

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

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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-Peñailllo 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 (Romanchuk 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 m<sup>2</sup>) (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.

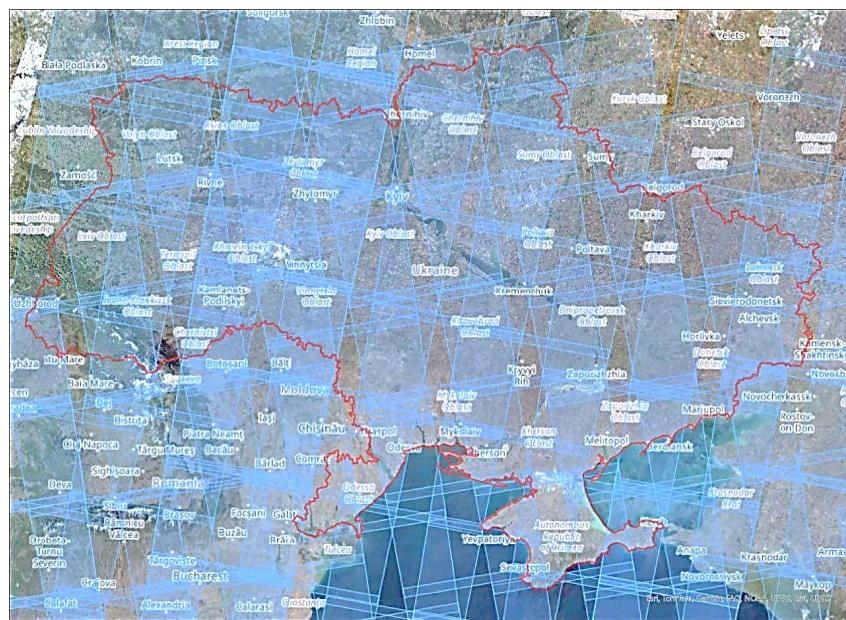
Here and further in the text: DP – double seed rate with subsequent herbicide application; DN – double seed rate without herbicide application; NP – standard seed rate with subsequent herbicide application; NN – standard seed rate without herbicide application.

**Table 1.** Variant coding principles

1 <sup>st</sup> code symbol – sowing density	2 <sup>nd</sup> code symbol - protection	Number
D double sowing norm P	Protection (herbicides application)	1,2,3 – replication
N Normal sowing N	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  $5 \times 5$  m and a bandwidth of  $20 \times 20$  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 (IW)	Detected (GRD)	(HR)	(VV/VH)	109 (eastern)
				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);  $\beta_i$  are coefficients, and  $\varepsilon$  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

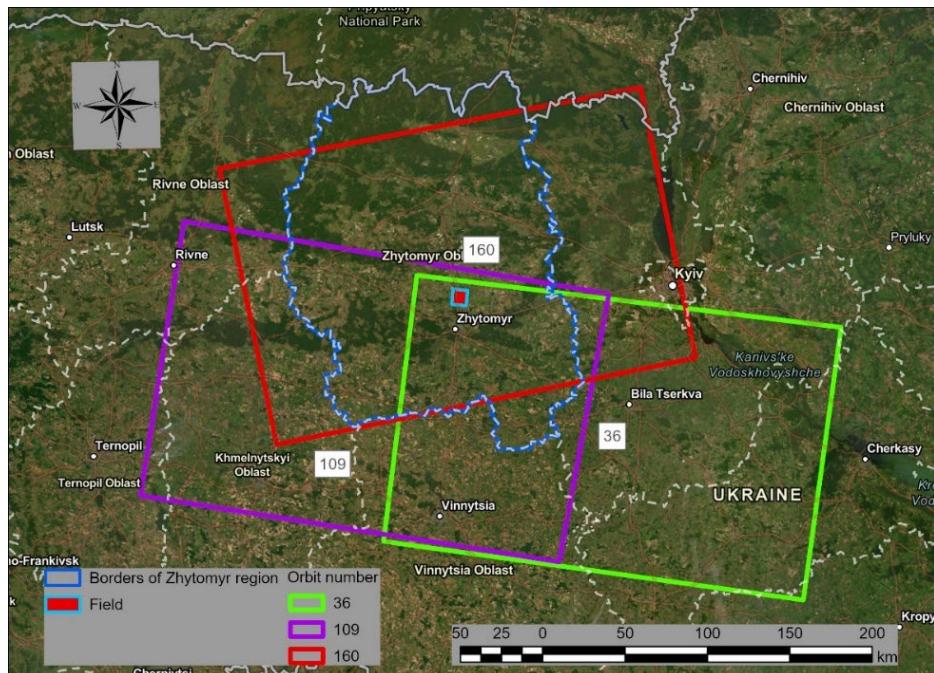
### The results of the search for satellite channels for surveys of the studied area

