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Assessing temporal variability in durum wheat performance and stability through multi-trait mean performance selection in Mediterranean climate

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Durum wheat, a staple crop in Italy, faces substantial challenges due to increasing droughts and rising temperatures. This study examines the grain yield, agronomic traits, and quality of 41 durum wheat varieties over ten growing seasons in Southern Italy, utilizing a randomized complete block design. Notably, most varieties were not repeated between trials and 45% of the data was missing. The results indicate that the interaction between genotype and environment (GEI) significantly impacted all traits. High temperatures, elevated vapor pressure deficit (VPD), and water deficits severely affected yield and quality during warm years, while cooler years with favorable water availability promoted better growth and higher yields. Broad-sense heritability (H^2) was generally low, suggesting that environmental factors played a major role in the observed traits. However, some traits, such as grain yield, ears per square meter, plant height, bleached wheat, thousand-grain weight, and hectoliter weight exhibited moderate to high heritability of the mean genotype (h^2_{mg}), indicating their potential for effective selection in breeding programs. Correlation analyses revealed strong connections between certain traits, such as protein content, and gluten index as well as between grain yield, and spike per square meter. Using the Multi-Trait Mean Performance Selection (MTMPS) index, the study identified six top-performing varieties. Among these, Antalis (G4) and Core (G18) consistently demonstrated strong adaptability and stability across different environments, particularly in hotter, drier conditions. Furio Camillo (G31) also exhibited valuable traits. This study highlights the challenges and complexities of breeding durum wheat for improved yield and quality in the face of climate change.

KEYWORDS

durum wheat, genotype by environment interaction, mixed model, MTMPS, unbalanced data

1 Introduction

Durum wheat (*Triticum turgidum* L.subsp. *durum* (Desf.) Husn.) is one of the most vital cereal crops globally, serving as a staple food that provides essential nutrients to a significant portion of the world's population. In the 2022/23 season, global durum wheat production was projected to rise by 10% to 33.9 million metric tons (MMT), driven by significant contributions from North American countries such as the United States, Canada, and Mexico (Euronext, 2023). However, this increase was not uniform across all regions. While North America experienced favorable production levels, Europe – especially Spain and France – and North Africa faced declines due to adverse weather conditions, with the European Union's production forecasted to drop to historically low levels (Euronext, 2023). Italy, the largest producer of durum wheat in Europe, has averaged around 4.26 million tons annually over the past decade. Despite this strong production history, Italy's durum wheat output was estimated to decrease by 8% to 3.5 MMT in 2023/24 due to severe drought conditions (Italianfood, 2024). This shortfall has necessitated increased imports, particularly from the United States, to meet domestic demand. Durum wheat holds a prominent place in Italian agriculture due to its economic importance and cultural value. It is a key ingredient in traditional Italian cuisine, particularly as the exclusive raw material for pasta production – a main component of the Mediterranean diet, which has gained increasing global appreciation (Viggiani, 2009; Bux et al., 2022). The growing consumption of pasta has transformed it into a significant export product and a major symbol of the “Made in Italy” brand (Nicola and Scaccia, 2021; Boncinelli et al., 2023).

The Mediterranean climate of Southern Italy, characterized by hot, dry summers and mild, wet winters, is conducive to durum wheat cultivation. However, this climate is also highly variable, with recent trends indicating rising temperatures and shifting precipitation patterns, posing challenges to wheat yields and quality (Tataw et al., 2016; Carucci et al., 2023; Bonfil et al., 2023).

Climate change has various effects on wheat plant breeding by inducing heat stress, drought, and elevated CO₂ levels. These factors lead to reduced grain quality, altered phenology, and decreased yield potential. Heat stress during the reproductive phase causes morphophysiological alterations, biochemical disruptions, and a reduction in the genetic potential of wheat (Kumar et al., 2017; Bishwas et al., 2021; Farhad et al., 2023). Moreover, drought and heat stress increase phytate contents, limiting essential mineral bioavailability, while elevated CO₂ concentrations and other climatic events alter grain quality components and composition (Zahra et al., 2022). Rising temperatures and increased aridity also affect wheat phenological development by shortening the life cycle and impacting gluten accumulation, ultimately influencing grain quality (Elahi et al., 2022).

It is crucial to develop heat-tolerant wheat varieties and improve crop management practices to mitigate these adverse effects (Khalid et al., 2022). Achieving this requires a comprehensive understanding of GEI and the application of advanced breeding techniques that incorporate climate resilience traits. Scholars such as Mehmet et al. (2011); Karaman et al. (2023)

and Ninou et al. (2024) have documented significant GEI for grain yield in wheat, highlighting the importance of understanding these interactions to optimize wheat breeding strategies and enhance yield stability and adaptability across diverse environments.

Evaluating GEI is particularly critical on a smaller scale, where the goal is to select varieties that not only perform consistently across multiple years but are also uniquely adapted to their specific local environments (Hanif et al., 2021; Kunze et al., 2024). A significant challenge in utilizing multiyear data is the inherent imbalance, as underperforming varieties are often excluded from further evaluation while promising ones continue to be assessed (Yan, 2015; Lado et al., 2016; Bernardo, 2020). This imbalance complicates analysis, necessitating the use of robust statistical methods to accurately interpret data and make informed breeding decisions.

