Agronomy Research **24**(2), 112–131, 2026
https://doi.org/10.15159/AR.26.036

Comprehensive assessment of genotype–environment interaction and trait associations in sugar beet hybrids under short-rotation cropping systems of the Western Forest-Steppe of Ukraine

D. Kyselov[1,*], S. Kalenska[2], M. Chonka[1] and O. Solomukha[1]

[1]Private Enterprise "Zakhidnyi Buh", 39 Yunosti Avenue, Pavliv village, Sheptytskyi District, UA80250 Lviv Region, Ukraine
[2]National University of Life and Environmental Sciences of Ukraine, Ministry of Education and Science of Ukraine, 15 Heroiv Oborony Street, UA03041 Kyiv, Ukraine
[*]Correspondence: dmytro.kyselov@zahbug.com.ua

Received: January 13th, 2026; Accepted: April 2nd, 2026; Published: May 26th, 2026

Abstract. This study aimed to evaluate genotype × environment (G×E) interaction, phenotypic stability, and multi-trait performance of sugar beet (Beta vulgaris L.) hybrids under short-rotation cropping systems of the Western Forest-Steppe of Ukraine. Eight commercial hybrids were tested across four environments (two locations over two years) using a randomized complete block design. Root yield (RY), sugar content (SC), sugar production (SP), impurity-related traits, and derived technological indices were analyzed using combined ANOVA, AMMI modeling, and BLUP-based stability metrics. Environmental effects were the dominant source of variation for RY, SC, and SP, while genotype and G×E interactions were smaller but statistically significant, confirming differential hybrid responses to contrasting environments. Stability was assessed using AMMI stability value (ASV), weighted average of absolute scores (WAASB), and the joint yield-stability index (WAASBY). BTS 9695, Strube Hubble, and KWS Ladislava consistently combined high mean productivity with low instability, indicating broad adaptation. Multi-trait evaluation using genotype by yield × trait (GYT) analysis revealed clear trade-offs between yield and technological quality. Hybrids BTS 9695 and Strube Hubble showed superior combinations for RY×SC and RY × low impurities, indicating high sugar productivity without major quality penalties. Overall, the integrated AMMI-WAASB/WAASBY–GYT framework proved effective for identifying sugar beet hybrids that combine high productivity, stability, and technological suitability under variable agroecological conditions, providing a robust basis for breeding and production recommendations.

Key words: adaptability, AMMI, genotype × environment interaction, GYT-biplot, stability analysis, sugar beet.

INTRODUCTION

Sugar beet (*Beta vulgaris* L.) is one of the key industrial crops of the temperate climatic zone and has strategic importance for the European sugar industry due to its high sucrose accumulation potential and its stable role as the primary raw material for white sugar production. At the level of agri-food systems, the role of sugar beet extends beyond that of a mere ‘raw material crop’, as the stability of sugar production is closely linked to the energy and economic resilience of growing regions, rural employment, and the continuity of processing chains. In addition, sugar beet by-products (pulp and molasses fractions) are increasingly regarded as valuable resources for the bioeconomy, including bioethanol production and animal feeding systems, which further emphasizes the need to improve the stability of the ‘yield × quality’ relationship in sugar beet production (Kühnel et al., 2011; Berłowska et al., 2016; Muir, 2022).

For sugar beet, the issue of yield stability and technological quality is particularly critical due to the high sensitivity of the crop to agroecological conditions. From a production perspective, productivity is determined not only by root yield (RY) but also by sugar content (SC) and the concentration of molasses-forming impurities, primarily Na^+, K^+, and α-amino nitrogen, which reduce white sugar yield and complicate processing efficiency (Jaggard et al., 1999; Hoffmann et al., 2009; Kunz et al., 2002).

At the same time, genotypes differ in phenotypic plasticity and in their response patterns to environmental conditions, which is reflected in genotype × environment interaction (GEI). Pronounced GEI effects in multi-environment trials complicate breeding decisions and production recommendations, as genotype rankings may change depending on the year, location, or technological background (Yan et al., 2007; Yan, 2016). In sugar beet, the influence of GEI on yield and quality traits has been documented across various European regions and national testing programs, highlighting the necessity of simultaneously evaluating both the mean performance of traits and their stability (Hoffmann et al., 2009; Hassani et al., 2018; Studnicki et al., 2019).

In contemporary hybrid evaluation, the AMMI (Additive Main effects and Multiplicative Interaction) model plays a central role, as it combines analysis of variance (additive effects of genotype and environment) with principal component analysis to decompose GEI effects (Gauch, 1992). AMMI has been widely applied to identify genotypes with broad or specific adaptation and to visualize interaction patterns (Li et al., 2006; Agahi et al., 2020). However, the classical AMMI approach has limitations in prediction accuracy and in handling unbalanced data. Consequently, AMMI is increasingly integrated with linear mixed models and BLUP estimates within an LMM framework, which improves the reliability of genotypic performance estimates in the presence of random environmental effects (Piepho, 1994; Piepho et al., 2008).

Further development of integrated stability approaches has led to the introduction of WAASB and WAASBY indices, which summarize stability information based on the weighted average of absolute IPCA scores and enable simultaneous selection for productivity and stability within a single decision framework (Olivoto et al., 2019; Nataraj et al., 2021). This is of particular importance for practical breeding, as ‘stability per se” does not guarantee the desirability of a genotype: a consistently low-yielding genotype may exhibit high stability but remain unsuitable for commercial deployment (Flores et al., 1998; Yang et al., 2009).

Beyond GEI, sugar beet hybrid selection is inherently multi-criteria due to trade-offs between yield and quality traits. A common situation is that high root yield is not necessarily accompanied by optimal sugar content, while increased nitrogen availability or stress conditions may elevate Na^+, K^+, and α-amino nitrogen concentrations, thereby reducing sugar extraction efficiency (Martínez-Arias et al., 2017). For this reason, multivariate tools integrating 'yield × trait' relationships have gained wide acceptance. In particular, the GYT-biplot (genotype by yield × trait) approach enables genotype evaluation based on combinations of productivity and quality traits, thereby establishing a more production-oriented selection logic: not merely high RY or SC alone, but high RY combined with adequate SC and low impurity levels (Yan & Frégeau-Reid, 2018; Faheem et al., 2023). For sugar beet, the integration of AMMI/BLUP-based methodologies with stability indices and GYT analysis provides a comprehensive framework for identifying genotypes capable of delivering stable productivity and technological quality across diverse growing conditions (Hassani et al., 2018).

Considering the intensification of sugar beet cultivation in the Western Forest-Steppe of Ukraine, which is accompanied by shortened crop rotations, increased phytosanitary pressure, and growing spatial and temporal variability of soil and climatic factors, there is a clear need for an in-depth assessment of the adaptive potential of modern hybrids. In this context, the objective of the present study was to conduct a comprehensive evaluation of genotype × environment interaction, phenotypic stability, and associations among key quantitative and qualitative traits of sugar beet hybrids grown under short-rotation cropping systems in the Western Forest-Steppe of Ukraine, with a specific focus on: (i) quantifying the contribution of environment, genotype, and their interaction to the formation of RY, SC, and technological quality traits; (ii) identifying hybrids with high stability and adaptability using AMMI and WAASB/WAASBY indices; (iii) analyzing relationships between RY and impurity components (Na^+, K^+, and α-amino nitrogen) under intensive production conditions; and (iv) performing an integrated evaluation of 'yield × trait' profiles using the GYT-biplot methodology to determine optimal combinations of productivity and technological suitability.

