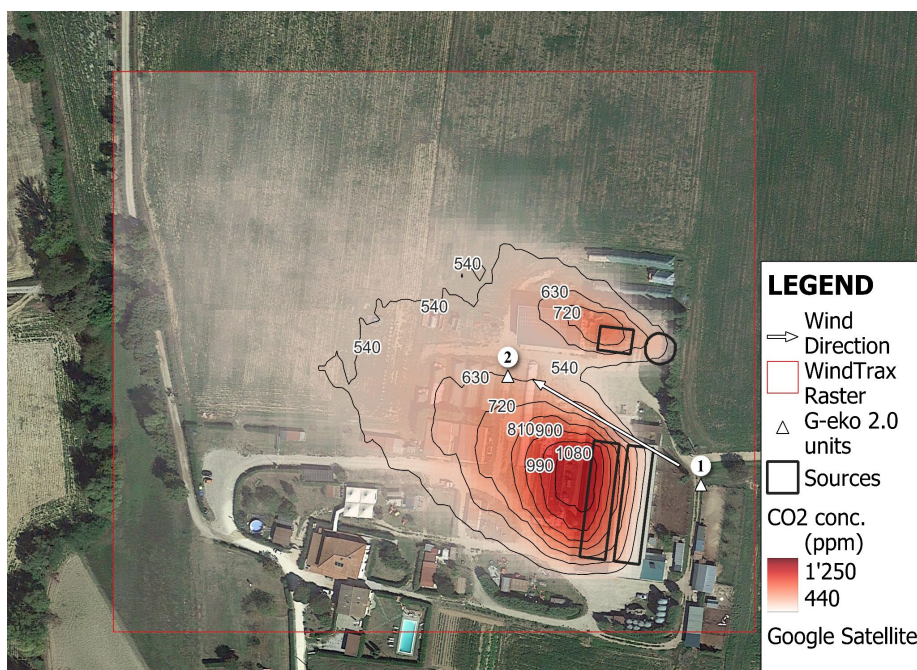


Figure 4. Concentration maps for estimated CO₂ horizontal dispersion at 2 m above ground level modeled with WindTrax simulations using CO₂ measurements averaged at 5-minute intervals. Horizontal contour plots (10 classes separated by 90-ppm intervals) for models computed with 50,000 particles. The sources are shown, as well.

Table 5 shows the results of the concentration maps corresponding to the four steps in terms of maximum and minimum values of the 10,000 estimated concentrations, while Fig. 5 shows the results of the concentration maps corresponding to the four steps in terms of median values. The median was selected to summarize the distribution due to the high number of minimum concentration values located in the periphery of the raster files for each step. Reporting mean values with standard deviation would have provided a misleading interpretation of the results of the simulations. A general trend was noted across all the steps: the median concentration values tend to stabilise with a high number of particles (30,000 and 50,000).

Table 5. Simulated CO₂ concentrations (maximum and minimum values) at 2 m above the ground level using CO₂ and environmental parameter (temperature and pressure) measurements averaged at 5-minutes intervals, using 5,000, 10,000, 30,000, and 50,000 particles for all the four steps

Step (run nr.)		Particles number			
		5,000	10,000	30,000	50,000
1	Max	1,250.00	1,140.00	1,130.00	1,140.00
	Min	450.14	450.14	450.14	450.05
2	Max	1,230.00	1,121.46	1,110.00	1,130.00
	Min	453.98	453.98	453.98	453.89
3	Max	1,210.00	1,110.00	1,100.00	1,120.00
	Min	448.51	448.51	448.51	448.42
4	Max	1,200.00	1,100.00	1,090.00	1,100.00
	Min	442.26	442.26	442.26	442.17

Minimum concentration values remained consistent with the measured mean background concentration at the sampling point 1 up to 30,000 particles, then it decreased by a few decimals for 50,000 particles.

Inside the distribution of calculated CO₂ values, the median value is subject to an upward shift to 30,000 particles and then to a downward shift with 50,000 particles for all the steps.

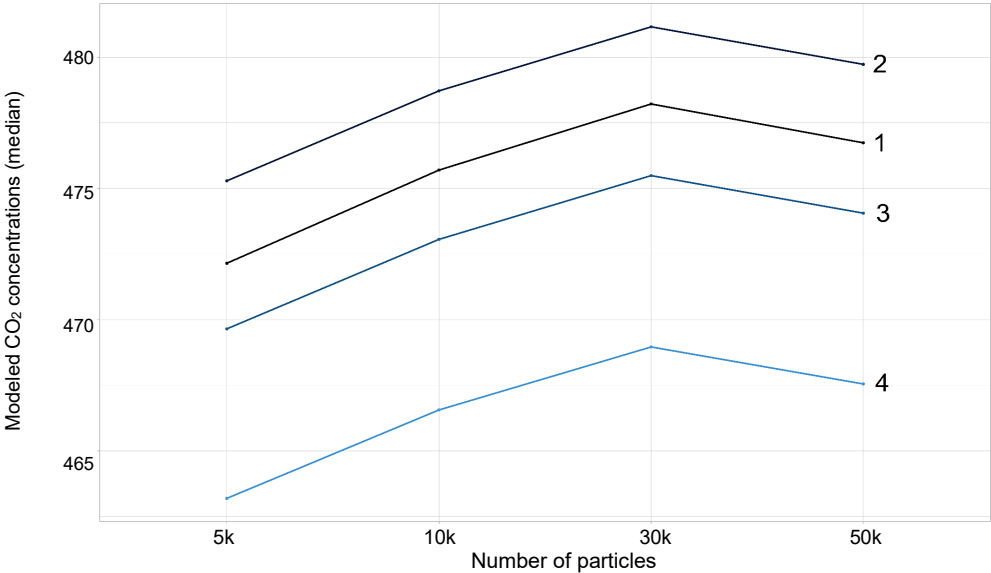


Figure 5. Median modeled CO₂ concentrations of the 16 concentration maps, increasing the number of particles in WindTrax for each step (1–4).

Extending the analysis to the calculated confidence intervals of the estimated CO₂ concentrations, horizontal dispersion maps by WindTrax calculated for the first step are shown in Fig. 6. The same scale of values was used for all the four confidence interval maps, by selecting values from a minimum value of 0 ppm to a maximum value of 290 ppm. It can be observed that by increasing the number of particles included in the simulations, the calculated confidence intervals decreased. Furthermore, as the distance from the source along wind direction increased, the confidence interval decreased.

Pedone et al. (2017) applied the WindTrax model using 2,000, 7,000, and 50,000 particles, obtaining a variability of 20% in CO₂ emission rate. Other authors (Shonkwiler & Ham, 2018; Shaw et al., 2020; Hrad et al., 2021) used the WindTrax model by selecting a number of particles greater than 50,000, mainly for reducing the uncertainty of the model. Studies that selected 50,000 particles adopted smaller distances of sensors from the source i.e. 100–300 m (Hrad et al., 2021), 30 m (Riddick et al., 2022), 0.5 m (Ricco et al., 2021). It should be considered that in studies where sensors are placed close to the source, their number tends to increase. In this study, G-eko units were positioned at 20–40 m from the closer emission source i.e. the bedding inside the livestock building and the manure storage. Hrad et al. (2021) stated that 50,000 particles is the default value to shorten simulation.

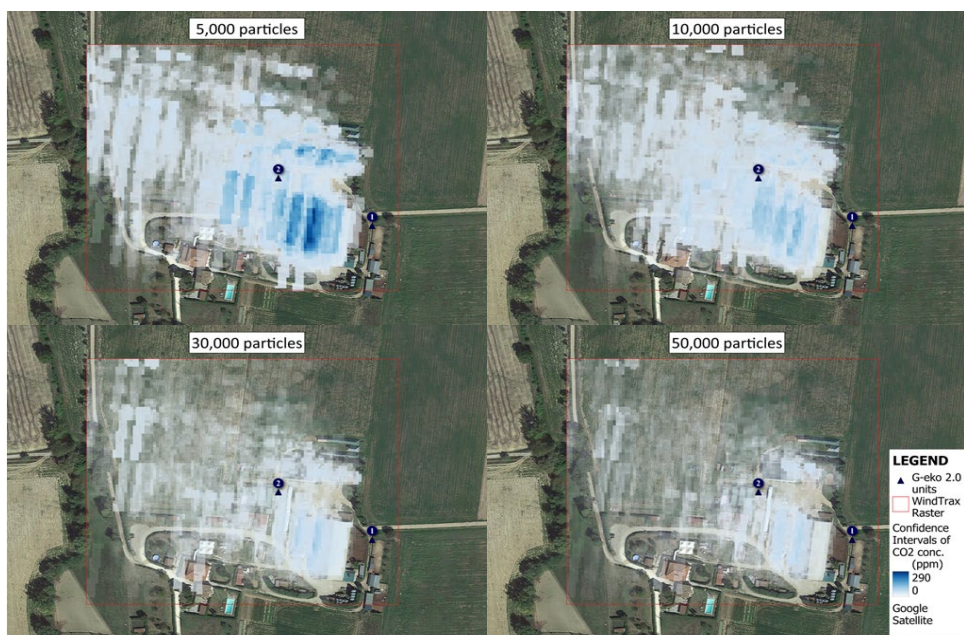


Figure 6. Confidence interval (CI) maps for estimated CO₂ horizontal dispersion at 2 m above ground level modelled with WindTrax simulation using CO₂ measurements averaged at 5-minute intervals. From top left, CI for models computed with 5,000, 10,000, 30,000, and 50,000 particles.

Therefore, simultaneous observation of the concentration maps and the confidence interval maps for the first step (Fig. 3 and 6) showed that the highest values of CO₂ concentration, represented with darker areas, have wider confidence intervals because they are close to the sources. On the other hand, the lowest values represented with lighter areas have smaller confidence intervals because they are further away from the sources. From these considerations, despite the simplicity of applying the bLS approach, the available sensors, type, and positioning have a great impact on atmospheric dispersion simulations.

Table 6 also shows results of the other confidence interval maps, referring to the other steps in terms of maximum and minimum confidence intervals, while Fig. 7 also shows results of the other confidence interval maps, referring to the other steps in terms of median confidence intervals.

Table 6. Simulated CO₂ concentration confidence intervals (maximum and minimum values) at 2 m above the ground level using CO₂ and environmental parameter (temperature and pressure) measurements averaged at 5-minutes intervals, using 5,000, 10,000, 30,000, and 50,000 particles for all the four steps

Step (run nr.)		Particles number			
		5,000	10,000	30,000	50,000
1	Max	285.77	144.77	117.00	88.81
	Min	0.00	0.00	0.00	0.16
2	Max	276.62	140.13	113.26	85.96
	Min	0.00	0.00	0.00	0.15
3	Max	274.50	139.06	112.39	85.31
	Min	0.00	0.00	0.00	0.15
4	Max	271.71	137.64	111.25	84.44
	Min	0.00	0.00	0.00	0.15

For the other steps as well, there is a reduction in the calculated confidence intervals by increasing the number of particles.

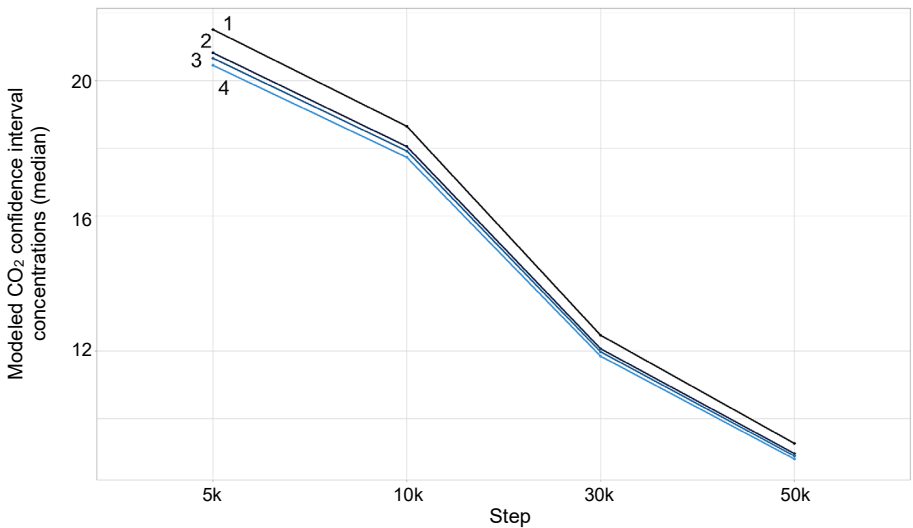


Figure 7. Median modeled CO₂ confidence interval concentrations of the 16 confidence interval concentration maps, increasing the number of particles in WindTrax for each step (1–4).

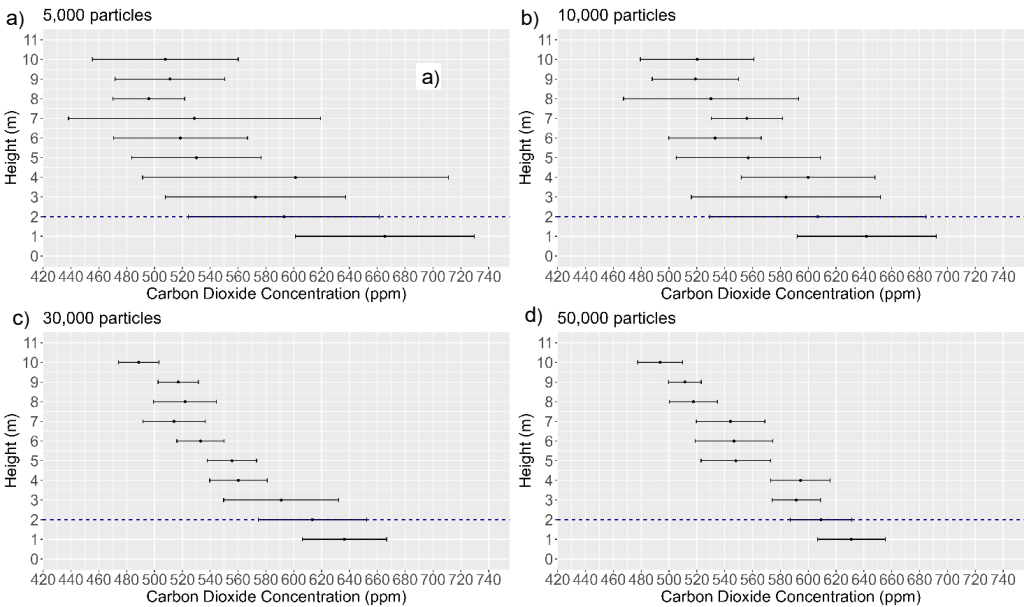


Figure 8. Vertical profile plots of estimated CO₂ concentration □ confidence intervals in the sampling point 2 of the G–eko 2.0. Simulations were run using 5,000 (a), 10,000 (b), 30,000 (c), and 50,000 (d) particles. Estimations are from heights equal to 1 m a.g.l. to 10 m a.g.l. The dotted blue line indicates the height at which simulations of the horizontal dispersion were carried out.

Additionally, vertical profile plots were calculated with the WindTrax software at the sampling point 2 for observing estimated CO₂ concentrations $\pm$ confidence intervals with several numbers of particles at different heights above the ground, i.e. from 0 to 10 m with 1 m intervals. Fig. 8 shows narrower CO₂ confidence intervals as the number of particles increases. Therefore, what has been observed horizontally with concentration maps and confidence interval maps also occurs vertically with vertical profile plots. Moreover, a better-defined vertical trend in concentrations is observed as the number of particles increases. Again, it is observed that a large number of particles is necessary for a better accuracy in estimating concentrations.

CONCLUSIONS

This study provided relevant insights into the performance of a Lagrangian atmospheric dispersion model for estimating CO₂ emissions from livestock facilities and mapping their dispersion in the surrounding environment.

The results highlight the importance of adapting the measurement protocol to the specific emission sources under investigation. In this case, overall CO₂ emission rates were estimated for three distinct sources: the livestock building, the manure pit, and the slurry tank. To improve source-specific estimates, it is recommended to deploy at least one sensing unit per emission source, along with one additional unit for background concentration measurements. All sensors should be positioned at appropriate distances within a 1 km radius from the sources, in accordance with model guidelines.

With regard to meteorological data processing, the choice of averaging intervals proved critical. Short averaging periods (e.g., 5 minutes) are more susceptible to wind gusts, potentially reducing the reliability of emission rate estimates, particularly under unstable atmospheric conditions. Simulations revealed that increasing the number of particles improved result stability and reduced the width of confidence intervals. Specifically, median concentration values from simulations of horizontal dispersion increased with higher particle counts up to 30,000. Confidence intervals also decreased with greater downwind distance and with increasing number of particles. A particle number of at least 50,000 is recommended to ensure robust model outputs, despite the increased computational demand.

The study also identified several limitations. The limited number of sensing units prevented the estimation of emission rates for individual sources, restricting the analysis of their relative contributions to overall CO₂ emissions. In addition, the proximity of the downwind sensor to the emission sources may have influenced concentration measurements due to local turbulence effects caused by nearby structures. The short duration of the measurement period (20 minutes) and the selected averaging time (5 minutes) may have amplified the influence of wind fluctuations on emission estimates. Furthermore, the use of an anemometer capable of measuring both wind speed and direction-preferably in 2D or 3D-would have improved the characterization of local atmospheric conditions.

Despite these limitations, the WindTrax protocol proved practical and applicable within a livestock farming context, provided that careful attention is paid to sensor placement. Future studies should incorporate a greater number of sensing units and extended monitoring periods to capture diurnal, seasonal, and annual variability in emission rates. Such efforts are essential to improve the bottom-up assessment of greenhouse gas emissions from livestock farming and to support the development of effective mitigation strategies.

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Exploring the economic viability and agronomic effects of green manure mixtures on winter wheat yields in organic farming in Latvia: a multi-location study

I. Morozova*, I. Jansone and S. Cerina

Institute of Agricultural Resources and Economics¹, Department of Plant Breeding and Agroecology, Zinatnes Str. 2, Priekule, Priekule parish, LV-4126 Cesis municipality, Latvia

*Correspondence: inga.morozova@arei.lv

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Abstract. This study explores the adaptation of green manure practices to Latvia's climatic and soil conditions to enhance soil productivity and economic returns in organic farming systems. The study aims to identify the most suitable green manure mixture by evaluating economic factors, dry matter yield, nutrient amount, and its impact on winter wheat yields in organic fields across different locations in Latvia, considering variations in meteorological conditions. Field trials compared three mixtures: oats-mustard-oilseed rape-buckwheat (non-legume), oats-buckwheat-peas (legumes < 50%), and oats-lupin-vetch (legumes > 50%) against a control (black fallow). Data were collected on dry matter production, nutrient accumulation (N, P, K amount), winter wheat yields, and economic performance. The results revealed a significant variation in dry matter yield depending on year and location. Mixture with non-legumes at the farms 'Gaikeni' and 'Geidas', as well as mixture with legumes below 50% at 'Gaikeni', Ltd. 'Mazbungas', and 'IRGK serviss', produced significantly higher dry matter yields ($P < 0.05$). Despite lower biomass yield in certain years, mixture with legumes above 50%, through the follow-up effect, significantly increased winter wheat yields under optimal conditions at Ltd. 'Mazbungas' and farm 'Gaikeni' being higher by 96.05% and 93.59%, respectively, compared to the control. Economic analysis revealed significant gross margin advantages for green manure cultivation, demonstrating its financial viability. This study underscores the potential of green manure practices in enhancing the sustainability of organic farming, improving yields, and increasing profitability, while highlighting the importance of selecting region-specific mixtures to account for climatic variability.

Key words: legume and non-legume mixtures, yield potential, nutrient amount, gross margin.

INTRODUCTION

Stockless farming systems often struggle with limited rotation options and increasing the risk of soil nutrient depletion. Green manure crops offer a valuable rotational break, helping to reduce soil fatigue and sustain productivity in long-term organic farming systems (Bedoussac et al., 2015; Baddeley et al., 2017). As livestock farming declines, stockless organic cropping systems are gaining traction in many intensive agricultural regions across Europe, highlighting the growing need for

sustainable farming solutions (Toleikiene et al., 2024). The importance of green manure practices in organic farming is becoming increasingly relevant as many countries in recent years have begun exploring ways to reduce soil nutrient loss during the plant-free period (Talgre, 2013; Wang et al., 2021; Toleikiene et al., 2024; Zhao et al., 2024). In recent decades, the expansion of organic farming in Latvia has highlighted a growing interest in sustainable agricultural practices. Non-legume and legume-based cover crop mixtures have emerged as a promising strategy to enhance ecosystem services within cropping systems, utilizing agroecological principles to maximize these benefits (Daryanto et al., 2018; Couédel et al., 2019; Auzins et al., 2023). The green manure market is projected to grow to €2.86 billion by 2028 at an annual growth rate of 7.1%, driven by climate change adaptation, regenerative agriculture, and increasing demand for sustainability. Key trends include the integration of leguminous and cruciferous cover crops, the adoption of no-till farming, and innovations in cover cropping (Tsytsiura, 2024).

Latvia is characterised by regionally variable climatic conditions and diverse soil-related nutritional challenges, making organic farming particularly demanding. Frequent fluctuations between periods of rainfall and moisture deficiency create challenges in maintaining soil moisture. Green manure crops significantly improve soil structure, enhance its water retention capacity, and reduce soil desiccation (Daryanto et al., 2018; Melander et al., 2020; Hu et al., 2023), which is especially important during dry summer periods. Additionally, they promote microbial activity, which is crucial for organic matter decomposition and soil fertility maintenance (Talgre et al., 2010; Couédel et al., 2019; Hu et al., 2023). In Latvian regions with sloping terrain or frequent rainfall, green manure helps mitigate nutrient runoff and soil erosion by providing vegetative cover during non-cropping periods. This also contributes to enhancing the yield of main crops, ultimately increasing economic returns for farmers.

Selecting an appropriate crop rotation scheme that incorporates green manure can be particularly challenging, as it requires managing trade-offs between crop yields and yield stability, all while ensuring the maintenance of profitability and long-term sustainability. Studies have demonstrated that integrating green manure into crop rotations can improve wheat yields by enhancing soil conditions (Nawaz et al., 2017; Zhao et al., 2024). Despite the long-term benefits, the adoption of green manure crops by farmers remains limited due to the additional costs and labour requirements. Green manure practices offer substantial advantages, such as enhancing soil fertility, increasing yields, and promoting sustainable agricultural methods (Nawaz et al., 2017; Ma et al., 2021). However, the implementation of green manure practices presents considerable financial and operational challenges. Additionally, the land allocated for green manure cultivation may lead to temporary reductions in cash crop yields, which can negatively impact overall farm profitability. Furthermore, the rising costs of agrotechnical operations, fuel, and labour have become significant factors driving up agricultural product prices, which, in turn, affect farmers' incomes (Chen, 2020). These combined challenges highlight the need for careful consideration of the economic feasibility of adopting green manure practices. Moreover, the effectiveness of green manure crops in terms of productivity, crop nutrition, and weed control can vary depending on factors such as crop species, soil type, climate, and the complexity of the cropping system (Wittwer et al., 2017; Wang et al., 2021; Zhao et al., 2022).

This variability highlights the need for more specific experimental studies to determine the precise effects of green manure cropping across different agricultural contexts. Therefore, field trials with the most suitable green manure mixtures were established on larger plots in various regions of Latvia on organic farming systems. Previous data and experience from other studies conducted in Latvia were also utilised (Auzins et al., 2023). The study aims to identify the most suitable green manure mixture by evaluating economic factors, dry matter yield, nutrient amount, and its impact on winter wheat yields in organic fields across different locations in Latvia, considering variations in meteorological conditions. This complex scenario necessitates more long-term and region-specific experimental research to better understanding of the trade-offs and benefits of green manure in diverse agricultural systems.

MATERIALS AND METHODS

Field trials of green manure mixtures were established in four organic farming enterprises: farms ‘Gaikeni’ (Ga), ‘Geidas’ (Ge), Ltds. ‘Mazbungas’ (M) and ‘IRGK Serviss’ (I), located in different regions of Latvia – Vidzeme, Kurzeme, Zemgale, and Latgale, respectively (Table 1). The trials were conducted from 2022 to 2024, with plot sizes of 0.3 ha. The study evaluated three green manure mixtures against a control (black fallow). The first mixture consisted of oats (*Avena sativa*) (50%), mustard (*Sinapis alba*) (20%), oilseed radish (*Raphanus sativus* ssp. *oleiferus*) (10%), and buckwheat (*Fagopyrum esculentum*) (20%) (non-legume). The second mixture included oats (50%), buckwheat (30%), and peas (*Pisum sativum*) (20%) (legumes below 50%). The third mixture comprised oats (45%), lupin (*Lupinus angustifolius*) (20%), and vetch (*Vicia sativa*) (35%) (legumes above 50%).

Table 1. Data on green manure and winter wheat growing practices and soil properties for farm or Ltd., 2022–2024

Farm/ Ltd.	Year	Sowing date of green manure	Soil incorporation date of green manure	Sowing date winter wheat	Harvesting date of winter wheat	The granulometric composition of the soil
Ga	2022	09.06.	25.07.	24.09.2022	13.08.2023	Sandy loam
	2023	01.07.	11.09.	22.09.2023	12.08.2024	Sandy loam
	2024	16.06.	03.08.	-	-	Sandy loam
Ge	2022	19.05	19.07.	09.09.2022	05.08.2023	Sandy loam
	2023	14.06.	19.07.	11.09.2023	12.08.2024	Loamy sand
	2024	04.06.	01.08.	-	-	Loamy sand
M	2022	27.05.	20.07.	26.09.2022	17.08.2023	Loamy sand
	2023	06.06.	26.07.	27.10.2023	07.08.2024	Sandy loam
	2024	11.06.	14.08.	-	-	Sandy loam
I	2022	20.05.	22.07.	14.09.2022	08.08.2023	Loamy sand
	2023	23.05.	23.08.	18.10.2023	12.08.2024	Loamy sand
	2024	27.05.	14.07.	-	-	Loamy sand

Sowing was carried out on an unfertilized background. Soil characteristics, including soil type, organic matter amount, pH, etc., were recorded (Tables 1, 2). The green biomass yield of green manure mixtures at the time of soil incorporation was

determined (t ha⁻¹) (Table 1). Aboveground and belowground plant biomass was measured at the full flowering stage (BBCH 64–67) in four randomised plots of 0.125 m². In each plot, shoots were cut, and roots were excavated to a depth of 20 cm in the topsoil. The shoots were subsequently weighed, and the roots were washed, air-dried, and then weighed using a laboratory scale with a precision of 0.01 g. Both shoots and roots were air-dried to completion before being weighed using the laboratory scale.

All laboratory chemical analyses were conducted in quadruplicate, with the determination of the basic biochemical components expressed on an absolutely dry weight basis (Undersander et al., 1993).

Dry matter content was measured by drying the samples in an oven at 105 °C, followed by ashing at 550 °C. The dried samples were subsequently re-weighed and ground using an electrostatic laboratory mill. Nitrogen amount in shoots and roots was determined in accordance with LVS EN ISO 20483:2014, while phosphorus and potassium amount were determined using the methods specified in ISO 6491:1998 and LVS EN ISO 6869:2002, respectively.

Green manure mixtures were incorporated into the soil from late July to August to allow adequate time for decomposition and nutrient release before cash crop sowing in September. In the crop rotation following green manure, the subsequent cash crop was winter wheat (*Triticum aestivum*), where grain yield being assessed. The evaluation focused on the impact of the specie, not on the specific variety. Data were collected on activities performed on individual fields for each green manure variant.

For the study, economic indicators were evaluated as gross margin (1), which corresponds to revenue minus variable costs. The following equations were used for the calculation of the economic results:

$$\text{Gross margin} = \text{gross income} - \text{variable costs} \tag{1}$$

Gross margin was expressed in EUR per hectare (EUR ha⁻¹). The average annual gross margin for the two-year period (2022–2023 and 2023–2024), including wheat yields for each farm, is presented.

The agricultural practices employed by each farm or company were distinct, with each utilising its own specific equipment, including specialised agricultural machinery. The assessment of the economic indicators for the farms was based on the agrotechnical operations collected throughout the study (Fig. 1). Annual costs for each farm were calculated by summing the variable costs associated with agrotechnical operations (ploughing, harrowing, disking, cultivating, combined soil preparation, sowing combined with or without soil tillage of green manure mixtures and winter wheat, green mass shredding, harvesting, and transportation of the harvested yield from the field) as

Table 2. Basic soil characteristics in locations, 2022–2024

Farm /Ltd.	Year	pH _{KCl}	Organic matter, %	N _{tot} , mg g ⁻¹	P, mg kg ⁻¹	K, mg kg ⁻¹
M	2022	5.75	1.29	1.34	105.35	65.12
	2023	6.57	1.76	1.16	57.64	77.50
	2024	5.66	2.33	1.37	121.25	190.90
Ge	2022	6.70	2.36	1.53	5.19	82.67
	2023	7.08	2.57	2.57	4.48	73.73
	2024	6.93	2.62	2.40	18.31	127.99
I	2022	5.48	1.56	1.40	19.20	101.26
	2023	6.13	1.97	1.97	4.70	114.65
	2024	5.31	1.62	0.88	14.76	87.57
Ga	2022	5.63	3.97	1.67	108.69	142.25
	2023	6.28	3.36	3.36	99.60	139.23
	2024	5.75	4.46	2.41	189.09	180.94

well as raw materials. Constant prices were used in the study to eliminate the impact of market fluctuations and the individual organizational characteristics of each farm.

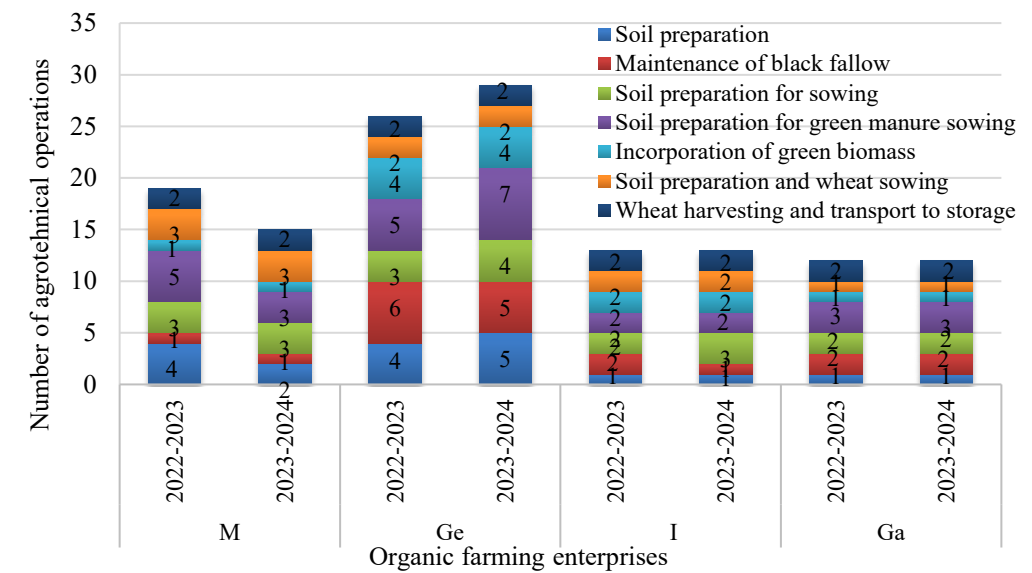


Figure 1. Field operations at Farms or Ltd. for the 2022–2023 and 2023–2024 growing cycles.

The seeding rate and price for winter wheat and green mass were identical across all farms. The price of organic winter wheat seeds was 0.4 EUR kg⁻¹, while the selling price was 230.0 EUR t⁻¹. The wheat prices were determined based on calculations by the Latvian Rural Advisory and Training Centre. The prices of green manure mixture seeds ranged from 0.8 to 1.4 EUR kg⁻¹ (Table 3).

Table 3. Seeding rate and seed price for field trials

	Seeding rate, kg ha ⁻¹	Price, EUR kg ⁻¹	Cost, EUR ha ⁻¹
L.0%	64	1.4	89.6
L.< 50%	104	0.8	86.3
L.> 50%	80	1.3	105.6
Winter wheat	230	0.4	92.0

Meteorological data were obtained from the nearest meteorological station of the Latvian Environment, Geology, and Meteorology Centre, which represented the regional conditions of the demonstration sites. The De Martonne Aridity Index (IDM) (Moral et al., 2016) was employed to characterise the arid/humid conditions of the territory over a month, according to Eq. (2):

$$I_{DM} = \frac{12P_m}{T_m + 10} \tag{2}$$

where P_m and T_m are the precipitation volume and mean air temperature in corresponding month, respectively.

According to the I_{DM} values calculated using the equation above, the climate of a region can be classified (type of climate according to the De Martonne aridity index (I_{DM} , adapted after Baltas, 2007) Arid $I_{DM} < 10$; Semi-Arid $10 \leq I_{DM} < 20$; Mediterranean $20 \leq I_{DM} < 24$; Semi-humid $24 \leq I_{DM} < 28$; Humid $28 \leq I_{DM} < 35$; Very Humid $35 \leq I_{DM} \leq 55$; Extremely humid $I_{DM} > 55$.

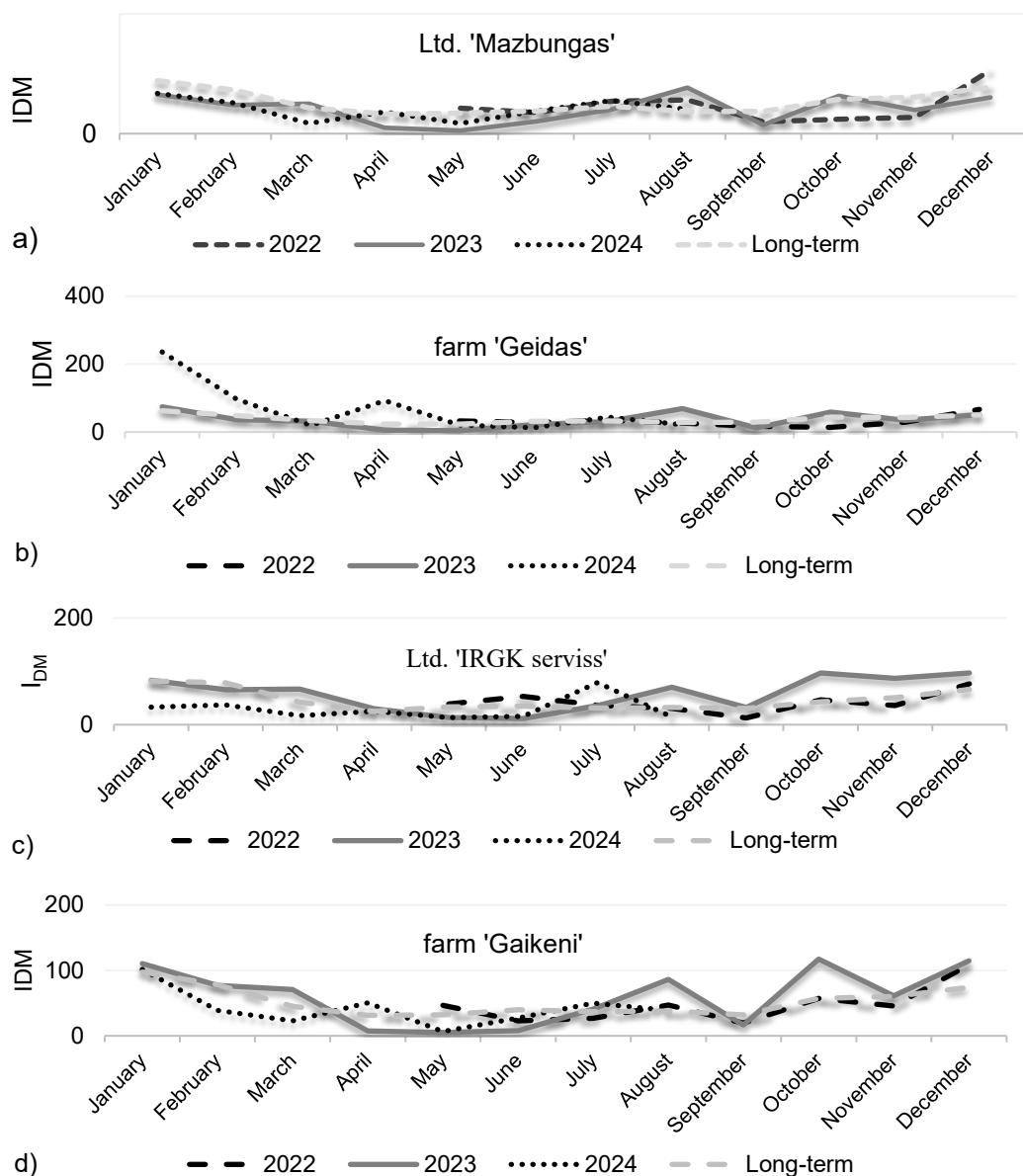


Figure 2. The values of the De Martonne Aridity Index (I_{DM}) for the vegetation periods of the green manure mixtures and winter wheat at the farm or Ltd. locations (a, b, c, d), 2022–2024.

A generalised assessment of the hydrothermal regimes during the vegetation periods of green manure and winter wheat across the research years is presented in Fig. 2. The De Martonne Aridity Index indicated that, under Latvian climatic conditions, May and June represent a critical period for green manure sowing, as these months are characterised by drier conditions across various locations, which may not always be conducive to successful seed establishment. Moreover, July and August are

characterised by rapid fluctuations between dry and rainy conditions, which can have both positive and negative effects on green biomass yield.

Dry matter, and nutrient amount data were statistically analysed using Microsoft Excel. Analysis of variance (ANOVA) was employed to assess the significance of differences, with calculations performed at a significance level of $P < 0.05$.

RESULTS AND DISCUSSION

Shoot and root dry matter yield and nutrient amount of green manure mixtures.

Field trial results conducted across various locations in Latvia revealed significant variations in green manure yield potential, both across different years and fields, as well as among farms or agricultural enterprises (Ltd.). An analysis of meteorological conditions, in comparison with regional data, highlighted notable differences between locations (Fig. 2). The findings demonstrated that humidity levels play a pivotal role in influencing variations in green manure mixture yield that are specific to particular locations. Teixeira et al. (2016) also emphasised that ensuring optimal cover crop emergence is a significant challenge in regions characterised by hot, dry summers. The optimal vegetation period for the green manure mixture, along with a significantly higher dry matter yield ($P < 0.05$), was observed at Ltd. 'Mazbungas' (M) and farm 'Geidas' (Ge) in 2022, as well as at Ltd. 'IRGK Serviss' (I) and farm 'Gaikeni' (Ga) in 2024. The yield potential of green manure is influenced by multiple interacting factors, including climatic conditions, soil properties, and species composition.

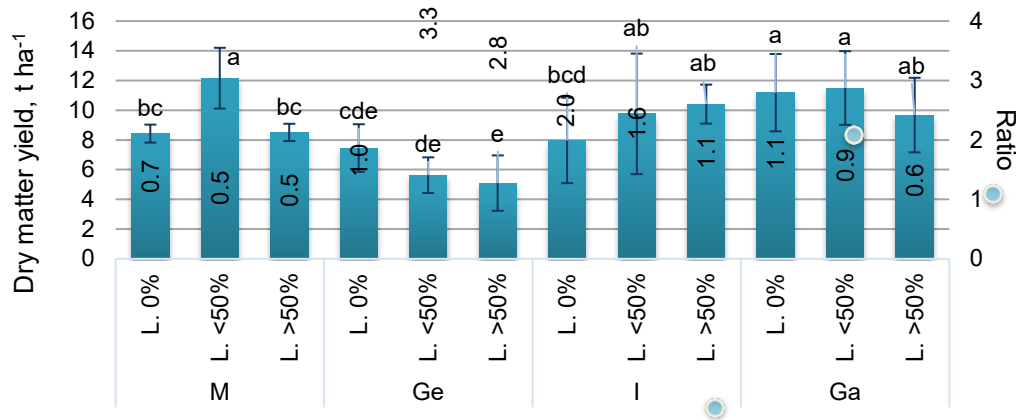


Figure 3. Combined dry matter yield and shoot-to-root ratio of green manure mixtures across different years and locations, 2022–2024.

abcde – Different letters indicate significant differences in dry matter yield across locations and years ($P < 0.05$), $LSD_{0.05}=2.7$.

The three-year comparison identified that the mixture with legumes below 50% was the most suitable for Ltd. M, achieving a significantly higher dry matter yield (Table 3). The significant dry matter yield at farm Ge depended on the year and whether the mixture with non-legume mixture. The most suitable mixture, either with legumes below 50% or non-legume, for achieving the highest dry matter yield was identified at

farm Ga. All mixtures at Ltd. I demonstrate variable yield performance, depending on the year climatic conditions and the adaptability of the mixture more suitable with legumes below and above 50%. At the farm Ge, shoot-to-root ratio comparisons showed that mixtures containing legumes developed a more extensive root system than non-legume mixtures, likely due to improved root-soil interactions, contributing to enhanced soil structure and fertility. The results indicated that, from a practical point of view across all locations, mixture with legumes above 50% was more sensitive to dry periods and required higher humidity for successful biomass development due to the larger seed size of legumes. These findings underscore the importance of selecting an appropriate species composition to optimise productivity and enhance adaptability to local environmental conditions. According to Tribouillois et al. (2016), a laboratory study revealed that the germination of legumes was more sensitive to high temperatures compared to crucifers.

The results indicated that the nitrogen (N) amount, expressed as a percentage, tended to be higher in mixture with legumes above 50% at most locations. However, these findings were not unequivocal, as other mixtures also exhibited elevated nitrogen levels depending on the year and location. Evaluating the total nitrogen amount in the green manure mixture, it does not correlate with higher yield (Fig. 4).

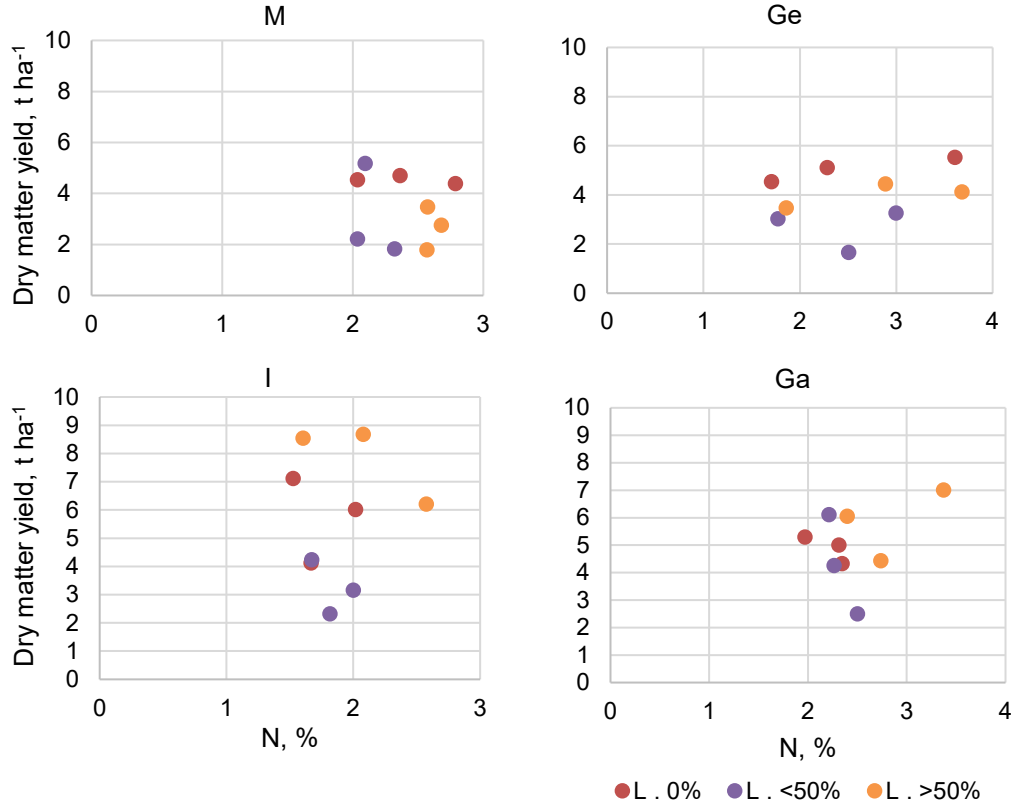


Figure 4. The aboveground nitrogen and dry matter yield of green manure mix in different years and locations, 2022–2024.

Furthermore, the proportion of nitrogen remaining plant-available for the subsequent crop remains uncertain, given that some nitrogen may be lost during residue decomposition. There is a notable lack of research addressing the timing of nitrogen release and its synchronisation with crop uptake, highlighting the need for further investigation.

The nitrogen (N) amount in plant dry matter yield ranged significantly ($P < 0.05$) among the tested green manure mixtures across different years and locations. The average total shoots and roots N amount ranged from 141.2 to 190.1 kg N ha⁻¹ for non-legume mixture, 114.8 to 173.9 kg N ha⁻¹ for mixture with legumes below 50%, and 112.8 to 205.1 kg N ha⁻¹ for mixture with legumes above 50% (Fig. 4). These variations highlight the influence of species composition on nitrogen fixation and uptake efficiency. The average nitrogen amount was not significantly higher in mixtures with legumes above 50%, suggesting that non-legume mixtures can also improve soil nitrogen levels, possibly through mechanisms like nutrient cycling or microbial activity. The higher average nitrogen amount at farm Ga for all green manure mixtures suggests that local factors, such as soil characteristics with higher organic and nitrogen level, climate, and farm-specific cultivation techniques, may have contributed to enhanced nitrogen assimilation in the plants. This highlights the need for site-specific management in selecting green manure mixtures, as species suitability varies by environment, affecting nutrient cycling and soil fertility.

The two-year results potassium (K) and phosphorus (P) amount in plant biomass demonstrated significant difference ($P < 0.05$) across both years and locations for the examined green manure mixtures. The average total shoots and roots K accumulation ranged from 171.5 to 299.9 kg K ha⁻¹ for non-legume mixtures, 174.5 to 278.8 kg K ha⁻¹ for mixtures with legumes below 50%, and 138.0 to 192.2 kg K ha⁻¹ for mixtures with legumes above 50%. The average total shoots and roots phosphorus content ranged from 22.4 to 60.8 kg P ha⁻¹ for non-legume mixtures, 14.7 to 58.8 kg P ha⁻¹ for mixtures with legumes below 50%, and 16.4 to 53.1 kg P ha⁻¹ for mixtures with legumes above 50% (Fig. 5). The range in average K and P amount in green manure shoots and roots across different locations suggests that both environmental conditions and species composition play a significant role in element uptake. Green manure mixtures of non-legumes or with legumes below 50% showed significantly higher K and P accumulation in most cases. This indicates that diverse or balanced species mixtures may be more efficient in K and P uptake under certain conditions. These data indicate that the potential of green manure varies between mixtures. However, field trials are ongoing, and results from the 2023–2024 growing cycle do not yet show any interactions leading to increased winter wheat yield.