Several statistical models have been developed to estimate genotype-environment interactions (GEI) in multi-environment trials (METs), with the additive main effects and multiplicative interaction (AMMI) model and the genotype main effects + genotype × environment interaction effects (GGE) model being particularly prominent (Scavo et al., 2023). The AMMI model combines additive main effects for genotypes and environments with multiplicative terms for G×E interaction, allowing for a comprehensive analysis of both main effects and interactions (Bishwas et al., 2021; Etana and Merga, 2021). The GGE model, on the other hand, focuses on genotype and G×E effects together, removing the environment main effects to emphasize genotype performance and stability across environments (Olanrewaju et al., 2021). Both models utilize biplot visualization techniques to aid in the interpretation of complex GEI patterns. Additionally, mixed model approaches using restricted maximum likelihood/best linear unbiased prediction (REML/BLUP) have gained traction for their ability to handle unbalanced data and incorporate pedigree information (Rout et al., 2022; Sugawara and Kubokawa, 2023). These powerful methodologies are widely employed in plant breeding programs to estimate genetic parameters, predict genotypic values, and select superior genotypes for further cultivation (Lanna et al., 2022; Tajalifar and Rasooli, 2022; Costa et al., 2023). The choice between these models often depends on the specific research objectives and the nature of the data, with some researchers opting to use multiple approaches complementarily to gain a more comprehensive understanding of GEI patterns.

Traditional breeding programs often focused on single traits, primarily yield. However, this approach can lead to unexpected problems such as increased susceptibility to diseases or reduced quality traits. Multi-trait selection, which considers a suite of desirable traits, offers a more holistic approach. This method aims to balance yield with other critical traits such as disease resistance, drought tolerance, and grain quality (Arnold, 2023). Integrating multi-trait selection into breeding programs can lead to the development of more resilient and high-performing wheat varieties.

The multi-trait mean performance and stability index (MTMPS) proposed by Olivoto et al. (2021) is a valuable tool in plant breeding for identifying genotypes with consistent performance across multiple environments. This index uses factor analysis to assess each ideotype's scores, considering

both desirable and undesirable traits. By computing the Euclidean distance between accessions and the ideotype, a spatial probability is derived, facilitating accession ranking. Varieties with the lowest MTMPS values are closer to the ideotype, indicating superior mean performance and stability across all analyzed variables (Olivoto et al., 2019).

Optimizing multi-trait selection indices allows breeders to address trade-offs between traits like grain yield and protein content, as well as combine traits of interest like yield and weed competitive ability. This approach can lead to continued genetic gain while maintaining genetic diversity in wheat populations (Silva et al., 2023). Additionally, including drought-tolerance indices in multi-trait selection strategies has been shown to provide superior gains in grain yield under stress conditions, emphasizing the importance of considering multiple traits in wheat breeding to enhance resilience to environmental challenges.

Therefore, this study aims to: (i) evaluate the GEI in wheat varieties across multiple traits, and (ii) identify superior varieties that demonstrate high performance and genotypic stability in Southern Italy under diverse environmental conditions, utilizing the MTMPS index.

This study adds significant value to the existing body of knowledge by employing advanced statistical techniques, addressing the complexities of long-term and unbalanced datasets, and providing a comprehensive multi-trait evaluation of durum wheat performance under Mediterranean climatic conditions. These contributions highlight the importance of multi-environment trials and advanced selection indices in breeding programs, offering practical insights for enhancing durum wheat resilience and productivity.

2 Materials and methods

2.1 Experimental site

A field screening experiment was conducted over ten years (2013–2022) at the experimental research station of the Department of Agriculture, University of Naples Federico II, located in Sant'Angelo dei Lombardi (40°55'12.0"N, 15°07'12.0"E, 667 m above sea level). This rural site, situated in the foothills of the Apennine Mountain range in the province of Avellino, southern Italy, experiences a warm-summer Mediterranean climate (Csb) as per the Köppen-Geiger classification (Beck et al., 2018). Utilizing 43 years of daily climatic data from the NASA-Power project (<https://power.larc.nasa.gov/>) covering the period from 1981 to 2023, this region displays an average daily temperature of 14.02°C ($\pm 0.60^\circ\text{C}$) and an average annual precipitation of 572.36 mm (± 119.38 mm). The soil in this area is predominantly clay loam in texture (clay, sand, and silt: 38.8%, 36.9%, and 24.3%, respectively). The chemical and physical characteristics of the soil at the beginning of the experiment at 0.20 m of soil depth were as follows: pH 8.07, Kjeldahl total nitrogen 0.97 g kg⁻¹, phosphorus pentoxide (P₂O₅: Olsen method) 14.4 mg kg⁻¹, and soil organic matter (SOM) content of 1.16%.

2.2 Climate influence assessment

The daily key weather parameters for each wheat growing season at the Sant'Angelo dei Lombardi location, including, precipitation, relative humidity, air temperature, and solar radiation, along with 11 additional climatic variables (Table 1), were obtained from the NASA-Power project (<https://power.larc.nasa.gov/>). The weather regime, including monthly precipitation (P) and minimum and maximum temperatures (Tmin and Tmax) for the ten growing seasons, is detailed in Supplementary Table S1. These data are compared against the historical means from 1981 to 2023. To precisely reflect the temporal dynamics of environmental conditions throughout crop development, the crop cycles were segmented into five main phenological stages based on days after sowing (DAS): 0 to 21 days (Emergence), 22 to 110 days (Tillering), 111 to 140 days (Jointing), 141 to 184 days (Heading), and 185 to 217 days (Maturity). These intervals were determined through field observations of various wheat varieties grown in Sant'Angelo dei Lombardi over ten growing seasons. This approach resulted in the generation of 900 combinations of environmental covariates (18 weather parameters) across growing seasons (10 years) and main phenological stages (5 time periods), providing a comprehensive dataset for analyzing climate impacts on wheat development.

TABLE 1 Weather variables analyzed in this study.