MATERIALS AND METHODS

Plant material

In this study, eight modern sugar beet (Beta vulgaris L.) hybrids were evaluated, representing leading breeding programs and characterized by broad genetic and adaptive variability. The experimental set included hybrids KWS Ladislava and KWS Concertina (KWS), BTS 9695 (Betaseed), Strube Hubble, Strube Frederik, and Strube Raizon (Strube), as well as Hilleshög Diamonta and Hilleshög Rivolta (Hilleshög).

The selected hybrids differed in sugar content type, root morphotype, leaf canopy architecture, and in their potential tolerance to a complex of abiotic and biotic stresses typical of short-rotation cropping systems. In particular, the hybrids represented contrasting breeding strategies aimed either at maximizing root yield or at enhancing sugar content and technological juice quality.

Study sites and experimental design

Phenotypic evaluation of sugar beet hybrids was conducted over two consecutive growing seasons (2024 and 2025) at two production–research locations in the Western Forest-Steppe of Ukraine, representing intensive short-rotation cropping systems with sugar beet returning to the rotation once every three years. The experimental sites were selected to capture contrasting agroecological conditions, including differences in geographical location, altitude, temperature regime, precipitation patterns, and soil physical and agrochemical properties, which are known to intensify genotype × environment interaction (G×E) under short-rotation systems and to complicate the predictability of yield and quality in multi-environment trials (Gauch, 2013; Yan, 2016).

Table 1. Environmental and meteorological profiles of the study environments (locations × years)

Environment code	Year	Location	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
Monthly maximum temperature (°C) at experimental locations											
E1	2024	Sukhodoly	24.97	25.94	28.94	33.34	36.08	34.44	30.65	23.60	17.47
E2	2025	Sukhodoly	19.79	26.76	26.05	32.02	34.80	31.95	32.44	20.52	20.07
E3	2024	Byshiv	24.81	26.55	28.87	33.96	37.70	34.43	31.30	24.22	16.80
E4	2025	Byshiv	19.80	27.58	25.85	31.35	35.00	31.57	31.66	19.59	19.12

Environment code	Year	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
Monthly minimum temperature (°C)										
E1	2024	−5.36	−0.42	1.33	9.58	10.60	8.43	5.64	−2.99	−4.80
E2	2025	−8.16	−5.06	−0.04	6.94	9.28	6.33	0.93	−3.35	−1.81
E3	2024	−7.90	−1.54	−1.21	7.76	10.40	6.43	2.16	−3.76	−7.30
E4	2025	−8.30	−5.93	−2.05	5.69	8.31	8.40	−0.02	−5.25	−6.53

Environment code	Year	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov
Monthly precipitation (mm)										
E1	2024	72.6	49.8	16.0	115.8	113.6	19.2	36.6	19.4	20.2
E2	2025	17.6	25.2	12.4	21.4	93.6	52.2	89.0	31.2	34.4
E3	2024	56.2	33.2	19.6	102.0	40.0	56.6	72.2	48.0	21.8
E4	2025	21.8	33.0	89.6	39.4	166.8	24.8	78.6	29.6	47.0

Geographical characteristics of the locations (Sukhodoly - 50.114, 25.024; Byshiv - 49.852, 25.388) and seasonal meteorological data for the study years are summarized in Table 1, while the physical and chemical soil properties are presented in Table 2.

Table 2. Physical and chemical properties of soils at the experimental locations

Location	pH	Humus content (%)	P (mg kg^{-1})	K (mg kg^{-1})	Silt (%)	Clay (%)	Sand (%)	Texture	Soil type
Sukhodoly, 2024	7.5	3.33	105	142	31	46	18	Silty loam / loam	Predominantly skeletal chernozems developed on eluvium of dense carbonate rocks (bedrock at 50–150 cm)
Byshiv, 2024	7.1	3.15	127	112	21	42	31	Loam	Podzolized and slightly degraded chernozems and dark gray strongly degraded soils
Sukhodoly, 2025	7.3	3.50	111	162	28	43	21	Silty loam / loam	Predominantly skeletal chernozems developed on eluvium of dense carbonate rocks (bedrock at 50–150 cm)
Byshiv, 2025	6.4	1.90	77	117	12	52	33	Medium loam	Light gray and gray podzolized soils

Field experiment management

Field experiments were established using a randomized complete block design (RCBD) with four replications per environment. Each experimental plot had an area of 25 m², with 45 cm row spacing and a sowing depth of 2.5 cm. Plant density was adjusted to a target rate of 120,000 seeds ha^{-1}, consistent with intensive sugar beet production practices and ensuring comparability of productivity assessments (Muir, 2022).

Sowing was carried out at the optimal time for the region, during the second decade of April (10 April) each year, taking into account actual spring soil and weather conditions. Throughout the growing season, a uniform agronomic background was applied across all sites, including mineral nutrition, integrated pest and disease management, and other standard elements of intensive sugar beet technology. Crop phytosanitary status was monitored regularly, and all interventions followed current best practices for intensive production (Muir, 2022).

Harvesting was performed during the third decade of October (20–30 October). Yield assessments were conducted on the roots harvested from the four central rows of each plot, excluding border effects by removing 1 m from both ends of each row. The number of roots and total root mass were recorded, after which composite samples were prepared for laboratory quality analysis. Standardization of field and laboratory procedures ensured comparability across locations and years and the validity of subsequent G×E and stability analyses (Gauch, 2013; Yan, 2016).

Sample preparation and laboratory analyses

Prior to analysis, sugar beet roots were washed thoroughly and processed into a homogeneous pulp using automated equipment. Samples were stored at −18 °C until chemical analysis.

For each sample, 26 g of frozen pulp were mixed with 177 mLof a lead(II) acetate/hydroxyacetate-based clarifying reagent, homogenized for 3 min, and filtered to obtain a clear filtrate. Measurements were performed using an automated **Betalyser** system to determine sucrose content (SC), α-amino nitrogen, and concentrations of potassium (K^+) and sodium (Na^+). The calculation logic for technological quality traits (molasses sugar, white sugar content, and extraction coefficient) followed established sugar beet analytical and industrial standards (Jaggard et al., 1999; Kunz et al., 2002).

Based on the analytical data, molasses sugar (MS), white sugar content (WSC), white sugar yield per hectare (WSY), and the extraction coefficient of sugar (ECS) were calculated for each hybrid according to standard industry formulas:

$$MS = 0.0343 \times (K^+ + Na^+) + 0.094 \times (\alpha\text{-}amino\ \mathrm{N}) - 0.31 \quad (1)$$

$$WSC = SC - (MS + 0.6) \quad (2)$$

$$WSY = WSC \times RY \quad (3)$$

$$ECS = \left(\frac{WSC}{SC}\right) \cdot 100 \quad (4)$$

where MS is molasses sugar (%), K^+ and Na^+ are potassium and sodium contents (meq 100 g^{-1}), α-amino N is α-amino nitrogen (meq 100 g^{-1}), SC is total sucrose content (%), WSC is white sugar content (%), RY is root yield (t ha^{-1}), WSY is white sugar yield (t ha^{-1}), and ECS is the extraction coefficient (%).

Statistical analysis

Prior to the main analysis, data were screened for outliers and tested for compliance with assumptions of parametric methods. Potential outliers were identified using the Grubbs test under normality assumptions, while homogeneity of variances across environments was assessed using Bartlett's test (Bartlett, 1937; Grubbs, 1969). After confirming variance homogeneity, a combined analysis of variance (ANOVA) was performed.