The variability in nutrient uptake across locations highlights the significance of location-specific factors, such as soil nitrogen, potassium and phosphorus availability and climate, in determining the effectiveness of green manure mixtures. According Zhao et al. (2024), who demonstrated that different green manure types exhibit varying nutrient effects. Muhammad et al. (2022) noted that bioavailable phosphorus is often the most deficient soil nutrient, while nitrogen and potassium are also essential. Soil fertility is dynamic, relying on nutrient cycling, where microbial decomposition mineralises plant material, releasing nutrients into the soil.

Ha et al. (2008) found that 40–60% of P in crop residues is water-soluble and rapidly released into the soil. Green manure crops, both pure and undersown, could fix up to 153 kg of K and 20 kg of P per hectare, depending on biomass size. Their study

emphasized that sustainable management of organic farms is possible through proper manure management, effective use of legumes, and strategic input of phosphorus and potassium. According to study by Talgre et al. (2012), in the tested common green manure legumes sown as pure crops, 114–196 kg of N, 17–24 kg of P, and 89–144 kg of K per hectare were returned to the soil each year.

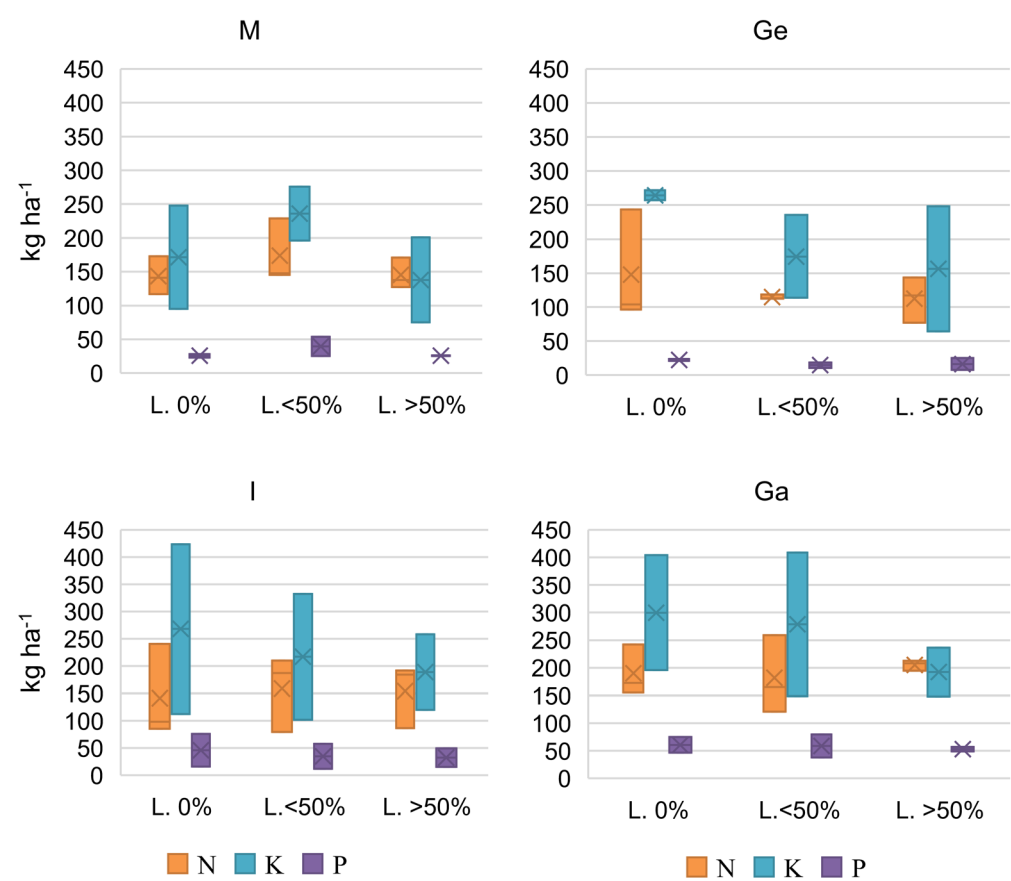


Figure 5. Range of nutrient amount in the total shoot and root dry matter of green manure mixtures across different locations, N kg ha⁻¹ 2022–2024 and P, K kg ha⁻¹ 2023–2024.

The findings underscore the necessity of tailoring green manure selections to local environmental conditions, as specific species or mixtures may demonstrate enhanced effectiveness in different soil types, thereby optimising nutrient management. Given that the benefits of green manure on crop yields accrue gradually, sustained long-term monitoring is essential to comprehensively assess its enduring impact on soil health and fertility.

Winter wheat productivity and economic return on farms

Winter wheat grain yield following green manure mixtures was evaluated under varying climatic conditions. Ltd. M and farm Ge experienced lower humidity, whereas Ltd. and farm Ga had higher humidity, with more intense rainfall and pronounced dry periods during the both vegetation periods.

The results suggest that while green manure yield and nutrient amount do not directly correlate with an increase in grain yield, certain green manure mixtures, particularly those with legume above 50%, can positively influence subsequent crop yields most locations under specific conditions. The highest increase in wheat yield compared to the control was observed at Ltd. M in 2024 and at Farm Ga in 2023, with respective increases of 96% and 94% (Fig. 6). Compared to the mixture effect, the impact of fallow on nitrogen availability is more dependent on the management system. In this study, black fallow was periodically kept free from weeds and volunteers by disc cultivation. While such soil disturbance can enhance nitrogen mineralisation, the released nitrogen was likely lost through leaching or volatilisation before the subsequent wheat crop was established, limiting its agronomic benefit.

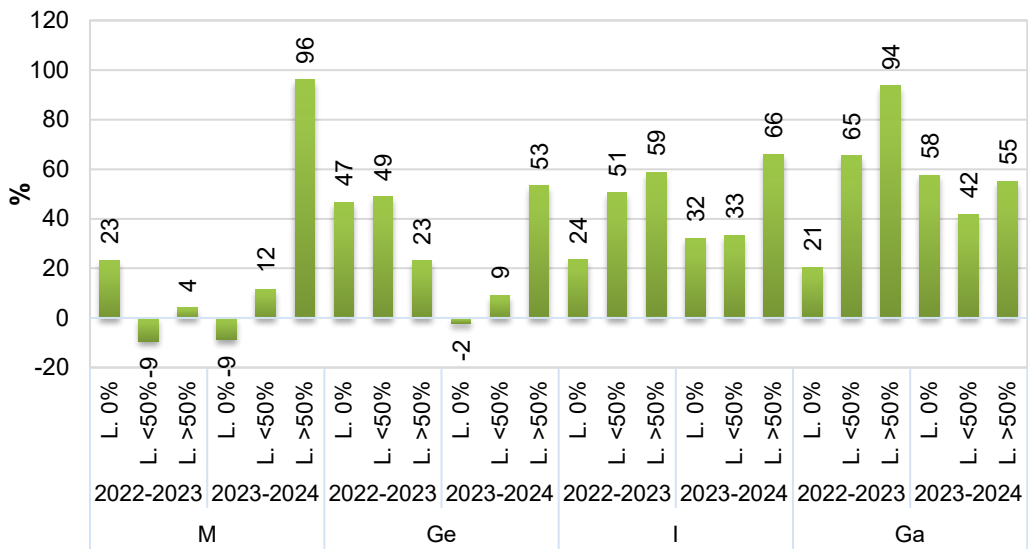


Figure 6. Grain yield increase of winter wheat compared to control across years and locations in the 2022–2023 and 2023–2024 growing cycles.

This highlights the importance of location-specific factors in green manure effectiveness, with significant differences observed between years and location. It emphasises the need to select the most suitable mixture for each year and location to optimise wheat yield. De Notaris et al. (2019) suggests that a well-established legume-based green manure can help stabilise crop yield over time. According to Zhao et al. (2024), a six-year study on green manure incorporation in a diversified crop rotation system found varying soil nutrient responses and cumulative enrichment effects, with significant differences emerging in later years. Crop yields showed inconsistent responses, highlighting the complexity of green manure's agronomic impact.

In 2022–2023, Ltd. I exhibited the highest gross margin, ranging from 81 to 114 EUR ha⁻¹, while Farm Ga recorded the lowest, with values ranging from -175 to -309 EUR ha⁻¹. In 2023–2024, several farms experienced improvements in gross margins, particularly Ltd. M, which achieved the highest average gross margin, ranging from 30 to 374 EUR ha⁻¹ (Table 4).

Table 4. Grain yield and gross margin in farms field trials for the 2022–2023 and 2023–2024 growing cycles

Farm/ Ltd. and years	*C, GMM	*GI:		*VC		Total VC, EUR ha ⁻¹	Gross margin, EUR ha ⁻¹	
		*GY, t ha ⁻¹	GI, EUR ha ⁻¹	Seed cost, EUR ha ⁻¹	*MO, EUR ha ⁻¹			
M 2022–2023	C	2.15	495	92	356	448	47	
	L.0%	2.65	610	182	403	585	25	
	L.< 50%	1.95	449	178	387	565	-117	
	L.>5 0%	2.24	515	198	393	590	-76	
	2023–2024	C	2.18	501	92	308	400	101
		L.0%	1.99	458	182	341	523	-65
		L.< 50%	2.43	559	178	351	529	30
		L.> 50%	4.27	982	198	410	608	374
Ge 2022–2023	C	2.29	527	92	506	598	-71	
	L.0%	3.36	773	182	503	685	88	
	L.< 50%	3.41	784	178	505	683	101	
	L.> 50%	2.82	649	198	487	684	-36	
	2023–2024	C	2.19	503	92	532	624	-120
		L.0%	2.15	495	182	531	712	-218
		L.< 50%	2.40	552	178	536	714	-162
		L.> 50%	3.36	773	198	563	760	12
I 2022–2023	C	1.70	391	92	218	310	81	
	L.0%	2.10	483	182	307	488	-5	
	L.< 50%	2.56	589	178	310	487	101	
	L.> 50%	2.70	621	198	310	507	114	
	2023–2024	C	1.51	347	92	254	346	1
		L.0%	1.99	458	182	293	475	-17
		L.< 50%	2.01	462	178	293	471	-9
		L.> 50%	2.50	575	198	296	493	82
Ga 2022–2023	C	0.78	179	92	306	398	-219	
	L.0%	0.94	216	182	344	526	-309	
	L.< 50%	1.29	297	178	322	500	-204	
	L.>5 0%	1.51	347	198	325	523	-175	
	2023–2024	C	1.58	363	92	298	390	-27
		L.0%	2.49	573	182	357	539	34
		L.<5 0%	2.24	515	178	327	505	10
		L.> 50%	2.45	564	198	331	529	35

* C – black fallow; GI – Gross income; GMM – green manure mixtures; GY – grain yield; MO – machinery operations; VC – variable costs.

Farm Ga consistently showed the lowest gross margins across both years, with all trials of green manure mixtures resulting in negative values. This suggests challenging growing conditions and low grain yield at this location.

Farm Ge demonstrated high variability between years. In 2022–2023, it achieved positive gross margins with two green manure mixtures, but in 2023–2024, three trials resulted in losses.

Ltd. M showed the most significant improvement from 2022–2023 to 2023–2024 growing cycles. The mixture with legumes above 50% trial in 2023–2024 yielded the highest gross margin (374 EUR ha⁻¹) among all farms and trials over the two growing cycles. Ltd. I maintained relatively stable gross margins across both growing cycles, with most trials of green manure mixtures yielding positive results.

The green manure mixtures trials showed variable effects across farms and years. In some cases, such as Ltd. M in 2023–2024, the mixture with legumes above 50% trial significantly outperformed the control (black fallow). However, in other instances, green manure mixtures resulted in lower gross margins compared to the control.

The variability in gross margins observed in this study aligns with findings from other research on winter wheat production. For instance, a study by Devkota & Yigezu (2020) reported significant fluctuations in winter wheat gross margins due to yearly weather variations and soil conditions.

The positive impact of green manure mixtures, particularly at mixtures with legumes above 50%, on gross margins in some cases is consistent with research by Ma et al. (2021), who found that green manure can enhance soil fertility and crop yields in certain conditions.

However, the inconsistent results across farms and years suggest that the effectiveness of green manure mixtures may be highly dependent on local factors. The poor performance of Farm Ga across both growing cycles indicates potential site-specific challenges: soil composition, weather conditions, equipment. Similar location-specific variations in winter wheat profitability were noted by Eltazarov et al. (2023) in a multi-site study across diverse agroecological zones. The substantial improvement in Farm M's gross margins in 2023–2024, especially with legumes above 50% mixture, warrants further evaluation. It may be attributed to favourable weather conditions, improved management practices, or a positive interaction between the green manure mixtures and local soil conditions. Kaš et al. (2019) reported comparable year-to-year variations in their long-term study of winter wheat production systems.

CONCLUSIONS

This study highlights the importance of location-specific cropping systems in optimising the potential of green manure within low-input organic growing system. The observed year- and site-specific variations in biomass yield emphasise the necessity of tailored green manure mixtures to enhance nutrient cycling and crop productivity. Mixture with non-legumes at the farms 'Gaikeni' and 'Geidas', as well as mixture with legumes below 50% at 'Gaikeni', Ltd. 'Mazbungas', and 'IRGK serviss', produced significantly higher dry matter yields ($P < 0.05$). Additionally, the results identified a tendency for the highest N in mixture legume above 50% and P, K amount in non-legume

mixture or legume below 50%. Despite lower biomass yield in certain years, mixture with legumes above 50%, through the follow-up effect, significantly increased winter wheat yields under optimal conditions at Ltd. ‘Mazbungas’ and farm ‘Gaikeni’ being higher by 96.05% and 93.59%, respectively, compared to the control. However, these findings underscore the necessity for long-term research to refine green manure strategies, with the goal of improving soil fertility and nutrient availability for more stable wheat production.

These two growing cycles study reveals significant differences in gross margins across farms. These were influenced by various soil cultivation technologies, their frequency of use, agroclimatic conditions, and the impact of green manure mixtures on winter wheat yields. While some farms and treatments showed promising results, the inconsistency highlights the complex nature of agricultural systems. Further research is needed to understand the factors driving these variations and to develop more reliable recommendations for green manure mixtures use in winter wheat production.

In conclusion, continued policy support and targeted management practices are essential to ensure the long-term viability of organic farming, including winter wheat production, under current conditions at Latvia.

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Iron content and qualitative composition in a waterlogged agricultural soil under long-term agrogenic influence, Western Ukraine

Y. Olifir^{1,*}, T. Partyka¹, O. Havryshko¹, H. Konyk¹, H. Panakhyd¹, N. Kozak¹
and V. Ivaniuk²

¹Institute of Agriculture of Carpathian Region of National Academy of Agrarian Sciences of Ukraine, 5, Hrushevskoho Str., UA81115 Obroshyne, Lviv region, Ukraine

²Stepan Gzhytskyi National University of Veterinary Medicine and Biotechnologies, 1, Volodymyra Velykoho Str., UA80381 Dublyany, Lviv region, Ukraine

*Correspondence: olifir.yura@gmail.com

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Abstract. Iron, a typomorphic element of hydromorphic and semi-hydromorphic soils, significantly influences soil formation processes. Despite being relatively well studied, there is a lack of data on the content of its mobile compounds in Albic Pantostagnic Luvisol. Therefore, the study's main objective is to determine the amount, profile distribution, and seasonal dynamics of Fe compounds in a waterlogged agricultural soil subjected to different levels of long-term anthropogenic influence. Research conducted in a long-term stationary experiment shows that the composition of mobile forms of iron in Albic Pantostagnic Luvisol is dominated by the oxide form Fe³⁺. The highest Fe³⁺ content (160.6 mg kg⁻¹) was found in the humus-eluvial layer of the control soil without fertilizer, while Fe²⁺ compounds reached 46.6 mg kg⁻¹ at pH_{KCl} 4.30. Long-term application of an organo-mineral fertilization system combined with liming by hydrolytic acidity reduced the content of mobile iron compounds to 128.0 mg kg⁻¹, of which Fe²⁺ accounted for 12.64 mg kg⁻¹ at pH_{KCl} 5.45. Under an identical fertilization system with liming by pH buffering capacity, the Fe²⁺ content was 28.0 mg kg⁻¹, with a total content of 118.0 mg kg⁻¹ and pH_{KCl} of 5.54. In the natural conditions of forest and fallow land, the highest contents of mobile iron were 231.7 and 383.1 mg kg⁻¹ in the 0–20 cm horizon with a significant predominance of Fe³⁺ compounds, 210.1 and 366.3 mg kg⁻¹, respectively.

Key words: acidity, fertilizer, iron, liming, Albic Pantostagnic Luvisol.

INTRODUCTION

An important indicator of soil's chemical state, properties, and genesis is its elemental composition. Iron is one of the soil's most abundant and important components, as it can significantly influence and actively participate in soil formation processes. At the same time, iron is a necessary element for plant life. Both an excess and a deficiency of iron lead to certain plant diseases. As an element with variable

valence, its mobility changes significantly with changes in redox conditions and acidity (Tripathi et al., 2018).

Iron ranks 4th among heavy metals and is an essential trace element for numerous physiological and biochemical processes and reactions that take place in all living organisms, in particular, DNA synthesis, respiration, and photosynthesis. However, most crops' requirement for a neutral or near-neutral soil reaction to ensure maximum productivity is confronted with the problem of the limited availability of iron ions under these conditions. It is estimated that approximately 30% of the world's cultivated soils, where liming is applied to neutralize excessive acidity as part of many crop cultivation techniques, are characterized by low availability of oxidized forms of iron (Römheld & Nikolic, 2006).

High soil pH, free calcium carbonate, and low organic matter often lead to iron deficiency in plants. Currently, about one-third of the world's soils are iron-deficient, limiting plant growth and development (Wei et al., 2010).

With the change in moisture regime and the prevalence of anaerobic conditions in the soil, ferric (Fe^{3+}) forms of iron are easily converted to the active soluble ferrous form (Fe^{2+}), leading to its excess in the soil solution and disruption of plant micronutrient nutrition (Truskavetsky & Palamar, 2020). Reducing ferrous (Fe^{2+}) compound concentration improves the trace element regime, especially Cu, Zn, and Mo as Fe^{2+} antagonists (Foy, 1977).

At the same time, it should be considered that climate change alters the stability of Fe-organic compounds, affecting the weathering of Fe-containing minerals and microbial activity, which contributes to the decomposition of organic matter and the release of CO_2 (Song et al., 2022). Rising temperatures and altered moisture regimes accelerate humus mineralization and stimulate biological processes, influencing soil structure, fertility, and carbon release.

Episodes of waterlogging under changing precipitation patterns may further lower redox potential, enhancing the reduction of Fe^{3+} to Fe^{2+} and mobilizing organic matter previously stabilized by Fe (Patrick & Jugsujinda, 1992; Fuss et al., 2011). The destabilizing effect of waterlogging on Fe–organic complexes is further supported by experimental evidence from paddy soils: Sun et al. (2019) showed that within only 5 days of flooding, up to 92% of Fe^{3+} was reduced to Fe^{2+} , which markedly enhanced the decomposition of soil organic carbon and increased dissolved organic carbon concentrations more than four-fold. This confirms that Fe reduction under anaerobic conditions plays a central role in mobilizing organic matter and accelerating C losses as CO_2 and CH_4 .

Iron oxides are widely recognized for preventing the degradation of organic matter and thus supporting soil carbon storage (Li et al., 2023). However, recent findings also emphasize their dual role: while stabilizing SOC under oxic conditions, reductive dissolution under anoxia may accelerate SOC mineralization and CO_2 release (Chen et al., 2020). Moreover, climate warming may alter soil organic matter dynamics by reshaping the formation and stability of mineral–organic associations (Nguyen et al., 2019), while Fe compounds continue to act as central drivers of redox processes and nutrient availability in soils worldwide.

Free iron compounds interact with soil solution phosphates and mobile organic matter to form organo-mineral complexes inaccessible to plants (Truskavetsky et al.,

2018). The presence of organic compounds (humus) in the soil also leads to the formation of various chelates of mainly trivalent iron (Boguta et al., 2019). These forms of iron are important for plants' uptake, as they cannot assimilate trivalent Fe (Briat et al., 2005).

Iron availability to plants depends primarily on the redox potential and pH of the soil. Increases in soil redox potential and pH (including during liming) result in the transition of iron to poorly soluble forms. On the contrary, in acidic soils, Fe compounds dissolve, making metal ions available for uptake by plant roots (Zaid et al., 2017). The amount of dissolved iron increases 1,000-fold when the pH decreases by one unit (Chorna & Vahner, 2016).

According to several researchers, the concentration of soluble Fe can increase by several orders of magnitude in waterlogged soils due to low redox potential. Under such conditions, iron can enter plants, but with negative consequences for them. The anthropogenic impact of soil acidification, resulting from the intensive use of fertilisers (mainly nitrogen), increases the mobility of iron (Jones, 2020).

Despite the relatively good study of the element, there is not enough data on the content of its mobile compounds in Albic Pantostagnic Luvisol. There is a limited number of studies on changes in the content of mobile iron compounds during the growing season. Therefore, the study's main objective is to determine the amount, profile, and seasonal dynamics of Fe compounds in Albic Pantostagnic Luvisol with different levels of anthropogenic load.

According to a number of researchers, the concentration of soluble Fe can increase by several orders of magnitude in waterlogged soils due to low redox potential. Under such conditions, plants can take up iron, often with negative physiological consequences. In addition, anthropogenic soil acidification, resulting from the intensive use of fertilizers (mainly nitrogen), increases the mobility of iron (Jones, 2020).

Although iron has been relatively well studied as a chemical element, there is still insufficient information on its mobile compounds' content and seasonal behavior in Albic Pantostagnic Luvisol. This soil type is of high regional importance: in Ukraine, about 2.3 million ha are represented by light gray (Albic Luvisol) and gray forest soils (Haplic Luvisol) (Polupan et al., 2005). Similar soils are widespread across Europe (Tóth et al., 2008). Given their wide distribution and intensive agricultural use, understanding Fe transformations in these soils is essential for improving management practices such as fertilization and liming. Therefore, the main objective of this study is to determine the content, vertical distribution, and seasonal dynamics of mobile Fe compounds in Albic Pantostagnic Luvisol under different levels of long-term anthropogenic influence. We hypothesize that long-term liming and organic fertilization systems induce more substantial modifications in the amount and profile distribution of mobile iron compounds than mineral fertilization alone, thereby contributing to a more balanced soil chemical environment and improved fertility.

MATERIALS AND METHODS

This research was carried out within a long-term stationary experiment framework at the Department of Agrochemistry and Soil Science, Institute of Agriculture of Carpathian Region NAAS (49°47'54.3" N, 23°52'26.9" E), established in 1965. The

experiment is located in the Western Forest-Steppe zone of Ukraine, characterized by a moderately continental climate with a mean annual temperature of about 7.5–8.0 °C, annual precipitation of 650–700 mm, and a vegetation period of 160–180 days (Nazaruk, 2018). According to recent climatic studies, the warm period in Western Ukraine increased to 300–320 days in 1991–2010 compared with 1961–1990, reflecting a clear regional warming trend (Krakovska et al., 2023). Snow cover usually lasts about 85 days, and in early spring, the soil may become waterlogged due to snowmelt and rainfall. Depending on weather conditions, such waterlogging may persist for several days, and in wet years for several weeks.

During the study years (2022–2023), mean air temperatures were consistently above the long-term norm, with January (+2.2 °C vs –4.6 °C) and August (+21.2 °C vs +16.9 °C) showing the largest deviations. Precipitation was highly variable: exceptionally high in September 2022 (130.1 mm vs 55 mm) and July 2023 (134.0 mm vs 102 mm), but very low in May 2023 (20.3 mm vs 85 mm). These fluctuations created alternating periods of excess moisture and drought stress, influencing soil waterlogging, redox conditions, and the mobility of Fe compounds.

The stationary experiment consists of three plots, each with 18 treatments replicated three times, following a single-row sequential layout. The total plot area is 168 m² with an accounting area of 100 m². The site is situated on flat terrain, ensuring homogeneous conditions across the experimental plots.

The crop rotation follows a four-field cycle: corn for silage, spring barley sown with meadow clover, meadow clover, and winter wheat. Standard agronomic tillage and crop management practices are applied consistently across the rotation.

The soil of the experimental plot is classified as Albic Pantostagnic Luvisol (WRB, 2022). The arable layer (0–20 cm) has the following average initial fertility indicators: humus content (according to Tyurin) 1.42%, pH (KCl) 4.2, hydrolytic acidity (according to Kappen) 4.5, exchangeable acidity (according to Sokolov) - 0.6 mg eq 100 g⁻¹ soil, mobile aluminium content 60.0, mobile phosphorus (according to Kirsanov) and exchangeable potassium (according to Maslova) - 36.0 and 50.0 mg kg⁻¹ soil, respectively.

A combination of organic and mineral fertilisers was used in the study, including semi-decomposed cattle manure from straw bedding, ammonium nitrate (34.5%), granulated superphosphate (19.5%), potassium salt (40%), and nitroammophoska (NPK 16%) (with NPK levels balanced according to the application of simple fertilisers). Manure application ranged from 40 to 60 tonnes per hectare under corn. Phosphorus-potassium fertilisers were applied in the autumn, while nitrogen fertilisers were applied before sowing.

Liming treatments were carried out according to the experimental protocol before the start of the 10th rotation (2016) within the crop cycle, with fertiliser doses adjusted accordingly. Limestone powder (93.5% CaCO₃) was used as the liming material. Starting from the 8th rotation (2008), the second mowing of meadow clover was integrated as an organic fertiliser in all experimental treatments.

The changes in the levels of mobile iron compounds were studied within the embedded soil profiles under the forest canopy, within the fallow areas, and within the most representative treatments of the stationary experiment during the 11th rotation. These treatments included: a control with no fertilisation (C), an organo-mineral fertilisation system (10 tonnes per hectare of manure + N₆₅P₆₈K₆₈) together with periodic

liming with 1.0 n CaCO₃ per hectare (equivalent to 6.0 tonnes per hectare of limestone flour) (OM1), an identical fertilisation system with liming using a pH buffering capacity (2.5 tonnes per hectare) (OM2), mineral fertilisation systems (N₁₀₅P₁₀₁K₁₀₁) with liming using 1.5 n CaCO₃ based on hydrolytic acidity (equivalent to 9.0 tonnes per hectare of limestone flour) (M1), a lime dose calculated by pH buffering capacity (2.5 tonnes per hectare) (M2) and a mineral fertilisation system (N₆₅P₆₈K₆₈) (M) (Table 1).

Table 1. Scheme of the studied treatments of the stationary field experiment (11th rotation)

Fertilization system		Per 1 ha of crop rotation area			Corn for silage	Spring barley + meadow clover	Mea-dow clover	Winter wheat
		rate of lime	Manure, t	NPK, kg of active substance				
Without fertilizers (control)	C	0	0	0	0	0	0	0
Organo-mineral with liming	OM1	1.0 norm by hydrolytic acidity (6.0 t ha ⁻¹)	10	N ₆₅ P ₆₈ K ₆₈	Manure, 40 t ha ⁻¹ + N ₁₂₀ P ₉₀ K ₉₀	N ₇₀ P ₉₀ K ₉₀	0	N ₇₀ P ₉₀ K ₉₀
	OM2	Optimal by the acid-base buffering capacity (2.5 t ha ⁻¹)	10	N ₆₅ P ₆₈ K ₆₈	Manure, 40 t ha ⁻¹ + N ₁₂₀ P ₉₀ K ₉₀	N ₇₀ P ₉₀ K ₉₀	0	N ₇₀ P ₉₀ K ₉₀
Mineral	M	0	0	N ₆₅ P ₆₈ K ₆₈	N ₁₂₀ P ₉₀ K ₉₀	N ₇₀ P ₉₀ K ₉₀	0	N ₇₀ P ₉₀ K ₉₀
Mineral with liming	M1	1.5 norms by hydrolytic acidity (9.0 t ha ⁻¹)	0	N ₁₀₅ P ₁₀₁ K ₁₀₁	N ₁₈₀ P ₁₃₅ K ₁₃₅	N ₁₂₀ P ₁₃₅ K ₁₃₅	0	N ₁₂₀ P ₁₃₅ K ₁₃₅
	M2	Optimal by acid-base buffering capacity (2.5 t ha ⁻¹)	0	N ₁₀₅ P ₁₀₁ K ₁₀₁	N ₁₈₀ P ₁₃₅ K ₁₃₅	N ₁₂₀ P ₁₃₅ K ₁₃₅	0	N ₁₂₀ P ₁₃₅ K ₁₃₅

Soil samples were collected from Albic Pantostagnic Luvisol and prepared for analysis according to DSTU ISO 11464-2001. The soil profile at the experimental site is characterized by a sequence of gleyic horizons. In the control treatment (without fertilizers), the profile consisted of an arable AEG horizon (0–0.18 m) underlain by a sub-arable AEG horizon (0.18–0.31 m), followed by an eluvial horizon Ehg (0.31–0.64 m). Below, the illuvial horizons Beg (0.64–1.10 m) and Bg (1.10–1.31 m) were observed, gradually transitioning into BCg (1.31–1.80 m) and CBg (1.80–2.00 m). Under long-term fertilization and liming, the thickness of individual horizons varied slightly: for example, the AEG horizon extended to 0.20–0.22 m, while the boundaries of eluvial and illuvial horizons shifted by several centimeters, reflecting modifications in soil structure and redox status (Olifir, 2021). Representative photographs of soil profiles under natural forest, unfertilized control, and long-term organo-mineral fertilization (OM1) are presented in Fig. 1.

For analytical purposes, composite soil samples were collected from standard depth intervals of 0–20 cm, 20–35 cm, and 35–50 cm, corresponding to the arable layer, the sub-arable layer, and the upper part of the eluvial horizon. Sampling was conducted from

three replicate plots for each treatment, with two replicates per plot. Within each plot, five subsamples were taken diagonally across half of the accounting area (50 m²) and pooled to obtain one composite sample. In total, each treatment was represented by six composite samples. All laboratory determinations (pH, Fe²⁺, Fe³⁺, and mobile Fe) were duplicated to ensure analytical reliability.

Soil pH was determined potentiometrically in a 1:2.5 soil to 1.0 N KCl suspension using a 'pH-301' pH meter with glass electrodes, according to DSTU ISO 10390:2001.

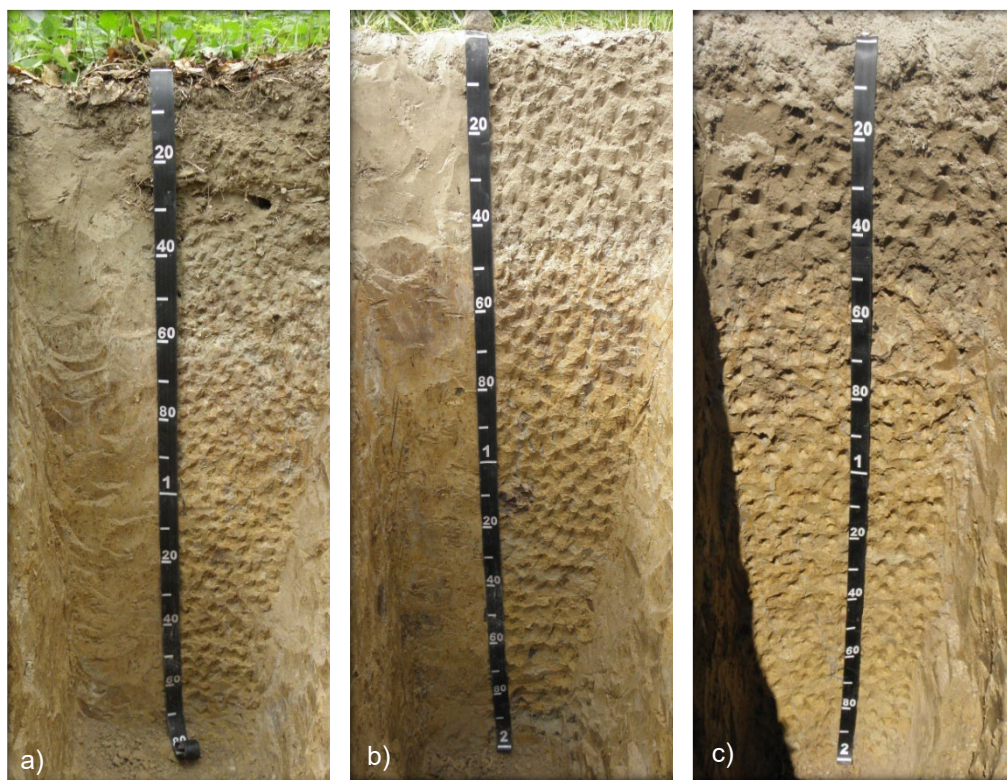


Figure 1. Soil profiles of Albic Pantostagnic Luvisol under different land use and management conditions: a) natural forest; b) control (no fertilization); c) organo-mineral fertilization system (OM1).

Mobile divalent and trivalent iron compounds were quantified according to DSTU 7913:2015, using an extract of 0.1 N sulphuric acid. The subsequent determination of divalent iron and total iron in the extracts (after the reduction of trivalent iron to divalent iron with hydroxylamine) was performed by photocolorimetric analysis using o-phenanthroline. The soil:extractant ratio was maintained at 1:10.

The obtained research data were analyzed using OriginPro 2019b software (OriginLab Corporation, USA, 2019). Data presented in tables as arithmetic means.

RESULTS AND DISCUSSIONS

Most soils contain sufficient amounts of iron to meet the requirements of plant growth and development, but chemical and environmental factors reduce its availability and lead to inhibited uptake or use by plants (Jones, 2020). Although the total Fe content of soils is usually high, the amount of available Fe is usually very low and is determined by the low solubility of Fe oxides (Colombo et al., 2014). Therefore, under a stationary experiment, we studied the changes in the content of mobile forms of iron during long-term periodic liming and fertilisation and compared them with similar indicators in a natural state on fallow land and under a forest.

The observations show that in the composition of mobile iron in the Albic Pantostagnic Luvisol, its oxidised form predominates, while divalent iron is much less abundant. This regularity is observed in all of the experimental treatments. Thus, the dynamics of changes in the content of mobile forms of iron according to the experiment in the spring period show that their highest amount of 207.2 mg kg⁻¹ of soil is observed in the humus-eluvial layer of the soil (0–20 cm) in the control without fertilisers. This includes Fe²⁺ compounds with 46.6 mg kg⁻¹ and Fe³⁺ with 160.6 mg kg⁻¹ of soil at a pH_{KCl} of 4.30. Subsequently, the content of Fe²⁺ compounds decreases to 8.2 mg kg⁻¹ in the subsoil layer (20–35 cm) and further to 7.00 mg kg⁻¹ in the eluvial-low humus horizon (Table 2).

Table 2. Dynamics of the content of mobile iron compounds in Albic Pantostagnic Luvisol in spring under different fertilisation systems, XI rotation, mg kg⁻¹ ($n = 6$)

	Soil layer, cm	C	OM1	OM2	M	M1	M2	Fallow	Forest
Fe ²⁺	0–20	46.6 ^a	12.6 ^b	12.8 ^b	18.1 ^{bc}	21.3 ^c	20.1 ^{bc}	16.8 ^{bc}	21.6 ^c
	20–35	8.2 ^a	11.4 ^{ad}	12.2 ^{ac}	18.3 ^b	19.2 ^b	17.7 ^{bc}	9.6 ^{ad}	14.3 ^{bcd}
	35–50	7.0 ^a	8.8 ^{ab}	11.7 ^{bc}	13.7 ^{cd}	15.8 ^d	14.9 ^{cd}	7.5 ^a	9.4 ^{ab}
Fe ³⁺	0–20	160.6 ^a	115.0 ^{bc}	104.9 ^b	128.1 ^c	105.1 ^b	99.0 ^b	366.3 ^d	210.1 ^c
	20–35	107.2 ^{ab}	104.6 ^{ab}	101.6 ^{ab}	123.9 ^a	114.7 ^{ab}	85.7 ^b	236.6 ^c	131.9 ^a
	35–50	106.9 ^a	93.9 ^{ac}	99.2 ^a	128.2 ^b	103.7 ^a	80.1 ^c	166.1 ^d	106.4 ^a
Total	0–20	207.2 ^a	127.6 ^b	117.7 ^b	146.2 ^c	126.4 ^b	119.1 ^b	383.1 ^d	231.7 ^c
	20–35	115.4 ^{ac}	116 ^{abc}	113.8 ^{abc}	142.2 ^{abc}	133.9 ^{bc}	103.4 ^c	246.2 ^d	146.2 ^c
	35–50	113.9 ^{ac}	102.7 ^{ad}	110.9 ^{ac}	141.9 ^b	119.5 ^c	95 ^d	173.6 ^e	115.8 ^{ac}
pH _{KCl}	0–20	4.30 ^a	5.45 ^b	5.54 ^b	4.35 ^a	5.23 ^{bc}	5.02 ^c	4.17 ^a	3.54 ^d
	20–35	4.21 ^a	5.35 ^b	5.57 ^c	4.15 ^a	5.52 ^{bc}	5.06 ^d	4.11 ^a	3.80 ^e
	35–50	4.20 ^a	5.60 ^b	5.43 ^c	4.28 ^a	5.42 ^c	5.32 ^c	4.03 ^d	3.85 ^e

Note: values labeled with the same letter are not significantly different from each other according to the results of comparison using the Tukey test ($p < 0.05$) within the same soil layer.

According to Patra et al. (2021), the availability of Fe to plants is influenced by soil reaction, the amount of soil organic matter, soil aeration, and the presence or absence of other macro- and microelements.

In the long-term and systematic application of the mineral fertiliser system (M) with a pH_{KCl} of 4.35, the total concentration of mobile iron compounds in the fertile topsoil reaches 146.2 mg kg⁻¹ soil. Of this, 128.1 mg kg⁻¹ consists of mobile trivalent iron compounds. Previous studies conducted under similar conditions with Albic

Pantostagnic Luvisol have shown that this mineral fertiliser system significantly increases hard-to-reach iron phosphate. Compared to the unfertilised control, the concentration increases by 1.9–2.5 times, reaching 562.0 mg kg⁻¹ soil compared to 280.0 mg kg⁻¹ in the unfertilised control (Habryiel et al., 2006).

A significant content of mobile forms of iron, including Fe²⁺ in the control, is because under conditions of high acidity of the soil solution (in this treatment the pH of the solution was 4.2) and a lack of calcium and magnesium (Ca content 1.8–2.0 mg-eq 100 g⁻¹ soil and mg content 0.42–0.52 mg-eq 100 g⁻¹ soil) the mobility of iron increases. Under these conditions, the content of mobile iron can increase to 175.0 mg kg⁻¹ and more.

Finally, it is known that one of the important properties of iron is its ability to change its valence depending on the soil regime. Under aerobic conditions, it is a trivalent oxide (Fe₂O₃) - practically insoluble in water, and under anaerobic conditions, it is divalent (FeO) and is the most soluble and mobile (Pankiv et al., 2023).

It should also be considered that high availability of Fe in soils can lead to toxic effects when excessive iron uptake damages cellular structures, resulting in reduced plant growth and leaf damage (Ayeeni et al., 2014).

Studies have shown that the stability of Fe in soils is closely related to the presence of organic carbon (Lalonde et al., 2012). As an electron donor, organic matter facilitates microbial dissimilatory reduction of Fe, leading to the dissolution of soil Fe³⁺ hydroxides and possibly the release of Fe²⁺ ions (Tittel et al., 2022). Therefore, the higher organic matter content caused by the application of organic fertilisers increases the mobility and solubility of Fe through the reduction reaction. In fact, the reduced form of Fe (Fe²⁺) is more mobile than the oxidised form, which increases plant uptake and facilitates leaching (Fuss et al., 2011).

In the organo-mineral fertilisation system combined with liming with 1.0 n CaCO₃ based on hydrolytic acidity (OM1), the total concentration of mobile iron compounds decreases to 127.6 mg kg⁻¹ soil during the period indicated. Within this, the concentration of Fe²⁺ compounds is 12.6 mg kg⁻¹ soil at a pH_{KCl} of 5.45. Conversely, within an identical fertilisation and liming system using the pH buffering capacity (OM2), the concentration of Fe²⁺ compounds is slightly higher at 12.8 mg kg⁻¹ soil, while the total content of mobile iron compounds decreases to 117.7 mg kg⁻¹ soil at a pH_{KCl} of 5.54. In the scenario of liming with a dosage of CaCO₃ based on pH buffering capacity alongside a mineral fertilisation system (M2), the concentration of Fe²⁺ compounds is recorded at 20.1 mg kg⁻¹ soil at a pH_{KCl} of 5.02, compared to 21.3 mg kg⁻¹ soil within an identical fertilisation system supplemented with 1.5 n CaCO₃ based on hydrolytic acidity (M1) (pH_{KCl} 5.23).

It is known that liming increases the pH value of the soil, which accordingly affects its physical, chemical, and biological characteristics (Čop, 2015). Ghorashi et al. (2016) showed that lime application reduced iron concentration and iron uptake by plants compared to unamended soil by improving the response of acidic soils and increasing the calcium and magnesium content of the soil.

Under natural conditions of soil formation, in particular, under the forest, the content of mobile compounds Fe²⁺ is 21.6 mg kg⁻¹ of soil, decreasing in the horizon more than 35 cm to 9.4 mg kg⁻¹, with the total content of compounds Fe²⁺ + Fe³⁺ - 231.7 mg kg⁻¹ of soil and 115.8 in the horizon more than 35 cm. On the fallow, the total

content of mobile iron compounds is 383.1 mg kg⁻¹ of soil, including the content of mobile iron oxide compounds 6.8 mg kg⁻¹, decreasing to 7.5 mg kg⁻¹ of soil below 35 cm.

In all treatments of the experiment, there was a consistent tendency for higher accumulation of mobile iron compounds in the humus-eluvial layer (0–20 cm). This pattern can be explained by the higher content of soil organic matter and more intensive biological activity in the topsoil, which provides favourable conditions for forming and stabilizing organo-ferrous complexes. The enrichment of the surface horizon with mobile Fe is of particular importance, as it directly influences nutrient cycling, redox processes, and the availability of iron to plants. Therefore, maintaining and preserving the humus-eluvial layer is essential for sustaining soil fertility and preventing degradation under long-term agricultural use.

Our findings are consistent with well-established mechanisms of organo-metal interactions in soils. Organic matter in surface horizons is a key sorbent for Fe, facilitating the formation of stable Fe-organic complexes, as demonstrated in temperate soils (Wagai & Mayer, 2007). The elevated concentrations of mobile Fe observed in our humus-eluvial horizon indicate the presence of reactive Fe species capable of interacting with dissolved organic matter. Previous studies demonstrated that DOM is strongly and often irreversibly sorbed onto Fe and Al oxyhydroxides, especially through aromatic functional groups, thereby reducing degradability and promoting long-term SOM stabilization (Kaiser & Guggenberger, 2000). This suggests that mobile Fe in our soils serves as an important pool of reactive species contributing to the development of stable Fe-organic associations.

Such associations play a central role in SOC stabilization (Wagai & Mayer, 2007), and organo-mineral complexes with Fe and Al remain key retention forms of organic matter even under land-use change (Mikutta et al., 2009). Further mechanistic insights are provided by Wen et al. (2019), who showed that long-term organic amendments significantly increase poorly crystalline Fe concentrations, closely linked to enhanced SOC storage. The proposed mechanisms include co-precipitation of DOM with Fe, inhibition of Fe crystallization by aromatic constituents, and microbial shifts that favour the retention of reactive Fe. These processes reinforce a positive feedback loop in which organic inputs sustain reactive Fe, which in turn stabilizes SOC. Together, this evidence underscores the ecological importance of the humus-eluvial horizon as a critical soil compartment for both agricultural productivity and carbon sequestration under changing climate conditions.

Observations of the dynamics of changes in mobile iron compounds in Albic Pantostagnic Luvisol by seasons showed that the highest number of mobile iron compounds is precisely in the spring period at a humidity of 15.3–17.8% (Table 2–4). It is known that in the spring, regenerative processes start in the soil due to the melting of snow and an increase in its humidity. The highest content of mobile forms of Fe is in the spring period in the control without fertiliser. The lowest effect of fertiliser on the content of mobile iron compounds according to the experimental treatments was observed in autumn (Table 3).

In acidic unsaturated soils, the role of iron is compared to the role of calcium in chernozems, as it performs a number of important functions and serves as a basis for the diagnosis of soil formation processes (Pankiv et al., 2023).

The studies have shown that the Albic Pantostagnic Luvisols under the forest and on the fallow land have not lost their connection with other components of the landscape, all processes and properties correspond to the natural factors of soil formation. The highest amount of mobile iron compounds occurs in the humus-eluvial horizon of 0–20 cm, and the lowest in the eluvial low-humus horizon of 35–50 cm.

Table 3. Dynamics of the content of mobile iron compounds in Albic Pantostagnic Luvisol in summer under different fertilisation systems, 11th rotation, mg kg⁻¹ (*n* = 6)

	Soil layer, cm	C	OM1	OM2	M	M1	M2	Fallow	Forest
Fe ²⁺	0–20	13.1 ^a	14.5 ^a	18.6 ^b	5.2 ^c	4.1 ^c	5.3 ^c	19.8 ^b	34.9 ^d
	20–35	10.9 ^a	12.9 ^a	13.6 ^a	4.4 ^b	4.4 ^b	5.0 ^b	20.7 ^c	32.3 ^d
	35–50	9.7 ^{ab}	10.1 ^a	9.6 ^b	21.3 ^c	3.2 ^d	4.3 ^d	11.7 ^a	16.8 ^c
Fe ³⁺	0–20	67.5 ^{ac}	54.1 ^b	55.9 ^{bc}	57.3 ^{bc}	38.7 ^d	32.7 ^d	158.0 ^c	74.1 ^a
	20–35	55.7 ^a	46.0 ^b	56.6 ^a	40.4 ^{bc}	33.0 ^d	33.2 ^{cd}	100.0 ^c	46.0 ^b
	35–50	57.7 ^a	39.3 ^b	50.7 ^c	10.8 ^d	26.0 ^c	31.2 ^f	79.7 ^g	36.9 ^b
Total	0–20	80.6 ^a	68.6 ^{ab}	74.5 ^{ab}	62.5 ^b	42.8 ^c	38.0 ^c	177.8 ^d	109.0 ^c
	20–35	66.6 ^{ab}	58.9 ^a	70.2 ^{bc}	44.8 ^c	37.4 ^c	38.2 ^c	120.7 ^d	78.3 ^c
	35–50	67.4 ^a	49.4 ^b	60.3 ^c	32.1 ^{de}	29.2 ^d	35.5 ^e	91.4 ^f	53.7 ^g
pH _{KCl}	0–20	4.19 ^a	5.40 ^b	5.52 ^b	4.54 ^c	4.70 ^c	4.90 ^d	4.07 ^a	3.21 ^e
	20–35	4.01 ^a	5.17 ^b	5.23 ^b	4.20 ^a	4.90 ^c	5.06 ^{bc}	4.09 ^a	3.48 ^d
	35–50	3.94 ^a	5.22 ^b	5.10 ^b	4.00 ^a	4.71 ^c	5.10 ^b	4.00 ^a	3.53 ^d

Note: values labeled with the same letter are not significantly different from each other according to the results of comparison using the Tukey test (*p* < 0.05) within the same soil layer.