Weather parameter	Abbreviation	Unit	Method
Daylight hours	N	hour	Estimated ⁽¹⁾
Actual duration of sunshine	n	hour	
Thermal infrared (longwave) radiative flux	DTIRF	MJ m ⁻² day ⁻¹	
All sky insolation incident on a horizontal surface	SIHS	MJ m ⁻² day ⁻¹	
Wind speed_2 m	WS	m s ⁻¹	
Maximum air temperature_2 m	Tmax	°C day ⁻¹	
Minimum air temperature_2 m	Tmin	°C day ⁻¹	
Mean temperature	Tmed	°C day ⁻¹	
Relative air humidity_2 m	RH	%	
Precipitation	PRECTOT	mm day ⁻¹	
Dew-point temperature_2 m	T2MDew	°C day ⁻¹	Computed ⁽²⁾
Deficit by precipitation	PETP	mm day ⁻¹	
Effect of temperature on radiation use efficiency	FRUE	(from 0 to 1)	
Growing degree day	GDD	°C day ⁻¹	
Global solar radiation based on latitude and Julian day	RTA	MJ m ⁻² day ⁻¹	
Vapor pressure deficit	VPD	kPa day ⁻¹	
Evapotranspiration	ETP	mm day ⁻¹	

⁽¹⁾ The data was estimated from NASA orbital sensors, as described in Sparks (2018). ⁽²⁾ The data was processed using methods building on the work of Allen et al. (1998) and Soltani and Sinclair (2012).

2.3 Agronomic management and experimental design

Eight-nine varieties were investigated. These varieties were certified by ENSE (Ente Nazionale Sementi Elette) and registered in either the national or community variety registry. Forty-eight varieties tested for less than three years were excluded from the analysis, leaving 41 varieties for genotype-by-environment interaction assessment. Not all varieties were evaluated every year, just 5 varieties were shared between all years (Figure 1). Consequently, the dataset is highly unbalanced, with 45% of the data missing. Comprehensive genealogy records, crop cycles, and breeding institutions for all 41 durum wheat varieties are detailed in Supplementary Table S2. Each year, a set of 23 ± 3 varieties was evaluated, ensuring that at least five varieties were common across all years (Figure 1). The trials were implemented using an experimental block design (RCBD), wherein varieties were randomized across the plots and replicated three times. The size of the plots was 5 m × 2 m. Sowing density was standardized at 400 grains per square meter for each variety. All varieties were grown under rainfed conditions. Each year, broad beans served as the preceding crop for wheat. Prior to sowing, phosphorus (P) and potassium (K) were applied in the form of superphosphate and potassium sulfate, respectively, at a rate of 100 kg ha⁻¹. The specific amounts of nitrogen applied as urea, as well as the sowing and harvest dates, are detailed in Table 2.

2.4 Phenotypic and quality traits

At harvest, a 1 square meter subplot in the center of each plot was hand-harvested to determine nine phenotypic and quality traits: 1) grain yield (GY), adjusting the moisture to 13% and converting the unit to tons per hectare (t ha⁻¹), 2) plant height (Alt), measured using a graduated scale from ground level to the tip of the tallest spikelet and is expressed in meters (m), 3) Thousand-grain weight (TGW), is expressed in gram (g), 4) number of ears per square meter (Sp, num m⁻²), 5) hectoliter weight (Pe) was determined according to the AACC method 55-10.01 (Cereals

and Grains Association, 2024) and reported in kilograms per hectoliter (kg/hL), 6) crude protein concentration (Pro), determined using the Kjeldahl method according to AACC 46-10.01 (Cereals and Grains Association, 2024). The Jones factor was used to convert it to protein (6.25) (Mariotti et al., 2008) and expressed in percentage (%), 7) gluten index value (Glu), analyzed according to AACC 38-12.02 (Cereals and Grains Association, 2024), and expressed in percentage (%), 8) shriveled wheat grain (Cs), referring to grain that is underdeveloped, small, and often misshapen expressed in percentage (%), and 9) bleached wheat grain (Cb), referring to wheat grain that has been exposed to environmental conditions causing them to lose their natural color, resulting in a paler, often whitish appearance, expressed in percentage (%).

2.5 Statistical analysis

2.5.1 Climatic impact on crop development

Principal component analysis (PCA) using the correlation matrix was employed to elucidate the characteristics of each of the ten consecutive growing seasons in relation to their associated environmental variables. These variables were collected using the 'get_weather()' function from the R package EnvRtype (Costa-Neto et al., 2021). The PCA was conducted with the software packages FactoMineR (Husson et al., 2014) and psych (Revelle, 2024) within the RStudio environment (R Core Team, 2013). Hierarchical cluster analysis (HCA) was also performed using the 'pheatmap' package (Kolde, 2019) in RStudio. This analysis utilized a single linkage approach and Euclidean distances to determine the similarities between the ten growing seasons. For a more detailed analysis of the climate data throughout the study duration, we utilized the env_typing() function from the EnvRtype package (Costa-Neto et al., 2021) to establish environmental patterns using quantile thresholds of 18 environmental covariates collected from sowing to harvest each growing season. Frequency distributions for each year and main phenological stage combination were computed using the 0.25, 0.50, and 0.75 quantiles. This approach facilitated the identification of extreme values for each environmental variable.