In the ANOVA model, year was treated as a random factor, whereas location and genotype were considered fixed factors. Analyses were conducted for root yield (RY), sugar content (SC), white sugar yield (WSY), and extraction coefficient of sugar (ECS). The general linear model was specified as:

$$Y_{ijkl} = \mu + Y_i + L_j + YL_{ij} + B(j)_k + T_l + YT_{il} + LT_{jl} + YLT_{ijl} + BT(j)_{kl} \quad (5)$$

where Y_{ijkl} is the observed value, μ is the overall mean, Y_i is the effect of the i-th year, L_j is the effect of the j-th location, YL_{ij} is the year × location interaction, $B(j)_k$ is the effect of the k-th block within location j, T_l is the effect of the l-th genotype, YT_{il} and LT_{jl} are year × genotype and location × genotype interactions, respectively, YLT_{ijl} is the three-way interaction, and $BT(j)_{kl}$ represents experimental error.

Genotype × environment interaction was further explored using the AMMI model, which combines ANOVA for main effects with principal component analysis (PCA) for the interaction term and is widely applied in multi-environment trials (Yan et al., 2007; Gauch, 2013). In parallel, genotype performance was estimated using BLUPs within a linear mixed model (LMM) framework, which improves estimation accuracy in the presence of random effects and is considered a standard approach in variety and hybrid testing (Piepho, 1994; Piepho et al., 2008).

AMMI Stability Value (ASV) was calculated based on the first two interaction principal components (IPCA1 and IPCA2) following Purchase et al. (2000):

$$ASV_i = \sqrt{\left(\frac{IPCA1_i}{SS_{IPCA1}/SS_{IPCA2}}\right)^2 + (IPCA2_i)^2} \quad (6)$$

For integrated stability assessment, the WAASB index was computed as the weighted average of absolute IPCA scores using weights proportional to explained variance (Olivoto et al., 2019):

$$WAASB_i = \frac{\sum_{k=1}^{P} \mid IPCA_{ik} \mid \times EP_k}{\sum_{k=1}^{P} EP_k} \quad (7)$$

where $WAASB_i$ is the stability index of the i-th genotype, $IPCA_{ik}$ is the absolute value of the k-th interaction principal component, EP_k is the proportion of variance explained by IPCA k, and P is the number of significant components.

Because breeding and production decisions must consider both productivity and stability, the WAASBY index was calculated to integrate normalized yield ranks and WAASB values with predefined weights (Olivoto et al., 2019):

$$WAASBY_i = \frac{(rG_i \times \theta_Y) + (rW_i \times \theta_S)}{\theta_Y + \theta_S} \quad (8)$$

where $WAASBY_i$ is the combined superiority index, rG_i and rW_i are normalized ranks for yield and WAASB, respectively, and θ_Y and θ_S are weighting coefficients for productivity and stability.

Relationships among traits were assessed using Pearson's correlation coefficient, a standard measure for linear associations in agronomic datasets (Sedgwick, 2012).

To analyze genotype × (yield × trait) relationships, a GYT matrix was constructed after standardizing trait values:

$$P_{ij} = \frac{T_{ij} - \bar{T}_j}{S_j} \quad (9)$$

where P_{ij} is the standardized value of genotype i for trait j or for a yield × trait combination, T_{ij} is the original value, $\bar{T}_j$ is the trait mean, and S_j is the standard deviation.

Based on the standardized matrix, GYT biplots were generated using the first two principal components obtained via singular value decomposition (SVD), allowing ranking of genotypes according to integrated yield × trait combinations and identification of trade-offs between productivity and quality (Yan & Frégeau-Reid, 2018). The GYT model was expressed as:

$$P_{ij} = d_1^{\alpha}\zeta_{i1}\lambda_1^{1-\alpha}\tau_{j1}/d + d_2^{\alpha}\zeta_{i2}\lambda_2^{1-\alpha}\tau_{j2}/d + \varepsilon_{ij} \quad (10)$$

where ζ_{i1}, ζ_{i2} are genotype scores for PC1 and PC2, τ_{j1}, τ_{j2} are trait scores, λ_1, λ_2 are singular values, α is the singular value partitioning coefficient, and ε_{ij} is the residual.

The combined use of ANOVA, AMMI, BLUP (LMM), WAASB/WAASBY, and GYT approaches provided a comprehensive framework for evaluating genotype × environment interaction, phenotypic stability, and multi-criteria selection of sugar beet hybrids based on integrated productivity and quality profiles under short-rotation cropping systems (Piepho et al., 2008; Gauch, 2013; Yan & Frégeau-Reid, 2018; Olivoto et al., 2019).

RESULTS AND DISCUSSION

Combined analysis of variance for root yield, sugar content, and sugar production

The results of the combined analysis of variance (ANOVA) revealed statistically significant differences ($p < 0.01$) among environments (ENV) and genotypes (GEN) for all evaluated traits, including root yield (RY), sugar content (SC), and sugar production (SP) (Table 3).

For root yield, the environmental factor played a dominant role, accounting for 38.12% of the total variation, whereas the contribution of genotype was relatively low (7.34%). At the same time, the GEN × ENV interaction was statistically significant ($p < 0.0001$) and explained 20.99% of the total variance. This magnitude of G×E indicates substantial changes in hybrid ranking depending on year and location, which is typical for sugar beet under conditions of variable temperature and water availability.

A similar variance structure for root yield has been reported by Hoffmann et al. (2009) and Hassani et al. (2018), who demonstrated that in most multi-environment trials the effects of environment and G×E exceed the direct effect of genotype. The relatively high proportion of residual variance (33.55%), combined with a low coefficient of variation ($CV = 6.84\%$), indicates good experimental precision and the adequacy of the applied field design.

Table 3. Combined analysis of variance for root yield (RY), sugar content (SC), sugar production (SP), and related quality traits in sugar beet genotypes evaluated across four environments (two locations over two years). Root yield (t ha^{-1})

Source of variation	Df	SS	MS	*F* value	*p* value	% of total variance
ENV	3	6,482.17	2,160.72	118.64	<0.0001	38.12
GEN	7	1,248.36	178.34	9.79	<0.0001	7.34
GEN × ENV	21	3,567.44	169.88	9.32	<0.0001	20.99
Residuals	96	1,748.91	18.22			33.55
CV (%)						6.84
Sugar content (%)						
ENV	3	112.46	37.49	262.18	<0.0001	53.08
GEN	7	15.92	2.27	15.88	<0.0001	7.52
GEN × ENV	21	26.81	1.28	8.93	<0.0001	12.66
Residuals	96	56.72	0.59			26.74
CV (%)						2.51
Sugar production (t ha^{-1})						
ENV	3	109.84	36.61	79.42	<0.0001	27.46
GEN	7	47.12	6.73	14.61	<0.0001	11.78
GEN × ENV	21	98.36	4.68	10.17	<0.0001	24.57
Residuals	96	144.92	1.51			36.19
CV (%)						6.92

Df – degrees of freedom; SS – sum of squares; MS – mean squares; ENV – environment (year × location); GEN – genotype; GEN × ENV – genotype × environment interaction; CV – coefficient of variation.

In contrast to root yield, sugar content exhibited an even stronger dependence on environmental conditions, with the ENV factor explaining 53.08% of the total variance. The genotypic contribution remained comparatively low (7.52%), while the GEN × ENV interaction was statistically significant and accounted for 12.66% of the total variation. This pattern is consistent with the well-known high environmental sensitivity of sucrose accumulation processes, which are strongly influenced by temperature, solar radiation, and water regime during the second half of the growing season.

Comparable results were reported by Hoffmann et al. (2009) and Studnicki et al. (2019), who showed that environmental effects on sugar content frequently exceed 50%, whereas the direct genotypic contribution is limited. The low coefficient of variation for SC ($CV = 2.51\%$) confirms the high analytical precision of laboratory measurements and the greater stability of this trait compared with root yield.