The seasonal alternation of wet and dry cycles alters the redox conditions of soils and soil solutions, affecting the mobility of their components due to different solubilities, including Fe (Gangloff et al., 2016). In the summer months, the amount of mobile iron compounds in the soil under the forest is the lowest and amounts to 109.0 mg kg⁻¹ of soil with a predominance of Fe³⁺ content up to 74.1 mg kg⁻¹ against 34.9 mg kg⁻¹ of soil of Fe²⁺. Instead, in autumn, the amount of mobile compounds increases slightly to 120.0 mg kg⁻¹ of soil with a significant predominance of Fe³⁺ - 104.7 mg kg⁻¹ of soil and 15.4 mg kg⁻¹ of soil of Fe²⁺. In general, trivalent iron predominates in the composition of mobile iron compounds under the forest, on the fallow land, and in experimental treatments.

As in the case of the experimental treatments, the number of mobile iron compounds on the fallow land is highest in the 0–20 cm soil layer and gradually decreases up to the 35–50 cm horizon. On the fallow, the highest content of mobile iron compounds is 383.1 mg kg⁻¹ of soil in the humus-eluvial horizon 0–20 cm in spring, decreasing to 167.8 in summer and to 130.2 mg kg⁻¹ of soil in autumn with a strong predominance of Fe³⁺ compounds.

Research in a long-term stationary experiment has shown that the gross content of mobile iron compounds and their mobile forms in Albic Pantostagnic Luvisol is within the optimal level. However, in the case of long-term (more than 50 years) inclusion of Albic Pantostagnic Luvisol with an initial pH_{KCl} of 4.2 into the agricultural system without the addition of fertilisers and lime, the content of mobile iron in the humus-eluvial horizon increases to 207.2 mg kg⁻¹ (including the content of Fe²⁺

compounds 46.6 and Fe^{3+} 160.6 mg kg^{-1}). As a result, in such conditions, the nutrient iron can turn from a trace element into a toxic substance, which worsens the conditions of trace element nutrition and reduces the productivity of crops.

Table 4. Dynamics of the content of mobile iron compounds in Albic Pantostagnic Luvisol in autumn under different fertilisation systems, 11th rotation, mg kg^{-1} ($n = 6$)

	Soil layer, C cm	OM1	OM2	M	M1	M2	Fallow	Forest	
Fe ²⁺	0–20	1.5 ^a	5.9 ^b	10.5 ^c	8.7 ^d	3.1 ^c	3.8 ^e	6.6 ^b	15.4 ^f
	20–35	1.8 ^{ad}	7.3 ^{bc}	8.8 ^{be}	9.6 ^{be}	5.2 ^c	4.6 ^{cd}	7.6 ^{bc}	11.0 ^e
	35–50	1.7 ^a	6.6 ^{bc}	6.6 ^{bc}	9.4 ^b	4.1 ^{ac}	5.5 ^{cd}	5.9 ^{cd}	7.9 ^{bd}
Fe ³⁺	0–20	47.9 ^a	43.9 ^a	56.5 ^b	43.4 ^a	32.7 ^c	35.6 ^c	123.6 ^d	104.6 ^c
	20–35	50.2 ^a	34.3 ^{bd}	41.7 ^{bc}	45.8 ^{ac}	32.1 ^d	31.8 ^d	99.9 ^e	44.0 ^{ac}
	35–50	59.5 ^a	37.0 ^{bd}	39.3 ^{bd}	58.8 ^a	31.1 ^b	29.8 ^b	73.1 ^c	44.8 ^d
Total	0–20	49.4 ^a	49.8 ^a	67.0 ^b	52.1 ^a	35.8 ^c	39.4 ^c	130.2 ^d	120.0 ^c
	20–35	52.0 ^a	41.6 ^{bc}	50.5 ^{ab}	55.4 ^a	37.3 ^c	36.4 ^c	107.5 ^d	55.0 ^a
	35–50	61.2 ^{ac}	43.6 ^{bc}	45.9 ^b	68.2 ^a	35.2 ^c	35.3 ^c	79.0 ^d	52.7 ^{be}
pH _{KCl}	0–20	4.40 ^a	5.07 ^b	5.28 ^c	4.40 ^a	5.10 ^b	4.98 ^b	4.23 ^d	3.80 ^e
	20–35	4.30 ^a	5.10 ^{bc}	5.17 ^b	4.26 ^a	5.30 ^b	4.96 ^c	4.25 ^a	3.96 ^d
	35–50	4.39 ^a	4.98 ^b	5.27 ^c	4.29 ^d	5.46 ^c	5.10 ^f	4.28 ^d	3.91 ^g

Note: values labeled with the same letter are not significantly different from each other according to the results of comparison using the Tukey test ($p < 0.05$) within the same soil layer.

With the long-term application of a mineral fertiliser system on Albic Pantostagnic Luvisol with a pH_{KCl} of 4.35, the content of mobile iron compounds in the humus-eluvial horizon in spring is 146.0 mg kg^{-1} soil, which is lower than the control without fertiliser. This is despite the additional application of 5,550 mg kg^{-1} of superphosphate and 454 mg kg^{-1} of iron with potassium chloride according to Shahid et al. (2016). The systematic use of mineral fertilisers increases the content of poorly soluble iron and aluminium phosphates that are inaccessible to plants. This led to a decrease in mobile iron compounds in this treatment.

In the summer months, the amount of mobile iron compounds in the soil under the forest is the lowest and amounts to 109.0 mg kg^{-1} of soil with a predominance of Fe^{3+} content up to 74.1 mg kg^{-1} against 34.9 mg kg^{-1} of soil of Fe^{2+} . Instead, in autumn, the amount of mobile compounds increases slightly to 120.0 mg kg^{-1} of soil with a significant predominance of Fe^{3+} – 104.7 mg kg^{-1} of soil and 15.4 mg kg^{-1} of soil of Fe^{2+} . In general, trivalent iron predominates in the composition of mobile iron compounds under the forest and on the fallow land as well as in the experimental treatments.

As in the case of the experimental treatments, the number of mobile iron compounds on the fallow land is highest in the 0–20 cm soil layer and gradually decreases up to the 35–50 cm horizon. On the fallow, the highest content of mobile iron compounds is 383.1 mg kg^{-1} of soil in the humus-eluvial horizon 0–20 cm in spring, decreasing to 167.8 in summer and to 130.2 mg kg^{-1} of soil in autumn with a strong predominance of Fe^{3+} compounds.

Research in a long-term stationary experiment has shown that the gross content of mobile iron compounds in Albic Pantostagnic Luvisol is within the optimal level. However, in the case of long-term inclusion of Albic Pantostagnic Luvisol with an initial

pH_{KCl} of 4.2 into the agricultural system without the addition of fertilisers and lime, the content of mobile iron in the humus-eluvial horizon increases to 207.2 mg kg⁻¹ (including the content of Fe²⁺ compounds 46.6 and Fe³⁺ 160.6 mg kg⁻¹). As a result, in such conditions, the nutrient iron can turn from a trace element into a toxic substance, which worsens the conditions of trace element nutrition and reduces the productivity of crops.

During the long-term application of the mineral fertiliser system at the pH_{KCl} of 4.35 on the Albic Pantostagnic Luvisol, the content of mobile iron compounds in the humus-eluvial horizon in spring is 146.0 mg kg⁻¹ of soil, of which Fe²⁺ compounds are 18.1 mg kg⁻¹. This is due to the fact that, according to Shahid et al. (2016), 5,550 mg kg⁻¹ of iron is applied with superphosphate and 454 mg kg⁻¹ of iron is applied with potassium chloride, which increases the content of this element in the soil.

Previous studies in a long-term stationary experiment indicate that it is the high toxicity of aluminium in the conditions of the Albic Pantostagnic Luvisol with a low concentration of magnesium and calcium ions that manifests the most harmful effect of soil acidity on the environment (Olifir et al., 2023). Research by experimental treatments and under natural conditions of soil formation under the forest and on the fallow land shows that the gross content of iron compounds and their mobile forms are within the optimal level in the Albic Pantostagnic Luvisol. Only in the long-term (50 years) use of this soil without fertilization (which is rare in production), iron, as a nutrient, can turn into a toxic substance that affects micronutrient nutrition. However, it is known that the limit values of iron content in soils are not legal norms and are not the main topic of discussion among scientists, since Fe is not a direct soil pollutant (Murtić et al., 2019).

CONCLUSIONS

The research under the conditions of a long-term stationary experiment demonstrated that in the composition of mobile iron in waterlogged Albic Pantostagnic Luvisol, the oxidized form (Fe³⁺) predominates. The maximum content of mobile Fe compounds was 207.2 mg kg⁻¹ in the unfertilized control, recorded in the humus-eluvial arable horizon (0–20 cm) at pH_{KCl} 4.30, of which mobile Fe²⁺ accounted for 46.6 mg kg⁻¹. Across all treatments, there was a consistent tendency for higher accumulation of mobile Fe in the humus–eluvial horizon, underlining the critical importance of this soil layer for nutrient cycling, redox processes, and soil fertility. Preserving and sustainably managing the organic-rich surface horizon is therefore essential for preventing degradation and maintaining productivity in acid soils under long-term agricultural use.

In the mineral fertiliser treatment, the content of mobile Fe compounds is significantly lower than in the no-fertiliser control, which is caused by a significant amount of iron supplied with mineral fertiliser. The greatest amount of mobile iron in the Albic Pantostagnic Luvisol is extracted in the spring, during the recovery of the winter wheat vegetation, at a moisture content of 15.3–17.8%.

In the treatments of organo-mineral and mineral fertilisation plus liming, both in terms of hydrolytic acidity and pH-buffering capacity, the total content of mobile Fe compounds, as well as Fe²⁺ compounds, does not differ significantly, which indicates

the economic feasibility and environmental safety of using a dose of lime on Albic Pantostagnic Luvisol, calculated by pH-buffering capacity.

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Psychosocial work environment risks for museum workers in Latvia

I. Priede¹, Z. Roja¹, H. Kalkis^{1,2,*} and B. Sloka^{1,2}

¹University of Latvia, Faculty of Medicine and Life Sciences, Department of Human Factors and Work Environment, Jelgavas street 1, LV-1004 Riga, Latvia

²University of Latvia, Faculty of Economics and Social Sciences, Department of Management Science, Aspazijas blvd. 5, LV-1050 Riga, Latvia

*Correspondence: henrijs.kalkis@lu.lv

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Abstract. In Latvia, as elsewhere in the world, psychosocial risks at work are considered to be a topical occupational risk in every sector of the economy, including the cultural sector. The aim of this study was to investigate the psychosocial risks of the working environment for museum workers in Latvia. The study involved 303 respondents from different museums in Latvia. A staff survey was conducted, and psychosocial risks at work were assessed using the short version of The Copenhagen Psychosocial Questionnaire - COPSOQ III. The survey found that 73–77% of museum employees are women, with about a quarter of respondents reporting working more than 40 hours per week. Work is often performed in a forced posture, 28.1% of respondents complain of overwork, 70.3% of respondents report an unsuitable working environment, almost half of respondents indicate that they are exposed to harmful chemicals at work, and almost all employees report low pay. The results of the COPSOQ survey show that the main reasons why the majority of respondents have chosen to work in the existing museum are: the support of colleagues, a good atmosphere, the opportunity to use knowledge and skills, as well as the meaning of work. Future research will focus on using cognitive tests to better understand the psychosocial risks faced by museum workers.

Key words: COPSOQ, museums, psychosocial risks, work environment.

INTRODUCTION

Psychosocial risks at work are identified as major concerns to occupational health and safety (Roussos, 2023). These risks at work have a serious economic impact on all types of enterprises, regardless of their size and sector (Leka et al., 2011). In Latvia, psychosocial risks at work are also considered to be important workplace risks in every sector of the economy, including the cultural sector.

According to the International Labour Organisation definition, psychosocial risks are interactions between the work environment, work content, organisational conditions and employees' abilities, needs, culture, personal considerations, which through perception and experience can affect health, work performance and work satisfaction

(International Labour Organization - ILO, 1986; Oakman et al., 2022). These risks include the culture and functions of the organisation, their role in the organisation, the workload and pace of work, and the relationships between employees. Ongoing changes at work, such as downsizing, outsourcing, the rapidly increasing use of information and communication technologies, flexible work schedules, demand for knowledgeable and skilled employees, shift work, lack of work experience, etc., create new psychosocial risks in organisations and have a drastic impact on the psychological health of employees (Dragano & Lunau, 2020; Rick & Brimner, 2000). The most common psychological health disorders are stress-related disorders. The spectrum of stress-related harm is quite broad. It includes insomnia, anxiety, migraine, stomach ulcers, diabetes, allergies, skin diseases, oncological diseases, headaches, back pain, joint pain, accidents, suicides (Sohail, et al., 2015; Roja et al., 2016). The sudden introduction of new working patterns often causes stress for employees (Di Tecco et al., 2023; Pavlista et al., 2024). Scientists have proved that long working hours have a negative impact on sleep and sleep quality (Leka & Jain, 2010). Particular attention is paid to cardiovascular diseases caused by stress at work (high blood pressure, atherosclerosis, ischaemic heart disease, etc.), depression and consequent work-related unproductivity. Employees' contribution at work is often not properly valued. Imbalances between employees' contribution at work and its material rewards have been shown to increase the risk of cardiovascular diseases and affect mental health (Peter & Siegrist, 1999; Belkic et al., 2004; Van Veldhoven et al., 2005). Unstable or insecure employment, including contract work, short-term contracts, can also cause stress, fatigue, back and muscle pain, accidents, can impair mental health and have a negative impact on the employee's behaviour (Leka & Jain, 2010; Backhaus et al., 2023). This is also confirmed by the International Labour Organisation, which points out that, according to studies, psychosocial risks at work not only cause serious physical and mental health problems for employees, but also undermine the image of the organisation and productivity in general (ILO, 2014).

The main psychosocial risks for museum staff are: high workload and time pressure, emotionally stressful environment, work-life imbalance and inequality between colleagues (Iordache et al., 2022). Museum workers are also exposed to other risks, the most common of which are dust, mould, pesticides, heavy metals, organic solvents, noise, microclimatic fluctuations, forced working postures, visual and bodily strain, which are often amplifiers of psychosocial risks (Lindstrom & Mantysalo, 1987; Bliese et al., 2017; Klicker-Wiechmann et al., 2022). Several researchers have shown that psychosocial risks at work contribute to work related musculoskeletal disorders - WRMSD-s (Gómez-Galán et al., 2017; Chen et al., 2022). For museum staff, the daily working environment could be emotionally stressful, as staff often engage in an exciting but self-traumatising presentation of exhibits (Hardin, 2020). Working in emergency situations such as war, floods, earthquakes could cause anxiety, anger, denial, guilt, sadness and other negative feelings (Kennedy & Lockshin, 2022). Research shows that a well-organised physical and psychosocial environment improves performance and personal development, as well as the mental and physical well-being of employees (Pastare et al., 2020; Kalkis et al., 2024; Lundqvist et al., 2024).

The aim of this study was to investigate the psychosocial risks for employees working in Latvian museums.

MATERIALS AND METHODS

1. A questionnaire was developed and applied. Respondents were briefed on the purpose of the study. They were guaranteed confidentiality and anonymity. The questionnaire was voluntary. The questions were semi-open-ended, giving respondents the option to tick one of the answers given or to write their answer in the 'other' section. At the end of the questionnaire, respondents had the opportunity to write a comment on the questions in free text. Respondents answered questions related to gender, age, profession, length of service in the profession, location of the museum in Latvia, job duties to be performed in the museum. The questionnaire included questions about risks in the work environment, working hours, weekend work, behavioural habits and leisure activities (smoking/non-smoking, drinking/non-drinking, daily physical activities and for how long).

2. The closed-ended questionnaire was The Copenhagen Psychosocial Questionnaire, developed by researchers at the Danish National Centre for Work Environment Research. Short, medium and long versions of this questionnaire are available, as well as national validated versions which necessarily include questions from the short version and some of the questions from the medium or long version. The questions in the short version are mandatory and the questionnaire can be supplemented with questions from the medium or long version as needed. The survey is anonymous, must ensure the protection of respondents' data and is voluntary (Llorens-Serrano et al., 2019). Since 2007, the COPSOQ survey has been maintained and developed by the COPSOQ International network in Germany. As of 2019, a third version of the survey, COPSOQ III, is available. The third version takes into account current trends in the work environment (e.g., work-life conflict, instability), integrates concepts and international experience with the questionnaire (Burr et al., 2019). Respondents are given the option to choose one of five answers. Answers to questions or statements on the scale are scored from 0 to 100 (0, 33.3, 66.7 and 100 points). The total value is the average of the answers given by the respondents (Llorens-Serrano et al., 2019).

In our study, to find out the most important psychosocial factors of the working environment for museum workers, respondents completed the short version of the COPSOQ which contains 32 statements. In this short version, respondents were asked to choose one of five response options, which are converted to a score of 100, 75, 50, 25 or 0 when the results are evaluated. Among the questions from the long version of the questionnaire, questions on self-rated health, sleep disturbances, burnout, stress, somatic stress, cognitive stress and depressive symptoms were included, as well as self-efficacy experienced by respondents in the last four weeks. Respondents in the short version of COPSOQ III had to choose such possible answers: not applicable to me (0), slightly applicable to me (33.3), partially applicable to me (66.7) and fully applicable to me (100), except in the health self-assessment, where health should be rated on a Likert scale from 0 to 10.

3. The selection criteria in our study was full consent to participate, work in full-time, no psychosocial risk impact on health (mandatory health check-up results), comprehension of psychosocial hazards in the workplace.

The data collected were electronically entered into data tables using Microsoft Excel and IBM SPSS Statistic 21.0 software. Data processing was carried out using descriptive statistical methods, frequency analysis and cross-tabulation with chi-square test of independence and the *Cramér's V coefficient* to determine the statistical reliability of differences. *Cramér's V coefficient*, also referred to as Cramér's ϕ , is a correlation statistic designed to assess the strength of association between two categorical variables. (McHugh, 2018). This nonparametric measure is particularly useful in the analysis of cross-tabulated data. Essentially, Cramér's V functions as a correlation coefficient for nominal variables and necessitates the use of a Chi-squared test statistic for its calculation. Results were classified as statistically significant if the p -value was below 0.05.

The study was approved by the Ethics Committee of the University of Latvia on 18 March 2024, No 14.

RESULTS AND DISCUSSION

The survey was completed by 303 museum staff, 86.8% of whom were females, 12.9% males and 0.3% other gender (see Table 1).

Analysing the respondents by gender, age and length of service in the profession, it was found that the largest number of employees is in the age group 31–45 (39.9%) and 46–60 (33.3%). Among the respondents in the age group 31–45, 42.2% have 6–20 years of service in the museum. Of the employees, 22.1% have more than 21 years of service in the profession and they are mainly in the age group 46–61 and over. This is in line with the study that in Latvian museums 73–74% of all employees are females (Vikmane, 2023), while 64.3% of the respondents have been employed in a museum for more than five years. This indicates that staff turnover in the sector is relatively low.

Analysing the survey results by museum location, the following results were obtained: slightly more than half of the respondents (50.8%) are employed in museums in the capital city, and the other half - in other regions of Latvia. A statistically significant relationship ($\chi^2 = 24.5$; $df = 9$, $p = 0.002$) was found between age and museum location: in the capital city, mainly young employees (under 45 years of age) are employed, in municipalities - respondents aged between 46 and 60 years, while in the centre of the regions, employees aged over 61 years are statistically slightly more likely to be employed than expected. This is due to the fact that there are many more museums in the Latvian capital than in the regions, the number of museum staff in the regions and regional centres is much smaller than in the capital, and the museums employ mainly local people with a long professional career.

Table 1. Characteristics of study participants ($n = 303$)

Variable	Features	Participants ($n = 03$)
Gender of employee	Female	263
	Male	39
	Another	1
Age group, years	Up to 30	38
	31–45	121
	46–60	100
	> 61	44
Length of service in the profession, years	Up to 1	28
	2 to 5	80
	6 to 20	128
	21 and over	67

The number of museum staff and the respondents' job responsibilities are shown in Table 2. The job duties of 27.4% of the employees include preservation, digitalisation, restoration of the museum collections, 23.8% - public information (PR specialist, museum educator, exhibition curator) and 11.2% indicated that the duties are related to management, including project management, department management.

Table 2. The number of museum staff and the respondents' job responsibilities

Number of museum staff							
Job responsibilities	Up to 5	6–10	11–25	26–60	61–100	Over 100	Number (n) %
Work with the museum collection, digitalisation, restoration	9	9	14	16	22	13	83 27.4
Work with the public	14	14	16	9	10	9	72 23.8
Management	8	12	7	19	15	8	69 22.8
Research	1	2	10	6	12	3	34 11.2
Technical work	4	4	3	2	2	1	16 5.3
All or nearly all of the above*	11	3	4	0	0	1	19 6.3
Accounting or bookkeeping*	0	1	0	3	0	0	4 1.3
Information technology, layout, digital content*	0	0	0	0	3	0	3 1.0
Safety, security *	0	0	0	0	0	2	2 0.7
Development plans, personnel*	0	0	1	0	0	0	1 0.3
Number (n)	47	45	55	55	64	37	303 100
Percentage breakdown	15.5	14.9	18.2	18.2	21.1	12.2	100

*Summarising respondents' answers in 'Other'.

Research work (historian, art expert) is carried out by 12.2% of respondents, and technical work (house manager, cleaner, hall supervisor) by 5.3% of respondents. The 'Other' section shows that 6.3% of respondents perform several or all of the above duties on a daily basis. This applies mainly to museums with up to five staff members. There is a marginally significant statistical correlation (*Cramer's V* = 0.198; *p* = 0.002) between the gender of the respondents and their job responsibilities in the museum. Comparing the results with the expected ones, it can be concluded that males do more research and technical work than statistically expected, while females do more public information and work with museum collections than statistically expected.

The majority of respondents (61.1%) sometimes work at weekends or on public holidays. Always or almost always 6.9% of respondents work at weekends and 17.2% of respondents often work at weekends or on public holidays. Similar results have been found in other studies (Michelbach, 2013). Studies show that long working hours and overtime are associated with stress, burnout and general health deterioration (Le et al., 2022).

The survey showed that respondents do not have sufficient knowledge of the potential risks of their occupation, with only 0.6% of respondents in the 'other' section indicating that they know all the potential risks. Meanwhile, 20.5% have some

knowledge of the risks of their occupation and 5.3% do not know the risks of their occupation. Respondents commented on the comfort of the working environment as follows: 59.4% of respondents indicated that the working environment is partially comfortable, 29.7% - fully comfortable; 56.4% indicated that it is possible to change between sitting and standing positions when performing work duties; 42.2% indicated that they perform work duties only sitting and 1.3% - only standing. A large proportion of respondents (46.2%) do not complain about the presence of noise in the work environment, but 37.6% believe that there is sometimes noise that interferes with work. Almost 80% of respondents note that it is possible to ventilate the premises during working hours.

More than half of the respondents (69.8%) indicate that they use an employer-provided health insurance policy that also includes rehabilitation (physiotherapy, psychological counselling and massages) to promote their health. Of respondents, 78.5% state that they do not smoke, while 12.5% smoke every day or almost every day and the rest smoke occasionally.

The leisure time survey of the employed showed that 35.3% of respondents used alcohol less than once a month, 21.5% never used alcohol and 2.6% used it every day or almost every day. It should be noted that respondents do not exercise much after work, with only 21.8% saying they exercise every day, 24.4% between 2 and 4 times a week, and 14.9% do not exercise at all.

The psychosocial risk assessment using the short version of the COPSQ III is presented in Tables 3 to 5.

Table 3. Summary of the assessment of psychosocial risk factors by COPSQ III (short version). Arithmetic mean (M) and standard deviation (SD) of respondents' answers

Domain	M ± SD	Item	M ±SD
Quantitative requirements	29.5 ± 23.2	How often do you run out of time to complete all your work tasks?	51.8 ± 24.8
		Do you delay in completing work tasks?	31.4 ± 23.4
Pace of work	49.7 ± 21.0	Do you need to work very fast?	56.4 ± 21.8
		Do you need to work at a high pace throughout the day?	44.1 ± 22.7
		Does your work involve dealing with other people's personal problems?	37.5 ± 26.4
Emotional requirements	48.0 ± 26.5	Is your work emotionally intense?	61.2 ± 26.2
		Do you influence decisions that concern your work tasks?	59.3 ± 23.0
Impact at work	59.3 ± 23.0	Do you have the opportunity to learn new skills at work?	69.4 ± 23.3
		Do you have the opportunity to use your skills or knowledge in your work?	77.6 ± 19.8
		Is your work important?	74.6 ± 19.8

When analysing the quantitative requirements, it should be noted that respondents rated them as medium and medium-low with a relatively medium standard deviation (29.5 ± 23.2). Respondents are relatively more likely to experience a lack of time. Despite this, employees very rarely delay the completion of work tasks. In the 'other' section, 6.3% of respondents indicated that they perform all or almost all duties in the museum.

These respondents were grouped together in the 'all or almost all duties' group. The lack of time to complete work tasks was higher for respondents performing all or almost all types of duties in the museum (59.2 ± 20.8) and lower for respondents performing technical work (37.5 ± 20.4) or other duties (30.0 ± 19.7) as indicated by the respondent.

Respondents rate the pace of work as average. As many as 38% of respondents said they often or always need to work fast, while 19.5% work at an increased pace throughout the day. Respondents who perform almost all types of duties in the museum (63.2 ± 24.1) and respondents who perform other duties (67.5 ± 23.7) are more likely to work fast. Sometimes it is necessary to work at an increased pace throughout the day (44.1 ± 22.7). Respondents in management (48.2 ± 21.2) and research (47.8 ± 23.3) reported a relatively high pace throughout the day, while those in technical work (34.4 ± 18.0) reported a slower pace.

The score for 'Emotional demands' is moderately low (37.5 ± 26.4). Frequently or always solving other people's problems is a concern for 16.5% of respondents, and this applies to respondents who perform management work (46.4 ± 23.2), and relatively less frequently for staff who work with the museum's collection (28.6 ± 25.9) and those who perform other duties (25.0 ± 23.6). Respondents consider that their work is often emotionally intense (61.2 ± 26.2). This is mainly the case for respondents who perform almost all duties (69.7 ± 24.4) and those who perform managerial duties (67.4 ± 21.2).

Respondents report that they can influence decisions affecting their work tasks moderately often (59.3 ± 23.0). Meanwhile, 16.2% report that they rarely or never influence decisions affecting their work tasks. Only 9.6% ($n = 29$) can always influence decisions affecting their work tasks. Respondents in management jobs are more likely to have influence on decisions concerning their work tasks (64.9 ± 28.8). Those in technical jobs are comparatively less likely to influence decisions on their work task (48.6 ± 32.2).

Respondents rate their opportunities for advancement as moderately high. Museum employees have a high potential to acquire new knowledge (69.4 ± 23.3) and to use knowledge at work (77.6 ± 23.3). Of respondents, 10% ($n = 30$) consider that there is a very low or low potential to acquire new knowledge and 3.7% consider that there is a very low or low potential to use skills at work. Respondents in management jobs (75.0 ± 22.7) and respondents in miscellaneous jobs (71.1 ± 25.4) are more likely to be able to acquire new knowledge (82.3 ± 17.7) and to use their skills (82.3 ± 17.7). Respondents in research jobs (67.7 ± 21.8) are relatively less likely to be able to use their knowledge and skills (71.1 ± 25.4).

Of museum employees, 76.1% consider their work to be highly important (74.6 ± 19.8), while only 3.3% consider their work to be very or somewhat important. Respondents with a variety of duties are more likely to consider their work important (82.9 ± 16.8), while respondents working in research are relatively less likely to do so (67.7 ± 21.8).

Transparency in the museum sector is moderately high. Respondents consider themselves to be moderately and moderately frequently informed about important decisions and changes at work (60.4 ± 24.1). Of respondents, 17.2% are informed to a low or very low degree about important decisions, changes or plans; 7% receive the necessary information to a low or very low degree. Respondents working in technical areas (53.1 ± 27.2) and those working with museum collections (55.4 ± 26.0) are comparatively less well informed. On average, respondents often receive the information they need to complete their work tasks (64.5 ± 19.8). Respondents in management

(67.0 ± 20.3) and other duties (67.5 ± 20.6) are relatively more likely to receive the information they need, while respondents performing all or almost all duties (57.9 ± 26.4) are less likely to receive it.

Table 4. Summary of the assessment of psychosocial risk factors by COPSOQ III (short version). Arithmetic mean (M) and standard deviation (SD) of respondents' answers

Domain	M $\pm$ SD	Item	M $\pm$ SD
Transparency of work	62.4 ± 21.9	Are you informed in advance about important decisions, changes or future plans at work?	60.4 ± 24.1
		Do you get all the information you need to do your job well?	64.5 ± 19.8
Evaluation	54.8 ± 26.2	Does your management appreciate and recognise your work?	54.8 ± 26.2
Role clarity	70.6 ± 20.7	Do you have clear objectives for your work?	70.6 ± 20.7
Conflict of roles	37.5 ± 24.3	Do you face conflicting demands in your work?	32.7 ± 25.9
		Do you tend to have work tasks that need to be done differently than usual?	44.0 ± 24.6
Leadership quality	59.1 ± 27.1	To what extent would you say that your direct manager is a good planner?	59.4 ± 26.1
		To what extent would you say that your direct manager is able to resolve conflict situations?	57.3 ± 29.1
Support from the direct manager	71.9 ± 27.0	How often do you get help and support from your direct manager if you need it?	71.9 ± 27.0
Colleague support	78.9 ± 20.4	How often do you get help and support from your colleagues if you need it?	78.9 ± 20.4
Atmosphere at work	78.8 ± 29.1	Is there a good atmosphere between you and your colleagues?	78.8 ± 29.1

Most respondents consider that they are rather appreciated by management (54.8 ± 26.2), while 25.7% of respondents consider that management appreciates their work to a small or very small extent. Respondents who carry out research work are comparatively more likely to receive recognition for their work (61.7 ± 21.5), while respondents who perform all or almost all duties are less likely to receive recognition (48.7 ± 31.7). The responses of respondents performing all or almost all duties have a relatively high standard deviation.

Those working in the museum sector noted that there are clear objectives to a large extent (70.6 ± 20.7). Only 7% of respondents indicated that the job has clear objectives to a small or very small extent, while 18.8% of respondents indicated that the objectives are clear to a very large extent. The clarity of objectives is relatively higher for respondents doing management work (74.6 ± 20.8) and relatively lower for respondents doing work with the public (66.0 ± 21.0).

Many respondents rated role conflict in museum work as low (conflicting demands 32.7 ± 25.9 ; different tasks 44.0 ± 24.6). Whereas 15% of respondents considered conflicting demands to be high or very high, 43.6% of respondents noted that there are very few or few tasks that need to be done differently. Respondents who perform all or almost all duties in the museum are relatively more likely to have conflicting demands at work (44.7 ± 22.8), which could be related to the variety of work. Respondents with other duties are relatively less likely to have conflicting demands (25.0 ± 20.4).

Respondents tend to have different job tasks to perform, more often different job tasks for respondents who have all or almost all of the job tasks (52.6 ± 24.9), but relatively less for technical staff (34.4 ± 28.7). A *Chi-square test* was used to analyse the relationship between respondents' length of service and the manager's conflict resolution skills score, and a statistically significant relationship was found ($\chi^2 = 31.1$; $df = 12$, $p = 0.002$). The *Cramer's V coefficient* is 0.185; $p = 0.002$, which means that there is a marginally significant relationship between the respondents' length of service and conflict resolution. Respondents with up to one year of seniority rate their direct manager's ability to resolve conflict situations higher than statistically expected, while respondents with between 1 and 5 years and between 6 and 20 years of seniority rate their direct manager's ability to resolve conflict situations comparatively lower than statistically expected. Respondents are more likely to perceive their direct manager as being able to resolve conflict situations (57.3 ± 29.10). The ability of the direct manager to resolve conflicts was rated higher by those with other responsibilities (65.0 ± 35.7), but respondents' ratings varied. Respondents who perform all or almost all of the duties (50.0 ± 25.9) rated their direct manager's ability to resolve conflict situations the lowest.

Respondents generally consider that the direct manager plans the work well (59.4 ± 26.1). Meanwhile, 20.9% of respondents consider that the manager plans the work well to a small or very small extent and 25.7% of respondents consider that the manager is able to resolve conflict situations to a small or very small extent.

A statistically significant relationship ($p < 0.05$) was found when applying the *Chi-square test* ($\chi^2 = 21.3$; $df = 12$; $p = 0.047$) and analysing the correlations of the location of the museums with the manager's time management score. The *Cramer's V coefficient* is 0.153; $p = 0.047$, indicating that there is a marginally significant relationship between the location of the museum and the time planning by the manager. In the capital city, the immediate manager's planning is rated higher than statistically expected, while in the county town it is rated lower than statistically expected.

Technical workers reported that their direct manager planned their work relatively well (68.8 ± 28.2). However, respondents who perform all or almost all of the duties are relatively less satisfied with their direct manager's time management (52.6 ± 21.9).

Overall, respondents perceive that they often receive support from their direct manager (71.9 ± 27.0), but the assessment is not unanimous. Of the respondents, 11.3% ($n = 34$) indicated that they rarely or never receive support from their direct manager. Respondents who work with the public are more likely to receive support from their direct manager (75.7 ± 26.9), while respondents who perform all or almost all duties are statistically least likely (55.2 ± 28.4) to receive support. Those with all or almost all responsibilities have comparatively lower scores in both leadership quality and support from direct manager.

Respondents consider that they receive support from colleagues frequently (78.9 ± 20.4). Meanwhile, 2.7% ($n = 8$) of respondents indicate that they rarely or never receive support from colleagues. Respondents who perform all or almost all duties at the museum are more likely to receive help from colleagues (85.5 ± 17.3), while those who perform technical work (73.4 ± 21.36) and research work (73.5 ± 21.3) are comparatively less likely. This could be explained by the specific nature of the work, as the job duties of technical staff are very different from those of museum staff.

Respondents believe that there is a good psychological atmosphere in the organisation (78.8 ± 29.1). Only 2.7% of respondents indicated that there is rarely or never a good atmosphere among colleagues. Technical staff (52.8 ± 17.6) have the lowest opinion of the atmosphere at work, while respondents working with the museum collection have the highest (75.6 ± 20.3) opinion.

Table 5. Summary of the assessment of psychosocial risk factors by COPSOQ III (short version). Arithmetic mean (M) and standard deviation (SD) of respondents' answers

Domain	M $\pm$ SD	Item	M $\pm$ SD
Job insecurity	41.1 $\pm$ 31.5	Are you worried about being out of work?	40.1 $\pm$ 30.7
		Are you worried about the difficulties you might have in finding another job if you become unemployed?	51.2 $\pm$ 32.2
		Are you worried about being transferred to another job against your will?	31.7 $\pm$ 31.4
Job satisfaction	70.2 $\pm$ 19.5	How satisfied are you with your work overall, all factors considered?	70.2 $\pm$ 19.5
Work-life balance	41.8 $\pm$ 29.0	Do you feel that your work consumes too much energy and that it has a negative impact on your private life?	44.3 $\pm$ 29.3
		Do you feel that your work takes up too much of your time and that it has a negative impact on your private life?	39.0 $\pm$ 28.7
Vertical reliability	71.7 $\pm$ 21.1	Does management trust staff to do their job well?	74.2 $\pm$ 20.0
		Can staff trust the information they receive from management?	70.4 $\pm$ 20.0
Fairness	58.3 $\pm$ 25.5	Are conflicts handled fairly?	58.3 $\pm$ 26.3
		Are workloads distributed fairly?	56.8 $\pm$ 21.2
Health	41.0 $\pm$ 19.1	How do you rate your state of health?	41.0 $\pm$ 19.1

The job insecurity was in total evaluated as moderate (41.5 ± 31.8). The uncertainty of being unemployed is moderately low (40.1 ± 30.7). However, 15.7% of respondents indicate that they are very or extremely worried about the possibility of being unemployed. Being unemployed is relatively more worrying for respondents who perform all or almost all duties (35.5 ± 34.6). The possible difficulty of finding another job is moderate for respondents (51.2 ± 32.2). Of the respondents, 39.2% indicated that they would have a great or very great difficulty in finding another job. Respondents who work with museum collections are relatively more worried about finding another job (55.1 ± 30.0). Respondents more often worry slightly about being transferred to another job against their will (31.7 ± 31.4). Relatively higher levels of concern about reassignment are found among respondents with technical jobs (39.1 ± 30.2) and lowest among respondents with all or almost all duties (21.1 ± 30.4).

Overall, respondents are satisfied with their job (70.2 ± 19.5). Only 5% of respondents are very dissatisfied or dissatisfied with their job in general. Statistically, respondents performing all or almost all duties are more satisfied with their job (75.0 ± 14.4), while respondents performing work with the public are least satisfied (64.6 ± 21.3).

Respondents have a moderately low work-life balance: 27.4% say that work consumes too much energy to a great or very great extent, 24.4% say that work consumes too much time to a great or very great extent. Most of those performing all or almost all duties consider that work consumes too much energy (55.3 ± 30.7) and too much time (46.1 ± 29.1). Those in technical jobs are relatively more likely to consider that work consumes too much energy (39.1 ± 27.3), while those in management jobs are relatively less likely to consider that work consumes too much time (34.1 ± 27.4).

In terms of vertical trust, respondents rated management trust in employees and employees' trust in information from management relatively highly (74.2 ± 20.0). Only 4.6% of respondents indicated that management relies on employees to a small or very small extent, while 8.6% indicated that they can trust management information to a small or very small extent. Vertical trust is the lowest for respondents who perform all or almost all of their job duties (70.0 ± 15.8 and 65.8 ± 32.5). Technical workers score relatively lower on trust in the information they receive from management (65.6 ± 18).

Respondents indicated that fairness at work is moderately high (58.3 ± 26.3 ; 56.8 ± 21.2). Meanwhile, 18.2% indicated that conflicts are handled fairly to a small or very small extent and 19.2% ($n = 58$) indicated that workloads are distributed fairly to a small or very small extent. Managers (63.8 ± 21.7) have a higher perception that conflicts are dealt with fairly, while respondents working with the museum collection (54.5 ± 26.8) have a comparatively lower perception. Those doing research work are relatively more likely to feel that workloads are distributed fairly (59.6 ± 20.4), while those doing all or almost all work have a relatively low score (52.6 ± 32.2).

The majority of respondents consider their health to be satisfactory (41.0 ± 19.1). However, 3.6% of respondents consider it to be poor, and 12.8% consider it to be very good or excellent. Respondents who do research work rate their health status the lowest (33.8 ± 16.2).

The results of the short version are in line with other studies that find that work meaning is important for museum staff (Hardin, 2020) and that communication with colleagues and valuable conversations with museum visitors are important support mechanisms for psychosocial risks (Svvdik, 2019; Hardin, 2020).

Overall, respondents to the short version of the Copenhagen Psychosocial Survey score on average highest on the following indicators: support from colleagues (78.9 ± 20.4), atmosphere at work (78.8 ± 29.1), ability to use knowledge and skills (77.6 ± 19.8), importance of work (74.6 ± 19.8). Comparatively lower scores were recorded for: delays in completing tasks (31.4 ± 23.4), insecurity of being transferred against one's will (31.7 ± 31.4) and conflicting demands in the work process (32.7 ± 25.9). In all the short questionnaire results, there was a wide range of responses (with both a minimum and a maximum value selected for each question), indicating that respondents had different opinions. The psychosocial risks identified in the survey were: fast pace of work (56.4 ± 21.8) and lack of time to meet all demands (51.8 ± 24.8), fair conflict resolution (58.3 ± 26.3) and manager's ability to resolve conflict (57.3 ± 29.1), fair distribution of workload (54.8 ± 21.2), sufficient recognition at work (54.8 ± 26.2), possible difficulties in finding another job (51.2 ± 32.2) and self-assessment of health (41.0 ± 19.1). These results are also in line with other studies finding that meaning at work is important for museum workers (Hardin, 2020) and that communication with colleagues and fruitful conversations with museum visitors are important support mechanisms for psychosocial risks (Svvdik, 2019; Hardin, 2020).

The questions and scores of the long version of the Copenhagen Psychosocial Survey are presented in Table 6. Respondents report that they have mainly experienced sleep-related health problems. Relatively more respondents had poor or restless sleep (44.4 ± 25.9). The most frequent sign of burnout cited by respondents was being physically tired (53.6 ± 24.6). This is in line with studies by other authors, which have shown that working more than 60 hours per week resulted in poorer health, more stress-related disorders and burnout. No differences were found between age or gender (Le et al., 2022).

Table 6. Summary of the assessment of psychosocial risk factors by COPSOQ III (short version). Arithmetic mean (M) and standard deviation (SD) scores for sleep problems, burnout, stress and depression symptoms

Topic	Question	M $\pm$ SD
Sleep problems	How often have you slept badly or restlessly?	44.4 $\pm$ 25.9
	How often have you found it difficult to fall asleep?	35.1 $\pm$ 28.7
	How often have you got up too early and been unable to fall back asleep?	34.3 $\pm$ 27.0
Burnout	How often have you felt tired?	59.2 $\pm$ 24.4
	How often have you felt physically tired?	53.6 $\pm$ 24.6
	How often have you felt emotionally exhausted?	52.2 $\pm$ 27.8
Stress	How often have you had problems relaxing?	47.4 $\pm$ 27.2
	How often have you been irritable?	38.5 $\pm$ 23.6
	How often have you been tense?	50.2 $\pm$ 25.4
Somatic stress	How often have you had headaches?	26.4 $\pm$ 23.7
	How often have you had palpitations?	18.7 $\pm$ 23.3
	How often have you had muscle tension?	39.6 $\pm$ 29.8
Cognitive stress	How often have you had difficulty concentrating?	38.0 $\pm$ 26.7
	How often have you had difficulty thinking clearly?	28.8 $\pm$ 24.5
	How often have you had difficulty making a decision?	28.3 $\pm$ 22.6
	How often have you had difficulty remembering?	31.4 $\pm$ 23.0
Symptoms of depression	How often have you felt sad?	38.0 $\pm$ 26.7
	How often have you lacked self-confidence?	37.5 $\pm$ 26.0
	How often have you felt remorse or guilt?	33.4 $\pm$ 26.3
	How often have you lacked interest in everyday things?	32.4 $\pm$ 27.9

Among the questions on stress, respondents scored highest on the question about being frequently stressed at work (50.5 ± 23.7). Respondents indicated that somatic stress manifested itself in the following ways: heart palpitations were absent or present only part of the time (18.7 ± 23.3); muscle tension was slightly more common some or part of the time (39.6 ± 29.8). Cognitive stress symptoms, such as difficulty concentrating, were rated by respondents as occurring some or part of the time (38.0 ± 26.7). Depressive symptoms were similar, with sadness being the most frequent symptom within four weeks (38.0 ± 26.7). For all indicators, respondents selected both minimum and maximum values, which means that respondents' ratings varied. The analysis of the results shows that respondents of all genders aged under 30 and between 31 and 45 show relatively higher scores for burnout, stress and depression than statistically expected. This could be compared with research finding that people in Europe have poorer mental health (Backhaus et al., 2023), which could be linked to this generation's more active use of different means of communication. Studies have shown that if employees use

work-related communication tools outside of work hours, they are more likely to experience anxiety symptoms (Kim et al., 2024). Younger generations have also been shown to have higher rates of anxiety, linking this to the availability of the internet and smart devices (Tzeses, 2022).

When analysing the relationship between employee age and burnout scores, statistically significant correlations were found with all questions on the burnout score ($p < 0.001$). There was a slight statistical association for feeling emotionally exhausted ($p = 0.001$). There was a statistical association between age of respondents and stress scores. When analysing the age of museum staff in relation to muscle tension, a statistically significant correlation was found ($p = 0.03$), *Cramer's V coefficient* 0.16, which means that the correlation is not significant. When analysing the association of age with muscle tension, a statistically significant difference ($p < 0.0001$) and a *Cramer's V coefficient* of 0.210 was found, indicating a non-significant association between the groups compared.

The age of respondents was also statistically correlated with questions about depression. A *Chi-square test* was used to analyse the age of museum staff in relation to sadness and a statistically significant relationship was found ($\chi^2 = 32.5$; $df = 12$; $p = 0.001$), with *Cramer's V coefficient* of 0.19, indicating a marginally significant relationship between the groups compared. Using *Chi-square test* and analysing the age of museum staff in relation to lack of self-confidence, a statistically significant relationship ($\chi^2 = 43.8$; $df = 12$, $p < 0.001$) was found, *Cramer's V coefficient* is 0.220, which means that there is a marginally significant relationship between age and lack of self-confidence. The analysis of the association of age with lack of interest in everyday life showed a statistically significant correlation ($p < 0.0001$) and a *Cramer's V coefficient* of 0.24, indicating a marginally significant association between the groups compared. When the data are compared, employees aged under 30 and between 31 and 45 have relatively higher than expected scores on these measures of burnout, stress and depression.

To identify respondents' self-efficacy capacities that could help them cope with psychosocial risks at work, a long version of the self-efficacy questions was included in the questionnaire. Overall, respondents score moderately high on self-efficacy, with the highest scores on the ability to always solve difficult problems (81.3 ± 21.5) and the ability to usually cope no matter what occurs (80.0 ± 21.5) (see Table 7).