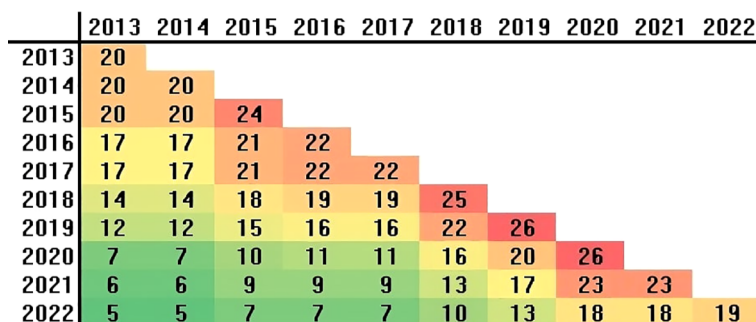


FIGURE 1

Connectivity of wheat varieties, measured by the number of shared varieties between years (below diagonal) and the total number of varieties per year (diagonal).

TABLE 2 Sowing date, harvesting, crop cycle and number of varieties, as well as amounts of nitrogen at the experimental site.

Cropping season	Code	Sowing	Harvesting	Crop cycle	No. Varieties	Nitrogen fertilization		
						Sowing	I coverage	II coverage
2013–2014	Y_13	31/10/2013	08/07/2014	250	20	30 kg (10/2013)	40 kg (02/2014)	40 kg (04/2014)
2014–2015	Y_14	14/11/2014	06/07/2015	234	20		80 kg (04/2015)	40 kg (05/2015)
2015–2016	Y_15	10/11/2015	10/07/2016	243	24		80 kg (04/2016)	40 kg (06/2016)
2016–2017	Y_16	22/11/2016	10/07/2017	230	22		80 kg (04/2017)	40 kg (05/2017)
2017–2018	Y_17	03/11/2017	18/07/2018	257	22		80 kg (04/2018)	40 kg (05/2018)
2018–2019	Y_18	23/11/2018	22/07/2019	241	25		80 kg (03/2019)	40 kg (04/2019)
2019–2020	Y_19	04/12/2019	14/07/2020	223	26		80 kg (03/2020)	
2020–2021	Y_20	10/11/2020	09/07/2021	241	26		80 kg (03/2021)	
2021–2022	Y_21	22/12/2021	22/07/2022	212	23		80 kg (03/2022)	40 kg (05/2022)
2022–2023	Y_22	23/12/2022	14/07/2023	203	19		80 kg (03/2023)	40 kg (04/2023)

2.5.2 Variance estimation with random effects model

A comprehensive evaluation was conducted on 41 durum wheat varieties to estimate variance components and predict genotypic values along with genotype-by-environment interactions (GEI). The random model applied in this analysis was as follows:

$$y_{ijk} = \mu + G_i + Y_j + GY_{ij} + \beta_{jk} + \epsilon_{ijk} \quad (1)$$

where y_{ijk} is the response variable (e.g., grain yield) observed in the k^{th} block of the i^{th} genotype in the j^{th} year ($i = 1, 2, \dots, g; j = 1, 2, \dots, e; k = 1, 2, \dots, b$); μ is the general mean; G_i is the random effect of the i^{th} genotype; Y_j is the random effect of the j^{th} year; GY_{ij} is the random interaction effect of the i^{th} genotype with the j^{th} year; β_{jk} is the random effect of the k^{th} replicate within the j^{th} environment; and ϵ_{ijk} is the random error.

The Restricted Maximum Likelihood (REML) method (Dempster et al., 1977) was employed for variance component analysis. The significance of the random effects was evaluated using the likelihood ratio test (LRT). This test compares -2 times the residual log-likelihood ($-2(REG)log$) of two models: one model contains all the random effects, whereas the other model omits a single random effect. Additionally, four heritability estimates were obtained to assess the genetic contribution to observed phenotypic variance. These estimates include:

Broad-sense heritability (H^2), which is the ratio of genetic variance to total phenotypic variance, indicates the proportion of observed variation in a trait that is due to genetic factors:

$$H^2 = \frac{\sigma_G^2}{\sigma_P^2}$$

where: σ_G^2 is the genetic variance, representing the portion of phenotypic variance attributed to genetic differences among individuals. σ_P^2 is the total phenotypic variance, which includes both genetic and environmental variance (σ_E^2).

Heritability of mean genotype (h^{2gm}), also known as the broad-sense heritability for the mean genotype, can be calculated using the formula:

$$h_{mg}^2 = \sigma_g^2 / [\sigma_g^2 + \sigma_{gxe}^2/e + \sigma_e^2/(eb)]$$

where e and b are the numbers of environments and blocks, respectively.

Heritability of Cullis et al. (2006) is a robust methodology for estimating heritability in the presence of unbalanced data and can be calculated using the formula:

$$H_{cullis}^2 = 1 - \frac{\Delta BLUP}{2\sigma_g^2}$$

where $\Delta BLUP$ is the mean standard error of the genotype BLUPs and Heritability of Piepho and Möhring (2007) is a robust methodology for estimating heritability in the presence of unbalanced data and can be calculated using the formula:

$$H_{Piepho}^2 = \frac{\sigma_g^2}{\sigma_g^2 + \bar{v}/2}$$

where \bar{v} is the mean variance of a difference of two best linear unbiased estimators (BLUE).

The REML/BLUP methodology was conducted using the metan package in RStudio (R Core Team, 2013), employing the functions gamem_met() (Olivoto and Lúcio, 2020). Heritability estimates were determined using the H2cal() function from the inti package (Lozano-Isla, 2021).