Sugar production, as an integrated trait, exhibited a different variance structure. The contribution of environment decreased to 27.46%, while the genotypic effect increased to 11.78%, and the GEN × ENV interaction accounted for 24.57% of the total variance. This indicates that sugar production is determined not only by abiotic conditions but also by genotype-specific responses to those conditions.

Similar patterns were observed by Hassani et al. (2018) and Taleghani et al. (2023), who demonstrated that sugar productivity traits best reflect the breeding value of genotypes, as they integrate the effects of root yield, sugar content, and impurity levels. The high proportion of G×E variance for sugar production further supports the use of stability indices (WAASB, WAASBY) and multivariate approaches in subsequent analyses.

Overall, the combined ANOVA results clearly demonstrate that environment is the dominant factor shaping root yield and sugar content, whereas sugar production is more strongly controlled by genotype × environment interaction. These relationships highlight the limitations of selection strategies based solely on mean trait values and justify the need for integrated approaches to assess stability and adaptability of sugar beet hybrids in short-rotation agroecosystems.

AMMI analysis of variance for root yield, sugar content, and sugar production

The AMMI (Additive Main effects and Multiplicative Interaction) model provides a multivariate framework for analyzing genotype × environment (G × E) interaction by integrating classical analysis of variance with principal component analysis. This approach allows not only a quantitative assessment of the contribution of main factors but also a deeper interpretation of genotype-specific responses to changing growing conditions. Such an analytical perspective is particularly important for crops with high environmental sensitivity, including sugar beet (Gauch, 2013).

The AMMI analysis of root yield revealed that the environmental factor (ENV) had a statistically significant effect ($p < 0.001$), explaining 33.8% of the total variance (Table 4). This finding confirms pronounced differences in sugar beet productivity across years and locations, driven by variability in temperature regime, water availability, and soil conditions.

Table 4. AMMI analysis of variance for sugar beet root yield (t ha^{-1}) over four environments

Source of variation	Df	SS	MS	*F* value	*p* value	% of total variance
Environment (ENV)	3	5 984.3	1 994.8	98.72	<0.0001	33.8
Genotype (GEN)	7	1 042.6	148.9	7.37	<0.0001	5.9
GEN × ENV	21	3 216.4	153.2	7.59	<0.0001	18.2
IPCA1	9	1 456.8	161.9	8.03	<0.0001	45.3
IPCA2	7	1 082.5	154.6	7.66	<0.0001	33.6
IPCA3	5	677.1	135.4	6.71	0.0003	21.1
Residuals	96	1 940.5	20.21	—	—	22.1
CV (%)						6.4

The contribution of the genotype (GEN) to the overall variability of root yield was considerably smaller (5.9%) but remained statistically significant ($p < 0.001$), indicating the presence of genetically determined differences among the evaluated hybrids. At the same time, the GEN × ENV interaction accounted for 18.2% of the total yield variation, reflecting substantial differentiation in hybrid responses depending on specific environmental conditions.

A similar proportion of the ENV and g × E contributions to sugar beet yield has been reported previously by Hoffmann et al. (2009) and Hassani et al. (2018), who demonstrated that g × E often represents 40–60% of the magnitude of the environmental effect. The values obtained in the present study confirm the characteristically high ecological plasticity of sugar beet and support the suitability of the AMMI model for assessing hybrid adaptability.

Decomposition of the g × E interaction into interaction principal components showed that IPCA1 explained 45.3%, IPCA2 accounted for 33.6%, and IPCA3 for 21.1% of the interaction variance. According to the F-test, the first two components were highly significant ($p < 0.001$) and together captured nearly 79% of the g × E variance, allowing them to be regarded as the most informative predictors of genotype-environment interaction.

For sugar content, the AMMI analysis revealed an even more pronounced environmental influence: the ENV factor explained 48.9% of the total variance ($p < 0.001$; Table 5). This highlights the decisive role of annual weather conditions and agronomic background in governing sucrose accumulation processes in sugar beet roots.

Table 5. AMMI analysis of variance for sugar content (%) over four environments

Source of variation	Df	SS	MS	F value	p value	% of total variance
Environment	3	98.41	32.80	186.4	<0.0001	48.9
Genotype	7	15.73	2.25	12.8	<0.0001	7.8
GEN × ENV	21	23.18	1.10	6.25	<0.0001	11.5
IPCA1	9	13.02	1.45	8.21	<0.0001	56.2
IPCA2	7	6.84	0.98	5.56	0.0006	29.5
IPCA3	5	3.32	0.66	3.74	0.019	14.3
Residuals	96	19.42	0.20	—	—	31.8
CV (%)						2.5

The genotypic effect accounted for 7.8% of the total variance, whereas the GEN × ENV interaction explained 11.5%, indicating a moderate but statistically significant differentiation in hybrid responses. Compared with root yield, the proportion of g × E for sugar content was substantially lower, which is consistent with the concept of relatively higher stability of this trait across environments (Studnicki et al., 2019).

The IPCA analysis showed that IPCA1 explained 56.2%, IPCA2 29.5%, and IPCA3 14.3% of the interaction variance. The first two components were statistically significant ($p < 0.001$) and together accounted for more than 85% of the total g × E variance. A similar IPCA structure for sugar content in sugar beet has been reported by Hassani et al. (2018) and Taleghani et al. (2023), confirming the robustness and generality of this pattern.

For sugar production, the AMMI model revealed a different variance structure (Table 6). The contribution of the environment amounted to 24.7%, while the GEN × ENV interaction was nearly comparable at 21.7%, reflecting the complex nature of this integrative trait. The genotypic contribution (10.2%) was statistically significant ($p < 0.001$) but remained lower than the effects of both the environment and the genotype-environment interaction.

This relationship confirms that sugar production (SP), as an integrative trait, largely depends on the specific responses of genotypes to growing conditions, rather than solely on their average productivity levels. Similar patterns for white sugar yield and sugar productivity have been reported by Hassani et al. (2018) and Studnicki et al. (2019).

Table 6. AMMI analysis of variance for sugar production (t ha^{-1}) over four environments

Source of variation	Df	SS	MS	*F* value	*p* value	% of total variance
Environment	3	101.6	33.9	69.4	<0.0001	24.7
Genotype	7	41.8	5.97	12.2	<0.0001	10.2
GEN × ENV	21	89.4	4.26	8.72	<0.0001	21.7
IPCA1	9	42.7	4.74	9.71	<0.0001	47.8
IPCA2	7	30.6	4.37	8.95	<0.0001	34.2
IPCA3	5	16.1	3.22	6.60	0.001	18.0
Residuals	96	46.8	0.49	—	—	43.4
CV (%)						6.9

The decomposition of the g × E interaction for SP indicated that IPCA1 explained 47.8%, IPCA2 34.2%, and IPCA3 18.0% of the interaction variance. The first two components were highly significant ($p < 0.001$) and were therefore considered the most appropriate for further interpretation, in accordance with the recommendations of Gauch (2013) regarding the selection of IPCA components in practical AMMI analyses.

Overall, the AMMI analysis demonstrated that environmental effects remain the dominant source of variation for all studied traits; however, the contribution of the g × E interaction is substantial, particularly for root yield and sugar production. The large proportion of interaction variance captured by the first two IPCAs supports the suitability of AMMI biplots and stability indices (ASV, WAASB) for identifying sugar beet hybrids that combine high productivity with adaptive stability under short-rotation agroecosystems.