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).

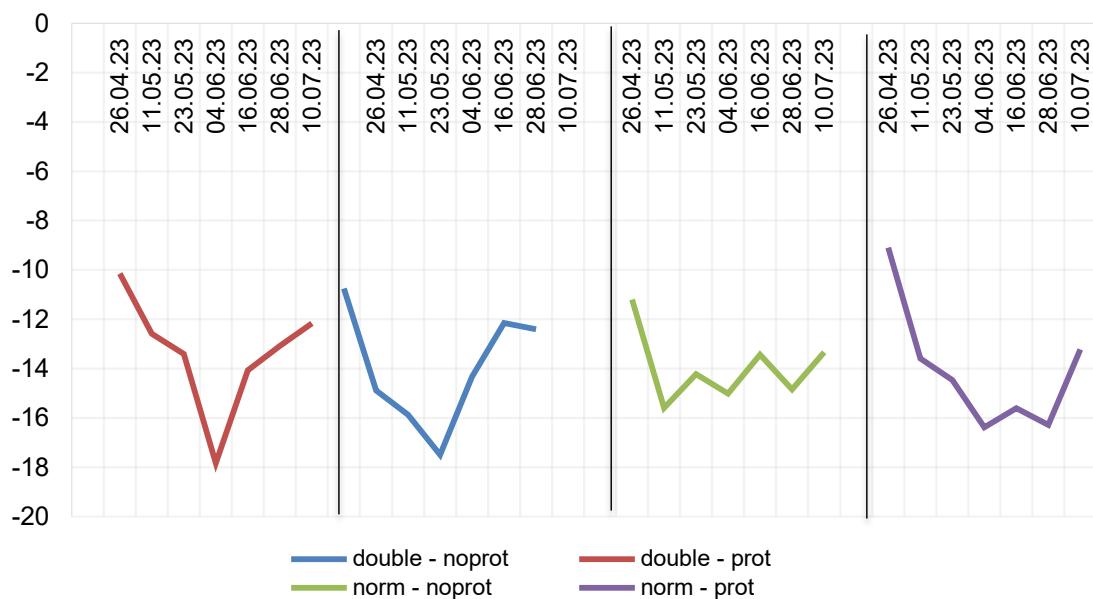
The characteristics of the signals emitted from the spacecraft, the type of land cover, the relative location of the experimental site, and the spacecraft's flight path determine the parameters of the registered image.