2.5.3 Mean performance and stability analyses

Durum wheat varieties were ranked using the Mean Performance and Stability (MPS) method for an individual trait across varying environments, which incorporates a linear mixed-effects model (LMM) structure to offer innovative graphical insights for concurrent selection. In this investigation, this method evaluates genotype-by-environment interactions (GEI) employing the stability approach proposed by Eberhart and Russell (1966), which is particularly effective for analyzing unbalanced data (Pour-Aboughadareh et al., 2022). According to Sampaio Filho et al. (2023), performance and stability were assessed using the

Weighted Average Absolute Scores of BLUPs (WAASB) method, with stability adjustments considering genotypic stability of deviations from regression (S^2_{di}), the root mean square error of the regression (RMSE), and the coefficient of determination (R^2). The main goal here is to rank different genotypes based on their stability and performance in terms of one specific trait, such as yield, protein content, or any other trait of interest, which limits its application when multiple traits need to be considered simultaneously. Before calculating the MPS index, we adjusted (rescaled) the agronomic performance and stability matrix so they could be easily compared using the following model:

For agronomic performance:

$$rY_i = \frac{nmax - nmin}{Ymax - Ymin} \times (Y_i - Ymax) + nmax$$

For the stability index:

$$rER_i = \frac{nmax - nmin}{ERmax - ERmin} \times (ER_i - ERmax) + nmax$$

where $nmax$ and $nmin$ are the new maximum and minimum values of the variables and the MPS index (S^2_{di} , RMSE, and R^2) after rescaling; Y_i and ER_i are the original values for the response variable and MPS index of the genotype i , respectively.

For the S^2_{di} and RMSE indices, genotypes with values of zero for both were ranked as the most stable. To adjust the environmental index, $ERmax$ was set to 0 and $ERmin$ to 100. On the other hand, for the R^2 parameter, genotypes with R^2 values close to 1 were considered well-adapted, so the values were set to $Ymax = ERmax = 100$ and $Ymin = ERmin = 0$. As a result, a genotype with the highest average and highest R^2 would receive $rY_i = rER_i = 100$. An exception applies to the "Alt," "Cb," and "Cs" traits, where smaller values are better, so $Ymax = 0$ and $Ymin = 100$ for these traits.

After adjusting the values for mean performance \bar{Y}_i and stability (ER_i), the best-performing genotype was given a score of 100, while the worst-performing one received a score of 0. Likewise, the genotype with the most stability was also scored 100, and the least stable genotype received a score of 0. This created a two-way table with scores ranging from 0 to 100 across the columns, matching the direction of the selection process. After that, the MPS was computed using this formula:

$$MPS_i = \frac{(rY_i \times \theta_Y) + (rER_i \times \theta_S)}{\theta_Y + \theta_S}$$

where MPS_i refers to the superiority index for genotype i , which weights between mean performance and stability; the values θ_Y and θ_S represent the weights for mean performance and stability, respectively; the terms rY_i and rER_i are the rescaled values for mean performance \bar{Y}_i and stability (ER_i), respectively of the genotype i . In this context, we used $\theta_Y = 70$ and $\theta_S = 30$ to give more importance to mean performance at the MTMPS index.

Next, the MTMPS index was used to calculate the mean performance and stability of multiple traits. The MTMPS index extends the MPS approach by integrating multiple traits into the stability analysis. This index provides a more holistic evaluation of genotypes compared to the single-trait MPS approach. This approach is based on factor analysis and ideotype design, where

the factorial scores of each ideotype are designed according to the desirable and undesirable factors. Then, a spatial probability is estimated based on genotype-ideotype distance, enabling genotype ranking. The results allowed for conducting a single and straightforward selection process of durum wheat varieties. The MTMPS index was computed using this model:

$$MTMPS_i = \left[\sum_{j=1}^f (F_{ij} - F_j)^2 \right]^{0.5}$$

The $MTMPS_i$ refers to the multi-trait stability index for each genotype, while F_{ij} is the j -th score for the i -th genotype, with i ranging from 1 to g (the total number of genotypes) and j ranging from 1 to f (the number of factors). F_j represents the j -th score of the ideal genotype. This approach aimed to identify varieties with superior values (positive gains) for grain yield (GY), thousand-grain weight (TGW), spike number (Sp), plant height (Pe), protein content (Pro), and gluten content (Glu). Consequently, the variety with the lowest MTMPS score is considered closest to the ideotype, demonstrating high performance and stability in all measured traits. Additionally, the study calculated the selection differential ($\Delta S\%$) for the chosen varieties, assuming a selection intensity of 15%. The calculation used the formula:

$$\Delta S\% = (X_S - X_0) / X_0 \times 100$$

where X_S is the value of the selected genotypes and X_0 is the average value of the population. We employed the `mgs()` and `mtmps()` functions from the `metan` package (Olivoto and Lúcio, 2020) in RStudio (R Core Team, 2013) to perform this analysis.

3 Results

3.1 Climatic impact on crop development

Figure 2 provides a comprehensive multivariate analysis of weather parameters and wheat traits over several years. The first two principal components (Dims), which have eigenvalues greater than one, account for 88.58% of the total variance after varimax rotation. Dim1 explains 59.24% of the variance, while Dim2 accounts for 29.34% (Figure 2A). Dim1 is positively correlated (>0.5) with most major weather parameters except for precipitation (PRECTOT), wind speed (WS), and dew-point temperature (T2MDEW), which are positively correlated with Dim2 (Supplementary Table S3). This analysis highlights significant climatic variability between growing seasons. A positive correlation was identified among minimum temperature (Tmin), fraction of radiation use efficiency (FRUE), vapor pressure deficit (VPD), maximum temperature (Tmax), mean temperature (Tmed), growing degree days (GDD), evapotranspiration (ETP), sunshine duration (N), and radiation at the top of the atmosphere (RTA). Conversely, these climate parameters showed a negative correlation with total precipitation (PRECTOT), precipitation deficit (PETP), and relative humidity (RH) (Supplementary Table S4).