Overall, the self-efficacy of museum professionals is rated as medium-high and high. Respondents also have high resilience and adaptability. However, respondents' answers were varied, including both the lowest and the highest values. On average, those

Table 7. Summary of the assessment of psychosocial risk factors by COPSOQ III (long version questions of self-efficacy domain). Arithmetic mean (M) of ratings and standard deviation (SD)

Item	M $\pm$ SD
I can always solve difficult problems if I try hard enough	81.3 $\pm$ 21.5
If people work against me, I find a way to achieve what I want	59.6 $\pm$ 27.7
It is easy for me to stick to my plans and achieve my goals	72.9 $\pm$ 21.8
I feel confident that I can cope with unexpected events	71.3 $\pm$ 25.2
If I have a problem, I can usually find several ways to solve it	75.8 $\pm$ 22.5
Whatever happens, I usually manage	80.0 $\pm$ 21.5

performing management work show slightly higher self-efficacy than those performing other duties in museums. This is consistent with research conducted in the UK on the self-efficacy of museum staff and the finding that museum staff have higher self-efficacy than the public average and that the highest self-efficacy in museums is for freelancers and management workers (Naylor et al., 2016).

Given that the Copenhagen Psychosocial Survey has not been validated in Latvia, the authors cannot compare the results with those of the local population, but time pressure, workplace conflicts and workload appear as one of the most important psychosocial factors in several studies in Latvia (Pastare et al., 2020; Kalkis et al., 2024). Other authors' studies on psychosocial risks of museum workers also mention lack of time and organisational effectiveness (Michelbach, 2013), as well as inequality among colleagues (Hardin, 2020). Comparing the results of Romanian researchers (Iordache et al., 2022) with those of our study, there are significant differences in several indicators. Comparatively similar scores were found for the theme 'Impact at work' (Romania 57.0, Latvia 59.3), with Romanian museum workers more likely to indicate quantitative demands and work pace (Romania 68.2, Latvia 46.6) and emotional demands (Romania 60.8, Latvia 49.4). Latvian museum staff rated leadership higher than Romanian museum staff (Romania 45, Latvia 58.4), and indicated higher job insecurity (Romania 28, Latvia 41). In contrast, Latvian museum employees have significantly higher levels of opportunities for promotion (Romania 43.4, Latvia 73.5), support from direct manager and colleagues (Romania 39.2, Latvia 75.4) and role clarity (Romania 25.2, Latvia 70.6).

In summary, all or almost all job holders score relatively higher on quantitative demands, work pace, emotional saturation, impact at work, opportunities for growth, meaning of work, role conflict, colleague support, work atmosphere, job satisfaction and work-life conflict. This group scores comparatively lower on job predictability, appraisal, role clarity, leadership quality, support from line manager, job insecurity, vertical reliability, fair distribution of workload, and health. Respondents rated self-efficacy as high.

CONCLUSIONS

The Copenhagen Psychosocial Survey risk analysis concluded that museum staff work at a fast pace and lack the time to meet all requirements. Fair handling of conflict situations, ability of the supervisor to handle conflict situations, fair distribution of workload, sufficient recognition at work, possible difficulties in finding another job and self-assessment of health are the psychosocial risks specific to museum workers according to this assessment, which is in line with the literature analysis. The Copenhagen Psychosocial Survey scores are comparatively higher for employees who perform all or almost all of the museum's duties (management work, work with the museum's collection, research work, work with the public, technical work), which means that this group of employees should receive greater attention when developing preventive measures. In the Copenhagen survey, those working in the museum sector rated support from colleagues, the atmosphere at work, the opportunity to use knowledge and skills, and the importance of the work relatively highly, and employees generally had high self-efficacy scores and moderately high social capital.

Future research will focus on using cognitive tests in order to have holistic view on the psychosocial risks faced by museum workers. Addressing current study limitations with larger, more diverse samples and objective data measures will offer a more thorough understanding. Additionally, longitudinal studies could track the long-term effects of these risks on the well-being of museum staff and compare the impact across different types of museum settings.

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Climate impact on electric vehicle energy consumption in the Baltic Region

A. Puusepp*, J. Jõgi and J. Lumi

Estonian University of Life Sciences, Institute of Forestry and Engineering, Kreutzwaldi street 1a, EE51006 Tartu, Estonia

*Correspondence: aimarpuusepp@gmail.com

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Abstract. Electric vehicles (EVs) have seen increased interest in recent years as a lower-emission alternative to internal combustion engine (ICE) vehicles, with much of their growth driven by government subsidies and incentives across Europe. However, as these incentives have slowed, the EV market faces new challenges, particularly in the Baltic countries where the climate significantly impacts EV performance. Low temperatures, common in Baltic weather, can notably affect EVs' range and energy efficiency, influencing operational costs and user satisfaction. Understanding how Baltic weather conditions, primarily temperature, influence the energy consumption of EVs is essential to gaining a deeper understanding of their efficiency in low temperatures and harsh weather conditions. The main aim of this study is to assess the impact of varying weather conditions on EV energy consumption, providing valuable insights into their efficiency under cold and variable climatic conditions. The primary goal is to identify the factors most responsible for increased energy consumption in these conditions. In this study, a series of controlled real-world driving tests were conducted, during which an EV (Nissan Leaf) was driven multiple times along identical routes under different weather conditions. The temperatures during these tests ranged from 20 °C to -15 °C. The 2024/2025 winter season was unusually warm in the Baltic region; therefore, tests could not be conducted at lower temperatures. Variables such as distance, temperature, battery state, and the use of accessories were recorded and subsequently analysed. Additionally, energy losses during EV battery charging were measured and evaluated. The collected data was analysed statistically, and mathematical models were developed to provide accurate predictions of battery usage under varying ambient temperatures. The results indicate that low temperatures increase EV energy consumption due to the additional energy required for battery and cabin heating. A more detailed analysis reveals that the most significant increase in energy consumption occurs at an ambient temperature of -10 °C. Overall, this study demonstrates that Baltic weather conditions can lead to a substantial decrease in EV range and efficiency, with low temperatures being the most impactful factor. By providing real-world data, this study contributes to a deeper understanding of EV efficiency in the Baltic region, offering practical insights for EV users and researchers.

Key words: Baltic climate, electric vehicle, energy consumption, range efficiency, real-world driving tests.

INTRODUCTION

Electric vehicles (EVs) have proven essential in cutting greenhouse gas emissions while reducing fuel dependence on petroleum products. The efficiency of EVs depends on various elements, including ambient temperature, driving speed, terrain conditions, and battery technological advancements (Harvey, 2020). All vehicle operations for EVs depend on drawing power from their batteries since they produce no waste heat for cabin heating like traditional internal combustion engine (ICE) vehicles do under adverse climate conditions such as high or low temperatures; electric vehicles' operational range and energy efficiency performance experience significant reductions. The efficiency of lithium-ion battery performance tends to be higher in warm climates since chemical reactions within the cells operate most effectively (Yao et al., 2023). Nonetheless, cold weather conditions reduce peak performance capabilities, thus increasing energy losses. Addressing the impacts of the environment on battery efficiency together with range anxiety reduction demands urgent focus to make EVs acceptable for mass markets.

Temperature is a significant element that affects the operational efficiency of EVs. Electrochemical reactions inside the batteries become slowed, internal resistance grows, and energy availability for propulsion decreases when temperatures are low. Low-temperature conditions decrease battery cell electrolyte fluid flow ability because of increased fluid viscosity, so charging efficiency suffers during regenerative braking. An EV performs worse in frigid climates because its driving range diminishes. At the same time, charging takes longer, and power losses increase relative to operating in normal ambient temperatures (Albatayneh et al., 2020). Evaporator and defrosting operations consume additional energy that negatively affects the vehicles energy efficiency. Battery-powered electric cars must distribute stored energy for cabin heating because they lack the capability of traditional ICE vehicles to heat interiors using engine heat, which increases battery consumption. The combination of high power requirements under such conditions shows why specific methods for improving energy utilisation in cold conditions need implementation. The two factors generally contributing to poor performance are higher internal resistance of the battery, increased heating demand, and reduced regenerative braking efficiency in the cold (Steinstraeter et al., 2021).

The scientific community now focuses research on battery performance in cold regions because the growing EV market expands into colder climates. The EV range decreases substantially during freezing weather conditions, as demonstrated by multiple studies and real-world driving tests, which also depend on battery chemistry, driving conditions, and the necessity of heating. The Nordic region, including Norway, Sweden, Finland, Denmark, and Iceland, as well as the northern parts of Canada and the United States, faces extensive cold winters where temperatures drop to -10°C and sometimes plunge even to -30°C or even lower in its northernmost regions (Harvey, 2020). The same conclusion can be drawn about the Baltic climate, as it is similar to the Nordic climate. EV battery functionality is significantly impaired during extreme weather conditions because temperature directly affects battery performance.

Many studies have shown how cold weather impacts EV efficiency (Wilber et al., 2021). According to research by the American Automobile Association (AAA), at -7°C , EVs can lose 41% of their range when heating the cabin (Sheldon, 2024). A Norwegian Automobile Federation (NAF) comparison of several EV models in winter conditions

has returned official Worldwide Harmonised Light Vehicles Test Procedure ranges were significantly reduced (Haber, 2023).

Manufacturers and researchers have investigated several tech-based solutions to reduce these efficiency drops, such as battery preheating, battery compartment insulation, and thermal management systems. Preheating, or thermal conditioning, entails warming a battery before using it via an external power source or drawing energy directly from it (Esch & Shabani, 2025). Preheating effectively mitigates the impacts, yielding up to 20% improvement in range while driving at subzero temperatures. Insulation of the battery has promising potential in that heat can be lost through battery walls, so maintaining an optimal operating temperature ensures minimal heat loss. According to findings some automakers introduced liquid-cooled battery systems capable of keeping battery temperature more stable in hot or cold climates than air-cooled designs (Wankhede et al., 2025).

Considerable research is devoted to the heat pump as an alternative to resistive heating. Unlike conventional electric heaters, heat pumps extract heat from ambient sources and transfer it into the vehicle, making them significantly more energy-efficient (Cortvriendt et al., 2025). The amount of energy needed to generate heat with a heat pump is considerably lower than the heat output itself. EVs equipped with heat pumps consume 30% to 50% less energy for heating, thereby extending their winter range. However, at extremely low temperatures, heat pumps become less efficient, necessitating supplementary resistive heating systems. Therefore, researchers have become interested in phase-change materials (PCMs) and thermoelectric generators (TEGs), which store heat and release it more effectively, thereby siphoning less power from the battery to run the climate control system.

Although the studies have yielded fascinating results, there is a lack of real-world quantitative analysis on energy loss for various driving conditions. Many laboratory-based tests do not measure wind resistance, snow accumulation, and real-world charging inefficiencies. This study intends to bridge this gap by analysing extensive on-road monitoring of EV performance under various Nordic-type climate conditions. This research will help provide more practical and efficient solutions for utilising EVs in colder regions by creating a mathematical model for analysing EV energy consumption under different temperatures and speeds, based on real-world driving tests conducted in varying conditions.

The existing research on cold temperature impacts on electric vehicle efficiency contains insufficient evidence because of the lack of real-world monitored testing and data acquisition. Many studies primarily rely on laboratory simulations and controlled driving cycles that fail to replicate actual driving conditions sufficiently (Park et al., 2024). Multiple vehicle energy consumption parameters determine results, including road conditions, wind resistance, traffic conditions, and driver actions, but these factors usually remain absent from experimental tests. Due to variations in battery types and heating methods, results from one EV model may not be transferable to others. Studies on this topic have focused on calculating the reduction of underlying range during cold conditions and concluded that more research needs to be conducted on this subject (Al-Wreikat et al., 2022). The current evidence lacks specific information about individual vehicles' efficiency characteristics, which would help consumers and vehicle makers optimise driving performance under wintry conditions.

The primary research objective focuses on investigating EV energy usage patterns as a response to changes in ambient temperature through real-world driving tests at different temperature points. The fieldwork component of this research will monitor how electrical battery power decreases while tracking efficiency during actual winter driving conditions. The test vehicle will engage in several journeys between +20 °C and -15 °C, during which the metered outcomes for battery discharge and power usage will be documented throughout the process. The gathered data will provide valuable insights to examine the different forms of electricity usage across various heating systems, preheating approaches, and cabin temperature adjustments. Understanding the extent of efficiency reduction across cold weather conditions will occur through quantitative analysis to identify the most effective ways of lowering driving energy usage in winter.

The research addresses the effect that vehicle speed requests have on power consumption. The power demand at different speeds serves as a major element that influences EVs energy usage (Feng et al., 2025). Recent investigations have identified that speed determines energy consumption, yet researchers have not objectively determined the specific speed-dependent model parameters in cold weather conditions. In this work, we will create a mathematical model that uses test data from 40 km h⁻¹ to 130 km h⁻¹ to develop a power-consumption-velocity relationship. The mathematical model created will determine the appropriate speed ranges for winter operation together with necessary driving practices to maximise the EV's range. Adopting these elements will create an improved comprehensive view of energy losses that depend on vehicle speed within winter conditions because of their integration. Energy-efficient EV driving depends on speed optimisation according to Nordic driving conditions because such climates demand strong range conservation (Egeli, 2023). A proper cruising speed helps EV drivers extend their range while driving at different speeds through the power-speed relationship (Ayevide et al., 2022). EV manufacturing companies benefit from this information to optimise drivetrain effectiveness by enhancing aerodynamics and adding better regenerative braking capabilities.

The third objective involves studying energy consumption losses between domestic vehicle charging stations and fast-charging terminals. The performance of EV charging directly impacts its energy consumption efficiency due to immediate power distributions affecting the overall battery power capacity (Kostopoulos et al., 2020).

Though measurement uncertainty has not been explicitly characterised in this study, it is recognised that applicable uncertainties are inherently associated with both measurement results and the measurement instruments. These may arise from factors such as sensor precision, data logging intervals, environmental fluctuations, and app-based limitations. While efforts were made to minimise external influences, such as maintaining consistent driving routes and weather conditions, the presence of systematic and random errors cannot be entirely excluded. Thus, the reported results must be cautiously interpreted considering possible measurement uncertainties.

Understanding these interrelated factors is crucial for improving EV performance in cold climates and reducing user uncertainty regarding range and energy use. This study addresses these challenges by combining real-world testing with mathematical modelling to evaluate EV behaviour in the context of Baltic climate conditions. The objectives of this research are as follows:

1. To investigate how ambient temperature affects electric vehicle battery energy consumption under real-world driving conditions typical of the Baltic region.

2. To analyse the relationship between vehicle speed and power consumption, and develop a mathematical model describing this dependency.
3. To evaluate charging efficiency under different charging scenarios, including home and fast-charging stations.
4. To assess the impact of cabin heating settings and preheating strategies on overall energy usage during winter conditions.

MATERIALS AND METHODS

Experimental setup and data collection

An experimental setup was conducted to evaluate EV energy consumption under real-world driving conditions based on ambient temperature conditions. A 2019 Nissan Leaf 40 kWh, a Battery Electric Vehicle (BEV) with a lithium-ion battery pack, single-speed transmission, and regenerative braking system functioned as the experimental vehicle. The vehicle operated on a 39.0 kWh usable battery system, which could reach a 235-km real range according to its manufacturer's information. A heat pump-based climate control system was operational in the car. It has a Type 2 home-charging port (6.6 kW AC) and CHAdeMO fast-charging port (max charge power 46 kW DC). This Nissan model does not have a battery pre-conditioning system, meaning it cannot warm the battery prior to departure, which may affect charging efficiency in cold weather (Autospirit Tartu OÜ, 2018).

The tests took place near Tartu, Estonia across blacktop roads, highways, and urban streets, which helped demonstrate actual roadside conditions. Measurements were performed under controlled road conditions to minimise variations in energy consumption caused by differences in road surface and contact friction. The roads were not snowy, although icy surfaces and frost-covered roads occurred during sub-zero temperatures. Testing included driving through a planned route, which reduced braking stops and maintained continuous speed changes. During the study, data collection was carried out using the LeafSpy Pro app. The vehicle's built-in analytics system monitored battery consumption, energy consumption and charging data providing kWh and state of charge (SoC) measurements. These measurements were recorded in the LeafSpy Pro app and the results obtained were used in this study. The average elevation of the test route was approximately 55 meters above sea level.

Battery energy consumption tests at different temperatures

The vehicle was tested at five different temperatures: +20 °C, +10 °C, 0 °C, -10 °C and -15 °C, to assess how ambient temperature affects the energy efficiency of EVs. Therefore, a seasonal range from mild weather to Baltic winter was covered. The winter of 2024/2025 was unusually warm for the region; therefore, tests could not be conducted at lower temperatures. The standardised distance of 23.6 km per trial during test drives also ensured that the intake data on energy consumption was comparable under temperature conditions. Each test drive began and ended at precisely the same location and took approximately 29 minutes to complete, resulting in an average speed of about 48.8 km h⁻¹. Weather conditions were kept as similar as possible for each ambient temperature to ensure the highest possible accuracy of the test results. The energy consumed was calculated from the moment the drive started until it finished, covering 23.6 km, and the total energy consumed in each test passing was recorded at the end of

that drive. SoC was also recorded before and after the test drive. To evaluate battery energy consumption, a total of 9 test drives were conducted with each outside temperature, but with -15 °C only 3 because of the mild winter this year. In total, 39 test drives were made on a 23.6-km track, so ca 1,000 km was driven to obtain the necessary results.

The research also looked into how the heating settings of the cabin affected battery energy consumption. The cabin heater was fixed at four temperature settings – 16 °C, 19 °C, 22 °C, and 25 °C – and a test where the cabin heater was turned off completely served as the baseline. The study varied regarding how these settings were set and how the performance in terms of added energy for the heater and this energy cap is compared to overall battery drain to measure the impact of the heater settings on battery use. Heating needs are fundamental in cold climates, as heating can consume considerable energy. The impact of cabin preheating on energy consumption was also examined, as cabin preheating is often used in cold environments. The study tested for two scenarios: the tests started with a cold cabin and a preheated cabin before the drive began.

Power demand at constant speeds

Our road testing was conducted on a horizontal track section that did not alter our results because of any uphill or downhill terrain. Takeover measurements for power consumption required us to maintain constant speed for an equivalent period to achieve steady-state power conditions. The recorded energy consumption data was displayed in near real-time on the LeafSpy Pro app. During each segment, the test driver maintained uniform throttle control for measuring power consumption while avoiding effects from regenerative braking and high-speed accelerations.

A polynomial regression model was developed to detect links between speed and power usage relationships. Power demand correlated directly to vehicle speed increases; however, the data indicates that this relationship remained nonlinear. The obtained best-fit equation comes from the least-squares curve fitting strategy, which describes the relationship between speed and power usage.

The resulting equation is

$$P = ax^2 + bx + c \quad (1)$$

where P is the power consumption (kW); x is the vehicle speed (km h⁻¹); a, b, and c are empirically determined constants derived from regression analysis of test data.

Power demand rises at a steady rate, as the equation demonstrates. The application of the quadratic function provides fundamental insights into automotive aerodynamics study. Therefore, the relationship follows this pattern. Knowledge has grown about opposing forces that significantly increase power consumption at high speeds compared to urban driving.

Charging efficiency analysis

This research examined charging situations involving home charger usage together with public charger operation. The installed home-charging system includes a 22 kW three-phase AC charger, which obtains power from the electrical grid to produce power for the battery storage. However, the EV used in this experiment is limited to receiving 6.6 kW single-phase AC power. To calculate the total charging losses in percentage, the following formula was used:

$$\text{Energy Loss (\%)} = \left(\frac{\text{Energy Supplied} - \text{Energy Stored}}{\text{Energy Supplied}} \right) \cdot 100 \quad (2)$$

In the case of home charging, energy consumption is measured at the point before the AC/DC conversion by the vehicles onboard charger. This means that the recorded energy not only includes the energy delivered to the battery but also the losses associated with the AC/DC conversion process. When using a fast charger, the energy measurement is taken after the AC/DC conversion has already occurred within the charging infrastructure. As a result, the reported energy consumption only reflects the energy delivered directly to the vehicles battery, excluding conversion losses.

Mathematical model for energy consumption prediction

The comprehension of EV energy efficiency in cold conditions requires empirical data and a mathematical model that forecasts energy consumption across untested situations. The testing of this study was conducted at five ambient temperature points ranging from +20 °C to +10 °C, 0 °C, -10 °C and -15 °C. The actual driving environment comprises temperatures between intermediate ranges and extreme conditions, which the authors did not evaluate through direct outside testing. The practical energy consumption rates diverge significantly from test measurements due to various real-world impacting factors, including the impact of the wind and the condition of the vehicles battery, as well as the current snow conditions on the road. Developing a predictive mathematical system requires implementation to forecast the efficiency of EV energy across different environmental situations. The predictive mathematical model provides essential insights to drivers and other stakeholders about range computations while helping them manage energy resources during cold weather conditions. When there is no predictive model available, EV users need to make decisions using imperfect empirical data that cannot reflect their particular situation.

The investigation of temperature-dependent utilisation required analysing the experimental data for patterns that described battery charge consumption per kilowatt-hour consumption. The fitted regression model for data trends used polynomial functions. A quadratic regression model was established from the test results to explain the connection between energy consumption E (kWh per 23.6 km) and ambient temperature t (°C). The model enables the prediction of energy consumption across a range of ambient temperatures based on empirical data.

The resulting equation is

$$E = at^2 + bt + c \quad (3)$$

where E is energy consumption per 23.6 km (kWh); t is the ambient temperature (°C); a , b , and c represent the empirically determined constants derived from regression analysis of test data.

The regression model produces distinct parameter values depending on the test drive conditions. Users of EVs can better predict their driving performance through the mathematical model when they need to assess range and energy spending across untested temperature conditions. The model needs additional variables for vehicle dynamic variables, such as wind resistance, snow-traction losses, and speed differences, in order to improve its prediction accuracy. Moreover, more values are needed for more extreme temperatures like -25 °C or -30 °C, because this formula might not apply there.

RESULTS AND DISCUSSION

Effect of temperature on battery energy consumption

A clear inverse relationship is shown with ambient temperature and battery efficiency, where the charge loss is more significant at lower temperatures based on data gleaned from test drives at various temps. Fig. 1 shows the battery energy consumption per test drive for temperatures between +20 °C and -15 °C, using various cabin heater settings. The results confirm that, at hot temperatures of +20 °C and +10 °C, the battery preserves more charge, while at subzero temperatures like 0 °C, -10 °C, and -15 °C, there is a significant increase in the energy consumption and therefore in the battery emptying. For the coldest test parameters (-15 °C), setting the heater at 25 °C caused the EV to drain 6.8 kWh of energy from the battery, compared to 3.2 kWh for a 16 °C heater setting at 20 °C, which is roughly double the difference in energy consumption. This demonstrates the impacts of outside temperature and energy use while driving an EV. All the results from test drives in different temperatures and cabin heating are shown in the table below.

Table 1. Energy consumption on the specific outside temperature

Test drive	Energy consumption on the specific outside temperature				
	20 °C	10 °C	0 °C	-10	-15
Test drive 1 (cabin heater at 16 °C, no preheater)	3.2	3.2	3.9	4.2	4.4
Test drive 2 (cabin heater at 19 °C, no preheater)	3	3.6	4.2	5.1	
Test drive 3 (cabin heater at 22 °C, no preheater)	2.9	3.3	4.6	6.1	
Test drive 4 (cabin heater at 25 °C, no preheater)	2.9	3.4	4.8	6.3	6.8
Test drive 5 (cabin heater at 16 °C, start with preheated cabin)	3.2	3.8	4.6	5.2	
Test drive 6 (cabin heater at 19 °C, start with preheated cabin)	3.1	3.5	5.2	6.5	
Test drive 7 (cabin heater at 22 °C, start with preheated cabin)	3.6	3.9	5.8	7.2	
Test drive 8 (cabin heater at 25 °C, start with preheated cabin)	3	3.3	6.2	7.6	
Test drive 9 (cabin heater is turned off)	2.5	3.1	3.2	3.3	3.2

The trend seen in Fig. 1 is consistent with other research on battery performance in cold weather, which finds that lithium-ion batteries experience around a 30% to 40% percent drop in efficiency when the temperature drops below 0 °C. There are some significant reasons why charge loss increases as temperatures fall. First, electrochemical reactions in the battery are slower at low temperatures than at high temperatures, resulting in higher internal resistance and lower energy supply (Senol et al., 2023). The second reason is that EVs depend on considerable battery power for cabin heating, resulting in higher energy consumption (Doyle & Muneer, 2019). Finally, the decreasing

efficiency of regenerative braking at lower temperatures means that less energy is recovered, which leads to a more significant overall depletion of the battery. The findings show that thermal management strategies must practically apply thermal insulation to the battery, enabling maximum performance to be calculated in freezing temperatures (Steinstraeter et al., 2021).

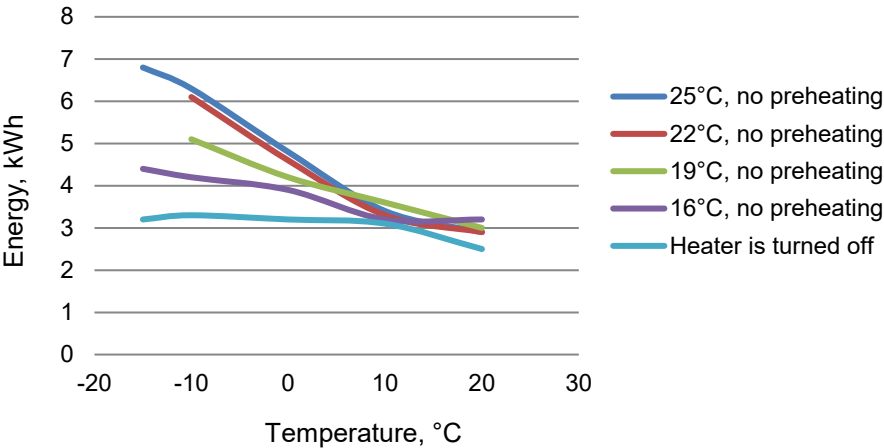


Figure 1. Test drives with no preheating.

Temperature and battery energy consumption are not linear when approaching lower temperatures. The rate of energy loss accelerates. In the warmer part of the experiment, the energy at +20 °C and +10 °C was not noticeably different, with just a tiny charge loss of 0.3%. As the temperature dropped from 0 °C to -10 °C, the energy consumption of the EV increased more sharply, exceeding 12% in some cases. For example, the values of the constants were established for test drive 4 (cabin heater at 25 °C, no preheater) at $a = 0.0015$, $b = -0.13$, and $c = 4.71$ by applying regression techniques to the assembled data. Therefore, the model equation is:

$$E = 0.0015 \cdot t^2 - 0.13 \cdot t + 4.71 \quad (4)$$

With an equation like this, the study can estimate energy consumption for temperatures that were not explicitly tested, for example, at -20 °C or intermediate values like -5 °C, as well as more general trends that we expect based on EV efficiency behaviour. Temperature has a negative coefficient; increasing it should reduce energy consumption. The constant c is the energy consumption without considering the linear extra losses caused at the level of heating systems that are applied without the temperature effect at 0 °C.

The results show that temperature is critical in determining the range of an EV, especially in cold climates because heating energy can make up more than 40% of total battery use. While internal combustion engine (ICE) vehicles can capture some waste heat produced by the engine for heating the cabin, EVs have no such benefit. The cars must generate heat through resistive heaters or heat pumps, requiring potentially significant additional energy costs. This is especially evident in examples of higher cabin temperatures, shown in Fig. 1. An EV with a cabin heater set to 16 °C used

4.2 kWh of energy from the battery at -10 °C, while the same model used 6.3 kWh with the heater at 25 °C – indicating that roughly one-third of the energy went to heating the additional 9 °C. Moreover, if the cabin heater was completely turned off, the EV only used 3.3 kWh for the test drive at the same outside temperature. These results demonstrate the apparent correlation between heating demand and total battery usage.

To further strengthen the analysis of temperature effects on energy consumption, a statistical correlation analysis was conducted. This included the Pearson correlation coefficient, which measures linear relationships, and the Spearman correlation coefficient, which assesses monotonic associations.

The analysis was based on energy consumption data from test drive 1 (cabin heater at 16 °C, no preheater) across five temperature points (+20 °C to -15 °C). The results showed a very strong negative correlation between ambient temperature and battery energy use:

- Pearson correlation coefficient: -0.980
- Spearman correlation coefficient: -1.000.

These results confirm that lower temperatures consistently increase EV energy consumption, and the perfect Spearman value indicates that this trend is strictly monotonic. The correlation analysis supports the earlier polynomial regression and underlines the significance of temperature as a dominant factor affecting winter EV efficiency.

Impact of cabin heater settings on overall efficiency

Fig. 2 demonstrates how cabin heater settings affect the total energy consumed, directly proportional to heater temperature and the amount of drained battery. Therefore, if the expectation is that higher heater settings draw significantly more power from the battery than lower settings, reducing climate controls role on battery efficiency is evident as even a difference in heater setting of around 9 °C in subzero temperatures leads to a nearly 30% difference in consumption.

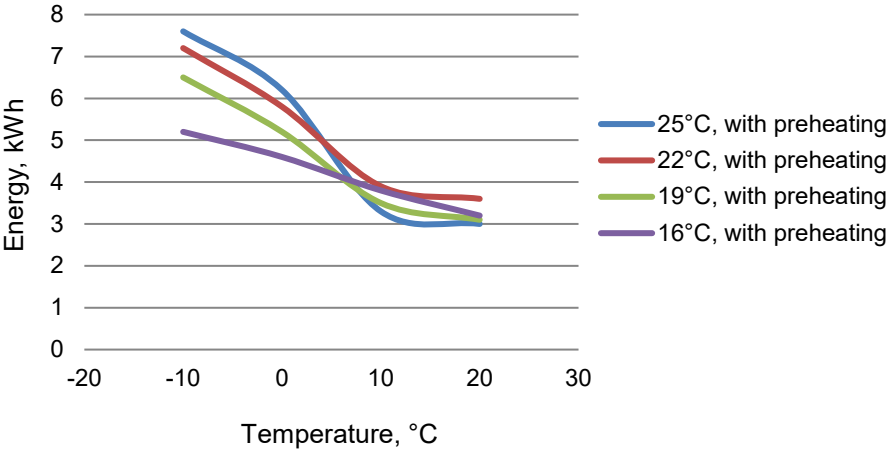


Figure 2. Test drives with preheating.

The most remarkable observation is that the vehicles overall range is sensitive to heater use, and extreme cold is widespread. When the temperature was warmer, above 10 °C, the difference in heater settings mattered less due to some outdoor passive heating as the external environment was also hot. While things were better at zero and below, the energy required to maintain higher cabin temperature increased sharply, becoming one of the more significant contributors to range cuts. This means that other heating solutions, like seat warmers, steering wheel heaters, and preheating strategies, may save considerable battery power while keeping passengers comfortable.

Input data, more commonly seen between graphs, such as energy consumption at different cabin heater settings, indicates that temperature changes of only several degrees significantly impact output. For example, when the heater’s temperature was changed from 22 °C to 19 °C, the energy consumption decreased by almost 10%. Still, when changed from 22 °C to 25 °C, the energy consumption increased by 15%. This shows that the connection between heater settings and energy loss is not linear. As the heater runs at higher temperatures, the energy use grows exponentially and is not a linear function. Test drives with preheating at -15 °C were not conducted in this study due to the unusually mild winter conditions in the region.

Relationship between vehicle speed and power consumption

In this section, we examine the dependency of power consumption on vehicle speed. The unit of speed used is km h⁻¹, as it is the standard convention in European traffic systems. The following analysis is based on the results obtained from real-world driving tests. Fig. 3 shows the correlation between vehicle speed and instantaneous power demand (kW). It shows a clear upward trend in power consumption as speed increases. The results show that the power demand is not too high at low speeds like 40 km h⁻¹ (~2.9 kW). However, increasing speed does increase power consumption significantly: it is 10.15 kW at 80 km h⁻¹ and jumps to 32.65 kW at 130 km h⁻¹, which means that more energy is needed per km at higher speeds, and the data confirms this.

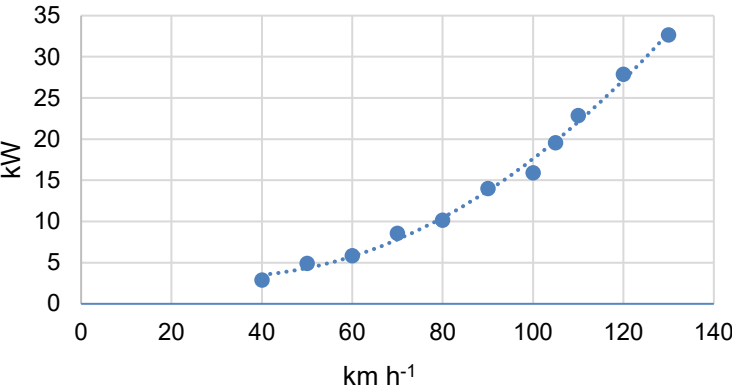


Figure 3. Power consumption compared to car speed.

The curve has a non-linear relationship. Thus, increasing speed results in a rise in demand for power. This is primarily due to aerodynamic drag and rolling resistance, both growing at speeds. Although there are power demands due to mechanical losses, such as

drivetrain and tyre friction, the aerodynamic forces dominate at highway speeds, so that EVs can be vastly less efficient at higher speeds. Driving an EV above 90 km h⁻¹ drastically increases its power consumption, primarily due to air drag. Therefore, driving on highways or high speeds becomes an area where considerable efficiency can be present.

The figures further emphasise that the increase in power draw from travelling 40 km h⁻¹ (2.9 kW) to 80 km h⁻¹ (10.15 kW) is relatively moderate in comparison to that of 80 km h⁻¹ to 130 km h⁻¹ (~10.15 kW to 32.65 kW). Moreover, the system consumed 2.9 kW at 40 km h⁻¹, which increased to 10.15 kW at 80 km h⁻¹ and further to 32.65 kW at 130 km h⁻¹, demonstrating this quadratic relationship that principally resulted from aerodynamic properties. The total power increase between 40 km h⁻¹ to 120 km h⁻¹ speed became more than 10 times greater beyond a simple factor of 3 because of increased air resistance effects. This shows that the faster they go, the higher their power demand, which is a basic power consumption for EVs. Based on the data, driving at moderate speeds between 50 and 80 km h⁻¹ maximises energy efficiency, while higher speeds of 100 km h⁻¹ and beyond negatively impact the range. This result is particularly relevant in cold climates where battery efficiency is decreased. As such, one of the top strategies for maximizing driving range in winter should be speed optimisation for EV drivers in the Nordic and Baltic territories.

Finally, a polynomial regression was applied that provided insights into the observed signal, including speed (x) versus power consumption (P), as presented below.

The equation of the trend line fitting the test data is:

$$P = ax^2 + bx + c \quad (5)$$

where P is the power consumption (kW); x is the vehicle speed (km h⁻¹).

Constants in the model were determined by applying polynomial regression techniques to the observed dataset, resulting in the values $a = 0.003$, $b = -0.193$, and $c = 6.358$. Consequently, the model equation is:

$$P = 0.003x^2 - 0.193x + 6.358 \quad (6)$$

This equation allows the estimation of power consumption at speeds not explicitly tested. It demonstrates that power consumption will increase dramatically as speed rises until highway velocities where the quadratic part of the equation controls the result. The polynomial nature of this model has been verified since it follows known aerodynamic principles leading to quadratic velocity-dependent drag forces. The model functions as a useful method for evaluating EV power consumption beyond the standard speed range, and this enables drivers and manufacturers to check their efficiency regarding range at other speeds.

The quadratic growth of power demand at high speed is primarily related to aerodynamic drag, rolling resistance, and drivetrain inefficiencies, all growing factors as speed increases (Kozłowski et al., 2024). At lower speeds below 60 km h⁻¹, up to 90% of power consumption is determined by rolling resistance and tyre friction, with relatively low aerodynamic drag. However, as the car speeds up past 80 km h⁻¹, air resistance takes over and quickly outgrows progress, demanding exponentially more power to compensate (Puma-Benavides et al., 2024). This trend agrees with the fundamental laws of fluid dynamics, which state that counteracting aerodynamic drag requires power proportional to speed cubed (Broniszewski & Piechna, 2022). The results obtained from our test drives support the findings presented in the referenced articles.

This means that when a driver increases vehicle speed, they increase aerodynamic drag power requirements by 8, reducing vehicle efficiency at highway speeds. Indeed, as the data in this study demonstrates, at 40 km h⁻¹, the vehicle pulls 2.9 kW, while 130 km h⁻¹ leads to 32.65 kW energy consumption, a steep and nonlinear increase that highlights the impact of aerodynamic drag on power demand at higher speeds.

Air resistance is one of the significant aspects that leads to energy inefficiency at high speeds, and it also plays an essential role in the efficiency of EVs (Kozłowski et al., 2024). Rolling resistance is the effort needed to keep the tyres moving over the road surface, and it rises with speed due to extra tyre deformation, more internal friction between rubber elements, and a higher contact pressure with the road. In winter, driving conditions such as snow and ice accumulation increase rolling resistance, which also causes inefficiency at higher speeds (Challa et al., 2025). Opting for the correct set of tyres, ideally winter-rated, low-rolling-resistance EV tyres, can minimise energy waste in the cold.

Drivetrain inefficiencies also contribute to increased energy consumption at higher speeds. EV motors, in contrast to internal combustion engines, produce almost no heat, but they are not necessarily energy efficient at all speed ranges (Jeong et al., 2025). At lower to moderate speeds, EV motors operate at their most efficient range, so almost all energy fed from the battery is transformed into motion with minimal losses. When speeds are high, motors rotate faster, translating to more heat waste, more electrical impedance, and, eventually, less overall efficiency. Consequently, with rising speed, the energy loss in the motor and drivetrain becomes exponential. Therefore, the energy consumption to travel the same distance increases.

Driving inefficiencies at high speeds are compounded in cold weather as rolling resistance increases, regenerative braking is less effective, and heating requires significant energy with an EV (Kaleli & Sungur, 2025). Even snow-covered roads, icy surfaces, and colder tyre compounds present higher friction and rolling resistance, making the motor work harder to maintain the same speed. In winter, however, regenerative braking is less effective, so less energy is recovered upon deceleration from high-speed travel (Steinstraeter et al., 2021), creating higher net energy consumption. This highlights the need for improved EV driving behaviour throughout winter, as lower speeds have a real benefit in stretching range while avoiding unnecessary energy losses.

The findings indicate that EV drivers could benefit from implementing a speed-management strategy to maximise energy efficiency, particularly in those areas where winter efficiency drops are notably high. For ICE vehicles, fuel efficiency is optimum at moderate to high speeds between 80 and 110 km h⁻¹, but EVs are most efficient at lower speeds between 50 and 80 km h⁻¹, especially in cold weather. This calls for the further education of consumers on how speed affects energy usage, as many drivers might unwittingly give up range by travelling at higher speeds than necessary without being aware of the impact on both aerodynamic drag and rolling resistance.

Driving at moderate speeds remains one of the best strategies for maximising the range of an EV, especially in cold-weather setups where the battery is already less effective. As vehicle speeds increase, aerodynamic losses, rolling resistance, and drivetrain inefficiencies increase, resulting in disproportionate energy consumption. An energy-efficient driving style can increase EV battery range and decrease frequent charges.

Charging efficiency comparison

The energy losses when charging at home and fast-charging facilities are compared in Fig. 4, showing the difference between the energy extracted from the grid and the energy stored in the vehicles battery. The findings suggest a limited range from home charging instead of fast charging, with average energy losses of 17.8% and 8.0%, respectively as seen in Fig. 5. The losses occur owing to various inefficiencies such as losses in AC/DC conversion, loss of energy in charging components due to heat dissipation, and differing rates of charge acceptance by the battery. Home charging, which relies on alternating current (AC) from the grid, requires an onboard inverter within the EV to perform an AC/DC conversion before the energy can be stored in the battery. The conversion is not 100% efficient, and energy is dissipated as heat due to electrical resistance power dissipation in the inverter and wiring system. The elements result in a net less effective amount of energy being taken from the grid to the battery. Therefore, the energy from the grid is always much higher than the battery that is charged when using a home charger, which leads to an increase in energy consumption for electric vehicles and longer charging times.

From a home-charging perspective, high energy loss is primarily due to the AC/DC converter within the EV onboard charger. This conversion process is not totally efficient, as some distributed energy is lost as heat power dissipation, electrical resistance, and inverter inefficiencies contribute to this loss. In this study, the home-charging configuration was a 22 kW three-phase AC charger with an internal power inverter for AC/DC conversion. According to the test data, for each 28.3 kWh of electricity drawn from the grid, only 23.2 kWh can be effectively stored in the battery, with an average energy loss of 17.8%. The numbers reveal how much energy can be lost with a home charger. The study notes that charging at low power levels can cause energy loss because of longer charging times, leading to increased power dissipation. The longer an EV is plugged into a home charger, the more

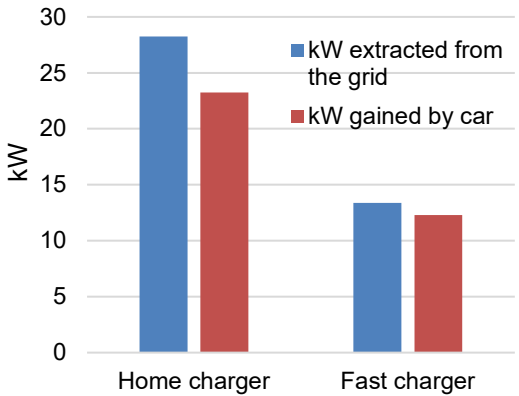


Figure 4. Consumed energy and actual received energy.

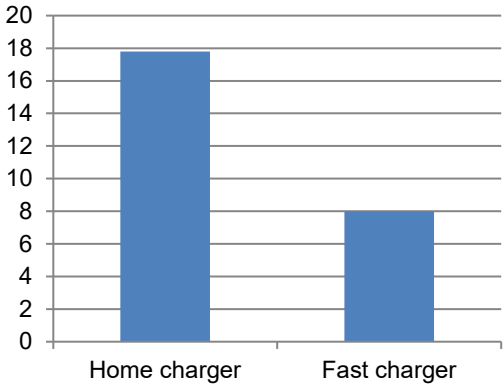


Figure 5. Energy loss % in home charger and fast public charger.

energy is lost through heat dissipation and passive energy consumption from auxiliary systems (Feng et al., 2025).

Fast charging offers many benefits, like a quicker charge and increased efficiency, especially for battery-charged systems (Martini et al., 2025). In this study, a 50 kW fast charger was used to charge the EV's battery. In a fast charger the energy extracted from the grid was measured after the AC/DC converter, so fast charging was, on average, 92% efficient, while home charging had only an 82% efficiency rate, making fast chargers nearly two times more efficient in preventing lost energy. The increased efficiency of fast chargers may be ascribed to various reasons, such as the fact that they run at higher voltage, have fewer steps in energy conversion, and, more importantly, can accept charge much faster (Prasad & Gudipalli, 2025).

In EV models that have a battery preheating system, fast charging also has an advantage in that it can grow the preheat on the battery before starting charging, allowing for improved charge acceptance and efficiency in colder conditions. Cold lithium-ion batteries show lower ion mobility and poorer charge acceptance at lower temperatures, resulting in longer charging phases and increased accumulated energy loss when charged at non-ideal temperatures (Tai et al., 2025). Preheating the battery before the charging process reduces the loss of charging efficiency. Temperature gets to the optimum point before charging is started. Therefore, fast chargers enable quicker charging with minimal energy loss, making them preferable for EV use in winter conditions. Lithium-ion batteries have high internal resistance and lower charge acceptance in cold conditions. Therefore, manufacturers must offer innovative isolation techniques and active heating solutions to minimise performance loss (Murugan et al., 2025).

The comparison between home and fast charging highlights significant differences in energy efficiency, power conversion losses, and charging effectiveness. Charging losses tend to be higher when using a home charger compared to public fast-charging stations. However, the overall cost of charging at home can still be lower, as electricity prices for residential consumers are often significantly cheaper. Additionally, home charging allows users to schedule charging sessions based on fluctuating electricity prices in the stock market, further optimising costs. Moreover, slow home charging is generally more beneficial for the long-term health and lifespan of an electric vehicle's battery compared to frequent fast charging, which can accelerate battery degradation due to increased heat generation and higher charging currents (Leijon, 2025).

Importance of adaptive heating strategies to minimise energy waste

As heating systems significantly impact EVs' efficiency, implementing adaptive heating strategies is necessary to reduce energy waste and maximise winter range. The analysis proved that the cabin temperature setting firmly influences battery consumption. Higher heating requests cause more considerable energy losses. Therefore, an intelligent climate control system that can synchronise heating based on occupancy, ambient temperature, and battery charge levels is a crucial solution. For instance, a vehicle that can intelligently control its climate based on its charge could automatically make the cabin cooler and rely on more seat and steering wheel heat when the EV's battery is critically low. Using energy-efficient heating approaches will allow EVs to keep passengers comfortable without pulling extra power (Swami et al., 2025).

Preconditioning is another effective way to mitigate energy losses. The vehicle's battery and cabin can be warmed up while remaining plugged into a charging station, lowering the energy demand of the battery during the drive (Esparza et al., 2025).

Aside from the updates to software, battery insulation improvements might also retain heat better, meaning there would not need to be continuous heating requirements (Yang et al., 2025). A certain amount of thermal insulation is already included in many modern EVs. Still, there is a need for further research into more advanced thermal insulation materials that can keep heat trapped within the battery pack while not adding too much weight. Insulation technologies could help EVs use less energy for battery heating, so more of that energy can go toward propulsion, which means a better range in cold climates.

Future research directions

This study-based mathematical model is a valuable tool for estimating the energy consumed by an EV at different temperatures. However, further field validation is needed to enhance its accuracy and applicability. The present model uses test drive data from one vehicle. Therefore, its predictions may not be generalisable across all EVs, especially those with different battery capacities, thermal management systems, and drivetrains. Since different EV manufacturers use different battery management strategies, which may include both passive and active heating levels, preconditioning methods, and regenerative braking optimisations, it is essential to validate the model for various brands and vehicle models. In addition, expanded validation of the model would help to identify efficiency variations that could be used to refine predictive algorithms to ensure drivers and manufacturers can depend on it for winter range estimation. Other variables not modelled in this study that are critical to real-world EV efficiency include vehicle age and battery degradation. For a car that has been in service for a long time, research could be conducted on how that affects cold-weather performance because older batteries can lose more energy than newer ones at subzero temperatures.