### 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.

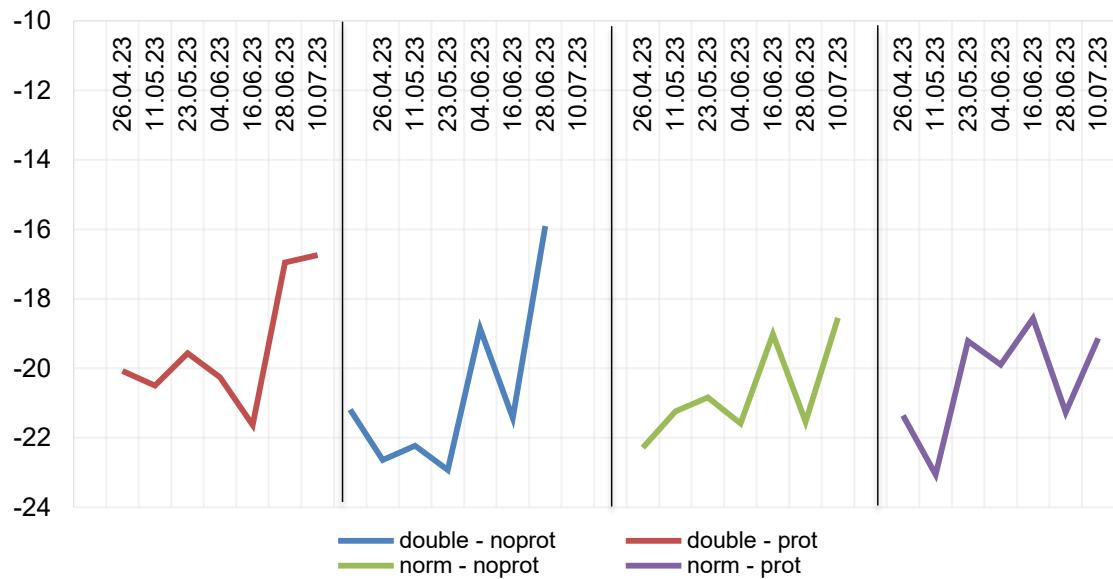
A study established that Sentinel-1 data, particularly the VH/VV ratio, can yield valuable insights on crop development. They specifically emphasised the findings from the time series study of the Sentinel-1 backscatter and ratio (VH/VV), noting their correlation with plant water content, height, and 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 -11dB (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  $\varepsilon$  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.

## REFERENCES

Beriaux, E., Jago, A., Luau-Danila, C., Planchon, V. & Defourny, P. 2021. Sentinel-1 Time Series for Crop Identification in the Framework of the Future CAP Monitoring. *Remote Sensing* **13**(14), 2785. <https://doi.org/10.3390/rs13142785>  
Copernicus Open Access: <https://dataspace.copernicus.eu>

El Hajj, M., Baghdadi, N., Zribi, M. & Bazzi, H. 2017. Synergic Use of Sentinel-1 and Sentinel-2 Images for Operational Soil Moisture Mapping at High Spatial Resolution over Agricultural Areas. *Remote Sensing* **9**(12), 1292. <https://doi.org/10.3390/rs9121292>

Fedoniuk, T.P. & Skydan, O.V. 2023. Incorporating geographic information technologies into a framework for biological diversity conservation and preventing biological threats to landscapes. *Space Science and Technology* **29**(2), 10–21. doi: 10.15407/knit2023.02.010

Fedoniuk, T.P., Pyvovar, P.V., Topolnytskyi, P.P., Rozhkov, O.O., Kravchuk, M.M., Skydan, O.V., Pazych, V.M. & Petruk, T.V. 2025. Utilizing Remote Sensing Data to Ascertain Weed Infestation Levels in Maize Fields. *Agriculture* **15**(7), 711. <https://doi.org/10.3390/agriculture15070711>

Fedoniuk, T., Fedoniuk, R., Klymenko, T., Polishchuk, O. & Pitsil, A. 2021. Bioindication of aerotechnogenic pollution of agricultural landscapes caused by the activities of industrial hubs. *Ekologia Bratislava* **40**(2), 115–123. <https://doi.org/10.2478/eko-2021-0013>

Finger, R., Swinton, S.M., El Benni, N. & Walter, A. 2019. Precision farming at the nexus of agricultural production and the environment. *Annual Review of Resource Economics* **11**(1), 313–335. <https://doi.org/10.1146/annurev-resource-100518-093929>

Fuentes-Peñaillido, F., Gutter, K., Vega, R. & Silva, G.C. 2024. Transformative Technologies in Digital Agriculture: Leveraging Internet of Things, Remote Sensing, and Artificial Intelligence for Smart Crop Management. *Journal of Sensor and Actuator Networks* **13**(4), 39. <https://doi.org/10.3390/jsan13040039>

Getahun, S., Kefale, H. & Gelaye, Y. 2024. Application of Precision Agriculture Technologies for Sustainable Crop Production and Environmental Sustainability: A Systematic Review. *The Scientific World Journal* **2024**(1), 2126734. doi: 10.1155/2024/2126734