Based on the hierarchical cluster analysis of 17 weather parameters, four distinct groups of growing seasons were identified, each

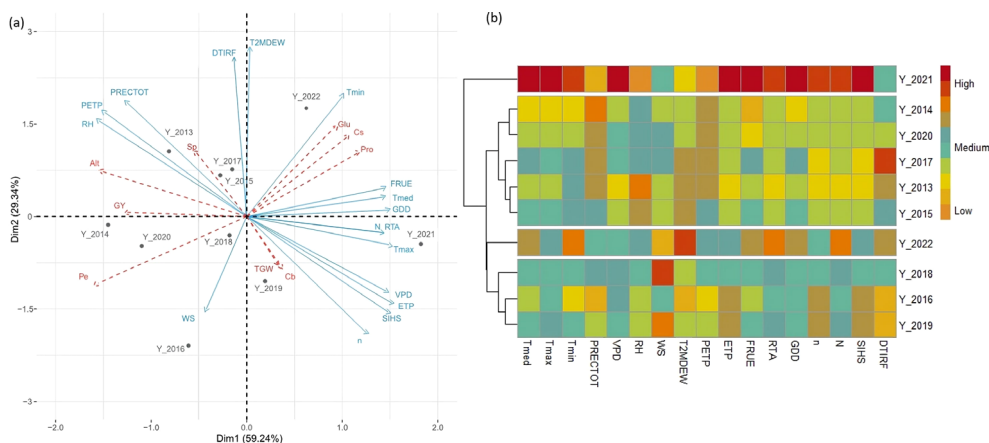


FIGURE 2 (A) Principal component analysis (PCA) biplot of weather parameters as a function of cropping seasons. Principal variables are indicated by blue arrows, while supplementary variables (morphologic and quality traits) are represented by dotted red arrows. For weather parameter abbreviations, refer to [Table 1](#). Key traits include: GY, grain yield; Alt, plant height; TGW, 1000-grain weight; Sp, number of ears per square meter; Pe, hectoliter weight; Pro, crude protein concentration; Glu, gluten index value; Cs, shriveled wheat grain; and Cb, bleached wheat grain. (B) Heat map showing the similarity between ten consecutive cropping seasons (2013–2014 to 2022–2023) based on 17 environmental covariates.

characterized by specific climatic conditions ([Figure 2B](#)). Group 1 (Y_2021) is marked by high values for most weather parameters, including maximum and minimum temperatures (Tmax, Tmin), average temperature (Tmed), vapor pressure deficit (VPD), evapotranspiration (ETP), fractional radiation use efficiency (FRUE), radiation absorption (RTA), growing degree days (GDD), daylight hours (N), actual duration of sunshine (n), and insolation incident (SIHS), further signifying very warm and dry conditions. Group 2, comprising the seasons Y_2014, Y_2020, Y_2017, Y_2013, and Y_2015, shows lower temperatures and higher precipitation (PRECTOT), relative humidity (RH), and a precipitation deficit (PETP), suggesting a cooler environment with favourable water availability. Group 3 (Y_2022) is distinguished by high values for dew-point temperature (T2MDew), the effect of temperature on radiation use efficiency (FRUE), sunshine duration (N), radiation at the top of the atmosphere (RTA), Growing Degree Day (GDD), minimum and mean temperatures (Tmin, Tmed), and thermal infrared (longwave) radiative flux (DTIRF). These high values indicate a warm environment during this growing season. Finally, Group 4 (Y_2018, Y_2019, Y_2016) is characterized by higher wind speed (WS), evapotranspiration (ETP), sunshine duration (N), and insolation incident (SIHS), along with moderate temperatures, precipitation, and humidity, delineating an intermediate environment.

During the warm years (2021 and 2022), higher vapor pressure deficit (VPD) values were frequently observed, particularly during the heading and maturity stages, with the maximum VPD reaching 2.83 kPa day⁻¹ ([Figure 3A](#)). High values of maximum temperature (Tmax) ranging from 22.4°C to 35.9°C were evident during almost the entire heading and maturity stages ([Figure 3C](#)). Both high VPD and Tmax values, causing heat and drought stress, can impair photosynthesis, reduce pollen viability, decrease grain setting, and ultimately impact yield. The precipitation deficit (PETP) data during these years show notable deficits, with values ranging from -13.9 to -9.35 mm day⁻¹ observed on approximately more than 80% of the days during the heading and maturity stages ([Figure 3B](#)).

This exacerbates the effect of both heat and drought stress, and consequently reducing grain yield.

In contrast, cooler years (2013, 2014, 2015, 2017, and 2020) exhibited lower VPD and Tmax values during almost 80% of the heading stage, with values ranging from 0.38 to 0.82 kPa day⁻¹ and 15.5 to 22.4°C, respectively ([Figures 3A, C](#)). This suggests reduced stress from high temperatures and dry air. These conditions are more conducive to optimal plant development and grain filling. Additionally, in these years, PETP values ranging from -1.83 to 13.4 mm day⁻¹ were displayed on 13% of days during the heading and maturity stages, indicating a certain availability of water in these two critical phenological stages ([Figure 3B](#)). Higher relative humidity (RH) observed during the cooler years, particularly at the emergence and tillering stages, showed maximum frequency distributions between 78.7% and 95.8% ([Figure 3D](#)), which can foster better early growth and establishment.

3.2 Variance estimation with random effects model

The likelihood-ratio test (LRT) revealed that only six durum wheat traits (GY, Sp, TGW, Alt, Pe, and Cb) had significant effects of environment, genotype, and genotype by environment interaction effects ([Table 3](#)). Additionally, all traits, except gluten, grain protein, and shriveled wheat grain, showed significant genotypic effects ([Table 3](#)). The genotype × environment interaction was significant for all traits, demonstrating the varying responses of different varieties to distinct growing seasons ([Table 3](#)).