Further model refinement should also incorporate extreme temperature conditions outside of this study's evaluation. The experimental dataset was limited to temperatures of +20 °C to -15 °C, but temperatures may be colder during winter driving, even below -30 °C in some cases. Including data for the extremes could help improve the model's predictive power in that range, allowing for more accurate assessments of the likely range under extreme winter conditions. Moreover, this study mainly focused on urban and highway driving over dry roads. However, winter often includes snow-covered roads, icy surfaces, and slush, all of which increase the rolling resistance and create a lower energy efficiency. It is essential to conduct controlled tests on multiple types of road surfaces to determine traction loss, excess energy required to maintain stability, and variations in tyre efficiency under differing winter conditions. By incorporating the variables, the model may become a more dynamic predictive tool used in various winter driving climates.

Another feature that needs to be included in future model versions is the impact of cold weather on regenerative braking efficiency. The current equations primarily consider temperature-dependent battery losses and speed-related power demand and do not explicitly include the lowered regenerative braking yield at low temperatures. Regenerative braking can recover up to 30% of an EV's lost energy in perfect

conditions, drastically enhancing range and efficiency. Nonetheless, when temperatures drop below zero, battery charge acceptance decreases, making energy recovery from braking less effective. Because EVs use regenerative braking as a central strategy for efficiency, inaccurate modelling of its variability in cold weather risks overinflating range predictions. Future studies will need to be performed to build a more comprehensive multi-variable equation that would include analyses of temperature, speed, regenerative braking efficiency, and battery preconditioning effects to create a better tool to estimate a winter range.

CONCLUSIONS

The energy efficiency of electric vehicles (EVs) during cold temperatures has been thoroughly explored in this study, with a detailed investigation of the effects on battery charge loss, power demand at different speeds, and charging efficiency in both home and fast-charging situations. The results show temperature has a key impact on overall EV efficiency, with below-freezing conditions causing increased energy consumption with reduced driving range. Battery degradation rate nearly doubles at $-15\text{ }^{\circ}\text{C}$ compared to $+20\text{ }^{\circ}\text{C}$, indicating a need for battery thermal-management systems to minimise cold-weather efficiency losses. Moreover, this study has examined the speed-versus-power-draw relationship, finding that energy consumption based on velocity increases as speed increases. The polynomial linear regression built in this study indicates that power demand is a quadratic function, with the significant impact of faster driving on EV range evident from 80 km h^{-1} onwards. The predominance of aerodynamic drag while driving slowly from 40 km h^{-1} to 120 km h^{-1} would imply a compound speed increase of three times. It is associated with the demand for more than ten times the power, underlining the effect of high-speed driving on EV range. Moderate driving speeds between 50 and 80 km h^{-1} provide the best energy efficiency in the vehicles. Therefore, speed is a significant component that drivers should pay attention to in order to maximise their range.

The findings from this study provide some actionable recommendations for EV operators seeking to maximise efficiency during wintertime driving. One of these strategies is preheating the whole vehicle. While the vehicle remains connected to an external power source, preheating reduces the battery's initial heating requirement and minimises energy loss during driving. Since charging losses, especially in home-charging systems, are relatively high, electricity prices should be kept in mind and the charging should be adjusted accordingly. By strategically timing charging sessions according to energy price fluctuation, users can minimise costs and improve overall charging efficiency. Driving speed should remain within moderate levels, as speeds exceeding 90 km h^{-1} significantly increase energy consumption. The higher the speeds, the greater the aerodynamic drag and the efficiency of the vehicle goes down. Reducing speed helps optimise energy usage and increase the EV's driving range.

Limitations of the study

Although this study offers essential insights into EV energy efficiency in cold climates, some limitations should be acknowledged. The key limitation is that the trials were performed with only one EV car, so the findings may not necessarily reflect those

of other EVs, especially those that use different battery chemistries and thermal management systems. The tested temperature range between -15 °C to +20 °C does not include extreme temperatures, for instance, -30 °C or lower, which might lead to even more significant energy losses. Testing under even harsher temperatures will give us a better idea of how EVs perform in winter weather. At the same time, recent climate trends, including this year's unusually warm winter, indicate that the Baltic region is experiencing a warming climate. As a result, extreme cold events are becoming less frequent, which positively affects EV energy efficiency.

Also, the study was mostly based on controlled test drives, which followed identical routes and steady driving behaviour, which does not reflect real-world driving situations that encounter highly variable factors, such as traffic jams, elevation changes, or varying road surface conditions. This particular study did not specifically test the types of surfaces on the road, for example, and therefore a requirement of more power to move the vehicle. Furthermore, real-world EV drivers likely have varying driving habits – such as increased acceleration and regenerative braking – and that should impact overall efficiency as well. To increase the real-world relevance of our results, future research should examine a wider range of driving scenarios, including stop-and-go urban driving and driving on highways with varying speed limits.

To summarise, future work can address the limitations identified in this study by applying heavier techniques for EV energy efficiency studies. This means testing a variety of EV models involving different battery chemistries and thermal management systems so that the findings have wider applicability. Further experiments need to be performed at even lower temperatures, for instance, -30 °C or below to evaluate the total energy losses over the coldest winter months. Although climate trends in the area indicate warming in the Baltic region, episodes of extreme cold still occur, and can substantially affect the performance of an EV. In addition, future studies must include more realistic driving scenarios that include variations in factors such as traffic flow, elevation gain, and road surface conditions (e.g., snow and ice). A greater focus in the research on how specific driving behaviours like aggressive acceleration, braking with energy recuperation and their overall efficiency would also add practical value to the benefits of the research.

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Acid composition of wines depending on grapevine (*Vitis* spp.) cultivars grown in Estonia

R. Rätsep^{1,2,*}, M. Maante-Kuljus¹, K. Karp¹, K. Seeme² and U. Moor¹

¹Estonian University of Life Sciences, Institute of Agricultural and Environmental Sciences, Chair of Horticulture, Fr. R. Kreutzwaldi 5, EE51006 Tartu, Estonia

²Estonian University of Life Sciences, Institute of Veterinary Medicine and Animal Sciences, Chair of Food Science and Technology, Fr. R. Kreutzwaldi 5, EE51006 Tartu, Estonia

*Correspondence: reelika.ratsep@emu.ee

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Abstract. In Estonia's very cool climate, excessive acid content in grapes can be a challenge due to delayed ripening. This study aimed to compare the acid profiles of commercial single-cultivar wines produced by Estonian winemakers, and assess the influence of grapevine cultivar. The wines were made from grapes of five different cultivars: 'Solaris', 'Regent', 'Leon Millot', 'Cabernet Cortis', and 'Marquette'. The results revealed significant variation in malic, tartaric, citric, and lactic acid concentrations among the wines. Marquette exhibited the lowest malic acid content (0.3 g L⁻¹), while Leon Millot had the highest (4.4 g L⁻¹). Tartaric acid levels in wines ranged from 2.2 g L⁻¹ in Leon Millot to 4.1 g L⁻¹ in Regent. Citric acid levels varied considerably, with Solaris containing the highest concentration (1.44 g L⁻¹). Marquette had the highest lactic acid content (2.27 g L⁻¹), contributing to its smooth character. Total acid content in wines ranged from 6.9 g L⁻¹ in Marquette to 9.4 g L⁻¹ in Leon Millot, while pH values varied between 2.9 and 3.3. These findings indicate that grape cultivar significantly influences wine acid composition. Contrary to the hypothesis, excessive acid content was not a major issue in commercial wines; however, grape-growing conditions, such as high plastic tunnels, could alter this outcome. This study provides valuable insights for winemakers seeking to optimize acid balance and enhance wine quality in cool-climate viticulture.

Key words: lactic acid, malic acid, pH, tartaric acid, total acid.

INTRODUCTION

As global temperatures rise, the traditional boundaries for grapevine growing are shifting, affecting the suitability of certain grape cultivars in specific regions and potentially altering the characteristic profiles of wines from these areas (Schultz & Jones, 2010). Increasing temperatures turning the current wine production areas too warm and causing excess sugar levels, whereas the production of dry wines shifts further on to North (Sustainable adaption...2017). Consequently, cooler climate conditions present both challenges and opportunities in winemaking, significantly influencing the flavors

and overall profiles of wines produced from specific cultivars. Viticulture in cooler regions is more labor-intensive and carries greater risks; however, it can also attract tourists and contribute to sustainable rural development. The unique climate and terroir may result in distinctive wine profiles that appeal to niche markets (Schernewski, 2011). Although Estonia is not widely recognized for grape cultivation due to its northern climate, interest in viticulture is growing as part of a niche industry. Since 2021, Estonia has been included in EU wine-growing zone A (Appendix I of Annex VII to Regulation (EU) No 1308/2013). In Estonian vineyards, the most common cultivar is ‘Solaris’, accounting for 43% of the total number of plants. It is primarily cultivated in high plastic tunnels, as it has not proven to be winter-hardy in open-field conditions. Other cultivars such as ‘Regent’, ‘Cabernet Cortis’, and ‘Leon Millot’ are also commonly grown exclusively in tunnels, and in recent years, wines produced from these cultivars have entered the Estonian market.

Wines from cooler regions are generally associated with higher acid content in grapes at harvest (Barnuud et al., 2014; Kemp et al., 2018; Riesterer-Loper et al., 2019). This is because cooler temperatures slow down metabolic processes that degrade organic acids during ripening. The slower ripening process leads to lower sugar concentrations and higher organic acid levels, particularly malic acid. The primary acids in grapes are tartaric and malic acid, but malic acid is affected by the temperature the most. In cold climates, the degradation of malic acid is slower, resulting in higher overall acidity in the grapes and, consequently, in the wines (Barnuud et al., 2014; Plantevin et al., 2024). The breakdown of malic acid begins once sugar accumulation starts and is more pronounced at higher temperatures (Rienth et al., 2016). The decrease in tartaric acid content is relatively small compared to malic acid degradation.

The total acid content of grapes is also reflected in wines, although it changes to some extent during the winemaking process. Wines from cooler regions tend to have significantly higher concentrations of organic acids compared to those from warmer locations. For instance, red wines from Nova Scotia cooler and warmer locations showed strong differences in acids composition, whereas no apparent differentiation was observed among white and rosé wines (Chahine & Tong, 2019). The wine acid profile can also be influenced by the growing region. Wines from different regions in the USA and Italy exhibit significant variations in tartaric and malic acid concentrations (Lima et al., 2022). Cool-climate wines are characterized by elevated levels of organic acids, particularly malic acid, which can contribute to a sharper taste (Riesterer-Loper et al., 2019; Wojdyło et al., 2020). Red wines generally have higher acidity and lower alcohol content compared to those from warmer regions (Kemp et al., 2018). High acidity in wines helps to preserve their freshness and stability over time (Morata et al., 2019), which is crucial for maintaining desirable sensory attributes during aging.

The primary organic acids in wine include tartrate ($\sim 1.5\text{--}4.0\text{ g L}^{-1}$), malate ($\sim 0\text{--}4.0\text{ g L}^{-1}$), lactate ($\sim 0.1\text{--}3.0\text{ g L}^{-1}$), acetate ($> 0.2\text{ g L}^{-1}$, measured as volatile acidity), citrate ($\sim 0\text{--}0.5\text{ g L}^{-1}$), and, in some cases, succinate ($0\text{--}2\text{ g L}^{-1}$) (Ribéreau-Gayon et al., 2006). The grapevine cultivar plays a crucial role in determining these characteristics. Different cultivars exhibit varying rates of malic acid degradation during ripening (Plantevin et al., 2024). Some cultivars metabolize malic acid more rapidly, which affects the overall acidity of the wine. Cultivars also differ in how they modulate tartaric acid, particularly under high temperatures, impacting the wine's acid content and

pH levels. White wines, such as Riesling, are often characterized by high acids. The choice of cultivar and the timing of malolactic fermentation significantly influence the final wines acid levels (Knoll et al., 2012; Wojdyło et al., 2020). Interspecific hybrid grape cultivars, such as ‘Brianna’, ‘Frontenac’, ‘La Crescent’, and ‘Marquette’, tend to exhibit high acid content, primarily due to elevated malic acid concentrations (Riesterer-Loper et al., 2019; Scharfetter et al., 2019). At the same time total acid levels in Danish Solaris wines were moderate to low considering the cool climate, which documented the good adaptation of these cultivar to the cool Scandinavian climate (Liu et al., 2015).

In addition to cultivar characteristics, acid content is also influenced by vine-growing techniques. For example, canopy management practices such as pruning time, leaf removal and shading can affect grape acid content (Rätsep et al., 2014; Lampiř & Žaloudek, 2018; Ghiglieno et al., 2023). Proper defoliation helps to maintain higher acid levels, which is particularly important for sparkling wines that require high acidity. Cluster thinning can also impact acids in grapes. For instance, early leaf removal and cluster thinning have been shown to decrease titratable acidity in certain cultivars, such as ‘Cabernet-Sauvignon’ (Ivanišević et al., 2020). Similarly, leaf removal at *véraison* combined with potassium foliar applications in ‘Beibinghong’ vines reduced titratable acidity (Le et al., 2022). A study on hybrid cultivars over three consecutive growing seasons demonstrated the significant beneficial influence of *pre véraison* leaf and lateral shoot removal on titratable acidity. This effect was associated with increased berry temperature and higher levels of photosynthetically active radiation in the fruiting zone (Scharfetter et al., 2019). The cultivation of wine grapes in high polytunnels significantly affected their technological maturity parameters: juice pH was significantly higher, and acid content was lower in tunnel-grown grapes compared to those grown in an open field (Maante-Kuljus et al., 2019a).

High acidity in cool-climate wines can make spontaneous malolactic fermentation problematic, yet this process is essential for developing desirable sensory characteristics (Vigentini et al., 2009; Mota et al., 2017). Spontaneous malolactic fermentation is a critical secondary fermentation process in winemaking, primarily driven by lactic acid bacteria such as *Oenococcus oeni*, *Lactobacillus*, and *Pediococcus* species. This process converts malic acid into lactic acid, reducing wine acidity while enhancing its stability and sensory profile (Alexandre et al., 2004; Lonvaud-Funel, 2022). High acidity can mask fruit flavors and result in a less balanced wine. Adjustments in winemaking practices, such as the use of specific yeast strains and fermentation techniques, are necessary to manage these effects (Knoll et al., 2012; Kemp et al., 2018). Properly managed malolactic fermentation can enhance the aromatic complexity and stability of wine, whereas improper management may lead to undesirable flavors and spoilage (Lasik-Kurdyś et al., 2017; Lasik-Kurdyś et al., 2018). The biological reduction of acidity has been shown to have no significant impact on phenolic content or antioxidant capacity (Wojdyło et al., 2020).

Based on the above, it could be hypothesized that excessive acid content may become a challenge in wines produced in Estonia’s very cool climate. The aim of this study was to compare the acid composition of commercial single-cultivar wines produced by Estonian winemakers and to determine the influence of grapevine cultivar.

MATERIALS AND METHODS

Viticulture and vinification

The grapes for the test wines were harvested from three different vineyards in 2023 in South Estonia (58°17'1"N, 26°33'41"E, 57°58'58.6" N 26°34'04.2"E, 57°55'24"N 26°43'9"E). The vines were grown in high plastic tunnels. These foundation-free tunnels measured 28 m in length, 7.6 m in width, and 4.6 m in height, and were covered with 0.18 mm thick UV-stable low-density polyethylene. The ends of the high plastic tunnels were open from spring to autumn.

Vines grafted onto SO₄ rootstock were planted in 1.6×2 m spacing, trained on low double-trunk trellises, and pruned using the spur method. The vine rows were oriented from north to south, with the ground covered by woven ground cover fabric. The vineyards' soil was high-productivity sandy loam *Haplic Luvisol*. Grapevines were cultivated in a tunnel without a foundation, and therefore, precipitation still affected the soil moisture regime within the tunnel. This can be explained by the fact that water in the soil moves not only vertically but also horizontally due to soil capillarity, porosity, and gradients in water potential. Consequently, rainfall outside the tunnel can spread laterally into the root zone soil, particularly in soils with good hydraulic conductivity and favourable structure. Therefore, the vine plants did not need fertilizers, or additional irrigation. At the beginning of *veraison*, leaves were removed from the cluster zone. In all vineyards, leaf removal was performed both below the grape clusters and on the side opposite to the clusters, in order to improve air circulation, enhance sunlight exposure, and reduce the risk of fungal diseases.

The experimental grapevine cultivars were as follows: 'Solaris', 'Regent', 'Leon Millot', 'Cabernet Cortis', and 'Marquette'. Harvest dates differed among cultivars and were determined by monitoring the °Brix level of grape samples collected from the vineyard using a portable refractometer. Harvest was carried out once the °Brix value had stabilized and showed no further significant increase. The grapes for the experimental wines were picked in the morning in mid-September, and the berries were crushed and destemmed with a destemmer on the day of harvest. The resulting juice had the soluble solids content as follows: 'Solaris', 'Regent', and 'Leon Millot' 16 °Brix; 'Cabernet Cortis' and 'Marquette' 23 °Brix. Total acids contents were: 'Solaris' 6.8, 'Regent' 8.8, 'Leon Millot' 9.4, 'Cabernet Cortis' 8.5 and 'Marquette' 8.7 g L⁻¹, and pH: 'Solaris' 3.07, 'Regent' 3.01, 'Leon Millot' 3.25, 'Cabernet Cortis' 3.08 and 'Marquette' 3.20. Dried active yeast of the *Saccharomyces cerevisiae* strain was added to the musts according to commercial specifications. Fermentation with skins and seeds took place over seven days (including Solaris but excluding Cabernet Cortis rosé wine), with cap punching performed four times a day. For the production of Cabernet Cortis rosé wine, the maceration time was limited to 24 hours only. Pressing of all treatments was carried out using a 20 L stainless steel water-pressure press. Further fermentation and maturation were conducted in 100 L stainless steel tanks with floating lids at a temperature of 18–20 °C. To enhance the final alcohol concentration (excluding 'Cabernet Cortis' and 'Marquette'), glucose was added prior to fermentation, based on findings that *Saccharomyces cerevisiae*, including commercial oenological strains, preferentially metabolizes glucose over other sugars due to its efficient uptake and rapid conversion via glycolysis (Berthels et al., 2004). Glucose was added based on the °Brix reading separately for each cultivar, and all wines were fermented to dryness (reducing sugar

$< 4 \text{ g L}^{-1}$). No malolactic fermentation was carried out. The finished young wine was used for instrumental analysis four months later. The alcohol content was: ‘Solaris’ 9.8, ‘Regent’ 9.8, ‘Leon Millot’ 10.8, ‘Cabernet Cortis’ 10.7 and ‘Marquette’ 12.7%.

Chemical analyses

The analysis of different organic acids in the tested wines was performed in three replicates. For the measurement of total acids, malic and tartaric acids, the wine samples were carried over to the 5 ml syringe and injected into the flow system, and scanned using a horizontal platinum diamond attenuated total reflectance (ATR) single reflection sampling module cell mounted in a Bruker Alpha FT-IR Wine analyzer (Bruker Optics GmbH, Ettlingen, Germany). Before scanning, wine samples were automatically stabilized in the cell at 40 °C as recommended by the manufacturing company with reference background spectrum recorded between different samples using deionised water. The ATR-NIR spectra were recorded by OPUS software version 7.5 provided by Bruker Optics (Bruker Optics GmbH, Ettlingen, Germany). The spectrum of each sample was obtained by taking the average of 120 scans. The maximum deviation from average of IR-analysis for prediction for total acid was $\pm 0.5 \text{ (g L}^{-1}\text{)}$, malic acid $\pm 0.6 \text{ (g L}^{-1}\text{)}$, tartaric acid $\pm 0.3 \text{ (g L}^{-1}\text{)}$ and pH ± 0.12 .

Weather Conditions

To characterize the weather conditions during the grapevine growing season (May–September) in Southern Estonia in 2023, temperature and precipitation data were presented alongside the 1991–2020 long-term average (Fig. 1 and Fig. 2; Estonian Environment Agency, 2025). The average temperature in May was 11 °C, which is exactly the same as the long-term average, but May was the most extreme month, with a minimum temperature of -6 °C, which is unusually cold for spring (Fig. 1).

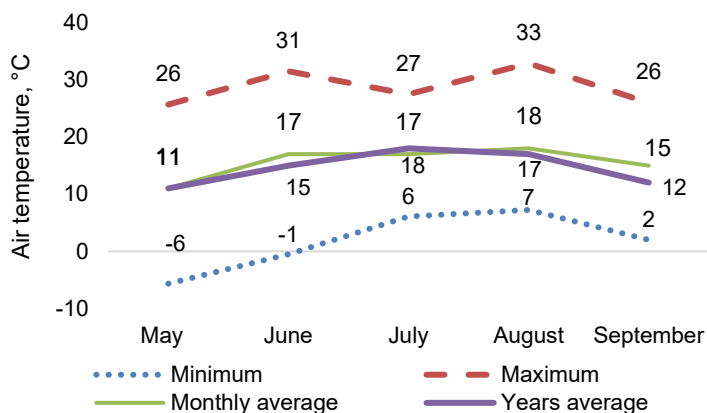


Figure 1. Monthly average, minimum and maximum air temperature (°C) from May to September 2023 in South Estonia, compared to the average of many years (1991–2020).

It was warmer than average during the ripening of the berries - the monthly average temperature in August was 18 °C, which is 1 °C higher than the long-term average of 17 °C, and in September 15 °C, which is 3 °C higher than the long-term average of

12 °C. The maximum temperatures during summer were consistent, ranging from 27 °C to 33 °C. September was still warm - the minimum temperature was 2 °C, suggesting cool nights, but the maximum reached 26 °C, which is quite warm considering early autumn. In general, it can be concluded that the weather in 2023 was highly variable, especially in spring. May was very cold and unstable, summer months were generally warm, and August was the warmest.

Spring and early summer (May and June) were unusually dry, with significantly less rainfall than average (Fig. 2). July was exceptionally wet, experiencing nearly twice the normal rainfall. August was near normal, and September was slightly drier than usual. Overall, 2023 had inconsistent precipitation patterns, with a very dry start, a wet mid-summer, and a slightly drier-than-normal early autumn.

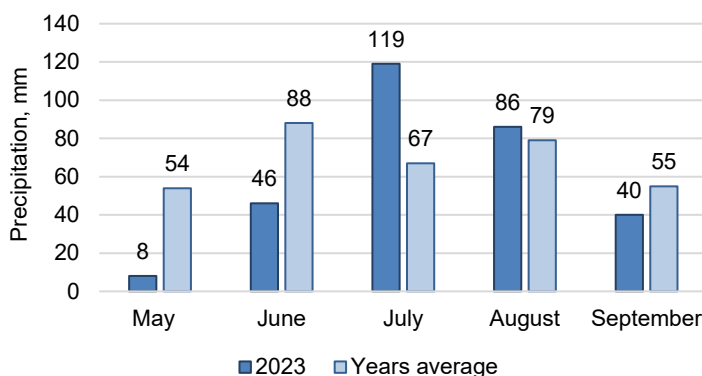


Figure 2. Monthly total precipitation (mm) from May to September 2023 in South Estonia, compared to the average of many years average (1991–2020).

Statistical Analysis

The results in figures were represented as three replicates means $\pm$ standard deviations. One-way analysis of variance (ANOVA) was performed to evaluate the existence of differences between experimental wines' acids. The coefficient of determination (R^2) was used to explain how much the variation in the dependent variable (acids, pH) can be explained by the independent variable (wines' cultivar). Comparison of means was done by using Fisher's Least Significant Difference (*LSD*) test to confirm the statistically significant differences. Different letters in the figures indicate statistically significant differences ($p \leq 0.05$).

RESULTS AND DISCUSSION

The malic acid content in different wines revealed significant variation among them (Fig. 3). The lowest malic acid concentration was observed in Marquette (0.3 g L^{-1}), whereas Leon Millot wine exhibited the highest content (4.4 g L^{-1}). The other wines fell within this range, with Solaris containing 2.4 g L^{-1} , Cabernet Cortis 2.9 g L^{-1} , and Regent 3.7 g L^{-1} . The coefficient of determination ($R^2 = 0.87$) indicates a strong correlation within the dataset, suggesting reliable variability in malic acid content across different wines.

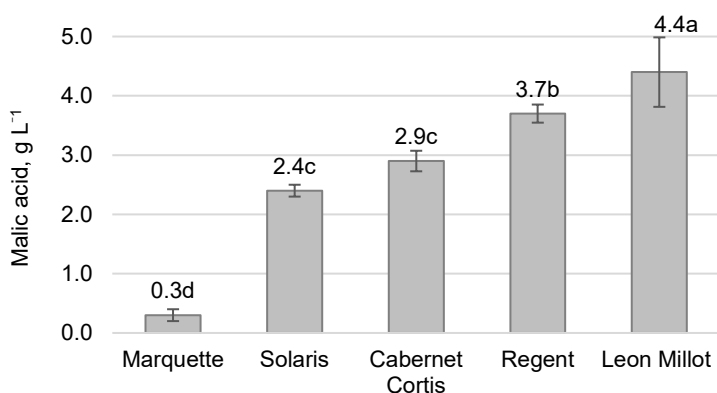


Figure 3. Effect of grapevine cultivar on malic acid content (g L^{-1}) in wine. Different letters present statistically significant differences at $p \leq 0.05$.

The tartaric acid concentrations varied among the tested wines (Fig. 4). The lowest level was detected in Leon Millot (2.2 g L^{-1}) and Solaris (2.5 g L^{-1}) whereas the highest was found in Regent (4.1 g L^{-1}), followed by Cabernet Cortis (3.7 g L^{-1}), and Marquette (3.6 g L^{-1}) wines. The R^2 value (0.96) suggests that 96% of the variation in tartaric acid content can be explained by cultivar differences.

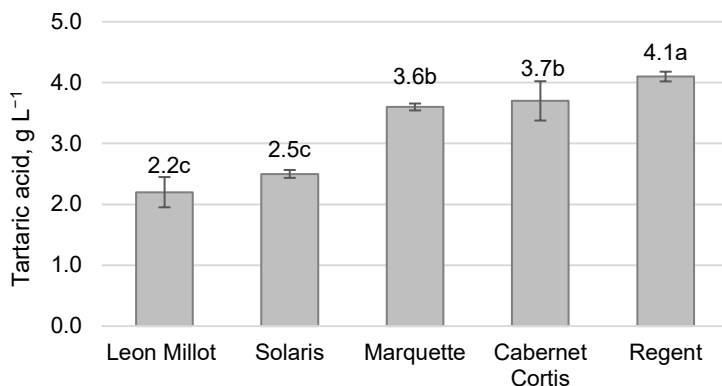


Figure 4. Effect of grapevine cultivar on tartaric acid content (g L^{-1}) in wine. Different letters present statistically significant differences at $p \leq 0.05$.

Citric acid concentrations in wines were generally lower than malic and tartaric acid levels, but substantial variation was observed (Fig. 5). The lowest concentrations were recorded in Marquette (0.13 g L^{-1}) and Regent (0.14 g L^{-1}), whereas Cabernet Cortis contained 0.36 g L^{-1} . Higher concentrations were observed in Leon Millot (0.70 g L^{-1}), with Solaris showing the highest level (1.44 g L^{-1}). The cultivar effect on citric acid content was highly significant: 87% of the variation in total acids content could be explained by cultivar characteristics.

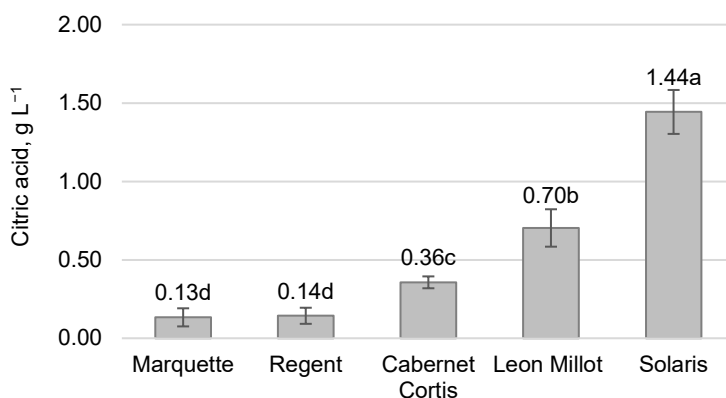


Figure 5. Effect of grapevine cultivar on citric acid content (g L⁻¹) in wine. Different letters present statistically significant differences at $p \leq 0.05$.

The results indicate significant variation in lactic acid concentration depending on the grape cultivar of wine (Fig. 6). Among the wines studied, Marquette exhibited the highest lactic acid concentration (2.27 g L⁻¹), which was considerably higher than the other wines. The lactic acid contents of the Leon Millot (0.52 g L⁻¹) and Regent (0.32 g L⁻¹) were similar, and Regent did not differ from the Solaris and Cabernet Cortis. The R^2 for the dataset was 0.98, indicating a very strong correlation between the observed values. This suggests that cultivar explains most of the variation in the lactic acid content.

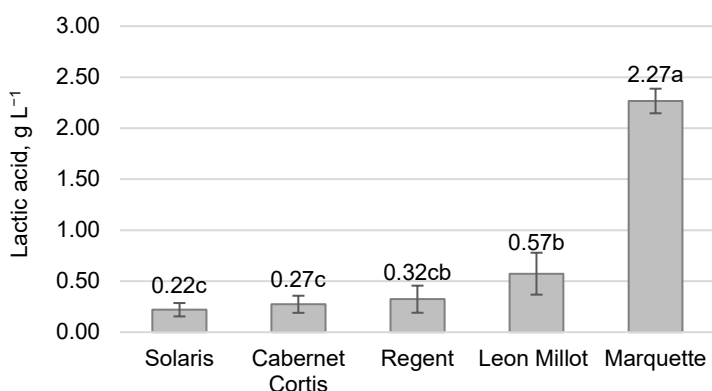


Figure 6. Effect of grapevine cultivar on lactic acid content (g L⁻¹) in wine. Different letters present statistically significant differences at $p \leq 0.05$.

The total acidity of the analyzed wines varied from 6.9 g L⁻¹ in wine Marquette to 9.4 g L⁻¹ in Leon Millot, which did not differ significantly from the wines Cabernet Cortis and Regent (Fig. 7). Intermediate value was recorded for Solaris (7.8 g L⁻¹). The R^2 value (0.87) in this dataset indicates that 87% of the variation in total acid content can be explained by cultivar differences.

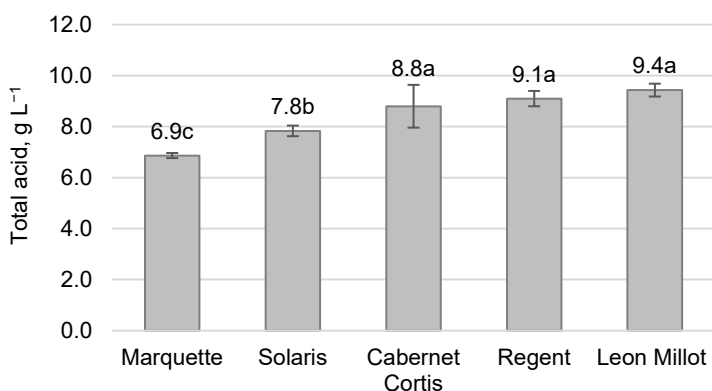


Figure 7. Effect of grapevine cultivar on total acid content (g L⁻¹) in wine. Different letters present statistically significant differences at $p \leq 0.05$.

The pH values of the analysed wines ranged from 2.9 to 3.3, indicating differences in acidity levels among the wine samples (Fig. 8). The lowest pH (2.9) was observed in Cabernet Cortis and Regent, suggesting a higher perceived acidity. Solaris and Marquette had similar pH values, whereas Marquette was similar to the wine Leon Millot (3.3). An R^2 of 0.76 indicates a moderately strong relationship between cultivar and pH level.

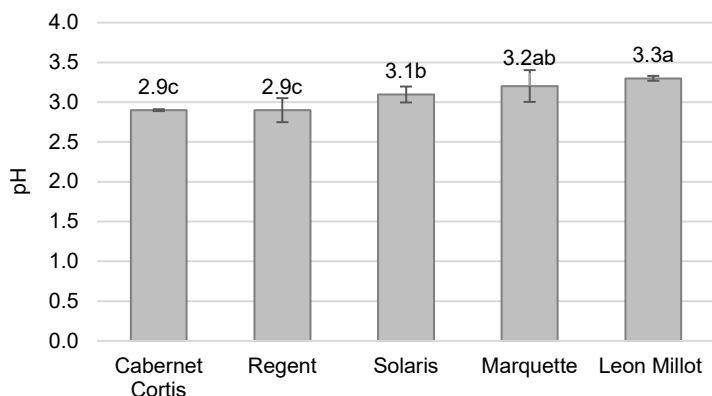


Figure 8. Effect of grapevine cultivar on pH in wine. Different letters present statistically significant differences at $p \leq 0.05$.

The results of this experiment illustrate the distinct acid profiles of the tested wines, which can significantly impact wine stability and aging potential. Acid content and pH play an important role in the sensory properties and equilibrium of wines (Comuzzo et al., 2019). At high pH values, red wines are naturally less protected against oxidation and are less stable (Forino et al., 2020). Meanwhile, tartaric acid, a key factor in wine acidity, exhibits notable differences that could affect overall sensory perception. Due to its stability and the fact that yeast and other microorganisms are unable to metabolize tartaric acid, it is the most commonly used acid for pH adjustment in the wine industry

(Volschenk et al., 2006). Tartaric acid levels in the tested wines ranged from 2 to 4 g L⁻¹, which is also common in wines from warmer climates (Ribéreau-Gayon et al., 2006).

In cooler climates, however, malic acid can become a problem. Under very cool climate conditions, malic acid can comprise up to 50% of the total acidity because malic acid-related respiration is slower at lower temperatures (Volschenk et al., 2006). According to Ribéreau-Gayon et al. (2006), the malic acid content in wines can reach up to 4 g L⁻¹. Based on this, it can be concluded that only Leon Millot wine had high total acidity (9.4 g L⁻¹) with a dominance of malic acid (4.4 g L⁻¹). Previous experiments in Estonia have shown that the cultivation method (either open field or tunnel) also has a significant effect, and malic acid levels were at an appropriate level in tunnel-grown grapes of 'Rondo' (Maante-Kuljus et al., 2019a). In Estonia, the temperature in high plastic tunnels for viticulture has been 2–4 °C higher than in the open field (Maante-Kuljus et al., 2019b). The tested wines in this study were all made from berries grown in a tunnel, and the weather in the tested year also had an impact - it was warmer than the average of many years, during the berry ripening period in August and September. In Estonia, a major viticultural challenge is early spring warming followed by late spring frosts, which can severely damage fruit-bearing shoots and subsequently affect both vine growth and berry ripening. During the experimental vintage, night frosts in spring reached as low as -6 °C, significantly delaying the onset of vine growth. However, the test year were distinguished by a warmer and drier September than average for many years, which positively affected grape ripening. For all cultivars, leaf removal was also performed around the grapes, which further enhances sunlight exposure and increases berry temperature. The breakdown of malic acid begins once sugar accumulation starts and is more pronounced at higher temperatures (Rienth et al., 2016). Therefore, the late summer weather has a significant impact on the malic acid content.

The variation in malic and citric acid content suggests differences in metabolic pathways among the tested wines, which may influence their suitability for malolactic fermentation. At the beginning of the production of Marquette wine, the initial acid content of the must was high, 8.7 g L⁻¹, but after fermentation 6.9 g L⁻¹. The wine had an extremely low malic acid content (0.3 g L⁻¹) and a high tartaric acid content (3.6 g L⁻¹), meaning it is naturally stable and smooth. However, this tested wine had a very high lactic acid content (2.2 g L⁻¹), suggesting that most of the malic acid may have been metabolized during fermentation, possibly due to spontaneous malolactic fermentation. When only alcoholic fermentation occurs, lactic acid levels in the wine remain low, typically below 0.3 g L⁻¹ (Bauer et al., 2005), as the conversion of malic acid to lactic acid has not taken place. Malolactic fermentation is recommended for wines with very high malic acid levels. For example, if the malic acid level is 9.5 g L⁻¹, successful malolactic fermentation can significantly reduce malic acid levels, often by more than 80% (Lasik-Kurdyś et al., 2017).

The pH of the grape juice across different cultivars ranged from 3.0 to 3.2, and that of the corresponding wines from 2.9 to 3.3. The common pH range of wines is between 3 and 4, and pH measurement is also important because, at high pH values, wines are naturally less protected against oxidation and are less stable (Forino et al., 2020). A significant drop in anthocyanin solubility was observed at pH 3.3, indicating that the red

tested wines also have good colour stability. Wines with high acidity typically have low pH values, and this is because organic acids, such as tartaric and malic acids, contribute to the overall acidity of the wine, thereby lowering the pH (Vilela, 2019). Cabernet Cortis and Regent wines exhibited the lowest pH (2.9), indicating a higher total acid content. However, this relationship was not observed in all wines. For example, Leon Millot wine had a high acid content but also a higher pH value, which was influenced by its higher malic acid content. Previous wine analyses have shown that different organic acids have varying strengths and buffering capacities (Picariello et al., 2019; Gancel et al., 2022). Therefore, pH is not always directly related to acid content, making it important to consider multiple acidity indicators.

CONCLUSIONS

These findings highlight the distinct acid profiles of test wines made from different grape cultivars grown in Estonia, allowing predictions about their stability and suitability for aging. The hypothesis was not confirmed, as excessive acid content did not become a problem in common commercial single-cultivar wines produced in Estonia, in a very cool climate condition. However, it should be noted that the hypothesis does not hold if the grapes used for winemaking are grown in high plastic tunnels.

Based on the grape cultivars of tested wines, the following conclusions can be drawn regarding wine acidity:

- Cabernet Cortis and Regent wines exhibit high acid content and relatively low pH, suggesting a fresh, crisp taste. Leon Millot wine has high total acid content, dominated by malic acid. These wines may benefit the addition of oak chips to soften acidity.
- Solaris wine has balanced acidity, moderate pH, and high citric acid content, making it a well-structured wine with potential for both freshness and stability.
- Marquette wine is naturally smooth, with very low malic acid content, indicating spontaneous malolactic fermentation.

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Peculiarities of quality formation of apples (*Malus domestica* Borkh.) of ‘Dmiana’ variety

L. Shevchuk^{1,2,*}, Y. Vintskovska², R. Grynyk², S. Babenko², B. Mazur¹ and
V. Tonkha²

¹National University of Life and Environmental Sciences of Ukraine, Henerala Rodimtseva Str. 19, UA03041 Kyiv, Ukraine

²Institute of Horticulture of the National Academy of Agrarian Sciences of Ukraine, Sadova Str. 23, UA03027 Kyiv, Ukraine

*Correspondence: l.shevchuk_2021@ukr.net

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Abstract. The appearance, size and taste of fruit are among the main indicators of quality and marketability. These characteristics are determined by the content and ratio of biochemical components, which are influenced by the biotic and abiotic factors involved in cultivation. Studies have shown that the dry matter content of Dmiana fruits is independent of rootstocks and planting schemes. However, the sugar content was significantly higher in fruits grown on M.26 rootstock with a planting scheme of 4.0×1.0 m and significantly lower in fruits grown on M.9 rootstock with the same planting scheme: 11.3% and 9.8%, respectively. Titratable acids were found in fruits grown on rootstock M.9 with a planting scheme of 4.0×0.5 m. In addition to the influence of planting scheme and rootstock, weather conditions also affected the biochemical content of Dmiana fruits. Cool nights during the initial growth and development period contributed to dry matter accumulation, but negatively affected sugar synthesis. The correlation coefficients for all rootstock variants were higher than 0.703 and 0.911, respectively. The content of titratable acids depended significantly on the average daily and night-time air temperatures in the month before harvesting; this dependence was indirect and the correlation coefficients were high in all variants with rootstocks.

Key words: dry matter, sugars, titrated acids, *Malus*.

INTRODUCTION

The fruits of fruit crops are an attractive and nutritious food product, thanks to their color, shape, unique taste and aroma, rich in minerals, vitamins and other useful components of the composition (Cassano et al., 2003; Vanolia & Bucchiri, 2012; Shevchuk et al., 2021a; Shevchuk et al., 2022). Cultivated apple tree (*Malus x domestica* Borkh) (family *Rosaceae*, subfamily *Maloideae*) originated and domesticated in Central Asia and then spread to Europe and Asia thousands of years ago (Robinson et al., 2001), is one of the most common targets worldwide (Juniper & Mabberley, 2006). World production of apples in 2021 reached 93.1 million tons, of which the

largest share fell on China - 45.9 million tons, the second place in terms of production was shared by Turkey and the United States at 4.5 million tons, slightly less of them were produced by the Poland (4.1 million tons). Ukraine in the world ranking of apple producers was in 12th place with a gross harvest of 1.3 million tons (<https://www.fas.usda.gov/data/production/commodity/0574000>).

Apples are among the most nutritious fruits in a healthy diet, particularly due to their sugar content (fructose > glucose > sucrose), organic acid content (0.2–0.8%) (Shevchuk et al., 2021b), vitamins (mainly vitamin C at 2.3–31.1 kg per 100 g of dry solids), minerals (ash content of 0.34–1.23%) and dietary fibres (2–3% with pectic substances accounting for less than 50% of apple fibres) (Kiczorowska & Kiczorowski, 2005). Campeanu et al. (2009) emphasise that apples have a well-known therapeutic value in treating various diseases; they reduce gastric secretion activity, remove toxins and have a diuretic effect. Furthermore, apples are among the most important fruits in temperate climates, renowned for their consumer value and suitability as a raw material for producing many processed goods (Mukhtar et al., 2010).

In addition to the genetic characteristics of varieties, the quality of fruits is determined by a number of environmental factors, in particular, air temperature and light regime, which significantly depends on their location in the crown (Musacchi & Serra, 2018). The weather of the growing year can greatly affect the appearance of the fruits (Bi et al., 2011; Zheng et al., 2009; McCluskey, 2010; Houston et al., 2018), that changes the commodity structure of the grown crop (Sugiura et al., 2013; Lesk et al., 2016; Dalhaus et al., 2020). Another corrective link for fruit quality is the orchard design, irrigation and pruning system (Sharma et al., 2008) and the cultivation technology itself (Tahir, 2006; Melke & Fetene, 2014). The choice of garden design and rootstock belongs to the latter. The latter has an important influence on apple productivity, including early fruiting (Tubbs, 1973), tree growth and development, fruit yield and quality, resistance to biotic and abiotic stresses, nutrient assimilation (Chaplin & Westwood, 1980), bud break (Brown et al., 1985) and fruit size (Jackson & Blasco, 1975). Currently, the dwarfing rootstocks M.9 and M.26 are used to create industrial apple orchards in many countries worldwide (Webster & Hollands, 1999). According to Lord et al. (1985), rootstock has a greater effect on tree growth and yield than on apple quality. This view is supported by other researchers, who have noted that apple quality is affected by variety and, within each variety, by rootstock and applied technology. The genotype of the variety, as well as the various physical characteristics of the fruit, such as its shape, size, weight, pulp hardness and organic substance content, is of maximum and decisive importance (Dowarah et al., 2021). While fruit quality can be modified, it cannot be radically changed without genetic manipulation (Castle, 1995). The results of the selection process are new varieties of apple trees that require a thorough study of their productivity and resistance to various biotic and abiotic factors. The influence of the rootstock and fruit quality must also be considered, as these factors significantly impact sales potential. One of the latest developments by breeders at the Institute of Horticulture of the NAAS of Ukraine is a late-ripening apple tree variety called 'Dmiana'. Consumers usually evaluate apples based on their appearance (colour, size, shape and lack of defects), followed by taste. However, the buyer's willingness to purchase the product again may depend on the latter (Musacchi & Serra, 2018). Our research aimed to determine the effect of rootstock and planting scheme on the organic matter content of 'Damiana' apples.

MATERIAL AND METHODS

Research into the characteristics of the Dima apple variety was conducted at the Institute of Horticulture of the National Academy of Agricultural Sciences of Ukraine, which is located in the village of Novosilky. It is 4 km from Kiev, 187 m above sea level (50°27'16"N, 30°13'25"W) and in the Forest-Steppe natural and climatic zone of Ukraine. This natural and climatic zone has a temperate continental climate, characterised by sufficient moisture. The average temperature in the coldest place in January is -6 °C and in the warmest place in July it is 19.5 °C.

The soil at the site is a grey forest medium loam with a humus content of 2.3–3.5%. The soil solution has a weakly acidic reaction (pH = 5.9–6.7). The garden was fertilised with nitrogen fertilisers in early spring and with phosphorus and potassium fertilisers at the end of October. The application rate was calculated based on the results of foliar diagnostics and agrochemical analysis of the soil. During the vegetation period, calcium chloride was applied foliarly four times in a total amount of 55 kg per hectare and 2,000 litres of water.

The Syngenta integrated protection system was used to control pests and phytopathogenic microorganisms in the experimental plantation.

The 'Dmiana' variety plantations, from which the fruit selection for research was made, were created in 2017 using rootstocks m.9 (dwarf), M.26 (semi-dwarf) and MM.106 (medium growth). Two planting schemes were used: 4.0×0.5 m (5 thousand/trees per hectare) and 4.0×1.0 m (2.5 thousand/trees per hectare), with ten trees in each variant. The plantations' crowns are formed using the spindle method and the plantations are pruned annually.

Apples with the characteristic shape and colour of the variety were selected at harvest for the study. The degree of ripeness was determined using an iodine-starch test and by measuring pulp hardness. The degree of starch degradation in 'Dmiana' apples in all variants and in all years of the study was 6–6.5 points out of 9, and the pulp hardness exceeded 9.5 kg cm². The weight of the apples in each sample selected for analysis was 2 kg.

The research was conducted in the Post-Harvest Quality of Fruit and Berry Products Laboratory at the Institute of Horticulture of the National Academy of Agrarian Sciences of Ukraine. All studies were performed in triplicate.

Weather conditions during the apple tree growing season were recorded by an 'Inspector Meteo' weather station installed by the Ukrainian company IT-Lynx in an experimental orchard area. The effect of the sum of night and average daily air temperatures, the sum of active air temperatures of 10 °C and above, and the sum of precipitation on the biochemical components of the fruit was analysed for the entire fruit growth and development period, as well as for the initial June–July period and the pre-harvest August–September period. The average night-time air temperature was calculated for each month separately. This was based on the average daily air temperature from 10 pm to 6 am.

Biochemical parameters

The laboratory sample was prepared by grinding fruit segments with a laboratory homogenizer.

Dry matter (DM)

The dry matter content of the apples was determined using the drying method. A weighed amount of crushed fruit (5–6 g) was added to a container of quartz sand, mixed thoroughly, covered with a lid, and placed in an oven to dry until it reached a constant weight. The boxes were weighed before and after drying. Prior to weighing, the boxes were pre-cooled in an oven (Kondratenko et al., 2008). The dry matter content of apples is presented as a percentage.