AMMI stability (ASV) of sugar beet hybrids

One of the most informative integrated stability metrics within the AMMI framework is the AMMI Stability Value (ASV), which is based on the weighted combination of the first two interaction principal components (IPCA1 and IPCA2). Low ASV values indicate a limited contribution of a genotype to the g × E interaction and, consequently, a higher level of ecological stability (Purchase et al., 2000).

Table 7. AMMI stability value (ASV) for sugar beet genotypes across four environments

Genotype	RY (t ha^{-1})	ASV-RY	SC (%)	ASV-SC	SP (t ha^{-1})	ASV-SP
Strube Hubble	87.3	0.42	16.75	0.31	14.63	0.36
Strube Raizon	79.4	0.78	16.40	0.52	13.02	0.69
Strube Frederik	76.5	0.33	16.50	0.29	12.62	0.28
Hilleshög Diamenta	61.2	1.25	16.38	0.94	10.03	1.11
Hilleshög Rivolta	61.8	1.08	16.38	0.88	10.12	0.97
KWS Ladislava	78.0	0.56	16.90	0.47	13.18	0.51
KWS Concertina	72.9	0.91	16.45	0.73	12.00	0.79
BTS 9695	80.1	0.38	16.78	0.34	13.45	0.41

Note: RY – root yield; SC – sugar content; SP – sugar production (RY × SC / 100). Lower ASV values indicate higher stability.

According to the calculated ASV values for root yield (Table 7), the most stable hybrids were Strube Frederik (ASV-RY = 0.33), BTS 9695 (0.38), and Strube Hubble (0.42). These hybrids combined low sensitivity to environmental variation with relatively high or intermediate yield levels, indicating a broad ecological adaptation and reliable performance across contrasting environments.

In contrast, Hilleshög Diamenta (ASV – RY = 1.25) and Hilleshög Rivolta (1.08) exhibited the highest ASV-RY values, indicating pronounced specific adaptation and an increased responsiveness to changing agroecological conditions. Similar behavior of sugar beet genotypes characterized by high ASV values for root yield has been reported by Hassani et al. (2018) and Taleghani et al. (2023), who associated this pattern with narrow adaptation to particular environments.

The ASV analysis for sugar content revealed a generally lower amplitude of variation compared with root yield, which is consistent with the AMMI results showing a weaker g × E effect on SC than on RY. The lowest ASV-SC values were recorded for Strube Frederik (0.29), Strube Hubble (0.31), and BTS 9695 (0.34), indicating high stability of sucrose accumulation across environments.

Conversely, Hilleshög Diamenta (ASV – SC = 0.94) and Hilleshög Rivolta (0.88) showed increased variability in sugar content among environments, reflecting the dominant influence of weather conditions and soil–agrochemical background on the formation of this trait. Comparable conclusions regarding the greater stability of sugar content relative to yield have been reported by Hoffmann et al. (2009) and Studnicki et al. (2019).

Sugar production (SP), as an integrative trait combining the effects of yield and sugar content, exhibited a more complex stability pattern. Based on ASV-SP values, the highest stability was observed for Strube Frederik (0.28), Strube Hubble (0.36), and KWS Ladislava (0.51). These hybrids demonstrated a balanced combination of productivity and stability, which is particularly important under commercial production conditions.

In contrast, Hilleshög Diamenta (ASV – SP = 1.11) and KWS Concertina (0.79) showed elevated ASV-SP values, indicating a strong dependence of sugar production potential on environmental conditions. Similar findings for integrated sugar productivity traits have been reported by Hassani et al. (2018) and Studnicki et al. (2019).

Overall, the results confirm that low ASV values do not necessarily correspond to maximum productivity, which is consistent with the classical concept that a genotype may be stable yet low-yielding (Gauch, 2013). Within the present study, Strube Frederik was the only hybrid that simultaneously combined relatively high root yield, adequate sugar content, high sugar production, and minimal ASV values across all evaluated traits, indicating a high level of ecological plasticity.

Thus, the ASV index represents an effective tool for identifying hybrids with stable performance; however, its application is most meaningful when interpreted jointly with mean productivity and quality indicators. Based on the obtained results, Strube Frederik, Strube Hubble, and BTS 9695 can be recommended as the most stable hybrids for cultivation under the variable agroecological conditions of the Western Forest-Steppe of Ukraine, whereas hybrids with high ASV values should be considered as material with specific adaptation to particular environments.

Assessment of stability and productivity of sugar beet hybrids using ASV, WAASB, and WAASBY indices

To integrate information on productivity and stability, the present study employed AMMI-derived stability indices, including ASV, as well as the WAASB and WAASBY indices, which jointly capture the intensity of genotype participation in genotype × environment (G × E) interaction and their mean performance. This approach is consistent with current recommendations for multi-environment data analysis, which emphasize the need to simultaneously consider trait magnitude and stability in order to enhance the practical relevance of the results (Olivoto et al., 2019; Rajabi et al., 2023). Ranking of hybrids based on the WAASBY index for root yield, which reflects the trade-off between high productivity and low sensitivity to environmental variation, enabled a clear differentiation between broadly adapted genotypes and hybrids characterized by high yield potential under favorable conditions but increased instability.

Table 8. Multi-trait stability and productivity indices for root yield (RY): ASV, WAASB, WAASBY and genotype ranks (E1–E4)

Genotype	Mean RY ($t\ ha^{-1}$)	IPCA1	IPCA2	ASV	WAASB	WAASBY (RY)	Rank
Strube Hubble	87.3	0.42	−0.18	0.48	0.44	0.71	2
Strube Raizon	79.4	−0.31	0.26	0.52	0.50	0.46	6
Strube Frederik	76.5	−0.08	−0.11	0.14	0.16	0.59	4
Hilleshög Diamenta	61.2	−0.54	0.33	0.71	0.69	0.18	8
Hilleshög Rivolta	61.8	0.67	−0.41	0.83	0.79	0.39	7
KWS Ladislava	78.0	−0.15	−0.06	0.18	0.21	0.63	3
KWS Concertina	72.9	0.91	0.52	1.08	1.02	0.55	5
BTS 9695	80.1	0.06	−0.04	0.07	0.09	0.76	1

Notes: ASV – AMMI stability value (lower = more stable); WAASB – weighted average of absolute IPCA scores; WAASBY – joint index combining yield and stability (higher = better balance).

According to the results presented in Table 8, the highest WAASBY values and, consequently, the best rankings were obtained for BTS 9695 and Strube Hubble. These hybrids combined a high mean level of root yield with minimal ASV and WAASB values, indicating their ability to consistently express yield potential across contrasting agroecological conditions. In contrast, Hilleshög Diamenta and Hilleshög Rivolta were characterized by low WAASBY values together with high ASV and WAASB indices, which points to pronounced specific adaptation and heightened responsiveness to environmental changes.

At the same time, analyses based exclusively on root yield do not provide a complete picture of the production value of sugar beet hybrids, as they neglect quality-related constraints associated with the technological suitability of raw material. For this reason, the present study additionally applied the GYT (genotype × yield × trait) concept, which allows genotypes to be evaluated using combined indices such as RY × SC and RY × low impurities, thereby minimizing the risk of selecting high-yielding hybrids at the expense of deteriorated quality parameters (Yan, 2016; Yan & Frégeau-Reid, 2018).

The GYT matrix results (Table 9) indicated that Strube Hubble and BTS 9695 exhibited the most favorable combinations for both RY × SC and RY × low impurities, demonstrating their ability to deliver high productivity without substantial technological trade-offs. In contrast, hybrids with lower values of these combinations, particularly Hilleshög Diamenta and Hilleshög Rivolta, lost competitive positions primarily due to an unfavorable balance between yield level and impurity content.