In the analysis of durum wheat traits, it was observed that, with the exception of gluten index, grain protein content, and shriveled wheat grain, the environmental variance (σ_e^2) contributed substantially more to the total phenotypic variance (σ^2P) than any other traits examined ([Figure 4](#)). The genotype-by-environment interaction (GEI) variance was stronger on shriveled wheat grain

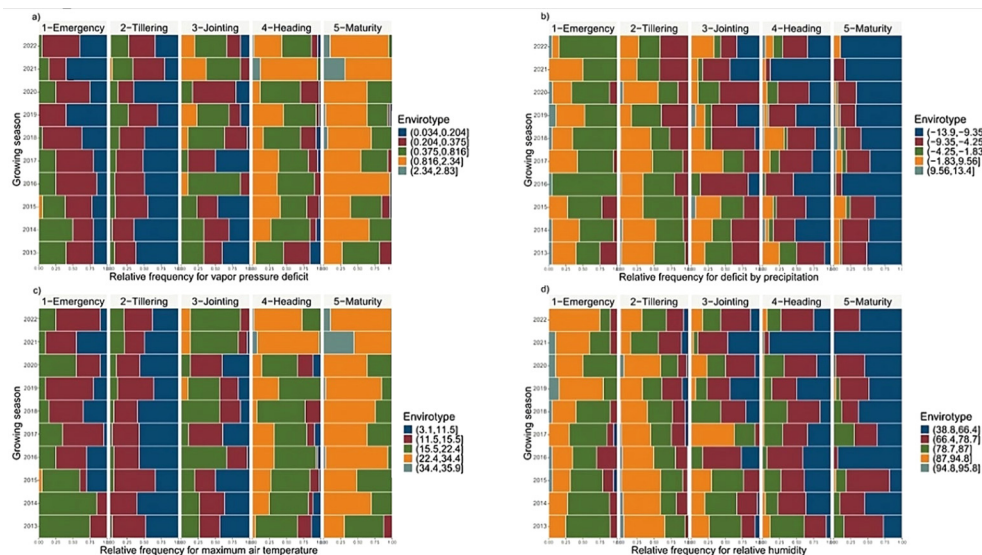


FIGURE 3 Framework for envirotyping analysis of: **(A)** vapor pressure deficit (kPa day^{-1}), **(B)** deficit by precipitation (mm day^{-1}), **(C)** maximum air temperature (T_{max} , $^{\circ}\text{C day}^{-1}$), and **(D)** relative humidity (%) impact on durum wheat across 10 growing seasons and 5 growth stages (emergency, tillering, jointing, heading and maturity).

traits, accounting for 50% of the overall phenotypic variation. For gluten content and grain protein, the residual variance (σ_r^2) was more substantial than the other variance components (Figure 4).

The distribution of grain yield for each variety is illustrated in Figure 5. Wheat grain yield varied significantly across years and varieties, with an average yield of $3.42 \pm 1.66 \text{ t ha}^{-1}$ among the 41 tested varieties. The lowest yield was recorded in 2021 at 1.66 t ha^{-1} , while the highest yield was observed in 2014 at 6.09 t ha^{-1} (Supplementary Figure S1). Grain yield (GY) ranged from 1.09 t ha^{-1} (variety G75 in 2018) to 7.22 t ha^{-1} (variety G65 in 2014), with a coefficient of variation (CV) of 48.61%. The coefficient of variation for durum wheat traits between varieties over the ten growing seasons showed maximum variability for traits such as bleached wheat grain (113.07%), shriveled wheat grain (97.8%), gluten content (32.72%), spikes per m^2 (31.43%), and grain protein (26.15%). Minimum variability was observed for hectoliter weight (6.1%), thousand-grain weight (13.45%), and plant height (14.53%).

The broad-sense heritability (H^2) values for all traits were generally low, ranging from 0 for shriveled wheat grain to 0.19 for thousand-grain weight, indicating that most of the variation in these traits is likely due to environmental or other non-genetic factors. Conversely, the estimate heritability of the mean genotype (h^2_{mg}) varied, being low for gluten index, grain protein, and shriveled wheat grain (ranging from 0 to 0.32), moderate for grain yield, ears per square meter, height, and bleached wheat grain (ranging from 0.48 to 0.66), and high for thousand-grain weight and hectoliter weight (ranging from 0.80 to 0.86).

Regarding Piepho heritability (H^2 Piepho), only thousand-grain weight and ears per square meter showed moderate heritability (ranging from 0.54 to 0.57), while bleached wheat grain exhibited high heritability (0.76), with the remaining traits showing low heritability. For Cullis heritability (H^2 Cullis), five traits – gluten index, grain protein, height, ears per square meter, and bleached

wheat grain – had moderate heritability (ranging from 0.41 to 0.64), with thousand-grain weight showing high heritability (0.72), and the remaining traits displaying low heritability. These differing heritability estimates highlight the complex nature of heritability and the importance of considering multiple perspectives when evaluating genetic contributions to trait variation.

The selection accuracy (AS) exceeded 0.70 for all traits except gluten index, protein content, and shriveled wheat grain. This high selection accuracy indicates reliable identification and selection of superior genotypes for breeding, ensuring effective genetic improvement in these traits.