Sugars

The crushed apple sample was extracted using hot distilled water. The extract was then purified of proteins and pigments using lead acetate. Sucrose was hydrolysed to produce glucose and fructose by heating with the addition of 10% hydrochloric acid. Fehling's solution was then used for oxidation. The resulting solutions' optical density was determined using a ULAB 102UV spectrophotometer at 640 nm. A calibration graph constructed using standard glucose solutions with different concentrations (kg mL^{-1}) (Kondratenko et al., 2008) was used to calculate the sugar content in apples. The content of titratable acids in fruit is given in $\text{kg } 100^{-1}$.

Organic titrated acids

A 25 g sample of apples was subjected to acid extraction and then washed with hot distilled water. The flask containing the extract was then placed in a water bath at 80 °C for 30 minutes and left to cool. Three to four drops of phenolphthalein were added to a 20 mL sample and the mixture was titrated with 0.1 N sodium hydroxide solution until a pink colour appeared, corresponding to a pH of 7.0. The average value was obtained from three parallel measurements. The content of titratable acids in the sample was calculated using the formula, the titration index of the 0.1 N sodium hydroxide solution, and the conversion factor to malic acid (kg mL^{-1}) (Kondratenko et al., 2008). The content of titratable acids in fruit is given in $\text{kg } 100^{-1}$.

Statistical analysis

Statistical data processing was performed using STATISTICA 13.1 (StatSoft, Inc., USA). The results are presented as mean values with their respective standard errors ($\text{mean} \pm \text{SE}$). Differences between replicates, as well as between-variety mean values, were determined by ANOVA. One-way ANOVA and the Tukey HSD post hoc test were employed for statistical analysis. The results were presented at a significance level of $P < 0.05$. The significance of the influence of weather and climatic factors on the content of dry matter, sugars, and titratable acids in apples was analysed using the 'Data Analysis' tab in Excel.

RESULTS AND DISCUSSION

During the period of fruit growth and development (June–September), average daily air temperatures did not differ significantly during the years of research. They were 21.2 °C in 2020, 19.8 °C in 2021, and 21.6 °C in 2023. However, analysing the average daily temperatures by month during this period revealed that June was the coldest month in 2020 and September in 2021, with average daily temperatures of 13.7 °C and 13.4 °C,

respectively. The sum of active air temperatures of 10 °C and above during the apple tree's growth and development periods varied from 2,427 °C in 2021 to 2,647 °C in 2020. In 2023, the sum of active air temperatures of 10 °C was 2595 °C. The highest night-time temperatures were recorded in June 2021 (639.0 °C); however, during the same year, the pre-harvest period was the coolest and the sum of night-time temperatures ten days before harvesting was 110.4 °C (Table 1).

During the apple growth and development period of the research years, the sum of active air temperatures of 10 °C and above ranged from 2,427 °C in 2021 to 2,647 °C in 2020, with an intermediate value of 2,595 °C in 2023. The lowest temperatures were recorded in June and July 2023 at 603.3 °C and 669.2 °C respectively. The hottest months in terms of the sum of active temperatures of 10 °C and above were July 2021 and September 2020, with respective sums of 564 °C and 775.0 °C (Table 1).

Table 1. Indicators of weather during the growth, development and ripening periods of apples

Years	June	July	August	September	Average
Average daily air temperatures, °C					
2020	13.7	22.7	22.2	18.8	21.2
2021	21.8	25.0	21.1	13.4	19.8
2023	20.1	21.6	24.0	19.2	21.6
Sum of night temperatures, °C					total
2020	544.1	555.8	520.7	168.6	1,789.2
2021	529.2	639.0	544.7	110.4	1,823.3
2023	481.1	552.5	615.5	151.9	1,801.0
Sum of active temperatures 10 °C and higher					
2020	689.0	705.0	689.0	564.0	2,647.0
2021	653.0	775.0	655.0	344.0	2,427.0
2023	603.3	669.2	745.3	577.2	2,595.0
Sum of precipitation, mm					
2020	56.5	38.1	14.6	23.2	132.4
2021	16.7	33.6	57.6	23.0	130.9
2023	38.1	72.7	8.6	7.1	126.5

The hydrothermal coefficients, namely the ratio of precipitation to the sum of active air temperatures of 10 °C and above throughout the apple growth and development period, did not differ significantly year on year. In particular, they were 0.50 in 2020, 0.54 in 2021 and 0.49 in 2023. However, during the period of fruit growth and development in the last of these years, there was significant unevenness of moisture. July was the wettest month in 2023, with 72.7 mm of precipitation, equating to a hydrothermal coefficient of 1.09. August and September were the driest months, with 8.6 and 7.1 mm of precipitation respectively, equating to a moisture coefficient of 0.12 in both months (Table 1).

Under these weather conditions, the dry matter content of ‘Dmiana’ apples grown on m.9 with a planting scheme of 4.0×0.5 m varied from 14.3% in 2021 to 15.8% in 2023. This tendency towards higher dry matter content was also observed in 2023 with the other two rootstocks and this planting scheme. Notably, on the M.26 rootstock, the dry matter content of ‘Dmiana’ apples was 15.7% in 2023, 15.2% in 2020, and 14.6% in

2021. Apples accumulated the least dry matter on the MM.106 rootstock with a planting scheme of 4.0×0.5 m in 2021 (14.6%), and the most in 2023 (16.2%) (Table 2).

Table 2. Dry matter content in apples of ‘Dmiana’ cultivar grown on different rootstocks and at different planting densities

Rootstock	2020	2021	2023	Average ± SE
Planting scheme 4.0×0.5 m				
M.9	14.6 ± 0.35 ^a	14.3 ± 0.43	15.8 ± 0.32 ^c	14.9 ± 0.48 ^a
M.26	15.2 ± 0.35 ^b	14.6 ± 0.38	15.7 ± 0.29	15.2 ± 0.38
MM.106	15.0 ± 0.38	14.6 ± 0.38	16.2 ± 0.32 ^{cb}	15.3 ± 0.48
Planting scheme 4.0×1.0 m				
M.9	14.8 ± 0.26	14.0 ± 0.32 ^d	15.5 ± 0.29	14.8 ± 0.43 ^a
M.26	15.6 ± 0.23 ^b	14.6 ± 0.17 ^d	16.2 ± 0.32 ^b	15.5 ± 0.47 ^b
MM.106	14.8 ± 0.20	14.5 ± 0.23	15.6 ± 0.26 ^c	15.0 ± 0.33

^{a, b} – indicates the level of significance of differences between rootstock variants within the same planting scheme at $P < 0.05$;

^{c, d} – values of indicators that are likely to differ from the average (x) for the years of the study for the studied group at $P < 0.05$.

No significant difference in dry matter content was observed in fruits grown on different rootstocks with a 4×1.0 m planting scheme. Apples from all rootstocks in the 2023 harvest had the highest SR, while the 2021 harvest had the lowest. In particular, the amount of dry matter in apples collected from trees with the M.9 rootstock was 15.5% in 2023 and 14.0% in 2022. For the M.26 rootstock, the respective values were 16.2% and 14.6%, and for the MM.106 rootstock, they were 15.6% and 14.5%. Intermediate values of dry matter content were recorded in 2020. Similar data regarding the influence of rootstock on dry matter content was obtained by a scientist in the US state of Florida. In particular, he noted that fruits collected from trees grown on rootstocks M.26, M.9 and M.27 did not differ in dry matter content (Castle, 1995). Budagovski 9 rootstock (Gjamovski et al., 2011). So the density of the trees has a significant impact on the quality of the fruit. The dry matter content of apples grown on rootstocks M.9, M.26 and MM.106 with a planting pattern of 4.0×1.0 m did not differ significantly from that of apples grown on the same rootstock with a planting pattern of 4.0×0.5 m. In 2020, the SR content of fruits grown on rootstock M.9 with planting schemes of 4.0×0.5 m and 4.0×1.0 m differed by 0.2%. In 2021 and 2023, the difference was 0.3%. On rootstock M.26, the difference in dry matter content was 0.4% in 2020, not detected in 2021, and 0.5% in 2023. The dry matter content of apples grown at different planting densities on rootstock M.26 did not differ significantly. In 2020, the dry matter (DM) content of trees planted at 4.0×0.5 m was 15.2%, which was 0.4% less than that of trees planted at 4.0×1.0 m. In 2021, no difference was found. In 2023, the dry matter content was 0.5% higher with an additional 5,000 trees per hectare. Apples grown in a 4×0.5 m planting pattern on MM.106 rootstock had a slightly higher dry matter content than those grown in a 4×1 m planting pattern. These differences were 0.2%, 0.1% and 0.6% in 2020, 2021 and 2023 respectively (Table 2).

Table 3. Correlation dependence of the content of dry solids, sugars and titrated acids in the fruits of apple trees of the Dmiana variety

Research options	Night, t °C			Average daily t °C			Sum of active temperatures of 10 °C and above			Sum of precipitation, mm		
	June–July	August–September	total	June–July	August–September	total	June–July	August–September	total	June–July	August–September	total
Dry matter												
M.9	-0.988	0.997	-0.528	-0.361	0.913	0.600	0.080	-0.193	-0.108	0.919	-0.948	-0.810
M.26	-0.999	0.966	-0.673	-0.524	0.971	0.446	0.259	-0.012	0.074	0.975	-0.990	-0.690
MM.106	-0.952	0.997	-0.388	-0.210	0.837	0.719	-0.078	-0.345	-0.263	0.845	-0.885	-0.892
Sugars												
M.9	-0.947	0.995	-0.372	-0.193	0.827	0.731	-0.095	-0.361	-0.280	0.836	-0.877	-0.900
M.26	-0.999	0.967	-0.669	-0.520	0.970	0.450	0.255	-0.017	0.069	0.974	-0.989	-0.693
MM.106	-0.911	0.793	-0.905	-0.811	0.988	0.068	0.610	0.373	0.451	0.985	-0.969	-0.359
Titratable acids												
M.9	0.914	-0.983	0.287	0.914	-0.983	0.287	0.184	0.444	0.365	-0.783	0.831	0.935
M.26	0.969	-1.000	0.441	0.969	-1.000	0.441	0.019	0.289	0.206	-0.875	0.911	0.864
MM.106	0.909	-0.980	0.274	0.909	-0.980	0.274	0.197	0.456	0.377	-0.775	0.823	0.940

When establishing the correlation between dry matter content and weather conditions during the growth and development of apple trees, the influence of plantation density was not taken into account, since statistical analysis did not reveal a significant difference in dry matter content depending on the tree planting scheme. Correlation analysis revealed an inverse relationship between dry matter content and night air temperature during the growth and development period (June–July) with correlation coefficients of 0.988, 0.999 and 0.952 for rootstocks M.9, M.26 and MM.106, respectively. A direct dependence of dry matter content on night temperatures was found for the period August–September, the correlation coefficient was 0.966 (Table 3).

According to the correlation analysis, the dry matter content is significantly and directly influenced by other temperature factors, namely the average daily air temperature and the sum of active temperatures of 10 °C and above for the period. The corresponding correlation coefficients were higher than 0.837 and 0.814. An inverse relationship was found between the dry matter content of Damiana apples and the amount of precipitation during the period of growth and development. The respective correlation coefficients were 0.948 for apples grown on M.9 rootstock and 0.961 for apples grown on M.26 rootstock, and 0.885 for apples grown on MM.106. Researchers from different continents have noted the negative impact of elevated night temperatures on dry matter content during apple ripening. In particular, Canadian researchers found that the dry matter content of the apple varieties they studied was higher in the cool growing season than in the warm one, by about 4% (or 30% relative) in absolute terms (Toivonen, 2015; Toivonen & Lannard, 2020). Similar data were obtained in our study: apples grown on M.9 rootstock with 4.0×0.5 and 4.0×1.0 m trees accumulated the highest dry matter content in 2023, 15.8% and 15.5%, respectively. In the same year, apples of the Dmiana variety grown on the other two rootstocks contained more dry matter than in 2020 and 2021, regardless of the density (Table 2). Nighttime air temperatures during the first months of fruit growth and development were the lowest in 2023, at 481.1 °C in June and 552.5 °C in July (Table 1). Richardson et al. (2004) argue that elevated nighttime temperatures can lead to a slowdown in photosynthetic production due to nighttime leaf respiration. Otherwise, plastic matter would be distributed in the fruit as starch, especially in the early stages of fruit development. Other researchers have noted that low temperatures during the half-growth period accelerate starch purification, i.e. its conversion to sugar (Smith et al., 1979; Ap Rees et al., 1981).

The total concentration of sugars soluble in cell juice is determined by the soluble solids in apple fruits, which account for 80%. The number of the latter in ‘Dmiana’ apples did not differ significantly depending on the rootstock in the 4.0×0.5 m planting scheme. However, apples grown on M.26 rootstock in 2020 and 2023 had significantly higher sugar content at 11.1 and 10.9 kg 100⁻¹ respectively, while fruits grown on MM.106 rootstock in 2023 contained significantly less sugar at 10.3% (Table 4).

A more significant effect of the rootstock on the amount of sugars in the fruits of the ‘Dmiana’ apple tree was established in the variant with a planting scheme of 4.0×1.0 m. In particular, fruits grown on rootstock M.9 in 2020 had a sugar content of 9.4 in 2021 – 9.8 and in 2023 – 10.3 kg 100⁻¹, the average for the years of research – 9.8 kg 100⁻¹. On the rootstock MM.106 in 2021 and 2023 – 9.9 and 10.4 kg 100⁻¹, respectively, the average for the years of research - 10.1 kg 100⁻¹, while the average value for the variants of the experiment was: in 2020 – 10, 1, in 2021 – 10.4 and in 2023 – 10.8 kg 100⁻¹. Apples harvested from the variant where the rootstock was M.26

had sugars significantly higher than the average for the rootstocks, namely in 2020 – 10.8, in 2021 – 11.4, in 2023 – 11.8 kg 100⁻¹, the average during the years of research – 11.3 kg 100⁻¹ (Table 4).

Table 4. The sugar content of ‘Dmiana’ fruits depends on the rootstock and planting density

Rootstock	2020	2021	2023	Average ± SE
Planting scheme 4.0×0.5 m				
M.9	10.5 ± 0.15 ^a	9.7 ± 0.15 ^{ad}	10.6 ± 0.14 ^A	10.3 ± 0.28 ^a
M.26	11.1 ± 0.12 ^{Ac}	9.6 ± 0.09 ^{ad}	10.9 ± 0.09 ^A	10.5 ± 0.47 ^A
MM.106	10.5 ± 0.15 ^a	9.8 ± 0.15 ^{ad}	10.3 ± 0.09 ^A	10.2 ± 0.21 ^a
Planting scheme 4.0×1.0 m				
M.9	9.4 ± 0.12 ^{Ab}	9.8 ± 0.12 ^{ab}	10.3 ± 0.06 ^{ac}	9.8 ± 0.29 ^{Ab}
M.26	10.8 ± 0.09 ^{Ad}	11.4 ± 0.06 ^A	11.8 ± 0.12 ^{Ac}	11.3 ± 0.29 ^A
MM.106	10.1 ± 0.09 ^A	9.9 ± 0.07 ^a	10.4 ± 0.12 ^{ac}	10.1 ± 0.15 ^A

^{A, a} – indicates the level of significance of differences between rootstock variants within the same planting scheme at $P < 0.05$;

^{c, d} – values of indicators that are likely to differ from the average (x) for the years of the study for the studied group at $P < 0.05$.

The analysis of the influence of the planting scheme on the sugar content in the fruits of the Dmiana variety did not reveal any significant difference in any variant with rootstocks, however, it was established that the sugar content is significantly affected by the weather conditions of the year of cultivation. In particular, a close inverse relationship was established between the content of sugars in ‘Dmiana’ apples and the sum of night temperatures in June–July, the corresponding correlation coefficient in the version with rootstock M.9 was 0.947, with rootstock M.26 - 0.999, and rootstock MM.106 - 0.911. A direct close relationship was found between the content of sugars and the sum of the same temperatures and average daily air temperatures, but in the last month before harvesting, the correlation coefficients in all variants with rootstocks were higher than 0.793 and 0.827, respectively. The dependence of the content of soluble solids, a significant proportion of which are sugars in apples, on the increased amount of the average annual air temperature in the last 40 days before harvesting was observed by Japanese scientists (Sugiura et al., 2013). Other researchers noted that the increase in dry soluble substances, and with them sugars, was not always caused by the short-term effect of elevated temperatures in the pre-harvest period (Blankenship, 1987). Wang & Camp (2000) proved that a hot pre-harvest period can contribute to the reduction of soluble solids.

In addition to temperature factors, the amount of sugars in ‘Dmiana’ fruits depends significantly on precipitation during the period of their growth and development. It was established that the level of moisture in June and July has a close direct relationship with the sugar content of apples of the studied variety, the correlation coefficients in the variant with rootstock M.9 - 0.836, with M.26 - 0.974 and with MM.106 - 0.985, and with precipitation of the latter month before harvesting, an indirect relationship was found, the correlation coefficients in the variant with rootstock M.9 - 0.877, with M.26 - 0.989 and in the variant with rootstock MM.106 - 0.969. A number of scientists from different countries of the world previously stated about the ambiguous influence of the total amount of precipitation during the period of growth and development of fruits on the content of soluble solids, and at the same time, sugars

(Wei et al., 1999, Zhu et al., 2001; Wei et al., 2003; Lakatos et al., 2012). Similar dependencies, but when studying blackcurrant fruits, were established by Finnish and Norwegian researchers (Zheng et al., 2009; Woznicki et al., 2015).

The amount of titrated acids in ‘Dmiana’ apples was higher than the average in the variant with the M.9 rootstock with a planting scheme of 4.0×0.5 m, in 2020 their content was 0.58%, which is 0.4% higher than the average, and in 2023 - 0.53 kg 100⁻¹, also 0.6 kg 100⁻¹ higher than the average. In the variant where fruits were grown on rootstock M.9 with a planting scheme of 1.0×4.0 m, the content of titrated acids was also higher than in fruits grown on rootstocks M.26 and MM.106, but this difference was not significant (Table 5). Similar data, but in comparison with other rootstocks, were obtained by Macedonian scientists, in particular, they found that apples grown on M.9 T 984 contained the highest levels of titratable acids compared to those grown on Budagovsky 9 (Gjamovski et al., 2011).

The titratable acid content of fruits grown on the MM.106 rootstock with a planting scheme of 1.0×4.0 m was significantly lower than average, particularly in 2021 and 2023, at 0.6 and 0.5 kg 100⁻¹ respectively. The average titratable acid content over the years of research was also significantly lower for fruits grown on MM.106 rootstock with a planting scheme of 1.0×4.0 m and was 0.45 kg 100⁻¹, which is 0.5 kg 100⁻¹ lower than the average (see Table 5).

Table 5. Titratable acids content of ‘Dmiana’ fruit grown on different rootstocks and at different planting densities

Rootstock	2020	2021	2023	Average ± SE
Planting scheme 4.0×0.5 m				
M.9	0.58 ± 0.02 ^a	0.54 ± 0.02	0.53 ± 0.01 ^a	0.55 ± 0.02 ^a
M.26	0.49 ± 0.01	0.57 ± 0.01 ^a	0.40 ± 0.02 ^{bd}	0.49 ± 0.05
MM.106	0.50 ± 0.01	0.53 ± 0.02	0.49 ± 0.01	0.51 ± 0.01
Planting scheme 4.0×1.0 m				
M.9	0.50 ± 0.01	0.56 ± 0.02 ^c	0.48 ± 0.02	0.51 ± 0.02
M.26	0.55 ± 0.02	0.53 ± 0.02	0.49 ± 0.02	0.52 ± 0.02
MM.106	0.48 ± 0.01	0.46 ± 0.01 ^b	0.41 ± 0.01 ^{bd}	0.45 ± 0.02 ^b

^{a,b} – indicates the level of significance of differences between rootstock variants within the same planting scheme at $P < 0.05$;

^{c,d} – values of indicators that are likely to differ from the average (x) for the years of the study for the studied group at $P < 0.05$.

The correlation analysis revealed a close inverse relationship between the titratable acid content of ‘Dmiana’ fruits and temperature factors. Specifically, increased night-time and average daily air temperatures in the month prior to apple harvesting were found to negatively impact the synthesis of titratable acids, with correlation coefficients exceeding 0.765 for the two weather factors. Our results are comparable to those obtained earlier by Canadian and Italian researchers, who noted that a cool growing season favours the synthesis of titratable acids and that their content in apples is usually higher during such periods than in years with hotter weather (Takashi & Hisashi, 1988; Toivonen & Lannard, 2020).

In addition to temperature, moisture levels during growth and development significantly impact titratable acid content. There is a direct relationship between the two: increased precipitation leads to higher acidity in ‘Dmiana’ apples. The correlation coefficients were 0.935, 0.864, and 0.940 for the M.9, M.26, and MM.106 rootstocks, respectively.

CONCLUSIONS

Weather conditions during the period of growth and development of apple fruit of the Dmiana variety significantly affect the content of dry matter, sugars and titratable acids. Apples harvested from trees with a semi-dwarf M.26 rootstock accumulated more sugars than those grown on M.9 rootstock. However, the content of titratable acids was higher in apples grown on dwarf rootstock M.9. Tree planting schemes of 4.0×0.5 m and 4.0×1.0 m did not affect the content of dry matter, sugars and titrated acids in the fruits of the variety Dmiana, the difference in content was within the error. Thus, to obtain apple fruits with a high sugar content, it is recommended to create plantations on rootstock M.26, with planting schemes of 4.0×0.5 m and 4.0×1.0 m. To establish the effect of rootstock and planting scheme on the content of other organic and biologically active substances in the fruits of apple variety Dmiana, it is necessary to deepen and continue the research.

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Formation of the root system of oilseed radish under long-term green manuring practices

Y. Tsytsiura *

Vinnitsia National Agrarian University, Faculty of Agronomy, Horticulture and Plant Protection, Soniachna street, 3, UA 21008 Vinnitsia, Ukraine

*Correspondence: yaroslavtsytsyura@ukr.net, yaroslav301974@gmail.com

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Abstract. The optimal selection of plant species for green manuring technologies is impossible without assessing the bioproductivity and morphometry of their root systems, which is an additional and significant factor in the effectiveness of both the growth processes of the green manure crop and its projected impact on the soil profile as a whole. Taking this into account for 11-year period, the bioproductivity of the root system of oilseed radish was assessed by morphological and weight parameters in the soil profile for two sowing dates of green manure: spring and summer. A wide range of methods based on Profile Wall, Monolith Method and Root maps of a profile wall were used to obtain the main functional indicators of the formation and spatial development of the root system.

It was determined that oilseed radish from the point of view of formation of morphological characteristics of the root system provided the yield of root biomass in dry matter of 1.19–1.77 t ha⁻¹ in active interaction with the soil profile 40–80 cm deep with the formation of the following components of the root system morphotype in the range of long-term average values for sowing dates: average diameter of the root taproot 5.13–5.67 mm at its taper 0.55–0.66, volume 26.92–39.09 cm³, volume of root spreading zone 36.75–66.39×10³ cm³, fractal dimension (D) 0.63–0.73, maximum root depth 47.36–64.41 cm, fraction of total root mass to the soil depth (0–30 cm) 0.77–0.79.

The dependence of the formation of indicators of bioproductivity of the root system with a direct nature on the amount of precipitation (determination 47.19–50.20%), water reserves in the soil (27.04–65.61%) and an inverse nature on the average daily temperature (21.44–25.70%), Vysotsky-Ivanov humidification coefficient (57.30–65.45), De Martonne Aridity Index (47.75–51.12) and soil hardness (37.21–59.29%) was determined.

Key words: plants' green manuring potential, root morphometrics, root maps, root biomass yield, root length density; root mass density, specific root length.

INTRODUCTION

The global trend of rising prices for both energy resources and agrochemicals (fertilizers, plant protection products, etc.) has led to changes in the planning approaches of relevant segments of agricultural crop production technologies (Li et al., 2024). A steady trend has been observed toward the transition to bio-organic fertilization systems

(Kaletnik & Lutkovska, 2020; Berezyuk et al., 2021). It has been proven that only 40–44% of applied mineral fertilizers ensure economic efficiency, while the rest pose a real threat to the agroecological sustainability of agricultural areas, are an additional factor in the chemical and agrophysical degradation of soils, and create prerequisites for increased carbon dioxide emissions (Lutkovska & Kaletnik, 2020; Tokarchuk et al., 2024).

Due to the shortage of traditional organic fertilizers caused by the development of organic matter bioprocessing from livestock (Honcharuk & Yemchyk, 2024), the described approach involves the use of green manure crops with high bioproductive potential and soil restoration capacity (Adetunji et al., 2020; Lei et al., 2022; Fonseca et al., 2023; Kucerik et al., 2024).

Green manure crops include plant species cultivated specifically to produce biomass (above-ground mass together with root residues), which is incorporated into the soil as green fertilizer. This may be done with variations, such as the addition of bio-organic fertilizers, decomposition agents, strains of various microorganisms, or conventional mineral fertilizers (Stradic et al., 2021; Lei et al., 2022; Kucerik et al., 2024).

In recent years, a comprehensive range of green manure crops has been established, comprising more than 60 plant species adapted to various soil and climate zones (Green Manure Global Market Report 2024, 2023). From the standpoint of efficiency and feasibility of using specific plant species for green manuring, the indicator of ‘green manure potential’ is crucial. This refers to the total biomass produced by a plant from germination to flowering, in conjunction with its biochemical composition, to evaluate its potential for enriching the soil profile with organic compounds as well as essential macro- and micronutrients (Fonseca et al., 2023). This indicator also includes the nature of the green manure crop's impact on the key dynamic processes in the soil profile, particularly in terms of humification, mineralization, and its influence on soil regimes and properties (Li et al., 2024).

Unfortunately, research on green manure mostly focuses on the quantity of above-ground biomass produced as the main source of organic matter. The role of root biomass is not always adequately assessed in terms of its dynamic impact on soil regimes and properties (Pisarčík et al., 2024; Zhang et al., 2024). It has been noted (Patra et al., 2023; Pandey & Kumar, 2024) that the effective role of a particular type of green manure should be considered by analyzing the morphological and spatial development of root systems in the context of adaptive and environmental factors.

It has also been observed (Saleem et al., 2020; dos Santos Nascimento et al., 2021; Tunguz & Pržulj, 2023) that different types of green manure plants demonstrate a wide range of root system responses to soil and climate conditions. In fact, the intensity of root development given the short growing period of green manure crops and under less favorable hydrothermal conditions, especially in the case of intermediate (summer-autumn) green manuring ensures an adequate level of green manure bioproductivity. For instance, according to estimates (Bublitz et al., 2022; Liang et al., 2023), an effective level of green manuring for areas with unstable moisture on soils of medium fertility potential is achieved when dry matter of above-ground biomass reaches about 2.5 t ha⁻¹, and root biomass at least 1.0 t ha⁻¹. It has also been noted that the root biomass of green manure crops serves as an additional source of organic carbon (Mahey et al., 2024). Moreover, due to the higher C/N ratio in root biomass compared to above-ground biomass, its decomposition in the soil occurs more slowly, which creates

additional advantages in terms of slow mineralization of plant biomass in the soil profile (Ansari et al., 2022; Prajapati et al., 2023). These processes make root biomass a component in forming the organic complex of the soil profile. Due to its biochemical composition differing from that of the above-ground mass, it ensures heterogeneity in the immobilization processes of decomposition biochemical components and qualitatively changes the structure of the soil microbiological complex (Ciaccia et al., 2017; Wang et al., 2024). It has been established that the degree of root system development in green manure crops - assessed by branching levels and the intensity of vertical and horizontal spread - affects soil agrophysical parameters such as density, porosity, aggregate dispersion, content of agronomically valuable soil aggregates, and their water resistance (Ma et al., 2021; Gentsch et al., 2024). This noted positive impact confirms the participation of root systems of green manure crops, when used regularly in crop rotations, in the gradual improvement of soil air and water properties and the reduction of humus depletion and decalcification (Bodner et al., 2019, 2021; Pisarčík et al., 2024).

At the same time, these features require detailed analysis of the growth patterns of green manure root systems from the standpoint of overall vegetative and spatial morphometry, accumulation and distribution of root biomass, and the role of soil properties and hydrothermal conditions during the growing season. Ultimately, this guarantees a sufficient assessment of the effectiveness and ecological feasibility of using green manure crops of specific plant types (Pimentel et al., 2023; Mueller et al., 2024; Ridgeway et al., 2024). In this context, recent years have seen increased scientific research on the formation of root systems of different green manure plant species (Bodner et al., 2019; Bublitz et al., 2022; Hudek et al., 2022; Kemper, 2024).

Among the plants used as green manure crops, cruciferous species are among the most widely applied (Ugrenović et al., 2019). Oilseed radish (*Raphanus sativus* L. var. *oleiformis* Pers. (= *Raphanus sativus* var. *oleifer* Stokes)), as a typical representative of this group, is gaining increasing popularity as a green manure crop, particularly in areas with a temperate continental climate and soils with low fertility potential, due to its well-defined adaptive traits (Tsytsiura, 2024a; 2025). From this perspective, evaluating the patterns of spatial and weight morphometry of its root system within the soil profile under various green manuring schedules - taking into account the hydrothermal conditions of the area and several soil properties - is a relevant issue that requires further scientific investigation, especially in terms of morphology and bioproductivity level.

MATERIALS AND METHODS

The research was carried out during 2014–2024 at the experimental field of Vinnytsia National Agrarian University (N 49°11'31", E 28°22'16") on Grey forest soils (Greyi-Luvic Phaeozems (Phaeozems Albic, Dark Gray Podzolic Soils) according to WRB (IUSS, 2015)) Haplic Greyzems according to FAO (IUSS, 2015)) of silty clay loamy texture. Weighted average soil fertility indicators: humus content: 2.68%, easily hydrolysable nitrogen 81.5 mg kg⁻¹ soil, mobile phosphorus 176.1 mg kg⁻¹ soil and exchangeable potassium 110.8 mg kg⁻¹ soil, pHCl 5.8, hydrolytic acidity 3.29 mg-equivalent 100 g⁻¹ soil. Additional average soil parameters are presented in Table 1.

The oilseed radish variety ‘Zhuravka’ was used in the research. The green manure type of crop design was used (seeding rate of 2.5 million seeds ha⁻¹ with row spacing of 15 cm). Two terms of green manure were studied: spring and summer. The spring term involved sowing in the first or second decade of April with the flowering phase (BBCH 64–67) reaching the optimum for green manure (according to Kemper, 2024) in the second or third decade of June. The summer term corresponded to sowing in the second to third decade of July with the flowering phase (BBCH 64–67) reaching the second to third decade of October. The green manure crop was grown on unfertilized soil with moisture provided by atmospheric precipitation.

Table 1. Detailed characteristics of the soil cover of the experimental plot in the year of the experiment (average across four transects)

The horizon of the soil, cm**	Soil density, G cm ⁻³		General porosity, %	The smallest moisture capacity, %	Maximal hygroscopicity, %	Humus, %	pH _{KCl}	Content, mg kg ⁻¹ soil		
	folding	solid phase						lightly hydrolysed nitrogen	mobile phosphorus	exchange potassium
0.0–0.1 (Oi, Oe)	1.28 ± 0.05	2.52 ± 0.04	48.24 ± 1.48	26.78 ± 1.05	8.22 ± 0.55	2.75 ± 0.21	5.8 ± 0.2	85.3 ± 1.9	177.5 ± 3.9	118.8 ± 2.9
0.1–0.2 (Ap)	1.31 ± 0.05	2.57 ± 0.04	48.25 ± 1.55	26.41 ± 1.23	8.35 ± 0.62	2.60 ± 0.18	5.8 ± 0.2	83.7 ± 1.6	179.1 ± 2.5	110.8 ± 3.9
0.2–0.3 (A ₁)	1.37 ± 0.05	2.62 ± 0.05	47.71 ± 1.61	25.51 ± 1.42	8.17 ± 0.68	2.15 ± 0.16	5.7 ± 0.2	75.5 ± 1.9	171.6 ± 3.1	105.7 ± 4.2
0.3–0.4 (A ₂)	1.41 ± 0.03	2.66 ± 0.07	46.99 ± 1.39	23.18 ± 1.33	8.14 ± 0.55	1.75 ± 0.12	5.6 ± 0.2	65.7 ± 1.5	158.5 ± 2.2	102.5 ± 5.6
0.4–0.5 (A ₂)	1.46 ± 0.04	2.69 ± 0.04	45.72 ± 1.42	23.49 ± 1.52	8.75 ± 0.57	1.10 ± 0.19	5.5 ± 0.3	61.4 ± 2.1	114.4 ± 4.2	98.8 ± 3.9
0.5–0.6 (B _a)	1.46 ± 0.04	2.69 ± 0.05	45.72 ± 1.89	24.15 ± 1.38	8.83 ± 0.67	0.85 ± 0.12	5.5 ± 0.1	49.7 ± 2.8	92.5 ± 2.7	96.7 ± 4.2
0.6–0.7 (B)	1.49 ± 0.06	2.71 ± 0.06	45.02 ± 2.17	23.85 ± 1.29	9.17 ± 0.67	0.71 ± 0.15	5.6 ± 0.3	47.4 ± 3.2	71.5 ± 3.9	102.8 ± 5.3
0.7–0.8 (B)	1.50 ± 0.06	2.70 ± 0.05	44.44 ± 2.12	24.28 ± 1.61	8.92 ± 0.54	0.57 ± 0.15	5.8 ± 0.4	41.5 ± 3.3	77.5 ± 4.2	111.3 ± 2.5
0.8–0.9 (B)	1.55 ± 0.07	2.73 ± 0.04	43.22 ± 2.25	23.00 ± 1.58	9.78 ± 0.58	0.52 ± 0.17	5.8 ± 0.3	40.2 ± 2.8	74.8 ± 2.3	110.7 ± 2.1
0.9–1.0 (B _c)	1.60 ± 0.07	2.74 ± 0.04	41.61 ± 2.47	21.48 ± 1.71	10.02 ± 0.63	0.50 ± 0.15	5.8 ± 0.3	39.3 ± 3.7	67.3 ± 3.1	114.7 ± 3.0

* SD – standard deviation; ** – according to Gupta et al. (2008).

The experimental plots were formed in quadruplicate by the method of randomisation with a plot area of 25 m². The growth stage of plants was identified using standard BBCH scales (Test Guidelines, 2017). The above-ground mass of plants was recorded during the flowering phase by the method of trial plots (1 m²) (4 in each replication, weighed on a laboratory balance (WALCOM LB3002 / ± 0.01 g)). The dry matter (DM) content of the aboveground and root mass of plants was determined by drying to constant weight at 105 °C and ashing at 550 °C (according to Undersander et al., 1993).

The field analysis of bioproductivity and morphogenesis of the root system of plants was carried out at the flowering stage using a combination of Profile Wall and Monolith Method (according to the recommendations of van Noordwijk et al., 2000; Cutforth et al., 2013; Talgre, 2013; Wahlström et al., 2015; Upendra et al., 2017).

Profile Wall Method: a trench was made approximately 1 m wide, across 6 rows of oilseed radish at the flowering stage of the plants (BBCH 64–67). The vertical wall across the rows was smoothed with a metal dust pan and a brush. Roots were exposed by removing a soil layer of about 1 cm thick by spraying water. For the vertical spatial delineation of the soil profile, a wooden marking frame (1 m × 1 m with a 10×10 cm grid) was used. Four such frames were included in the assessment for each replication.

The length of the exposed roots was estimated by counting the number of root-length units of 0.5 cm inside each grid. Based on this, data were obtained for the construction of root maps of a profile wall in a two-dimensional coordination system (according to Atkinson & Dawson, 2000; Pagès, 2012; Atkinson & Dawson, 2014; Pagès, 2014).

Monolith Method. Monoliths were formed from a vertical soil profile in 10 cm increments. Two rows of plants were included in the analysis with a depth of coverage of up to 10 plants in quadruplicate for each replication. Open-topped metal boxes with pointed edges (scoop type, wall thickness 3 mm) measuring 30 cm × 33.3 cm × 10 cm (accounting volume ~0.01 m³) were used. To trim the monolithic layer along the outer front wall, a vertical pointed metal plate measuring 10 cm × 34 cm × 0.3 cm was used. This made it possible to compact the walls of the monolith. Micromonoliths were labelled and packed in airtight sampling bags and then stored at 5 °C until washed out for soil removal. A sieve column (laboratory wire mesh sieves of 4.0 mm, 2.0 mm, 1.0 mm, 0.5 mm and 0.25 mm) was used for the washing separation of roots. Non-root materials were removed manually. The selected roots were stored in plastic containers at 5 °C and subsequently air-dried for 24 h.

The dynamics of root system growth in depth was carried out at intervals of 10 days from the beginning of germination on a preliminary profile soil section along a 50 cm long row (covering at least 15 plants) in 4 locations selected in the middle part of the experimental plots in two non-contiguous replications (according to the recommendations of Atkinson & Dawson, 2000). At the same time, a micromonolith (in quadruplicate for each replication) was taken according to the above-mentioned method to the depth of root penetration to determine the dynamics of root mass growth g m⁻². This analysis was accompanied by soil hardness (SH, kg cm⁻², Walcom FM-204TR penetrometer), soil moisture (W, %, Walcom MS-7828SOI soil moisture tester) and bulk density (BD, g cm⁻³, cylinder (core) method procedure (Blake & Hartge, 1986)).

Water reserves in the soil (WRS, mm) were determined on the basis of Eq. 1 (respectively до Dobriyal et al., 2012)

$$WRS = 0.1 \cdot h \cdot BD \cdot W \quad (1)$$

where h is the thickness of the soil layer, cm; W is the moisture content, %; BD is the bulk density, g cm⁻³; 0.1 is for conversion to mm.

The diameter of the root system was determined by direct measurement using an electronic caliper (Digital Caliper, Germany (± 0.01 mm)).

The taperiness of the core part of the root systems, ignoring the curvature of the root shape, and the average diameter of the core part of the root (r_{aver}) were determined by Eqs. 2–3 (according to Yang et al., 2017).

$$Taperiness = \frac{(D - d)}{l} \quad (2)$$

$$r_{aver} = \frac{\sqrt{D^2 + Dd + d^2}}{3} \quad (3)$$

where D is the root diameter at the root neck, cm; d is the root diameter at the lower fixation point, mm; l is the root length between the two points of diameter fixation, mm.

To determine the volume of the root system (V_{root}), a volumetric meter was used, consisting of a cylinder with a rubber tube connected to a 0.01 mL graduated pipette. The pipette was placed at such an angle that the meniscus of water was at the beginning of the pipette. When the roots were immersed in water, the water level in the cylinder increased, which in turn led to the movement of the meniscus in the graduated tube. The volume of the root system was determined by the amount of distilled water that needed to restore the same position of the meniscus in the graduated tube. To estimate the volumetric intensity of the development of the root system of oil radish, its fractal dimension (D) was calculated (according to the approaches of Tatsumi et al. 1989; Berntson et al., 1998; Edger, 2008) based on the measurement of root length (L_i) and the number of roots (N_i) of the i -th order. The order of root branching was identified: the last lateral branching was assigned to the first order, and the main root to the last order. The coefficient of the average length of branching of roots of the corresponding order (k_L) and the coefficient of the number of roots of the corresponding order (k_N) were calculated (Eqs. 4–5).

$$k_L = \frac{L_{i+1}}{L_i} \quad (4)$$

$$k_N = \frac{N_i}{N_{i+1}} \quad (5)$$

where L_i is the length of the roots of the i -th order, L_{i+1} is the length of the roots of the next branching order, cm; where N_i is the number of roots of the i -th order, N_{i+1} is the number of roots of the next branching order, pcs.

The average root length coefficient (K_L) and the average root number coefficient (K_N) were calculated as the arithmetic mean of the k_L and k_N coefficients.

The fractal dimension of the root system of oilseed radish (D) was determined by Eq. 6.

$$D = \frac{\ln K_N}{\ln K_L} \quad (6)$$

To calculate the root spreading zone of the root system, we used the methodological approaches of Rouse (2019) and Jung et al. (2019) for the approximation of the configuration of the cut and full elliptical cones due to the longer branching length of the root system in the inter-row compared to the row (Fig. 1). In accordance with the parameters of Fig. 1 (based on Leonard et al. (2014)), the volume of root spreading zone (R_{vsz}) was determined (Eq. 7).

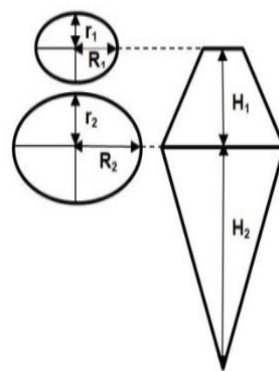


Figure 1. Shape of the root spreading zone of oilseed radish based on data from the Monolith and Profile Wall methods.

$$R_{vsz} = \frac{1}{3} \pi [(R_1 r_1 + R_1 r_1 R_2 r_2 + R_2 r_2) H_1 + R_2 r_2 H_2] \quad (7)$$

where the relevant components of the equation correspond to those presented in Fig. 1.

The coefficient of root system productivity in dry matter (CRP_{DM}) was calculated as the ratio of formed aboveground dry biomass to formed root dry biomass of the plants. The share of root residues in total dry plant biomass (SRR_{DM}) was calculated using the inverse ratio compared to CRP_{DM} and was expressed as a percentage.

To estimate the spatial distribution of root mass, we used the Michaelis-Menten function of root distribution with depth (z ; cm) (Eq. 8 according to Kätterer et al., 2011).

$$R_{m(z)} = \frac{z(z_{50} + z_r)}{z_r(z_{50} + z)} \quad (8)$$

where $R_{m(z)}$ is the fraction of total root mass to the soil depth of z (cm), z_r is maximum root depth (z_r was set at 100 cm), z_{50} is the depth of 50% of the root mass.

Based on the root length and root mass obtained from the monolith samples (according to Pagès et al. (2012) and Bardgett et al. (2014)), the following indicators were determined root length density (RLD , cm cm⁻³, Eq. 9), root mass density (RMD , mg cm⁻³, Eq. 10) and specific root length (SRL, m g⁻¹, Eq. 11), percentage of root weight distribution ($PRWD$ (in raw weight after 3 h normal air drying), %, Eq. 12).

$$RLD = \frac{\text{root length}}{\text{soil volume}} \quad (9)$$

$$RMD = \frac{\text{root dry mass}}{\text{soil volume}} \quad (10)$$

$$SRL = \frac{\text{root length}}{\text{root dry mass}} \quad (11)$$

$$PRWD = \frac{\text{root mass for a specific soil horizon}}{\text{root mass in the general soil profile}} \cdot 100 \quad (12)$$

To analyze the patterns of distribution of oilseed radish roots along the soil profile, nonlinear regression models were estimated using CurveExpert Professional v. 2.7.3 software package (Hyams Development). Additionally, RhizoVision Explorer 2.0.2 (Noble Research Institute, LLC, USA) and electronic scanning and USB microscopy method (CanoScan LIDE 700F scanner, Sigeta MCMOS 5100 5.1 MP USB 2.0) were used.

To analyze the hydrothermal conditions, we used the following indicators: average daily temperature (°C), precipitation (mm), relative humidity (%), hydrothermal coefficient (HTC) (Eq. 13), De Martonne Aridity Index (I_{DM}) (Eq. 14), Vysotsky-Ivanov humidification coefficient (K_h) (Eq. 15).

$$HTC = \frac{\sum R}{0.1 \cdot \sum t_{>10}} \quad (13)$$

where $\sum R$ – the sum of precipitation (mm) over a period with temperatures above 10 °C, $\sum t_{>10}$ – the sum of effective temperatures over the same period. Ranking of HTC values conditions: $HTC > 1.6$ – excessive humidity, $HTC 1.3–1.6$ – humid, $HTC 1.0–1.3$ – moderately dry, $HTC 0.7–1.0$ – dry, $HTC 0.4–0.7$ – very dry.

$$I_{DM} = \frac{12P_m}{T_m + 10} \quad (14)$$

where P_m and T_m are the precipitation volume and mean air temperature in the corresponding month, respectively (according to the I_{DM} the climate can be classified:

Arid $I_{DM} < 10$; Semi-Arid $10 \leq I_{DM} < 20$; Mediterranean $20 \leq I_{DM} < 24$; Semi-humid $24 \leq I_{DM} < 28$; Humid $28 \leq I_{DM} < 35$; Very Humid $35 \leq I_{DM} \leq 55$; Extremely humid $I_{DM} > 55$).

$$K_h = \frac{P}{E} \tag{15}$$

where K_h is the moisture coefficient; P is the amount of precipitation for the analyzed period, mm; E is the evapotranspiration for the analyzed period, mm, which was calculated according to Eq. 16 (the different moisture degrees of K_h : $K_h > 1.0$ – excessive, K_h close to 1 – optimal, $K_h = 1.0-0.6$ – unstable, $K_h = 0.6-0.3$ – insufficient).

$$E = 0.0018 \cdot (25 + t)^2 \cdot (100 - a), \tag{16}$$

where t is average air temperature, °C; a is average air humidity, %.

A summary assessment of hydrothermal conditions is presented in Table 2.