The obtained results confirm that under short-rotation cropping systems and contrasting weather conditions across years and locations, the key criterion for hybrid selection is not the maximum mean yield per se, but rather the combination of high productivity with stability and technological quality. This fully agrees with contemporary approaches to g × E analysis, in which AMMI- and BLUP-oriented methods are recommended to improve the accuracy of genotype evaluation and to ensure a correct interpretation of genotype responses to environmental variation (Taleghani et al., 2023). At the same time, it is emphasized that biplot interpretations should be supported by numerical stability indices rather than relying solely on visual patterns, as the latter may be sensitive to data structure and variance scaling (Yang et al., 2009).

Table 9. GYT matrix for the combinations RY×SC and RY×low impurities with ranking of genotypes

Genotype	RY × SC	RY × LI
Strube Hubble	**High**	**High**
BTS 9695	**High**	High
KWS Ladislava	High	Medium
Strube Frederik	Medium	Medium
Strube Raizon	Medium	High
Hilleshög Rivolta	Low	Low
Hilleshög Diamenta	Low	Low
KWS Concertina	Medium	Low

Particular attention in this study was given to the role of quality traits and impurity components as limiting factors for the realization of yield potential. The inclusion of sugar content (SC) and impurity indicators (Na^+, K^+, and α-amino N) substantially alters the selection ‘profile’ of leading genotypes, as hybrids with high root yield (RY) may lose their advantage due to elevated impurity levels, which reduce effective sugar yield and processing efficiency. In this context, the use of sugar production (SP = RY × SC / 100) and GYT-based combinations provides a more realistic representation of the actual production value of sugar beet hybrids than the analysis of yield as an isolated trait (Hassani et al., 2018; Studnicki et al., 2019).

Overall, the integrated application of ASV, WAASB, and WAASBY indices for root yield, combined with GYT analysis of RY × SC and RY × low impurities, establishes a more comprehensive and practically relevant framework for sugar beet hybrid selection. The results demonstrate that production-oriented recommendations should be based on the simultaneous evaluation of productivity, stability, and technological quality rather than on maximum mean yield alone, which is critically important under conditions of high agroecological variability.

Multi-trait stability and productivity assessment based on Y × WAASB biplots

The Y × WAASB approach was applied for an integrated assessment of productivity and stability of sugar beet hybrids across the main quantitative and quality traits, as it enables the simultaneous comparison of the mean trait value (X-axis) with the weighted average of absolute AMMI interaction principal component scores (WAASB; Y-axis), which reflects the intensity of genotype participation in genotype × environment (G × E) interaction (Fig. 1).

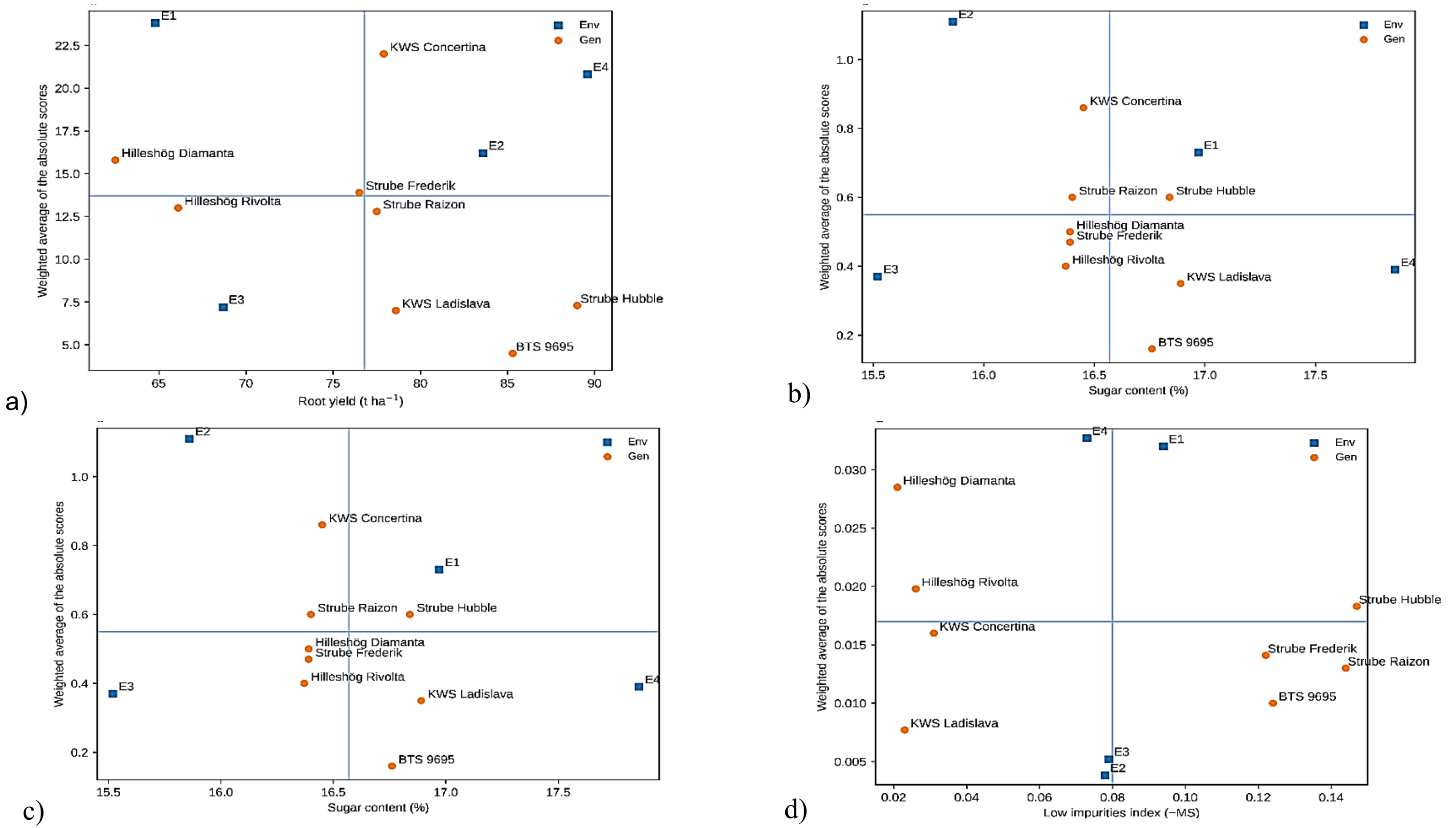

Figure 1. Y × WAASB biplots illustrating the relationship between mean performance and stability of sugar beet hybrids across four environments.
a) Y × WAASB biplot illustrating the relationship between mean root yield and stability of sugar beet hybrids across four environments; b) Y × WAASB biplot illustrating the relationship between mean sugar content and stability of sugar beet hybrids across four environments; c). Y × WAASB biplot illustrating the relationship between mean sugar production and stability of sugar beet hybrids across four environments. d) Y × WAASB biplot illustrating the relationship between mean low impurities index (−MS) and stability of sugar beet hybrids across four environments.

Conceptually, this approach represents a logical extension of AMMI-BLUP integration in multi-environment trials. Unlike conventional one-dimensional stability indices, Y × WAASB biplots clearly discriminate between genotypes exhibiting high potential but unstable performance and those combining high performance with stability, thereby providing direct practical value for production-oriented recommendations and breeding decisions (Olivoto et al., 2019).

In the biplots, the vertical and horizontal reference lines correspond to the overall mean of the trait and the mean WAASB value, respectively, thereby defining four quadrants that are interpreted according to the joint expression of trait level and stability. Lower WAASB values indicate greater stability, whereas higher WAASB values reflect a stronger, potentially specific, responsiveness of genotypes to environmental variation. This graphical framework facilitates an intuitive yet statistically grounded interpretation of genotype performance, supporting the identification of broadly adapted hybrids as well as genotypes with environment-specific advantages.