Greifeneder, F., Notarnicola, C., Hahn, S., Vreugdenhil, M., Reimer, C., Santi, E., ... & Wagner, W. 2018. The added value of the VH/VV polarization-ratio for global soil moisture estimations from scatterometer data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* **11**(10), 3668–3679. doi: 10.1109/JSTARS.2018.2865185

Harfenmeister, K., Spengler, D. & Weltzien, C. 2019. Analyzing Temporal and Spatial Characteristics of Crop Parameters Using Sentinel-1 Backscatter Data. *Remote Sensing* **11**(13), 1569. <https://doi.org/10.3390/rs11131569>

Holtgrave, A.-K., Röder, N., Ackermann, A., Erasmi, S. & Kleinschmit, B. 2020. Comparing Sentinel-1 and -2 Data and Indices for Agricultural Land Use Monitoring. *Remote Sensing* **12**(18), 2919. <https://doi.org/10.3390/rs12182919>

IUSS Working Group WRB. World Reference Base for Soil Resources. In *International Soil Classification System for Naming Soils and Creating Legends for Soil Maps*, 4th ed.; International Union of Soil Sciences (IUSS): Vienna, Austria, 2022. [https://www.isric.org/sites/default/files/WRB\\_fourth\\_edition\\_2022-12-18.pdf](https://www.isric.org/sites/default/files/WRB_fourth_edition_2022-12-18.pdf)

Kansakar, P. & Hossain, F. 2016. A review of applications of satellite earth observation data for global societal benefit and stewardship of planet earth. *Space Policy* **36**, 46–54. <https://doi.org/10.1016/j.spacepol.2016.05.005>

Kaushik, S.K., Mishra, V.N., Punia, M., Diwate, P., Sivasankar, T. & Soni, A.K. 2021. Crop health assessment using Sentinel-1 SAR time series data in a part of central India. *Remote Sensing in Earth Systems Sciences* **4**(4), 217–234. doi: 10.1007/s41976-021-00064-z

Khabbazan, S., Vermunt, P., Steele-Dunne, S., Ratering Arntz, L., Marinetti, C., van der Valk, D., Iannini, L., Molijn, R., Westerdijk, K. & van der Sande, C. 2019. Crop Monitoring Using Sentinel-1 Data: A Case Study from The Netherlands. *Remote Sensing* **11**(16), 1887. <https://doi.org/10.3390/rs11161887>

Kumar, S., Meena, R.S., Sheoran, S., Jangir, C.K., Jhariya, M.K., Banerjee, A. & Raj, A. 2022. Remote sensing for agriculture and resource management. In *Natural Resources Conservation and Advances for Sustainability* (pp. 91–135). <https://doi.org/10.1016/B978-0-12-822976-7.00012-0>

Liu, S., Baret, F., Andrieu, B., Burger, P. & Hemmerlé, M. 2017. Estimation of wheat plant density at early stages using high resolution imagery. *Frontiers in Plant Science* **8**, 739. <https://doi.org/10.3389/fpls.2017.00739>

López-Granados, F. 2011. Weed detection for site-specific weed management: mapping and real-time approaches. *Weed Research* **51**(1), 1–11. doi: 10.1111/j.1365-3180.2010.00829.x

Mani, P.K., Mandal, A., Biswas, S., Sarkar, B., Mitran, T., Meena, R.S. 2021. *Remote Sensing and Geographic Information System: A Tool for Precision Farming*. In: Mitran, T., Meena, R.S., Chakraborty, A. (eds) *Geospatial Technologies for Crops and Soils*. Springer, Singapore, pp. 49–111. [https://doi.org/10.1007/978-981-15-6864-0\\_2](https://doi.org/10.1007/978-981-15-6864-0_2)

Parisi, A.V., Igoe, D., Downs, N.J., Turner, J., Amar, A. & Jebar, M.A. 2021. Satellite Monitoring of Environmental Solar Ultraviolet A (UVA) Exposure and Irradiance: A Review of OMI and GOME-2. *Remote Sensing* **13**(4), 752. doi: 10.3390/rs13040752