Table 2. Assessment of hydrothermal regimes during the active vegetation period of oilseed radish under summer and autumn green manure use (Dfa/Dfb zone according to the Köppen-Geiger climate classification), 2014–2024

Year	Precipitation, mm (IV–VI)	t_{aver} , °C (IV–VI)	Months of the growing season											
			IV			V			VI					
			HTC	I_{DM}	K_{h}	HTC	I_{DM}	K_{h}	HTC	I_{DM}	K_{h}			
A variant of summer green manure														
2014	339.6	13.84	0.725	45.7	1.18	3.928	88.9	2.11	1.545	34.8	0.83			
2015	142.3	14.36	0.645	37.3	0.78	0.917	20.6	0.41	0.715	16.9	0.27			
2016	193.4	15.06	0.296	21.6	0.44	0.489	40.4	0.99	1.265	29.9	0.75			
2017	125.1	14.07	3.919	39.2	0.75	0.777	16.8	0.34	0.504	11.9	0.22			
2018	170.8	16.38	0.290	10.8	0.19	0.308	7.2	0.12	4.404	103.7	2.31			
2019	398.5	15.39	0.565	33.5	0.72	4.902	111.0	3.29	1.682	41.4	0.96			
2020	343.8	13.67	0.091	36.4	0.50	5.327	106.4	3.18	1.548	37.3	0.89			
2021	282.8	13.26	0.233	38.8	0.96	3.125	66.7	1.64	1.679	39.8	1.00			
2022	242.1	14.30	0.563	57.4	2.33	1.430	31.3	0.79	1.496	36.1	0.85			
2023	239.8	14.18	1.543	91.5	3.33	0.085	1.90	0.04	1.640	38.9	0.87			
2024	262.1	16.27	3.259	47.5	3.18	0.577	13.19	0.24	1.660	40.4	0.98			
Year	Precipitation, mm (IV–VI)	t_{aver} , °C (IV–VI)	Months of the growing season											
			VII			VIII			IX			X		
			HTC	I_{DM}	K_{h}	HTC	I_{DM}	K_{h}	HTC	I_{DM}	K_{h}	HTC	I_{DM}	K_{h}
An variant for autumn green manure														
2014	250.8	15.4	1.312	32.7	0.77	1.049	26.0	0.51	1.252	25.7	0.56	1.770	35.8	0.93
2015	160.8	16.6	0.321	8.1	0.14	0.124	3.1	0.05	1.184	26.8	0.63	3.039	49.4	1.25
2016	212.7	15.6	1.056	26.5	0.55	0.898	22.0	0.43	0.014	2.5	0.05	0.548	63.4	2.45
2017	318.0	16.0	1.524	37.5	0.72	0.819	20.7	0.38	3.100	61.2	1.57	1.065	30.0	1.26
2018	273.4	16.4	2.158	53.4	1.63	0.585	14.6	0.30	1.378	27.2	0.71	0.873	27.6	0.95
2019	161.7	16.0	1.013	24.4	0.56	0.237	5.9	0.11	0.994	20.7	0.42	0.383	27.4	0.93
2020	245.4	17.6	0.589	14.7	0.31	0.527	13.2	0.22	0.859	27.5	0.54	2.544	60.6	3.05
2021	176.9	15.4	0.782	20.1	0.45	1.459	35.7	0.91	0.705	17.6	0.51	0.000	1.7	0.04
2022	436.6	16.0	0.900	22.4	0.58	1.712	43.1	1.06	4.960	98.1	2.60	3.167	51.4	1.50
2023	247.1	18.3	1.414	35.8	0.82	0.652	16.9	0.36	1.015	23.4	0.63	1.025	29.9	0.93
2024	219.8	19.6	1.190	31.1	0.66	0.771	19.8	0.41	0.445	10.6	0.22	1.173	30.5	1.06

To assess the stability of oilseed radish bioproductivity formation, we used (according to Sych, 2006) the absolute elasticity coefficient (EA), the relative elasticity coefficient of type I (E_I), and the relative elasticity coefficient of type II (E_{II}) according to Eqs. 17–19.

$$E_A = \frac{\Delta y}{\Delta x} \quad (17)$$

$$E_I = \frac{\Delta y x_{av}}{100 \Delta x} \quad (18)$$

$$E_{II} = \frac{\Delta y x_{av}}{\Delta x y_{av}} \quad (19)$$

where Δy is the range of variability of the resultant indicator y ; Δx is the range of variability of the environmental factor x ; x_{av} , y_{av} is the average value of the indicators between the maximum and minimum values in the respective years.

Statistical analysis. To statistically evaluate all multi-year average values of root system morphometric indicators, the standard deviation (SD) was used based on a consolidated data set covering the entire evaluation period. Statistical significance of interannual comparisons was assessed using Tukey's test (Tukey HSD Test) with the Bonferroni correction at a significance level of $p < 0.05$, with letter-based indication of statistically different data. Additionally, interannual variation was assessed using the coefficient of variation (Cv) for the time series of average annual data.

For the main indicators of root system bioproductivity based on fresh and dry biomass yields and related parameters, as well as for indicators of root system development intensity in the soil profile (RLD, RMD, SRL, PRWD), standard ANOVA analysis was applied to determine the statistical significance of interannual differences at a significance level of $p < 0.05$. The statistical analyses were performed using Statistica 10 software (StatSoft – Dell Software Company, USA) and R (version R statistic i386 3.5.3). Correlation and regression analysis was conducted according to the standard procedure for levels of statistical significance $p < 0.05$ and $p < 0.01$ (Wong, 2018) using the coefficient of determination (R^2 , with an estimate according to the Chaddock (1925)), adjusted coefficient of determination (R^2_{adj}), root mean square error (RMSE), relative root mean square error (RRMSE) and prediction efficiency index (PE), the coefficient of determination of the closeness of the correlation (d_{xy} , Eq. 20).

$$d_{xy} = r_{ij}^2 \cdot 100 \quad (20)$$

where r_{ij} is the correlation coefficient.

RESULTS AND DISCUSSION

Sidereal Bioproductive Potential of the Root System. The multi-year research period, characterized by interannual variability in precipitation levels of 33.78% and in average daily temperatures of 17.55%, defines the hydrothermal regime of the study period (according to Gardner et al., 2020) as unstable - ranging from extremely arid conditions amid rapidly rising average daily temperatures (IDM 2.5; K_h 0.05; HTC 0.014 (Table 2)) to excessively humid conditions under moderate temperature levels (IDM 111.0; K_h 3.29; HTC 4.902).

This allowed for the evaluation of the ecological adaptive strategy of root system formation in oilseed radish over a multi-year scale and, based on the obtained indicators of its bioproductive potential (Figs 2–3), to classify it as a highly productive and adaptive cover crop suitable for a wide range of sowing periods – under conditions of either increasing (spring sowing) or decreasing (summer sowing) average daily temperatures.

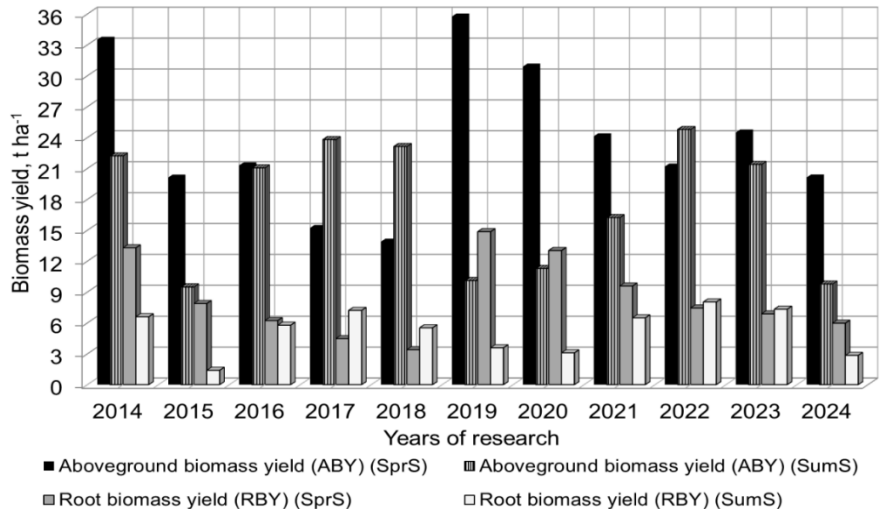


Figure 2. Formed raw aboveground and raw root biomass of oilseed radish plants for spring (SprS) and summer (SumS) sowing, $t\ ha^{-1}$ (LSD_{05} springABY 1.42; LSD_{05} summerABY 1.24; LSD_{05} spring RBY 1.09, LSD_{05} summer RBY 0.65), 2014–2024.

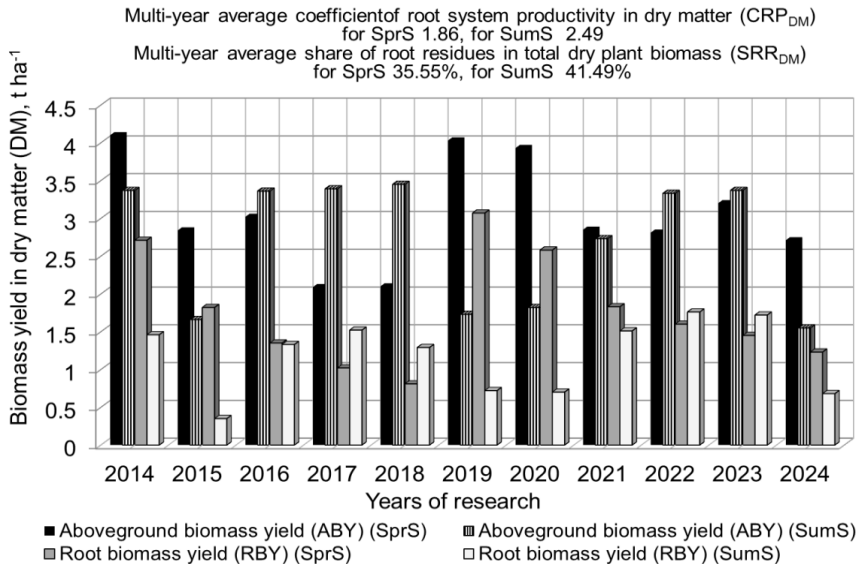


Figure 3. Formed aboveground and root biomass (in dry matter (DM)) of oilseed radish plants for spring (SprS) and summer (SumS) sowing, $t\ ha^{-1}$ (LSD_{05} springABYDM 0.23; LSD_{05} summerABYDM 0.37; LSD_{05} spring RBYDM 0.25, LSD_{05} summer RBYDM 0.14), 2014–2024.

According to the results of long-term studies conducted across different soil-climatic zones, the feasibility of using specific plant species as cover crops for green manure and phytoremediation purposes has been confirmed, provided that aboveground phytomass in dry matter reaches $1.5\text{--}2.0\text{ t ha}^{-1}$ and root mass $0.8\text{--}1.0\text{ t ha}^{-1}$, with a corresponding root system productivity coefficient of $1.8\text{--}2.0$ and a total root biomass share not exceeding 50% of the overall plant biomass (Wagg et al., 2021; Zhang et al., 2023). These parameters provided a sufficient level of green manure potential in terms of replenishing soil with organic biomass, optimizing its agrophysical and agrochemical properties, and ensuring plant adaptability to limiting hydrothermal factors in specific regions - taking into account the potential of the developed root systems (Dzvene et al., 2023; Wong et al., 2024).

The presented results, along with our previous assessments (Tsytisiura, 2024a, 2024b) on grey forest soils - whose fertility potential is classified as medium (Kolbe, 2022) - determined the long-term average level of aboveground biomass formation at 23.68 t ha^{-1} for spring sowing and 17.56 t ha^{-1} for summer sowing, with interannual variation of 29.84% and 35.68%, respectively. When converted to dry matter equivalent, these values amounted to 3.06 and 2.71 t ha^{-1} (with interannual variation of 22.96% and 30.68%, respectively). At the same time, the root biomass formed was 8.45 and 5.26 t ha^{-1} in raw weight and 1.77 and 1.19 t ha^{-1} in dry matter, with interannual variation ranging between 40.86% and 44.72%. The average long-term interannual variation of the root productivity coefficient (RPC) was 21.99% (with a long-term average RPC of 1.86) for spring sowing and 32.20% (RPC = 2.49) for summer sowing, against background interannual RPC variation levels of 13.94% and 24.11%, respectively.

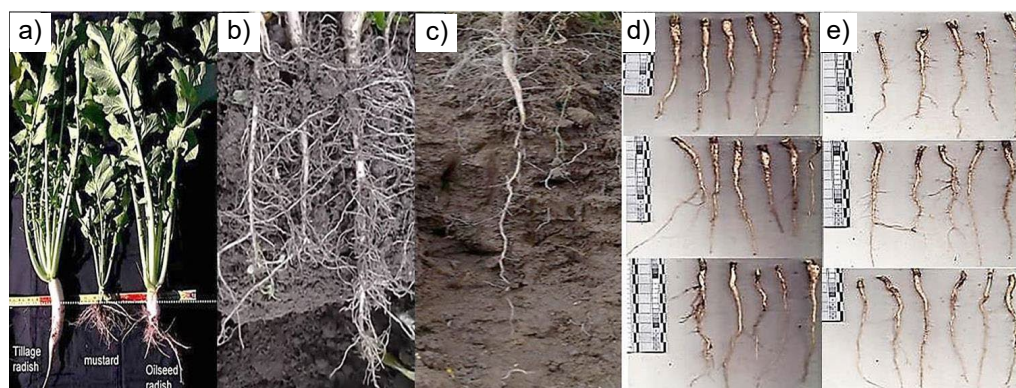


Figure 4. General morphology of root systems in cruciferous species. (a) General comparative characteristics (Radish cover crop, 2024); (b–c) Structure of the root system of oilseed radish (*Raphanus sativus* L. var. *oleiformis* Pers. [syn. *Raphanus sativus* var. *oleifer* (Stokes) Metzg]); (d) Taproot of oilseed radish with elements of primary branching under spring sowing; (e) Taproot under summer sowing conditions.

These results highlight the significant influence of the hydrothermal regime on the realization of the root productivity potential in oilseed radish. Compared to other cruciferous species (Fig. 4), the development of the oilseed radish root system under green manure usage throughout the study period exhibited certain bioproductive and

morphological distinctions. Identifying these differences allowed for a more detailed characterization of its root productivity potential as a green manure crop.

Root System Morphotype and Development Intensity in the Soil Profile. The integrated system for evaluating the morphological characteristics of the root system (Table 3) has proven its value in terms of active morphogenesis and potential impact on the soil profile. In particular, oilseed radish was characterized by the formation of a taproot (Fig. 4, g, d) and an intensive network of lateral branches of corresponding orders (Fig. 4, b). The parametric morphological development of the taproot section exhibited significant differences depending on the sowing dates of oilseed radish as a green manure crop and, in our case, was defined by the average diameter and conicity (Table 3).

Table 3. General indicators of oilseed radish root system development based on the combined use of the Profile Wall and Monolith Method at the flowering stage (BBCH 64-67), 2014–2024

Year	Average diameter of the root taproot (r_{aver}), mm	Taperiness	Volume (V_r), cm^3	Volume of root spreading zone (R_{vsz}), $\times 10^3 cm^3$	Fractal dimension of the root system (D)	Maximum root depth (z_r), cm	Fraction of total root mass to the soil depth 0–30 cm ($R_{m(z)}$)
Spring sowing							
2014	7.94 ± 2.59^e	0.48 ± 0.13^a	57.39 ± 9.32^g	84.89 ± 8.41^d	0.85 ± 0.12^e	58.8 ± 7.19^c	0.83 ± 0.07^d
2015	4.68 ± 1.09^b	0.47 ± 0.15^a	21.93 ± 7.18^d	28.49 ± 6.69^a	0.72 ± 0.18^c	75.7 ± 8.53	0.78 ± 0.05^b
2016	5.03 ± 1.55^c	0.62 ± 0.17^c	45.39 ± 8.35^e	34.54 ± 4.58^a	0.70 ± 0.13^b	57.9 ± 8.07^c	0.81 ± 0.09^d
2017	4.20 ± 1.17^a	0.58 ± 0.12^b	25.58 ± 6.59^a	51.90 ± 5.52^b	0.61 ± 0.19^a	78.9 ± 10.19^c	0.74 ± 0.08^a
2018	4.02 ± 1.08^a	0.66 ± 0.19^d	21.96 ± 5.87^d	33.88 ± 7.18^a	0.55 ± 0.15^a	79.1 ± 9.39^c	0.73 ± 0.05^a
2019	8.48 ± 2.05^f	0.48 ± 0.11^a	55.33 ± 7.14^b	65.76 ± 8.29^c	0.89 ± 0.09^f	49.5 ± 7.21^a	0.83 ± 0.10^d
2020	7.41 ± 1.87	0.48 ± 0.08^a	50.28 ± 8.41^f	105.69 ± 12.79^{g0}	0.81 ± 0.12^d	58.4 ± 7.09^c	0.80 ± 0.09^c
2021	5.77 ± 2.06^d	0.56 ± 0.11^b	41.27 ± 5.28^b	95.29 ± 10.88^e	0.78 ± 0.08^d	55.4 ± 7.07^b	0.76 ± 0.11^b
2022	5.08 ± 1.54^c	0.52 ± 0.14^b	38.29 ± 5.59^a	87.04 ± 9.52^f	0.75 ± 0.10^c	68.4 ± 7.22^d	0.74 ± 0.05^a
2023	4.73 ± 1.14^b	0.58 ± 0.11^b	37.37 ± 4.11^c	69.47 ± 6.87^c	0.71 ± 0.14^b	69.2 ± 8.19^d	0.76 ± 0.07^b
2024	5.06 ± 1.25^c	0.61 ± 0.14^c	35.19 ± 4.69^a	73.36 ± 9.08^d	0.67 ± 0.17^b	57.2 ± 6.74^c	0.73 ± 0.10^a
Summer sowing							
2014	4.96 ± 1.19^b	0.54 ± 0.08^a	23.39 ± 4.77^c	34.89 ± 2.56^f	0.69 ± 0.11^d	42.8 ± 6.52^b	0.85 ± 0.07^d
2015	4.23 ± 0.97^a	0.62 ± 0.12^b	15.15 ± 3.59^a	19.82 ± 1.47^b	0.43 ± 0.18^a	57.6 ± 5.89^g	0.86 ± 0.05^d
2016	5.34 ± 1.12^c	0.64 ± 0.16^b	25.36 ± 7.18^d	26.50 ± 2.09^d	0.64 ± 0.09^c	46.9 ± 5.07^d	0.80 ± 0.11^c
2017	5.44 ± 1.29^d	0.56 ± 0.11^a	46.15 ± 6.59^f	30.26 ± 3.89^e	0.72 ± 0.14^e	41.3 ± 8.42^a	0.84 ± 0.04^d
2018	5.12 ± 1.58^c	0.65 ± 0.14^b	26.77 ± 5.08^c	31.85 ± 3.52^c	0.67 ± 0.11^c	40.9 ± 7.09^a	0.81 ± 0.05^c
2019	4.81 ± 0.73^b	0.76 ± 0.11^c	23.18 ± 4.25^c	22.75 ± 2.41^c	0.58 ± 0.15^b	58.9 ± 6.14^h	0.78 ± 0.08^b
2020	4.59 ± 1.05^a	0.72 ± 0.15^d	21.39 ± 4.09^b	42.58 ± 4.07^g	0.52 ± 0.12^a	42.5 ± 5.18^b	0.76 ± 0.12^a
2021	5.47 ± 1.55^d	0.76 ± 0.09	25.56 ± 3.56^d	24.20 ± 2.59^c	0.64 ± 0.18^c	48.7 ± 3.96^e	0.74 ± 0.08^a
2022	5.86 ± 1.07^e	0.67 ± 0.11^c	34.38 ± 3.77^f	70.03 ± 9.07^h	0.78 ± 0.10^f	40.9 ± 5.12^a	0.75 ± 0.05^a
2023	6.20 ± 1.74^f	0.68 ± 0.12^c	30.28 ± 5.02^e	15.42 ± 1.49^a	0.73 ± 0.11^c	44.7 ± 4.35^c	0.77 ± 0.08^b
2024	4.41 ± 0.72^a	0.67 ± 0.14^c	24.47 ± 3.91^c	85.96 ± 10.22^i	0.52 ± 0.07^a	55.8 ± 5.71^f	0.76 ± 0.06^a

Note: Different letters indicate values that differ significantly from one another within each column, based on Tukey's test with Bonferroni correction.

The first indicator, in the long-term average for spring sowing, was 5.67 mm, and the second – 0.55. For summer sowing, their values were lower by 10.6% and 16.7%, respectively. Compared to other cruciferous green manure crops (spring and winter

rapeseed, various mustard species), the diameter of the central (core) part of the oilseed radish taproot was smaller than that of winter rapeseed (Gan et al., 2009; Gao et al., 2017; Louvieaux et al., 2020; Kemper, 2024), equal to or greater than that of white mustard (Chaudhary et al., 2016; Hajzler et al., 2018; Amgain & Sharma, 2021; Kemper, 2024), and greater than that of spring rapeseed (Čepulienė et al., 2013; Marcinkevičienė et al., 2013; Liyanage et al., 2022; Kemper, 2024).

At the same time, the taproot of oilseed radish is characterized by a flexible formation of a conical profile, with an active adjustment of the main axial line of the root in response to changes in soil density and the presence of mechanical obstacles (Fig. 4, g, d). This trait creates preconditions for deep root penetration and enables growth in compacted soils. This is further confirmed by a conicity index value below 0.75, which, according to Goodman et al. (2001), Jeudy et al. (2016), and Duan et al. (2023), indicates both the intensive narrowing of the lower taproot section at maximum rooting depth (z_r) and the high penetration potential of narrow-diameter root crops into the deeper horizons of the soil profile, as supported by the findings of Duan et al. (2023) and Wu et al. (2020).

This specific morphology of the core section of the root has demonstrated the value of oilseed radish as a green manure crop for improving the agrophysical properties of the soil profile up to a depth of 50 cm (based on the long-term average rooting depth (z_r) of 64.41 cm (interannual $C_v = 20.97\%$) for spring sowing and 47.36 cm ($C_v = 18.57\%$) for summer sowing). This effect is analogous to the so-called 'root drainage effect' observed in white mustard (Dharmasri et al., 1993) and winter rapeseed (Fan et al., 2016), and has been identified as a key factor in the effectiveness of these plant species when used as green manure crops (Kemper, 2024).

The green manure and phytoremediation potential of oilseed radish for both green manuring periods was also confirmed by the root system volume indicator (V_r).

On average over the study period, the root system volume (V_r) of oilseed radish was 39.09 cm^3 (with interannual $C_v = 31.93\%$) for spring sowing and 26.92 cm^3 ($C_v = 29.78\%$) for summer sowing, which is 45.22% lower. This supports the findings of Schenk & Jackson (2002), Wu et al. (2018), Kashyap et al. (2023), Maan et al. (2023), Boter et al. (2023), and Ullah et al. (2024) regarding the response of root systems - including cruciferous species - to aridization during their vegetation period, manifested in a reduction of total morphological development by 30–75%. This was also confirmed by the hydrothermal evaluation of oilseed radish's vegetation period in both spring and summer sowing conditions (Table 2). At the same time, the obtained V_r values, according to the assessments of Talgre (2013), Duff et al. (2020), Bublitz et al. (2022), and Kemper (2024), are comparable to those of such crops as white mustard, brown mustard, and both spring and winter rapeseed, for which the range of V_r was reported to be between 20 and 117 cm^3 .

It is worth noting that under similar climatic conditions of the study area (climate zone Dfa/Dfb according to the Köppen-Geiger classification), the average V_r values of oilseed radish were 31.7% lower than those of winter rapeseed in long-term measurements (Talgre, 2013; Ullah et al., 2024; Chen et al., 2024), but 21.5% and 12.9% higher than those of spring rapeseed and white mustard, respectively, when used as green manure crops (Dharmasri et al., 1993; Wahlström et al., 2015; Jeudy et al., 2016; Hajzler et al., 2018).

At the same time, based on the root spread zone volume (R_{vsz}) - an important factor in the spatial distribution of root systems within the soil profile (Liu, 2009) - oilseed radish was classified as a crop with wide adaptability in the formation of spatial root morphometry. On average over the study period, this indicator was $66.39 \times 10^3 \text{ cm}^3$ (interannual $C_v = 39.63\%$) for spring sowing and $36.75 \times 10^3 \text{ cm}^3$ ($C_v = 59.82\%$) for summer sowing. The $R_{vsz}:V_r$ ratio for oilseed radish as a green manure crop was 1.70 in spring sowing and 1.37 in summer sowing, indicating a high intensity of root system expansion through lateral branching. This ratio reflects the relationship between root system compactness and its areal spread - i.e., the extent of horizontal and vertical penetration of lateral roots under a given plant density.

Taking into account the estimates of Deus et al. (2022) and Kemper (2024), in full-fledged green manure crops, especially in the intermediate group of cultivation, a ratio above 1.25 is important to achieve the appropriate green manure and soil rehabilitation effect. From this point of view, oilseed radish, when used as green manure, meets the criteria of efficiency in terms of full root mass formation in terms of soil rehabilitation and bioorganic fertilization.

This conclusion is consistent with the results of the fractal dimension (D) of the root system. This parameter displayed specific characteristics in oilseed radish that further detail its adaptive root system architecture. The D value for spring sowing was 0.73 (with interannual $C_v = 13.76\%$) and 0.63 ($C_v = 16.87\%$) for summer sowing. According to Berntson (1996; 1998), the fractal dimension of root systems is a highly variable parameter, ranging from 0.35 to 1.95 across assessed crop species. Higher D values indicate a greater number of branches relative to their length. It has been reported (Gao et al., 2024) that for winter rapeseed under primary cultivation, depending on fertilization, the D index ranged from 1.56 to 1.76. As plant density increases in the absence of additional fertilization and under unfavorable agrophysical conditions of the soil profile, the fractal dimension of the root system tends to decrease, which may serve as an indicator of the species' response to the effectiveness of stand structure design (Berntson et al., 1998; Yang et al., 2022).

For cruciferous crops, which are sensitive to sowing dates and spatial parameters of nutrient zones, the D index can vary broadly from 0.50 to 2.10, and for cruciferous species with a spring development cycle – from 0.5 to 1.2 (Berntson, 1996). The obtained value for oilseed radish, under high-density green manure cropping (up to 2.5 million plants per hectare), and based on its demonstrated response to stand density and fertilization (Tsytsiura, 2020), confirms the presence of adaptive potential for intensive radial development and root system penetration under increasing ecological-coenotic stress, as noted by Fitter & Stickland (1992). This characteristic is also supported by the low interannual variation in both sowing terms, with only a 3.11% difference in C_v between them, and D variability being nearly half that of the hydrothermal conditions observed during the study period (Table 2). These conclusions are consistent with the findings of Wang et al. (2009), Upendra et al. (2017), and Ullah et al. (2024).

It is also important to note the characteristics of maximum rooting depth (z_r) formation, which plays a key role in the vertical distribution of the root system (Schlüter et al., 2018; Kafarski et al., 2019) and significantly determines the adaptive potential of this plant species in terms of water supply and its ability to maintain growth rates under declining optimal environmental factors during the vegetation period (Fan et al., 2017). This was a major factor in ensuring the bioproductivity of summer and early autumn

green manure crops (Bublitz et al., 2022). During the research period, the long-term average z_r was 64.41 cm for spring sowing and 47.36 cm for summer sowing. Thus, the ratio between maximum rooting depth for these sowing terms was 1.36:1. The level of interannual variation in this parameter did not exceed 15.0% on average, indicating the presence of adaptive mechanisms in oilseed radish, associated with so-called hydrological deepening (Schenk & Jackson, 2002; Cutforth et al., 2013; Jabbari et al., 2016; Fan et al., 2017; Ullah et al., 2024). This effect is caused by an increase in the z_r index in response to reduced total soil moisture availability under precipitation deficit conditions and rising average daily temperatures. This is confirmed by comparisons between years with minimal precipitation and the z_r values of oilseed radish for both green manuring sowing terms (Table 2). In spring sowing, during the driest years (2015, 2017, 2018), the average z_r was 77.9 cm, which exceeded the long-term average by 21.0%. For summer sowing, in years with moisture deficit (2015, 2019, 2024), the corresponding value was 57.4 cm, exceeding the average by 24.3%.

It should also be noted that in terms of rooting depth, among other cruciferous green manure crops grown under comparable conditions (according to Cutforth et al., 2013; Amgain & Sharma, 2021; Deus et al., 2022; Boter et al., 2023; Chen et al., 2024; Kemper, 2024), oilseed radish was second only to winter rapeseed used in the autumn-winter cycle, where rooting depth reached 90–115 cm. At the same time, despite the recorded deep root penetration of oilseed radish in both sowing terms, it was found that the majority of roots were concentrated within the 0–30 cm soil layer. This is supported by the root mass distribution ratio to the 0–30 cm soil layer ($R_{m(z)}$), with an average value of 0.77 (interannual $C_v = 7.91\%$) for spring sowing and 0.79 ($C_v = 9.54\%$) for summer sowing. Overall, this pattern of vertical root accumulation is typical for cruciferous crops of both winter and spring types. In particular, Dharmasri et al. (1993), Bublitz et al. (2022), and Kemper (2024) noted this characteristic, indicating the depth intervals of maximum root system concentration as follows: 25–60 cm for winter rapeseed, 22–35 cm for spring rapeseed, 18–40 cm for oilseed radish, and 20–45 cm for white mustard. It has also been demonstrated (Kemper, 2024) that the vertical tropism share of roots in oilseed radish is sensitive to fertilizer application and increases in individual plant nutrient area. In densely planted cruciferous green manure agroecosystems, the majority of the root mass tends to concentrate within the upper 1-meter soil profile, accounting for 25–50% of total root biomass (Talgre, 2013; Wahlström et al., 2015).

These findings, along with the spatial distribution patterns of the oilseed radish root system in the long-term average, are supported by the results of root map construction along the profile wall in a two-dimensional coordinate system for the row spacing arrangement in both sowing terms (Fig. 5). The root map analysis was conducted according to the approaches described by Bucksch et al. (2017), Landl et al. (2018), Bublitz et al. (2022), and Faye et al. (2022). Based on the obtained data, the average geometric structure of the root spread zone of oilseed radish over the study period was confirmed and is presented in Fig. 1. It was determined that in the vertical projection of the soil profile, the root system of oilseed radish exhibited a complex, layered structure under both sowing conditions. In spring sowing, the share of roots with an identification probability of 85–100% was concentrated horizontally at a distance of 5–8 cm from the taproot and vertically at 24–28 cm from the soil surface (Fig. 5, a). The maximum horizontal spread of the root system in the long-term average occurred at a depth of 10–12 cm and at a horizontal distance of 8–12 cm from the taproot. The gradation step in horizontal spread variation ranged from 3 to 7 cm.

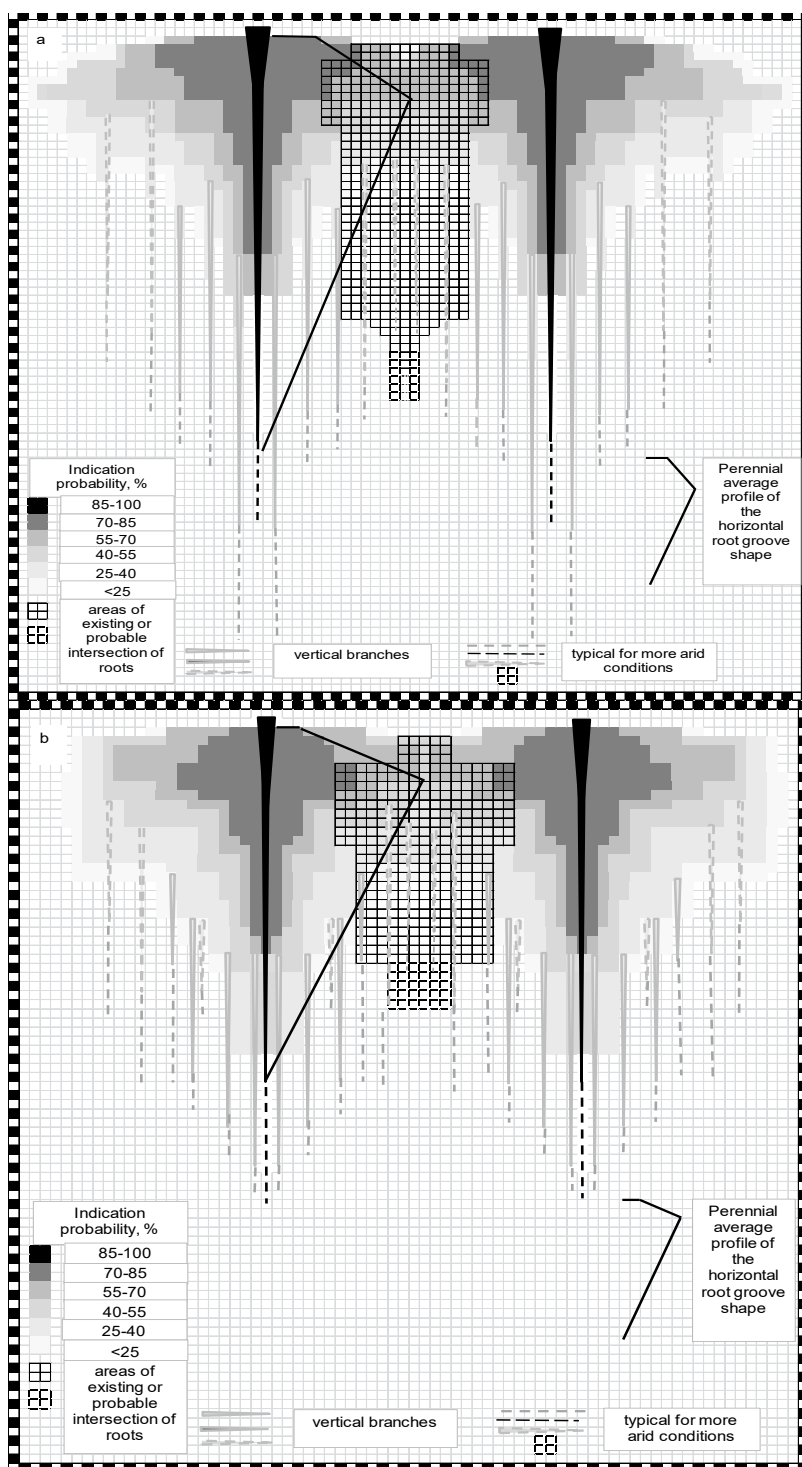


Figure 5. Root maps of the profile wall in oilseed radish, covering two rows of plants under spring (a) and summer (b) sowing conditions. Grid square size: 0.5×1.0 cm (width × depth). Maps are based on long-term analysis of the full dataset from 2014 to 2024.

Vertically oriented lateral root branches were recorded in profile zones with an identification probability of 40–85%. The length of these branches ranged from 8 to 24 cm. The intensity of such branching - in both depth and frequency - increased from the periphery toward the axial center of the taproot. The root system branch overlap zone under the studied sowing method was located within 7–9 cm from the axial centers of the plant roots in the row and peaked at depths of 6–12 cm, with a pronounced tendency to decrease beyond 14–16 cm depth, where vertical tropic lateral root interactions dominated.

Thus, the maximum compactness of root branch tropism in oilseed radish under spring sowing was observed within the 2–24 cm depth interval, while the maximum diffuseness was found in the 44–70 cm depth range.

According to the studies by Diggle (1988) and Shukla et al. (2023), based on a total average number of 3,150 root map grid squares per plant within a defined feeding area (as per the dimensional grid in Fig. 4, a), 1,854 squares remained unoccupied.

This indicates that the root system occupied 41.14% of the total grid area. Within the 0–30 cm soil layer, this occupancy increased to 61.07%, which showed a positive correlation with the $R_{m(z)}$ value (Table 3). In the summer sowing variant, roots with an identification probability of 85–100% were predominantly located horizontally at a distance of 4–7 cm from the taproot, and vertically at a depth of 18–24 cm from the soil surface (Fig. 5, b). The maximum horizontal spread of the root system, in the long-term average, was observed at a depth of 8–10 cm and at a distance of 6–8 cm from the taproot. The gradational interval for changes in horizontal spread ranged from 3 to 5 cm. The intensity of vertical branching, measured by the frequency of occurrence in the profile grid, was 22.77% higher than in the spring sowing period. These branches were predominantly located along horizontally spreading roots with an identification probability of 40–70%. However, the average depth-wise length of these vertical branches was 15.92% shorter compared to that in the spring sowing period.

The maximum compactness of root branch tropism in oilseed radish at the specified sowing time was observed in the depth range of 2–14 cm, while maximum diffusivity occurred between 22–40 cm. The zone of overlapping root branches consisted primarily of higher-order roots and, as a result, was 18.45% smaller in terms of occupied area within the root profile grid squares. The degree of root system development across the entire vertical profile was 34.85%, and 72.25% within the 0–30 cm soil layer. This indicates that during summer sowing, the root system of oilseed radish tends to develop a larger proportion of higher-order branches, accompanied by a reduction in the morphological and biomass parameters of these branches, as well as a decrease in overall rooting depth.

In general, based on assessments of the intensity of root development within the soil profile - a significant factor influencing soil parameters in addition to total organic carbon input - oilseed radish exerts a potentially strong effect on properties such as porosity, bulk density, structure, water-holding capacity, and air permeability (Han et al., 2016; dos Santos Nascimento et al., 2021; Hudek et al., 2022; Gentsch et al., 2024). Previous studies on various green manure crops (Gan et al., 2009; Cutforth et al., 2013; Duff et al., 2020; Bublitz et al., 2022; Deus et al., 2022; Kemper, 2024) confirm that oilseed radish can be classified as a valuable green manure species with potentially high impact on the physicochemical and agrophysical dynamics of the soil profile to depths of up to 70 cm. These conclusions are clearly supported by the data in Figs 5 (d, e) & 6

and are further detailed in the main morphological indicators of root system development (Table 4). According to the presented results, root system development in oilseed radish showed a consistent downward trend in both the absolute values of measured parameters and their relative proportions as depth increased. As noted by Bublitz et al. (2022) and Kemper (2024), this development pattern is common among most cruciferous species used as green manure.

Table 4. Morphological characteristics of the oilseed radish root system within the soil profile at the flowering stage (BBCH 64-67), average for the period 2014–2024

Depth, m	PRWD, %			RLD, cm cm ⁻³			RMD, mg cm ⁻³			SRL, m g ⁻¹		
	$\bar{x}$	± SD	C _v	$\bar{x}$	± SD	C _v	$\bar{x}$	± SD	C _v	$\bar{x}$	± SD	C _v
For spring sowing												
0.0–0.1	38.36*	9.11	23.75	3.57*	1.605	44.97	0.2400*	0.0916	38.17	163.88*	56.30	34.35
0.1–0.2	29.85*	8.86	29.68	2.73*	1.248	45.68	0.1151*	0.0415	36.02	246.27*	100.89	40.96
0.2–0.3	14.59*	3.28	22.51	1.95*	0.864	44.32	0.0689*	0.0254	36.86	286.97*	108.17	37.69
0.3–0.4	10.42*	2.47	23.70	1.33*	0.449	33.75	0.0382*	0.0149	38.93	368.55*	118.98	32.28
0.4–0.5	3.92**	2.04	52.04	0.62**	0.269	43.39	0.0142**	0.0083	58.45	453.82**	195.27	43.03
0.5–0.6	2.12**	0.99	46.90	0.36**	0.200	56.12	0.0075**	0.0034	45.33	494.58**	246.38	49.82
0.6–0.7	1.56*	0.45	29.88	0.20*	0.059	29.50	0.0031*	0.0009	29.03	607.37*	180.45	29.71
0.7–0.8	0.83*	0.42	28.55	0.14*	0.037	26.43	0.0019*	0.0005	26.32	701.89*	181.23	25.82
For summer sowing												
0.0–0.1	44.28*	8.34	18.83	2.66*	0.612	23.01	0.170*	0.0364	21.40	190.85*	45.27	23.72
0.1–0.2	32.78*	7.55	23.03	1.96*	0.488	24.90	0.097*	0.0276	28.44	258.44*	70.53	27.29
0.2–0.3	12.98**	4.33	33.34	0.93**	0.261	28.09	0.029*	0.0094	31.79	365.46**	121.26	33.18
0.3–0.4	8.60**	4.02	46.77	0.56**	0.165	29.17	0.015**	0.0069	46.00	414.54**	148.53	35.83
0.4–0.5	1.18*	0.45	38.08	0.19*	0.041	21.58	0.004**	0.0018	49.61	606.93**	216.49	35.67
0.5–0.6	0.63*	0.22	34.92	0.18*	0.041	22.78	0.003*	0.0012	43.30	825.98*	271.42	32.86

Note. PRWD – percentage of root weight distribution; RLD – Root length density; RMD – root mass density; SRL – specific root length, m g⁻¹; Duncan’s for interannual matching in the data set for 2014–2024: * – $p < 0.05$; ** – $p < 0.01$.

For spring and winter rapeseed, as well as different types of mustard and radish root crops, the percentage of root system metric and biomass characteristics found at 50–80 cm depth, compared to the upper 0–20 cm layer, ranged from 1.8% to 10.3% depending on the year (Dharmasri et al., 1993; Gan et al., 2009; Čepulienė et al., 2013; Gao et al., 2017; Duff et al., 2020; Bublitz et al., 2022; Deus et al., 2022; Boter et al., 2023). In winter cruciferous crops, these values were toward the upper end of this range, while spring–summer types typically exhibited values at the lower end.

In oilseed radish, the average values for spring sowing ranged from 1.40–2.58% for biomass and 3.51–5.39% for metric traits. For summer sowing, corresponding values were slightly higher: 2.35–3.28% for biomass and 6.77–8.14% for metric traits. This suggests that oilseed radish maintains a relatively high proportion of root presence at deeper soil layers under both sowing dates when used as green manure. In view of findings by Han et al. (2016) and Hudek et al. (2022), this root distribution has a positive impact on improving agrophysical properties in the deeper active root zone of the soil.

It should also be emphasized that several observed features of the oilseed radish root system are highly beneficial in the context of green manure practices, particularly on soils requiring fertility improvement. It was found that the bulk of the root system (as indicated by the PRWD index) was concentrated within the top 30 cm of the soil profile

for spring sowing, and within 20–30 cm for summer sowing. This distribution corresponded with the primary formation zone of the taproot (Figs 5, d–e, Figs 6, a–b).

According to the RLD index values and based on several studies using the Monolith Method (Talgre, 2013; Wahlström et al., 2015; Bublitz et al., 2022; Kemper, 2024), oilseed radish demonstrates a high level of spatial development in both horizontal and vertical directions within the soil profile. This is further supported by the R_{vsz} index (Table 4) and the data presented in Figs 3 & 4 (I, e–f). On average, oilseed radish ranks just below winter rapeseed in terms of dynamic values recorded across the 0–60 cm profile depth, with 18–25% lower values for spring sowing and 27–37% lower for summer sowing.

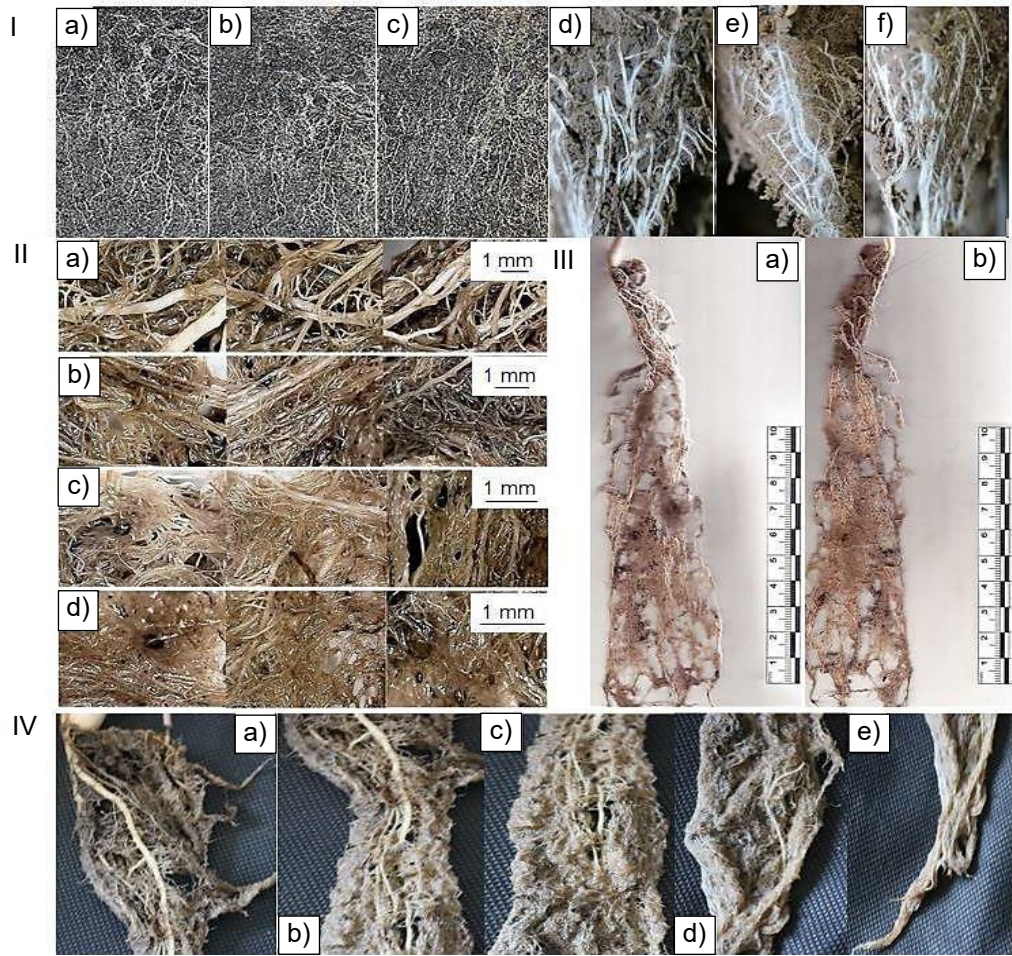


Figure 6. Spatial branching features of the oilseed radish root system at different sowing dates. I: Vertical branching of the root system at the spring sowing date (a – 2014, b – 2019, c – 2022), and magnified views using a USB microscope (x200): d – 2014, e – 2019, f – 2022. II: Root system branches of 1st (a), 2nd (b), 3rd (c), and 4th (d) order after sequential washing (first and second columns – spring sowing; third column – summer sowing), 2024. III: Root systems of two plants washed from the 0–20 cm soil layer from two adjacent rows at the summer sowing date, 2023. IV: Sequential segmental parts of the oilseed radish root system washed from the soil profile at 10 cm intervals, from top (a) to bottom (f), under spring sowing, 2024.

The crop also exhibited intensive differentiation in the weight saturation of the soil profile, as indicated by the RMD index, which showed vertical variability with a coefficient of variation (C_v) of 62.87%. This vertical stratification by root biomass created a distinct zonation across the corresponding root branches, especially in terms of length and transverse diameter. This is clearly illustrated in Fig. 6 (position II), particularly in the summer sowing variant (Fig. 4, II, third column of images), and is further confirmed by SRL values. These values dropped to 600–900 m g^{-1} at limiting profile depths in spring and to 700–1,100 m g^{-1} in summer sowing - differences that were not statistically significant when oilseed radish was used as a sole-component cover crop (Kemper, 2024). Simultaneously, the formation of vertical root branches was observed, originating from the horizontal tier of lateral roots at a depth of 15–25 cm, with intensive penetration reaching 35–60 cm, particularly in the summer green manure variant (Fig. 5, a–b). As a result, when grown as a green manure on Grey Forest Soils, oilseed radish develops a vertical interaction gradient with the soil profile in the form of a ‘channel’ located along the taproot axis.