In the white sugar yield × WAASB biplot, genotypes located in the quadrant combining a high mean trait value with a low WAASB are characterized by an optimal balance between productivity and stability, as they ensure a high white sugar yield without strong dependence on contrasting year-to-year or location-specific conditions. According to the observed scatter configuration and in agreement with rankings based on integrated indices, this group includes BTS 9695, Strube Hubble, and KWS Ladislava, confirming their broad adaptability and practical suitability for deployment under production conditions characterized by high agroecological variability. In contrast, genotypes expressing high trait values together with elevated WAASB are interpreted as highly responsive types, capable of achieving superior performance primarily under favorable or technologically optimized environments. Such hybrids may be promising for intensive production systems but require more precise agroecological zoning and risk-oriented environmental management, which is consistent with established concepts of g × E analysis in applied breeding programs (Yan, 2016).

The root yield × WAASB biplot clearly differentiates hybrids according to the level of root yield and the stability of its expression. The quadrant representing high root yield combined with low WAASB includes genotypes that form the basis for stable increases in total root production across diverse environments. In the present study, this group comprises BTS 9695 and Strube Hubble, as well as Strube Frederik, which, despite a slightly lower mean yield than the leading genotype, is distinguished by reduced sensitivity to genotype × environment interaction. The opposite quadrant, characterized by low yield and high WAASB, reflects genotypes with limited practical value due to the simultaneous lack of both yield potential and predictability. The quadrant combining low WAASB with moderate or lower yield represents genotypes with relatively high ecological stability, which may be valuable in breeding programs as sources of adaptability or as ‘insurance’ options under increased environmental risk. This interpretation is methodologically consistent with the concept of selecting for stability as an independent breeding objective in multi-environment trials (Olivoto et al., 2019).

In the sugar content × WAASB biplot, the dominance of environmental effects on sugar content is reflected by a relatively wide variation in stability among genotypes. Even within a narrow range of mean sugar content values, differences in responsiveness to environmental conditions may substantially alter the technological value of the raw material. The quadrant combining high sugar content with low WAASB includes genotypes that unite elevated sucrose concentration with predictable expression of this trait; in the present study, KWS Ladislava and BTS 9695 occupy this position. This is particularly important given that sugar content represents a key determinant of sugar yield and economic efficiency in sugar beet production (Hoffmann et al., 2009). Conversely, genotypes exhibiting high sugar content together with increased WAASB should be interpreted as having a quality advantage restricted to a narrow range of optimal soil and climatic conditions, indicating a form of specific rather than broad adaptation.

The extraction coefficient of sugar × WAASB biplot has direct technological relevance, as the extraction coefficient integrates the efficiency of converting total sucrose into white sugar while accounting for impurities and molasses losses. Genotypes located in the quadrant defined by high extraction coefficient and low WAASB combine high technological suitability with stable extraction performance across environments. In this study, BTS 9695, Strube Hubble, and KWS Ladislava belong to this group, which is consistent with their strong performance based on integrated indices and productivity × quality combinations. In contrast, genotypes with elevated WAASB for the extraction coefficient indicate instability of technological traits, potentially leading to increased sugar losses in years or locations with less favorable moisture, temperature, or nitrogen regimes. Such instability represents an additional technological risk that cannot be compensated for solely by high root biomass (Jaggard et al., 1999).

The integrated interpretation of all four Y × WAASB biplots indicates that BTS 9695 is the most balanced genotype within the evaluated set, as it consistently combines high root yield, increased white sugar yield, competitive sugar content, and a stable, high extraction coefficient. A similar, albeit slightly narrower, adaptive profile is exhibited by Strube Hubble and KWS Ladislava, supporting their candidacy for production use in environments characterized by pronounced spatial and temporal variability. Overall, the results align with current perspectives on the value of WAASB-oriented approaches in multi-environment trial analysis, as they reduce risks associated with genotype × environment interaction while maintaining a strong focus on high productivity and technological quality (Olivoto et al., 2019).

CONCLUSIONS

This study demonstrates that the integrated use of the AMMI approach, stability indices (ASV, WAASB, WAASBY), and multi-trait evaluation methods (GYT-biplot) is an effective framework for in-depth analysis of genotype × environment (G×E) interaction and for selecting promising sugar beet hybrids under multi-environment conditions. This approach enables the simultaneous assessment of productivity level, stability of trait expression, and trade-offs between quantitative and qualitative characteristics.

The combined analysis of variance and AMMI modeling confirmed that the environment is the dominant source of variation for root yield (RY), sugar content (SC), and derived productivity traits, while the effects of genotype and G×E, although smaller in magnitude, were statistically significant. These results highlight the strong dependence of sugar beet performance on growing conditions and justify the use of stability-oriented criteria in breeding and hybrid evaluation.

Assessment based on ASV and WAASB revealed pronounced differences among hybrids in their response to environmental variability. BTS 9695, Strube Hubble, and KWS Ladislava combined relatively low instability indices with high mean yield, indicating broad adaptation and stable realization of yield potential. In contrast, Hilleshög Diamenta and Hilleshög Rivolta exhibited higher environmental sensitivity and lower productivity, reflecting limited adaptation.

The WAASBY index, which integrates yield and stability into a single selection criterion, provided clearer ranking of hybrids according to breeding value and further confirmed the superiority of BTS 9695, Strube Hubble, and KWS Ladislava under conditions of high agroecological variability. Multi-trait analysis incorporating sugar production and the low-impurity index (LI), based on Na^+, K^+, and α-amino N contents, revealed distinct trade-offs between yield and technological quality. The GYT-biplot effectively visualized these relationships and identified hybrids with superior trait combinations. In particular, BTS 9695 and Strube Hubble showed advantages for both RY × SC and RY × low impurities, indicating their potential to deliver high sugar output without major quality penalties.

Overall, the results confirm that no single trait is sufficient to fully describe the breeding value of sugar beet hybrids. Only the combined application of AMMI modeling, WAASB/WAASBY stability indices, and the GYT approach provides a comprehensive and practically relevant evaluation framework. From a practical perspective, BTS 9695, Strube Hubble, and KWS Ladislava can be recommended for cultivation under variable agroecological conditions of the Western Forest-Steppe, whereas less stable hybrids are more suitable for narrowly defined or environmentally stable production environments.

This study demonstrates that the integrated use of the AMMI approach, stability indices (ASV, WAASB, WAASBY), and multi-trait evaluation methods (GYT-biplot) represents a robust analytical framework not only for sugar beet cultivar selection but also for broader applications in crop breeding and agronomic research. The methodological combination applied in this work can be effectively extended to other crops where genotype × environment (G×E) interaction plays a decisive role in determining yield stability and technological quality, including cereals, oilseeds, and legumes. In particular, the joint evaluation of productivity, stability, and technological traits provides a more realistic basis for selecting genotypes adapted to increasingly variable agroecological conditions associated with climate change. From a practical perspective, the results of this study may contribute to improving current cultivar evaluation protocols by encouraging the adoption of multi-criteria analytical frameworks in breeding programs and regional variety testing. The integration of stability-oriented indices with multi-trait visualization tools allows breeders and agronomists to identify genotypes that combine high productivity with consistent performance across environments, thereby supporting more reliable cultivar recommendations and risk-aware crop management strategies in diverse agricultural systems.