Pasternak, M. & Pawluszek-Filipiak, K. 2022. The Evaluation of Spectral Vegetation Indexes and Redundancy Reduction on the Accuracy of Crop Type Detection. *Applied Sciences* **12**(10), 5067. <https://doi.org/10.3390/app12105067>

Petropoulos, G.P., Ireland, G. & Barrett, B. 2015. Surface soil moisture retrievals from remote sensing: Current status, products & future trends. *Physics and Chemistry of the Earth, Parts a/b/c* **83**, 36–56. <https://doi.org/10.1016/j.pce.2015.02.009>

Romanchuk, L.D., Fedonyuk, T.P. & Fedonyuk, R.G. 2017. Model of influence of landscape vegetation on mass transfer processes. *Biosystems diversity* **25**(3), 203–209. <https://doi.org/10.15421/011731>

Sarvia, F., Xausa, E., De Petris, S., Cantamessa, G. & Borgogno-Mondino, E. 2021. A Possible Role of Copernicus Sentinel-2 Data to Support Common Agricultural Policy Controls in Agriculture. *Agronomy* **11**(1), 110. <https://doi.org/10.3390/agronomy11010110>

Shebanina, O., Burkovska, A., Petrenko, V. & Burkovska, A. 2023. Economic planning at agricultural enterprises: Ukrainian experience of increasing the availability of data in the context of food security. *Agricultural and Resource Economics: International Scientific E-Journal* **9**(4), 168–191. <https://doi.org/10.51599/are.2023.09.04.08>

Shelestov, A.Yu., Yalymov, B.Ya., Yalymova, G.O., Bilokonska, Yu.V., Nivyevskyi, O.V. 2020. Satellite monitoring of crops in Ukraine. *Space science and technology* **26**(6), 27–37. <https://doi.org/10.15407/knit2020.06.027>

Singh, P., Tomar, M., Singh, A.K., Yadav, V.K., Saini, R.P., Swami, S.R., ... & Singh, T. 2024. International scenario of oat production and its potential role in sustainable agriculture. In *Oat (Avena sativa)* (pp. 47–68). CRC Press.

Skydan, O.V., Dankevych, V.Y., Fedoniuk, T.P., Dankevych, Y.M. & Yaremova, M.I. 2022. European green deal: Experience of food safety for Ukraine. *International Journal of Advanced and Applied Sciences* **9**(2), 63–71. <https://doi.org/10.21833/ijaas.2022.02.007>

Skydan, O.V., Fedoniuk, T.P., Pyovarov, P.V., Dankevych, V.Y. & Dankevych, Y.M. 2021. Landscape fire safety management: The experience of Ukraine and the EU. *News of the National Academy of Sciences of the Republic of Kazakhstan, Series of Geology and Technical Sciences* **6**(450), 125–132. <https://doi.org/10.32014/2021.2518-170X.128>

The European Space Agency: Sentinel-1B journeys back to Earth [https://www.esa.int/Applications/Observing\\_the\\_Earth/Copernicus/Sentinel-1/Sentinel-1B\\_journeys\\_back\\_to\\_Earth](https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-1/Sentinel-1B_journeys_back_to_Earth), 23/09/2024

Wang, J., Xiao, X., Bajgain, R., Starks, P., Steiner, J., Doughty, R.B. & Chang, Q. 2019. Estimating leaf area index and aboveground biomass of grazing pastures using Sentinel-1, Sentinel-2 and Landsat images. *ISPRS. Journal of Photogrammetry and Remote Sensing* **154**, 189–201. <https://doi.org/10.1016/j.isprsjprs.2019.06.007>

Weiss, M., Jacob, F. & Duveiller, G. 2020. Remote sensing for agricultural applications: A meta-review. *Remote sensing of environment* **236**, 111402. doi: 10.1016/j.rse.2019.111402

Zou, K., Chen, X., Zhang, F., Zhou, H. & Zhang, C. 2021. A Field Weed Density Evaluation Method Based on UAV Imaging and Modified U-Net. *Remote Sensing* **13**(2), 310. <https://doi.org/10.3390/rs13020310>