According to Yang et al. (2017), the diameter of this root channel can be equated to the average diameter of the taproot (r_{aver}), which was 5.67 mm for spring and 5.13 mm for summer sowing (Table 4), with an average vertical channel length of 17–25 cm and 14–18 cm, respectively. Following the recommendations of Kolb et al. (2012) and Han et al. (2016), an active zone should be considered around this channel, with a radius of at least 25% of the maximum horizontal length of lateral branches. This equates to 2–3 cm in spring sowing and 1.0–1.7 cm in summer sowing, based on the lateral branch spread observed in root profile wall maps (Fig. 5, a–b). The full vertical extent of this channel zone can reach 40–60 cm in spring sowing and 30–40 cm in summer sowing under green manure conditions.

An intensive diffuse zone, consisting of root branches with a pronounced reduction in diameter (morphometric tapering), forms around the central ‘channel’ zone (as shown in Fig. 6, sections II and IV). According to the conclusions of Hatano et al. (1988), Han et al. (2015), and Hudek et al. (2022), in the case of oilseed radish, this configuration is expected to actively contribute to the restoration of microporous soil structure - particularly under spring sowing conditions for green manure application. These findings support the presence of the so-called ‘root drainage’ effect in oilseed radish, previously observed in other green manure crops, as reported by Rosenfeld & Rayns (2010) and dos Santos Nascimento et al. (2021).

The spatial morphological and biomass distribution patterns of the oilseed radish root system described above were further confirmed through the analysis of root fresh mass accumulation during the dynamic growth phase of the plants. The growth models describing the formation of root fresh biomass followed a power function pattern in both spring (Fig. 7) and summer sowing variants (Fig. 8), demonstrating several clear trends.

First, the exponential and stepwise nature of development indicates a gradual increase in the growth rate of the root system’s fresh mass, with uneven accumulation during the course of phenological development. Under spring sowing conditions, the average root biomass accumulation rate increased from 10.22 $\text{g m}^{-2} \text{ day}^{-1}$ (interannual $C_v = 40.16\%$) during the 10–20 days after full germination, to 22.78 $\text{g m}^{-2} \text{ day}^{-1}$ ($C_v = 45.75\%$) during the 40–50 day period, with the peak occurring in some years between 35–45 days.

For summer sowing, root biomass accumulation increased from 5.47 g m⁻² day⁻¹ ($C_v = 41.90\%$) during the 10–20 day period to 12.85 g m⁻² day⁻¹ ($C_v = 42.10\%$) in the 40–50 day window, with the peak shifted in some years to 25–40 days after full germination. As a result, the total root biomass accumulation under spring versus summer green manure sowing averaged a 1.5:1 ratio (Figs 5–6, a). Under moisture-deficient years, this ratio increased to 3:1, while in years with excessive moisture, it was 1.8:1 (Figs 7–8, b–c).

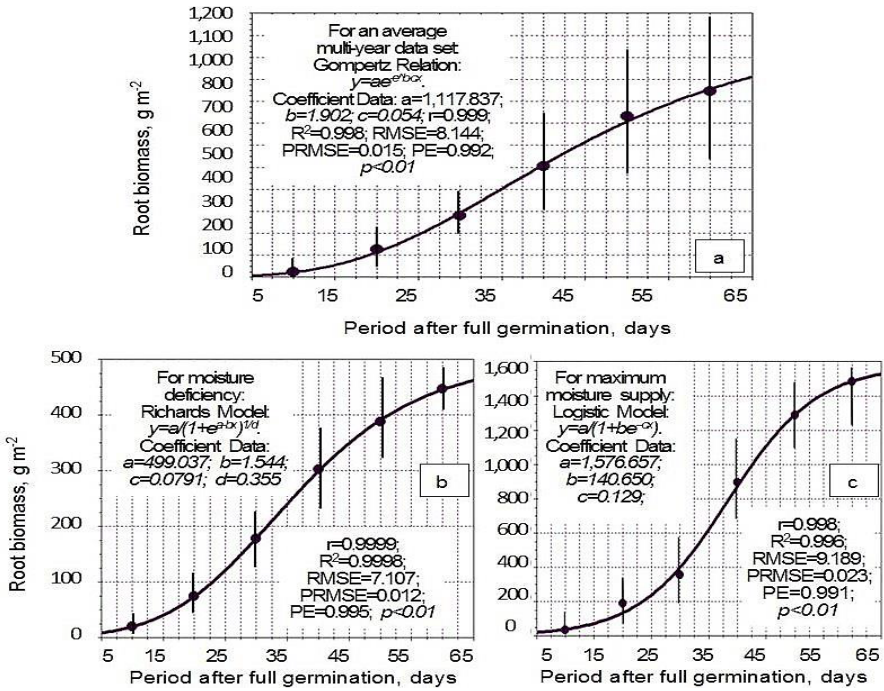


Figure 7. Functional patterns of oilseed radish root fresh weight formation under spring sowing: (a) long-term average data; (b) years with moisture deficit; (c) years with excessive moisture. Vertical lines represent standard deviation (SD). Data averaged for the period 2014–2024.

It was also found that the variability of root biomass measurements across the sampling dates (based on standard deviation) was, on average, 43.5% higher in the summer sowing period compared to spring sowing. Additionally, notable differences were observed in the mathematical models describing root biomass accumulation. In the case of spring sowing, the growth was best described by exponential models such as Gompertz, Richards, and Logistic functions, which, as noted by Tjørve & Tjørve (2017), are characterized by a gradual decline in growth rate around 55–60 days after full germination. In contrast, during summer sowing, root biomass accumulation followed classical power functions, with sustained dynamic growth beyond the 55–60 day threshold. Taking into account the previously determined peak aboveground biomass accumulation in oilseed radish under green manure conditions - 42.38 g m⁻² day⁻¹ for spring sowing and 32.00 g m⁻² day⁻¹ for summer sowing during the critical 40–50 day period after germination (Tsytisura, 2024b) - the average value of the CRP_{DM} (Coefficient of Root Productivity in DM) over the full study period was 1.86 for spring

and 2.49 for summer sowing. According to this indicator, oilseed radish belongs to the same productive niche as other cruciferous green manure crops such as mustard and rapeseed (Dupuy et al., 2010; Feller et al., 2015; Kupcsik et al., 2021; Kemper, 2024; Tsytsiura, 2024a). This confirms the existence of an ecologically adaptive mechanism characterized by the dominance of aboveground biomass growth rates over root biomass accumulation.

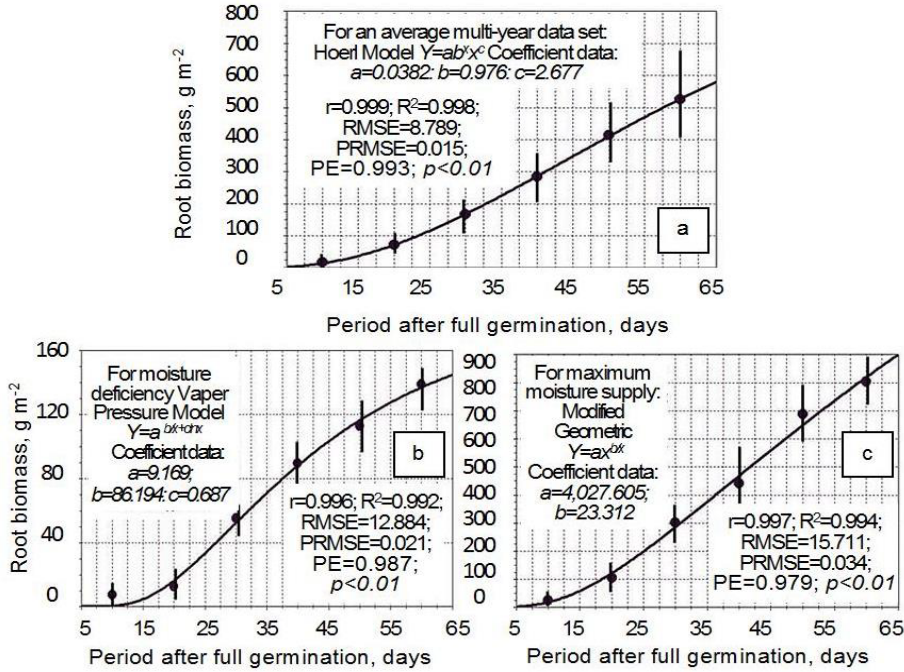


Figure 8. Functional patterns of oilseed radish root fresh weight formation under summer sowing: (a) long-term average data; (b) years with moisture deficit; (c) years with excessive moisture. Vertical lines indicate standard deviation (SD). Data averaged for the period 2014–2024.

Determinant Factors of Root Sidereal Bioproductivity. This finding is supported by the results of correlation analysis (Table 5) and is particularly valuable in the context of using oilseed radish as a cover crop for intermediate sowing periods (summer, autumn) followed by green manuring. The importance of this mechanism in selecting appropriate green manure species has been emphasized in several studies (Duff et al., 2020; Dzvene et al., 2023; Kemper, 2024; Zhang et al., 2024a).

At the same time, the high interannual variability of the morphological and biomass characteristics of the oilseed radish root system - ranging from 18% to 60% (Table 5), with maximum variation observed in the 40–60 cm soil horizon for spring sowing and in the 20–40 cm horizon for summer sowing - confirms the significant influence of environmental and edaphic factors on the morphological and biomass development of the root system. This conclusion is further supported by correlation analysis of the main parametric indicators of oilseed radish root bioproductivity, which takes into account soil properties and conditions, as well as hydrothermal parameters of the growing season,

using an integrated dataset for the 2014–2024 period (Table 2). According to the coefficient of determination of correlation strength (d_{xy}), it was established that the total plant bioproductivity, represented by the share of root biomass yield (RBY), under spring sowing conditions for green manure, was directly determined by several key factors. Specifically, RBY was explained by: 77.44% by the total precipitation during the growing season prior to green manuring, 65.61% by soil moisture reserves (WRS), 81.00% by root length density (RLD), 96.04% by root mass density (RMD), 86.49% by specific root length (SRL), 94.01% by the average diameter of the core part of the root (d_{aver}), 68.89% by root system volume (V_{root}), 59.29% by the volume of the root spreading zone (R_{vsz}), 73.96% by the fractal dimension of the root system.

Table 5. Pearson's correlation coefficients for the relationship between oilseed radish root morphological and bioproductivity parameters and the hydrothermal conditions of the growing season and soil properties (combined dataset by sowing dates-replicates-years, 2014–2024; N = 88)

	2	3	4	5	6	7	8	9	10	11	12	13	14
Spring sowing													
1	-0.14	-0.94	0.97	0.88	-0.84	0.89	0.82	0.21	0.92	-0.51	0.73	0.51	0.85
2		-0.01	-0.12	-0.39	0.37	-0.27	-0.34	0.37	-0.25	0.55	-0.34	-0.43	-0.46
3			-0.87	-0.76	0.86	-0.77	-0.73	0.27	-0.80	0.40	-0.60	-0.51	-0.77
4				0.81	-0.83	0.81	0.77	-0.36	0.83	-0.46	0.59	0.57	0.81
5					-0.71	0.90	0.98	0.93	0.97	-0.41	0.83	0.77	0.86
6						-0.78	-0.55	-0.70	-0.76	0.30	-0.59	-0.34	-0.76
7							0.82	0.55	0.97	-0.72	0.86	0.71	0.93
8								0.02	0.90	-0.78	0.74	0.63	0.84
9									0.43	0.02	0.41	0.65	0.40
10										-0.69	0.90	0.43	0.91
11											-0.55	-0.39	-0.81
12												0.18	0.73
13													0.63
Summer sowing													
1	-0.07	-0.72	0.68	0.64	-0.73	0.58	0.67	0.12	0.53	-0.31	0.77	0.42	0.71
2		0.68	-0.54	-0.44	0.44	-0.51	-0.45	0.49	-0.21	0.17	-0.41	-0.48	-0.34
3			-0.75	-0.61	0.74	-0.61	-0.52	0.41	-0.34	0.40	-0.53	-0.59	-0.61
4				0.96	-0.69	0.60	0.52	-0.24	0.79	-0.29	0.83	0.45	0.96
5					-0.73	0.88	0.92	0.90	0.91	-0.22	0.87	0.63	0.82
6						-0.49	-0.22	0.04	-0.58	0.36	-0.65	-0.02	-0.72
7							0.52	0.04	0.18	-0.44	0.39	0.58	0.62
8								-0.48	0.34	0.23	0.34	0.52	0.56
9									-0.09	-0.31	0.22	0.51	0.52
10										0.03	0.83	-0.22	0.89
11											-0.12	0.01	-0.52
12												0.19	0.90
13													0.51

Level of significance for $r = |0.209| - |0.264|$ $p < 0.05$; $r = |0.265| - |0.328|$ $p < 0.01$; $r = > |0.328|$ $p < 0.001$.
1 = Precipitation (Pr, mm); 2 = Average daily temperature (t_{av} , °C); 3 = Soil hardness (SH, kg cm⁻²);
4 = Water reserves in the soil (WRS, mm); 5 = Root biomass yield (RBY, t ha⁻¹); 6 = Maximum root depth (z_r , cm); 7 = Root length density (RLD, cm cm⁻³); 8 = Root mass density (RMD, mg cm⁻³); 9 = Specific root length (SRL, m g⁻¹); 10 = Average diameter of the core part of the root (d_{aver} , mm); 11 = Taperiness;
12 = Volume of the root system (V_{root} , cm³); 13 = Volume of root spreading zone (R_{vsz} , x10³ cm³);
14 = Fractal dimension of the root system (FD).

Conversely, the reverse (negative) influence on the RBY index was associated with: 15.21% by average daily temperature (t_{av}), 75.69% by soil hardness (SH), 50.41% by maximum root depth (z_r), and 16.81% by the Taperiness Index.

Under summer sowing conditions, although the nature of the relationships between RBY and the explanatory variables remained consistent, the overall strength of these relationships - reflected in the determination coefficients - was on average 11.7% lower than in the spring sowing scenario. This indicates that the general decline in hydrothermal optimality due to increasing aridity during the summer-autumn growing season has a mitigating (depressive) effect on oilseed radish bioproductivity. These results are in positive agreement with the findings reported by Fletcher et al. (2015), Jabbari et al. (2016), Dayoub et al. (2022), and Shoaib et al. (2022).

For the main indicators of oilseed radish root system development - namely, root length density (RLD) and root mass density (RMD) - the determination coefficients for direct dependence on precipitation ranged from 67.24% to 79.21% for spring sowing and from 33.64% to 44.89% for summer sowing. In contrast, the relationship with average daily temperature was inverse, with determination values of 7.29–11.56% for spring and 20.25–26.01% for summer sowing. At the same time, the strength of the correlation (d_{xy}) with precipitation was weak for both sowing dates (1.44–4.41%), while the relationship with average daily temperature was of medium strength (13.69–24.01%). Based on this, and considering the nature of the SRL (specific root length) calculation, the root mass density (RMD) indicator exhibits a stronger hydrothermal response than the root length density (RLD) indicator. This suggests that oilseed radish maintains stable rates of linear and fractal root system development under varying hydrothermal conditions, with more substantial reductions or increases occurring in the mass of lateral root branches depending on the behavior of individual SRL components.

Such a trend highlights the adaptive capacity of oilseed radish to intensify root branching despite a reduction in total root mass, particularly under increased precipitation or elevated average daily temperatures. This is further confirmed by the degree of determination of RLD, RMD, and SRL in relation to the fractal dimension (FD) of the root system, which ranged from 16.0% to 86.49% in spring and 27.04% to 38.44% in summer sowing. These findings are consistent with the conclusions of Kashyap et al. (2022), who described the adaptive potential of wild cruciferous species, and Jabbari et al. (2016), who studied root development response to drought in rapeseed. Thus, the existence of an adaptive mechanism in oilseed radish has been confirmed - allowing for the maintenance of root system development rates even under increasing environmental repressiveness during the growing season.

It was also found that the intensity of root system development in oilseed radish (as indicated by RLD and RMD) is significantly influenced by soil hardness (SH) and soil water reserves (WRS). An inverse relationship with soil hardness was observed, with determination coefficients (d_{xy}) ranging from 53.29% to 59.29% for spring sowing and from 27.04% to 37.21% for summer sowing. For soil water reserves, the relationship was direct, with d_{xy} values of 52.29% to 65.61% in spring and 27.04% to 36.00% in summer.

In the case of specific root length (SRL), increased soil density was associated with an increase in SRL, while higher soil moisture reserves led to a decrease. The relatively moderate levels of these dependencies indicate a heterogeneous influence of soil moisture and density on the formation of RLD and RMD parameters when considered independently. This further confirms the adaptive nature of root system development

dynamics in oilseed radish in response to combined changes in hydrothermal vegetation conditions and the physical and hydrological characteristics of the soil regime.

This is further supported by the strong relationships between these soil parameters and such indicators as root system volume (V_{root}) and root spreading zone volume (R_{vsz}), with d_{xy} values ranging from 26.01% to 36.00% in spring and 28.09% to 68.89% in summer sowing, all showing the same directional trend. Taking into account the findings of Fan et al. (2016), Bucksch et al. (2017), Boter et al. (2023), and Colombi et al. (2024), the observed discrepancy between the factor-based determination of RLD and RMD highlights a functional elasticity and plasticity in root system formation. This plasticity occurs in response to both hydrothermal variability and changes in soil water and mechanical properties, including those driven by weather conditions.

According to the ratio of the sum of the absolute values of correlation coefficients (as per Snedecor & Cochran, 1991), which was 1.23 for spring and 1.11 for summer sowing, it can be inferred that the morphometric traits of the root system are less adaptive than its biomass-related traits in response to environmental and edaphic factors. As a result, under increasingly stressful environmental conditions - primarily related to moisture availability and soil compaction - a more pronounced reduction in the linear dimensions and spatial distribution of the root system in the soil profile can be expected compared to reductions in root biomass. This conclusion is supported by comparative data on the distribution of roots in the soil profile under spring (Fig. 6, a) and summer (Fig. 6, b) sowing conditions.

Regarding temperature influence, it is important to consider that air temperature and soil temperature often differ significantly, with soil functioning as a buffering medium that mitigates extreme temperature fluctuations, thereby reducing the negative impact of thermal stress on plant root system development (Kaspar & Bland, 1992; Calleja-Cabrera et al., 2020; Gavelienė et al., 2022; Yamori et al., 2022; González-García et al., 2023). Under this premise, the relationship between average daily temperature (t_{av}) and root biomass yield (RBY) in oilseed radish showed a consistent inverse correlation, with a moderate strength of association as indicated by determination coefficients (d_{xy}) ranging from 15.21% to 27.36% – similar to trends observed in other root system parameters. This suggests a higher temperature tolerance in oilseed radish compared to white mustard (Amgain & Sharma, 2021), spring rapeseed (Čepulienė et al., 2013), and even winter rapeseed (Jabbari et al., 2016).

At the same time, the effect of hydrothermal conditions on the maximum root depth (z_r) demonstrated that the oilseed radish root system exhibits adaptive deepening under conditions of soil moisture deficit - itself driven by reduced precipitation and increased air temperatures. This is reflected in the direct relationship between z_r and average daily temperature ($d_{xy} = 13.69\%$ for spring and 19.36% for summer sowing), and the inverse relationship with total precipitation ($d_{xy} = 53.29\%$ for spring and 70.56% for summer sowing). Based on these results, the root system of oilseed radish shows clear signs of moisture tropism, a phenomenon previously reported by Koch et al. (2018) and Fonseca de Lima (2021). Specifically, the plant forms a more compact root system under sufficient soil moisture and moderate air temperatures, and a more diffuse, deeper-penetrating system under conditions of moisture stress and rising temperatures. This functional plasticity allows oilseed radish to perform effectively as a green manure crop under unstable moisture conditions, particularly in intermediate (summer-autumn)

sowing systems - in line with the hydrothermal adaptability criteria described by Calleja-Cabrera et al. (2020).

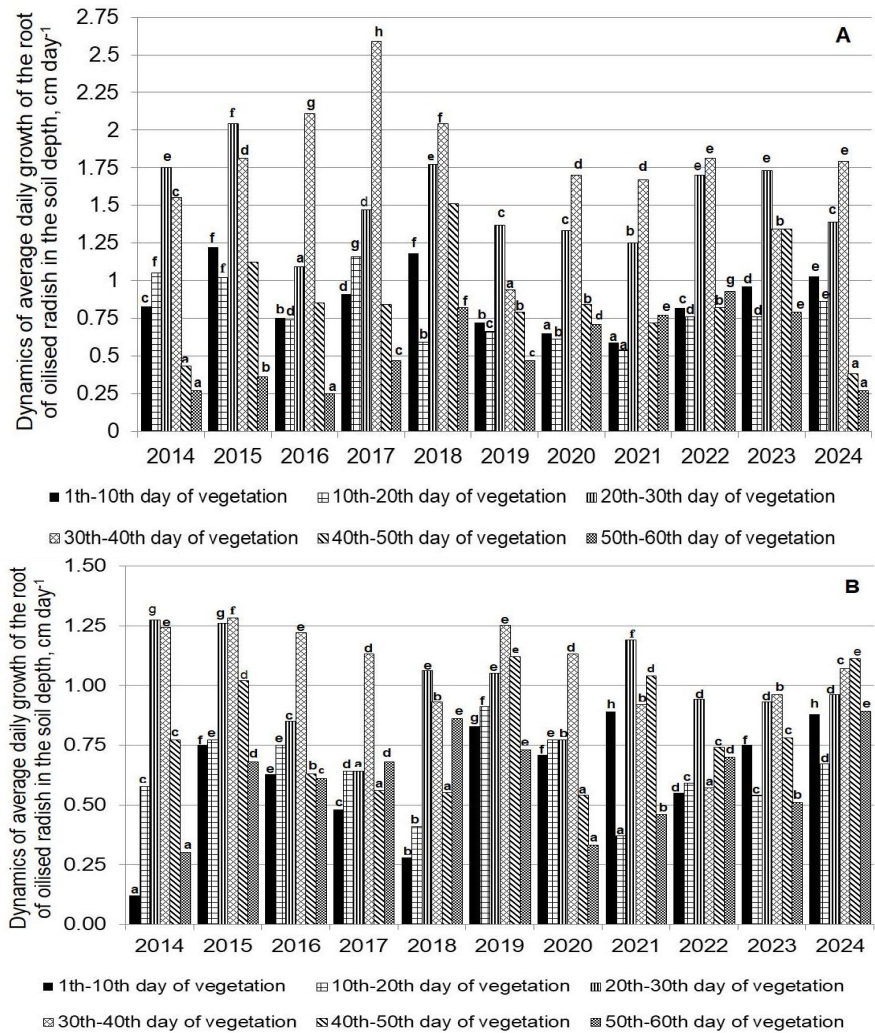


Figure 9. Dynamics of average daily root system growth in depth for oilseed radish over ten 10-day intervals during a 60-day vegetation period (A – spring sowing period; B – summer sowing period), 2014–2024.

Note: Different letters indicate values that differ significantly from one another ($p < 0.05$).

The established pattern of maximum root depth (z_r) formation in oilseed radish was further confirmed and clarified through an assessment of the dynamics of average daily root system elongation over ten 10-day accounting intervals during a 60-day vegetation period (Fig. 9). The maximum average daily root growth in depth was recorded during the 30–40 day interval prior to green manure incorporation for both the spring sowing variant (Fig. 9, A) and the summer sowing variant. For spring sowing, the peak growth rate was 1.80 cm day⁻¹, while the overall average across all periods of observation was

1.07 cm day⁻¹. For summer sowing, these figures were 1.06 cm day⁻¹ and 0.79 cm day⁻¹, respectively. The lowest growth rates for both sowing periods were recorded during the 1–20 day and 50–60 day intervals, ranging from 0.46 to 0.61 cm day⁻¹.

Based on these indicators, oilseed radish demonstrates a high-intensity rooting process, which, when compared with long-term research and species-level generalizations (Dharmasri et al., 1993; Morrison, 1993; Laghari et al., 2014; White, 2015; The Biology of *Brassica napus* L. (2017); Wu et al., 2020; The Biology of *Sinapis alba* L. (2022); Kemper et al., 2024; Zhang et al., 2024a), corresponds to the upper limit of root growth rates typical for cruciferous crops with a spring development cycle. It is also important to note that the difference in average root system growth in depth between the two sowing periods was significantly influenced by hydrothermal conditions across the study years. In particular, for spring sowing, the most moisture-deficient years were 2017, 2015, and 2018 (Table 2). In those years, the average daily root elongation rates were 1.32 cm day⁻¹, 1.26 cm day⁻¹, and 1.19 cm day⁻¹, respectively, all exceeding the general average of 1.07 cm day⁻¹ for the spring sowing period (Fig. 9, A). By contrast, in years with optimal or excessive moisture (e.g., 2014 and 2019), the root growth rate was 15.8% to 43.7% lower. A similar trend was observed under summer sowing conditions, confirming the inverse relationship between moisture availability and depth-wise root elongation in oilseed radish.

During the studied period, the years 2015, 2019, and 2021 were identified as moisture-deficient based on the average daily root growth rates for summer sowing, which reached 0.96 cm day⁻¹, 0.98 cm day⁻¹, and 0.81 cm day⁻¹, respectively (Fig. 9, B), compared to the overall average of 0.79 cm day⁻¹. In contrast, during years with optimal or excessive moisture supply (e.g., 2017 and 2022), the same indicator was 10.6% to 31.0% lower. This pattern can be attributed to the adaptive response of the plant root system to soil moisture stress, for which the root architecture functions as the primary compensatory mechanism.

Numerous studies (Schenk & Jackson, 2002; Guswa et al., 2012; Fan et al., 2017; Wu et al., 2018; Maan et al., 2023; Tomobe et al., 2023; Wankmüller et al., 2024) have shown that the spatial development of root systems is closely tied to the level of soil water reserves and to the dynamics of moisture retention and release in accordance with the agrophysical and hydrological properties of specific soil types (De Baets et al., 2008; Thomas et al., 2020). Furthermore, it has been well documented (Fan et al., 2017; Ni et al., 2019; Guo et al., 2023; Maan et al., 2023) that root elongation ceases when soil moisture declines below a critical osmotic threshold. Under conditions of increasing average daily temperatures combined with prolonged precipitation deficits, soil moisture is depleted more rapidly. According to several studies (Allen et al., 1998; Feddes & Raats, 2004; Gerke & Kuchenbuch, 2007; Leenaars et al., 2015; Kou et al., 2022; Guo et al., 2024), this leads to the formation of a gradient boundary between moist and critically dehydrated soil layers, which gradually deepens as drought stress persists - especially under elevated air temperatures. In perennial species and in annuals with drought-adaptive mechanisms, this stress response often results in the development of thinner, more finely branched root structures (Berntson, 1997; Dong et al., 2018), thereby increasing the absorptive surface area of the root system. This morphological shift acts as a compensatory mechanism for diminished moisture availability and has

been widely observed in perennials (Faye et al., 2019; Zhang et al., 2019), cereals (Wasson et al., 2012; Zhang et al., 2020; Li et al., 2022), and various herbaceous species (Liu et al., 2020; Parkash et al., 2021; Guo et al., 2024). It is also considered a key trait in breeding programs for drought tolerance (Wasson et al., 2012; Dayoub et al., 2022; Guo et al., 2024), including in cruciferous crops such as rapeseed (Jabbari et al., 2016).

Given the higher values of maximum root depth (z_r) (Table 3) and the increased rate of root system elongation in moisture-deficient years (Fig. 9, A, 9, B), oilseed radish can be classified as a crop with this adaptive trait. This supports its high potential for use as a green manure crop, especially under intermediate summer sowing conditions with variable moisture availability. One important remark should be made regarding specific root length (SRL): under summer sowing, SRL values in the range of 700–1,100 m g⁻¹ (Table 4) indicate a pronounced stress response in the deepest soil horizons, where the fine root branches may have reduced water transport capacity - a pattern consistent with findings by Schenk & Jackson (2002), Feddes & Raats (2004), and Ni et al. (2019). This limitation is indirectly supported by the observed distribution patterns of the root system in the soil profile (Fig. 5, a, b) and further confirmed by the observations of Kemper (2024). Taking into account the findings of McMichael & Quisenberry (1993), Bengough (2003), Cutforth et al. (2013), Jabbari et al. (2016), Cavalieri-Polizeli et al. (2022), Deus et al. (2022), Lynch et al. (2022), Duan et al. (2023), Carvalho et al. (2024), and Colombi et al. (2024), the established patterns and correlations clearly support the effectiveness of the adaptive strategies employed by oilseed radish in root system formation to ensure its long-term viability as a green manure crop. The summarized results above are logically integrated into a system of regression equations that incorporate both hydrothermal conditions during the vegetation period and key soil properties, as presented in Table 6.

In particular, it was statistically confirmed (based on the Chaddock scale, 1925) that precipitation during the growing season prior to green manure incorporation plays a direct formative role, while average daily air temperature has an inverse formative role in shaping key root system parameters (RBY, RLD, RMD, and FD). This relationship was reflected in a mean multiple regression coefficient (R) of 0.783, with an adjusted R^2 of 0.667 ($p < 0.001$), indicating a moderate but statistically significant relationship. Likewise, the direct effect of soil water reserves (WRS) and the inverse effect of soil hardness (SH) were statistically validated for the same indicators, with a mean regression coefficient of 0.790 and an adjusted R^2 of 0.670 ($p < 0.001$). The most stable model was identified in the three-factor combination of precipitation (P), soil hardness (SH), and water reserves in the soil (WRS), which collectively influenced the main morpho- and bioproductivity parameters of the root system. This model exhibited a multiple regression coefficient of 0.890, with an adjusted R^2 of 0.746 ($p < 0.001$) – indicating a strong relationship.

It is worth emphasizing that the polynomial (degree-based) character of the second- and fourth-order models supports the conclusion that these factors function in a complementary manner, governing the bioproductivity potential of oilseed radish root system development under green manure use. This also points to the existence of adaptive regulatory mechanisms that enable plants to buffer or compensate for adverse environmental conditions, thereby facilitating the realization of their genotypic potential.

Table 6. Regression relationships describing the intensity of oilseed radish root system development as a function of hydrothermal vegetation conditions and selected soil characteristics (average data for 2014–2024)

Qualitative indicator	Equation of dependence	Parameters of the equation			Statistical evaluation of components				
		x	y	z	Multiple R	Multiple $R^2_{(adj.)}$	F	df1, df2	p
SH	$7.37-0.04x+1.67y$	Precipitation (Pr, mm)	Average daily temperature (T_{av} , °C)		0.892	0.774	37.039	2.190	< 0.0001
WRS	$156.60+0.32x-8.35y$				0.891	0.773	36.785	2.190	< 0.0001
RBV	$17.09+0.027x-1.09y$				0.854	0.751	25.891	2.190	< 0.001
RSPD	$132.71-0.087x-3.55y$				0.700	0.436	9.119	2.190	< 0.05
RLD	$2.82+0.005x-0.164y$				0.735	0.622	11.163	2.190	< 0.01
RMD	$0.132+0.00018x-0.0069y$				0.682	0.519	8.269	2.190	< 0.05
SRL	$143.23+0.286x+8.492y$				0.603	0.545	4.892	2.190	< 0.05
V_{root}	$35.14+0.067x-1.037y$				0.730	0.483	10.803	2.190	< 0.01
R_{vsz}	$249.96+0.33x-16.96y$				0.540	0.320	3.926	2.190	< 0.05
FD	$1.06+0.00091x-0.039y$				0.861	0.763	27.114	2.190	< 0.001
RBV	$-1.99-0.0084x+0.086y$				0.859	0.682	26.950	2.190	< 0.01
RSPD	$108.21-1.153x-0.236y$				0.556	0.309	3.687	2.190	< 0.05
RLD	$0.577-0.017x+0.012y$				0.727	0.618	11.623	2.190	< 0.01
RMD	$0.005-0.00011x+0.00058y$				0.690	0.589	8.612	2.190	< 0.05
SRL	$260.54+1.516x+0.474y$				0.597	0.318	3.125	2.190	< 0.05
V_{root}	$16.34+0.043x+0.17y$	Soil hardness (SH, kg cm ⁻²)	Water reserves in the soil (WRS, mm)		0.706	0.550	10.436	2.190	< 0.01
R_{vsz}	$83.64-3.173x+0.566y$				0.582	0.347	6.477	2.190	< 0.05
FD	$0.381-0.00069x+0.003y$				0.885	0.790	34.107	2.190	< 0.0001
Qualitative indicator	Equation of dependence	x	y	z	Multiple R	Multiple $R^2_{(adj.)}$	F	df1, df2	p
RBV	$-12.41-0.022x+1.504y-0.103z+0.00001x^2-0.027y^2+0.0011z^2$	Precipitation (Pr, mm)	Soil hardness (SH, kg cm ⁻²)	Water reserves in the soil (WRS, mm)	0.905	0.767	12.461	6.150	< 0.0001
RSPD	$293.71-0.40x-11.91y+0.009z+0.0004x^2+0.20y^2+0.0001z^2$				0.807	0.609	8.196	6.150	< 0.05
RLD	$-3.47+0.005x+0.228y-0.014z-0.0001x^4-0.0001y^4+0.0001z^4$				0.930	0.811	15.989	6.150	< 0.0001
RMD	$-0.101+0.00012x+0.0065y-0.0001z-0.0001x^4-0.0001y^4-0.0001z^4$				0.828	0.684	8.971	6.150	< 0.01
V_{root}	$-5.01+0.00043+1.528y+0.02z+0.0001x^4-0.0002y^4+0.0001z^4$				0.845	0.648	9.128	6.150	< 0.01
FD	$0.289-0.00049x+0.0074y+0.0031z+0.000001x^4-0.000001y^4+0.000001z^4$				0.895	0.723	10.099	6.150	< 0.001
d_{aver}	$-5.07+0.005x+0.378y+0.0021z-0.000001x^4-0.000001y^4+0.000001z^4$				0.921	0.796	14.621	6.150	< 0.0001

These findings align with the conclusions of Gupta & Shrestha (2023) and Zhang et al. (2023a, 2025) concerning the adaptive potential of plant organisms in response to environmental variability.

The generalizations presented here are further supported by the environmental elasticity assessment of key parameters, as shown in Table 7. According to the coefficient of absolute elasticity (EA), the environmental factor of precipitation had a direct influence on the formation of root system productivity indicators in oilseed radish. When comparing spring and summer green manure sowing dates, the gradient of change in precipitation responsiveness was twice as high under summer sowing - 0.03 t ha⁻¹ mm⁻¹ versus 0.015 t ha⁻¹ mm⁻¹ for spring sowing. In contrast, average daily air temperature showed a pronounced inverse effect on the adaptive response of oilseed radish, with only minor differences between spring and summer sowing variants.

The average gradient of absolute elasticity under temperature influence indicated a decrease in fresh root biomass by 11.32 t ha⁻¹ °C⁻¹ and by 2.32 t ha⁻¹ °C⁻¹ in dry matter equivalent. Based on the ratio of these values, the dry matter content in root biomass was estimated at 20.46%, with a direct tendency to increase as average daily temperature rose. Taking into account the findings of several studies (Mohammadi et al., 2010; Ali et al., 2017), precipitation can be considered the decisive factor in the formation of oilseed radish root biomass, as indicated by the elasticity gradient expressed in biomass units over the evaluation period.

Table 7. Coefficients of phenotypic stability and elasticity in the formation of oilseed radish bioproductivity at the flowering stage (BBCH 64–67) across different sowing dates, 2014–2024

Indicators of bioproductivity		E _A	E _I	E _{II}
By the factor of precipitation (P, mm)				
Root biomass yield (RBY), t ha ⁻¹	SprS	0.050	0.125	1.484
	SumS	0.024	0.059	1.125
Root biomass yield in dry matter (RBY _{DM}), t ha ⁻¹	SprS	0.010	0.025	1.397
	SumS	0.005	0.013	1.060
By the factor of average daily temperature (t _{aver} , °C)				
Root biomass yield (RBY), t ha ⁻¹	SprS	-11.576	-1.692	-20.021
	SumS	-11.067	-1.840	-34.995
Root biomass yield in dry matter (RBY _{DM}), t ha ⁻¹	SprS	-2.283	-0.334	-18.851
	SumS	-2.350	-0.391	-32.961

*SprS – Spring sowing; SumS – Summer sowing.

Therefore, oilseed radish demonstrated a higher level of adaptability to insufficient moisture supply than to rapid increases in air temperature. This trait is positively correlated with the general characteristics of the root systems of cruciferous crops - particularly the compensatory response involving deeper rooting and increased branching under conditions of atmospheric and soil moisture deficit, as previously noted in the studies of Dharmasri et al. (1993), Gan et al. (2009), Jung et al. (2019), and Kupcsik et al. (2021).

These conclusions are further supported by the values of the relative elasticity coefficients of type I (EI) and type II (EII), which showed a significant increase compared to the absolute elasticity coefficient (EA), especially in response to

precipitation. For type I elasticity, a reduction in environmental suppression of root development and biomass formation was observed under scenarios of increased precipitation accompanied by either rising or stable average daily temperatures. In contrast, when these environmental factors operated in opposition, they caused a marked decline in root system growth. Moreover, the significantly higher values of EII compared to EI point to the existence of flexible ecological mechanisms in the formation of the oilseed radish root system. This flexibility is evident in the fact that intensive environmental variation was met with a relatively low degree of variation in the resultant bioproductivity traits.

According to the findings of Jabbari et al. (2016), Konuntakiet (2020), and Colombi et al. (2024), the identified elasticity profile of oilseed radish root productivity indicators enables its classification among cruciferous cover crops with broad adaptive potential, particularly under suppressive and environmentally stressful hydrothermal conditions. The pivotal role of hydrothermal factors was further substantiated by the results of multiple regression and correlation analyses, which incorporated the De Martonne Aridity Index (I_{DM}) and the Vysotsky-Ivanov Humidification Coefficient (K_h), along with correlation analysis applied to both basic and derived indicators of oilseed radish root system bioproductivity (Table 8). The analysis confirmed the high sensitivity of root bioproductivity formation to climatic parameters, with: a positive formative effect of precipitation, with determination coefficients (d_{xy}) ranging from 47.19% to 50.20%, an inverse effect of average daily temperature, with $d_{xy} = 21.44$ –25.70%, a strong positive relationship with K_h , at $d_{xy} = 57.30$ –65.45%, and a similarly high correlation with IDM, at $d_{xy} = 47.75$ –51.12%.

All these relationships were integrated into a single multiple regression model, with high values of R and adjusted R^2 , demonstrating strong statistical associations as defined by the Chaddock scale (1925). Furthermore, the observed dry matter content in root biomass is consistent with findings by Liu (2009), Hudek et al. (2022), and Kemper (2024), which indicate that the aridization of the growing season leads to increased dry matter content in both aboveground and root biomass of green manure crops. This is attributed to increased salinity in physiologically active tissues and the intensification of biochemical transformations under drought-related stress.

The dry matter content in the root biomass of oilseed radish is consistent with the findings of Liu (2009), Hudek et al. (2022), and Kemper (2024), who reported that seasonal aridization increases dry matter accumulation in both aboveground and root components of green manure crops. This is attributed to changes in the salinity of physiologically active tissues and the intensification of biochemical transformation processes under drought stress. Regarding the root system productivity coefficient in both fresh (CRPRM) and dry matter (CRPDM), the observed results are in line with the studies by Thornley (1972), Bláha (2019), and Lopez et al. (2023). These authors emphasized that the ecological adaptation of plants, reflected in the ratio between the development of aboveground and root biomass, is closely linked to the climatic conditions of a given environment.

Table 8. Correlation and regression relationships between oilseed radish root system bioproductivity indicators and hydrothermal vegetation regimes (average data for 2014–2024; N = 88)

Qualitative indicator	Equation of dependence	Parameters of the equation			Statistical evaluation of components				
		<i>x</i>	<i>y</i>	<i>z</i>	Multiple <i>R</i>	Multiple <i>R</i> ² _(adj.)	<i>F</i>	<i>df1, df2</i>	<i>p</i>
RBY	17.335+0.097 <i>x</i> -0.994 <i>y</i> -20.916 <i>z</i> -0.0001 <i>x</i> ² -0.0056 <i>y</i> ² +10.073 <i>z</i> ²	Precipitation (mm)	Average daily temperature, (°C)	<i>K_h</i>	0.907	0.751	11.54	2.19	< 0.001
RBY _{DM}	1.931+0.019 <i>x</i> -0.015 <i>y</i> -4.290 <i>z</i> -0.00002 <i>x</i> ² -0.0074 <i>y</i> ² +2.029 <i>z</i> ²			0.874	0.670	8.10	2.19	< 0.001	
RBY	19.728+0.062 <i>x</i> -1.006 <i>y</i> -0.492 <i>z</i> -0.00008 <i>x</i> ² +0.00085 <i>y</i> ² +0.0072 <i>z</i> ²	Precipitation (mm)	Average daily temperature, (°C)	<i>I_{DM}</i>	0.914	0.769	12.62	2.19	< 0.001
RBY _{DM}	3.318+0.011 <i>x</i> -0.099 <i>y</i> -0.094 <i>z</i> -0.000014 <i>x</i> ² -0.0027 <i>y</i> ² +0.0013 <i>z</i> ²			0.872	0.665	7.94	2.19	< 0.001	
Correlation pairs				1	2	3	4	5	6
Total formed plant biomass in raw matter (RM), t ha ⁻¹				0.78	-0.47	0.29	0.65	0.83	0.78
Total formed plant biomass in dry matter (DM), t ha ⁻¹				0.75	-0.41	0.31	0.56	0.75	0.66
RBY, t ha ⁻¹				0.71	-0.51	0.15	0.61	0.81	0.72
Dry matter content in biomass of root, %				-0.52	0.60	-0.32	-0.42	-0.68	-0.65
RBY _{DM} , t ha ⁻¹				0.69	-0.46	0.22	0.58	0.76	0.69
The coefficient of root system productivity in raw matter (CRP _{RM})				-0.40	0.41	-0.36	-0.28	-0.42	-0.41
The coefficient of root system productivity in dry matter (CRP _{DM})				-0.45	0.49	-0.31	-0.36	-0.53	-0.47
Share of root residues in total dry plant biomass (SRR _{RM}), %				0.31	0.17	0.38	0.20	0.25	0.31
Share of root residues in total dry plant biomass (SRR _{DM}), %				0.48	0.21	0.44	0.26	0.32	0.42

Significance for $r = |0.209| - |0.264|$ $p < 0.05$; $r = |0.265| - |0.328|$ $p < 0.01$; $r = > |0.328|$ $p < 0.001$. Indicators: 1 = Precipitation (P, mm); 2 = Average daily temperature (*T*_{av}, °C); 3 = Average relative humidity (RH_{av}, %); 4 = HTC; 5 = *I*_{DM}; 6 = *K_h*.

As a result, under unfavorable environmental conditions, the formation rate of aboveground biomass tends to outpace root development, leading to an increase in the productivity coefficient of the root system (CRPRM and CRPDM) with increasing environmental repressiveness. This pattern was also confirmed for oilseed radish. As shown in Table 5, the average d_{xy} values for most parameters included in the analysis were 19.72% higher compared to the same dependencies for root biomass formation alone. However, it should also be emphasized that oilseed radish demonstrates specific adaptive features compared to other cruciferous crops traditionally used as green manure. According to Jabbari et al. (2016), Singh et al. (2021), and Kashyap et al. (2023), the determining influence of precipitation and average daily temperatures in cultivated cruciferous species exceeds 50–60% and 30–43%, respectively, whereas wild cruciferous species exhibit nearly half these values. Based on this, oilseed radish displays valuable ecological adaptations characteristic of highly adaptive wild cruciferous forms, as reflected in the determined dependency levels. This supports its recommendation for use in green manure systems under high-risk or environmentally unstable conditions, in agreement with Tsytsiura (2024c).

CONCLUSIONS

It has been proven that under conditions of unstable moisture supply (during the research period, the coefficient of variation (Cv) for the hydrothermal coefficient (HTC) was 42.84%, Cv for the De Martonne Aridity Index (IDM) was 38.32%, and Cv for the Vysotsky-Ivanov Humidification Coefficient (Kh) was 38.92%), on soils with medium fertility (Greyi-Luvic Phaeozems with humus content of 2.68%) and without the application of mineral fertilizers, oilseed radish exhibits high root mass bioproductivity. This was observed under both spring and summer sowing conditions, amounting to 8.45 and 5.26 t ha⁻¹ in fresh weight and 1.77 and 1.19 t ha⁻¹ in dry matter, respectively. The average long-term root system productivity coefficient was 1.86 for spring sowing and 2.49 for summer sowing.

It was established that oilseed radish, during its short sidereal growth period, formed a root system with branching up to the fourth order. The maximum vertical penetration in the multi-year average was observed in the 40–60 cm interval, while radial spread was in the 15–25 cm range, with the highest diffuse branching of the third and fourth orders occurring at depths of 10–30 cm. The developed root morphometry, in comparison to other cruciferous green manure crops, corresponded to an adaptive drainage morphotype, valued for its positive impact on soil agrophysical properties. The long-term average parameters were as follows: average diameter of the taproot – 5.67 mm (spring sowing) / 5.13 mm (summer sowing), taperiness – 0.55 / 0.66, root volume (Vr) – 39.09 / 26.92 cm³, root spread zone volume (Rvsz) – 66.39 / 36.75×10³ cm³, fractal dimension of the root system (D) – 0.73 / 0.63, maximum rooting depth (zr) – 64.41 / 47.36 cm, and the ratio of total root mass to the mass formed in the 0–30 cm soil layer (Rm(z)) – 0.77 / 0.79.

It was found that the bioproductivity of oilseed radish's root system, based on both primary and derivative parameters, was influenced by the following factors in order of increasing effect for spring sowing: average daily temperature (tav) – soil hardness (SH) – soil water reserves (WRS) – precipitation during the vegetation period (P). For summer sowing, the sequence was: average daily temperature (tav) – soil hardness

(SH) – total precipitation during the vegetation period (P) - soil water reserves (WRS). A direct relationship was identified between key parameters of spatial morphological development of the root system (RMD, RLD, FD) and precipitation sum, while an inverse relationship was observed with average daily air temperature (multiple regression coefficient: 0.667). A direct relationship was also found with water reserves in the soil (WRS) and an inverse one with soil hardness (SH) (multiple regression coefficient: 0.670). It was demonstrated that the root system of oilseed radish exhibits an adaptive mechanism of additional vertical and horizontal branching under conditions of moisture deficiency combined with rising average daily temperatures.

In the overall conclusion, the effectiveness and feasibility of using oilseed radish as a green manure crop for spring and summer (intermediate) sowing in monoculture in areas with unstable moisture supply and low soil fertility potential have been substantiated. The maximum realization of the root sidereal potential of oilseed radish is predicted to occur under conditions of adequate moisture, moderate thermal regime (climate zone Dfa/Dfb according to the Köppen–Geiger classification), and medium-textured soils with average fertility potential.

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