REFERENCES

Agahi, K., Ahmadi, J., Oghan, H.A., Fotokian, M.H. & Orang, S.F. 2020. Analysis of genotype × environment interaction for seed yield in spring oilseed rape using the AMMI model. *Crop Breeding and Applied Biotechnology* **20**, https://doi.org/10.1590/1984-70332020v20n1a2

Bartlett, M.S. 1937. Properties of sufficiency and statistical tests. *Proceedings of the Royal Society of London. Series A* **160**, 268–282. https://doi.org/10.1098/rspa.1937.0109

Berłowska, J., Pielech-Przybylska, K., Balcerek, M., Dziekońska-Kubczak, U., Patelski, P., Dziugan, P. & Kręgiel, D. 2016. Simultaneous saccharification and fermentation of sugar beet pulp for efficient bioethanol production. *BioMed Research International* **2016**, 3154929. https://doi.org/10.1155/2016/3154929

Faheem, M., Arain, S.M., Sial, M.A., Laghari, K.A. & Qayyum, A. 2023. Genotype by yield × trait (GYT) biplot analysis: A novel approach for evaluating advance lines of durum wheat. *Cereal Research Communications* **51**, 447–456. https://doi.org/10.1007/s42976-022-00298-7

Flores, F., Moreno, M.T. & Cubero, J.I. 1998. A comparison of univariate and multivariate methods to analyze G× E interaction. *Field crops research* **56**(3), 271–286. https://doi.org/10.1016/S0378-4290(97)00095-6

Gauch, H.G., Jr. 2013. A simple protocol for AMMI analysis of yield trials. *Crop Science* **53**(5), 1860–1869. https://doi.org/10.2135/cropsci2013.04.0241

Grubbs, F.E. 1969. Procedures for detecting outlying observations in samples. *Technometrics,* **11**(1), 1–21. https://doi.org/10.1080/00401706.1969.10490657

Hassani, M., Heidari, B., Dadkhodaie, A. & Stevanato, P. 2018. Genotype by environment interaction components underlying variations in root, sugar and white sugar yield in sugar beet (Beta vulgaris L.). *Euphytica*, **214**(4), 79. https://doi.org/10.1007/s10681-018-2160-0

Hoffmann, C.M., Huijbregts, T., van Swaaij, N. & Jansen, R. 2009. Impact of different environments in Europe on yield and quality of sugar beet genotypes. *European Journal of Agronomy* **30**(1), 17–26. https://doi.org/10.1016/j.eja.2008.06.004

Jaggard, K.W., Clark, C.J.A. & Draycott, A.P. 1999. The weight and processing quality of components of the storage roots of sugar beet (*Beta vulgaris* L.). *Journal of the Science of Food and Agriculture* **79**(11), 1389–1398. https://doi.org/10.1002/(SICI)1097-0010(199908)79:11%3C1389:AID-JSFA377%3E3.0.CO;2-B

Kühnel, S., Schols, H.A. & Gruppen, H. 2011. Aiming for the complete utilization of sugar-beet pulp: Examination of the effects of mild acid and hydrothermal pretreatment followed by enzymatic digestion. *Biotechnology for Biofuels* **4**, 14. https://doi.org/10.1186/1754-6834-4-14

Kunz, M., Martin, D. & Puke, H. 2002. Precision of beet analyses in Germany explained for polarization. *Zuckerindustrie* **127**, 13–21.

Li, W., Yan, Z.-H., Wei, Y.-M., Lan, X.-J. & Zheng, Y.-L. 2006. Evaluation of genotype × environment interactions in Chinese spring wheat by the AMMI model, correlation and path analysis. *Journal of Agronomy and Crop Science* **192**, 221–227. https://doi.org/10.1111/j.1439-037X.2006.00200.x

Martínez-Arias, R., Müller, B.U. & Schechert, A. 2017. Near-infrared determination of total soluble nitrogen and betaine in sugar beet. *Sugar Tech*. **19**, 526–531. https://doi.org/10.1007/s12355-016-0496-0

Muir, B.M. 2022. Sugar beet processing to sugars. In *Sugar beet cultivation, management and processing* (pp. 837–862). Singapore: Springer Nature Singapore.

Nataraj, V., Bhartiya, A., Singh, C.P., Devi, H.N., Deshmukh, M.P., Verghese, P., ... & Gupta, S. 2021. WAASB-based stability analysis and simultaneous selection for grain yield and early maturity in soybean. *Agronomy Journal* **113**(4), 3089–3099. https://doi.org/10.1002/agj2.20750

Olivoto, T., Lúcio, A.D., da Silva, J.A.G., Sari, B.G. & Diel, M.I. 2019. Mean performance and stability in multi-environment trials I: Combining features of AMMI and BLUP techniques. *Agronomy Journal* **111**(6), 2949–2960. https://doi.org/10.2134/agronj2019.03.0220

Piepho, H.-P. 1994. Best linear unbiased prediction (BLUP) for regional yield trials: A comparison to additive main effects and multiplicative interaction (AMMI) analysis. *Theoretical and Applied Genetics* **89**, 647–654. https://doi.org/10.1007/BF00222462

Piepho, H.-P., Möhring, J., Melchinger, A.E. & Büchse, A. 2008. BLUP for phenotypic selection in plant breeding and variety testing. *Euphytica,* **161**, 209–228. https://doi.org/10.1007/s10681-007-9449-8

Purchase, J.L., Hatting, H. & van Deventer, C.S. 2000. Genotype × environment interaction of winter wheat in South Africa: II. Stability analysis of yield performance. *South African Journal of Plant and Soil* **17**(3), 101–107. https://doi.org/10.1080/02571862.2000.10634878

Rajabi, A., Ahmadi, M., Bazrafshan, M., Hassani, M. & Saremirad, A. 2023. Evaluation of resistance and determination of stability of different sugar beet genotypes in rhizomania-infected conditions. *Food Science & Nutrition* **11**, 1403–1414. https://doi.org/10.1002/fsn3.3180

Sedgwick, P. 2012. Pearson's Correlation Coefficient. *BMJ* **345**, e4483-e4483. https://doi.org/10.1136/bmj.e4483

Studnicki, M., Lenartowicz, T., Noras, K., Wójcik-Gront, E. & Wyszyński, Z. 2019. Assessment of stability and adaptation patterns of white sugar yield from sugar beet cultivars in temperate climate environments. *Agronomy* **9**(7), 405. https://doi.org/10.3390/agronomy9070405

Taleghani, D., Rajabi, A., Saremirad, A. & Fasahat, P. 2023. Stability analysis and selection of sugar beet genotypes using AMMI, BLUP, GGE biplot and MTSI. *Scientific Reports* **13**, 10019. https://doi.org/10.1038/s41598-023-37217-7

Yan, W. 2016. Analysis and handling of g × E in a practical breeding program. *Crop Science,* **56**(5), 2106–2118. https://doi.org/10.2135/cropsci2015.06.0336

Yan, W. & Frégeau-Reid, J. 2018. Genotype by yield × trait (GYT) biplot: A novel approach for genotype selection based on multiple traits. *Scientific Reports* **8**, 8242. https://doi.org/10.1038/s41598-018-26688-8

Yan, W., Kang, M.S., Ma, B., Woods, S. & Cornelius, P.L. 2007. GGE biplot vs. AMMI analysis of genotype-by-environment data. *Crop Science* **47**(2), 643–653. https://doi.org/10.2135/cropsci2006.06.0374

Yang, R.C., Crossa, J., Cornelius, P.L. & Burgueño, J. 2009. Biplot analysis of genotype × environment interaction: Proceed with caution. *Crop Science* **49**(5), 1564–1576. https://doi.org/10.2135/cropsci2008.11.0665