The correlation of genotype–environment interaction effects (rge) varied in magnitude, being low for gluten index, grain protein, and thousand-grain weight (ranging from 0.08 to 0.39), moderate for grain yield, spikes per square meter, height, and ears per square meter (ranging from 0.42 to 0.53), and high for shriveled wheat grain and bleached wheat grain (ranging from 0.75 to 0.84). The genotypic coefficient of variation (CVg) exhibited a wide range, from 0% for Cs to 22.7% for Cb, demonstrating significant genetic diversity among the varieties. Conversely, the residual coefficient of variation (CVr) ranged from 1.91% for ears per square meter (Pe) to 31.2% for shriveled wheat grain (Cs). Additionally, the ratio between the genotypic and residual coefficients of variation (CVratio) was below 1 for all traits except for bleached wheat grain (Cb).

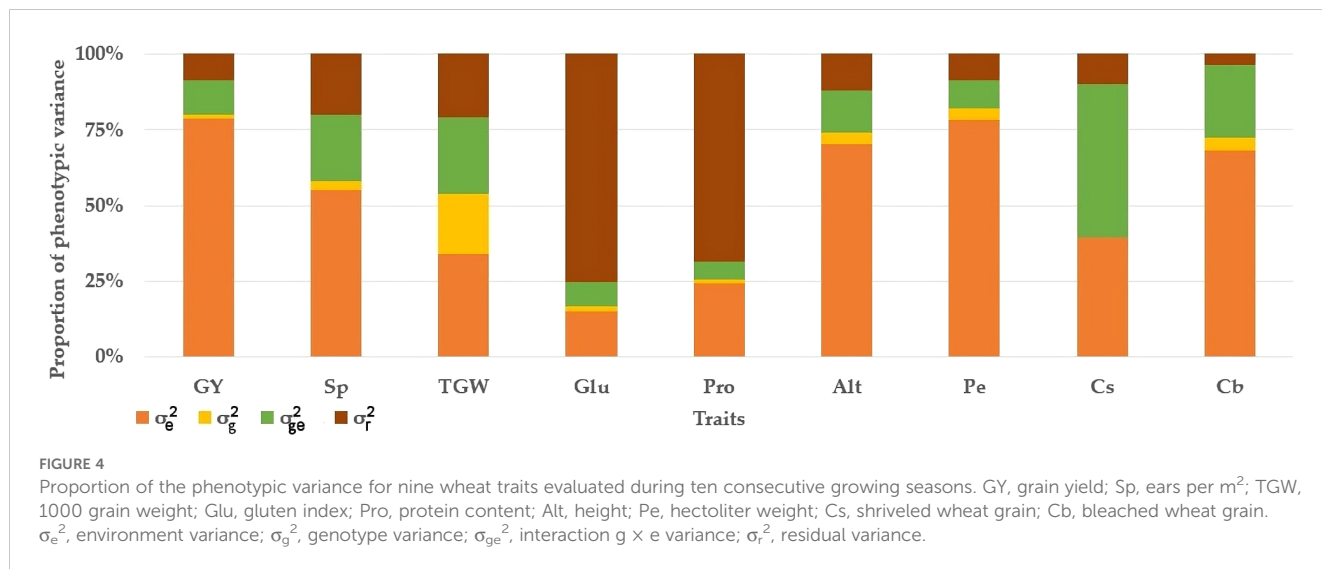
3.3 Factor analysis of durum wheat traits

Due to the data being unbalanced, Sampaio Filho et al. (2023) recommend evaluating performance and genotypic stability using factorial analysis, and they suggest focusing on the deviations from regression (S^2_{di}), the coefficient of determination (R^2), and the root mean square error of the regression (RMSE). This approach is

TABLE 3 Likelihood ratio test, estimated variance components and genetic parameters for nine traits of 41 wheat varieties, evaluated in 10 growing seasons.

Source of variation	Grain yield (t ha ⁻¹)	Ears per m ²	Thousands grain weight (g)	Gluten index (%)	Protein content (%)	Height (cm)	Hectoliter weight (kg hl ⁻¹)	Shriveled wheat grain (%)	Bleached wheat grain (%)
Environment (E)	47.9 ****	48.4 ****	30.6 ****	19.7 ****	27.3 ****	51.6 ****	55.7 ****	49.1 ****	55.8 ****
Genotype (G)	2.83*	4.28*	38.5***	1.11 ns	0.96 ns	10.1 **	26.7 ****	-5.83 10 ⁻⁰⁸ ns	9.64 **
G×E	182 ****	154 ****	169 ****	5.43 *	3.63 *	164 ****	146 ****	558 ****	618 ****
CV (%)	48.61	31.43	13.45	32.72	26.15	14.53	6.1	97.8	113.07
Genetic parameters									
σ^2_p	3.13	8.89 10 ³	40.6	10.4	11.5	121	26.9	22.6	475
H ²	0.01	0.0281	0.191	0.0151	0.0116	0.0337	0.0399	0.00	0.0396
h ² _{mg}	0.476	0.498	0.86	0.315	0.289	0.658	0.802	0.00	0.598
H ² _{Piepho}	0.212	0.149	0.569	0.314	0.331	0.29	0.536	0	0.764
H ² _{Cullis}	0.308	0.327	0.726	0.442	0.473	0.474	0.641	0.00	0.412
AS	0.649	0.707	0.927	0.561	0.538	0.81	0.879	0.00	0.786
GEI ^{r2}	0.534	0.492	0.385	0.097	0.079	0.478	0.418	0.837	0.753
rge	0.562	0.525	0.55	0.099	0.080	0.542	0.514	0.837	0.863
CVg	5.18	5.46	6.06	4.06	2.84	2.75	1.31	0.00	22.7
CVr	15.1	14.4	6.22	28.4	21.7	5.11	1.91	31.2	21.9
CV ratio	0.343	0.379	0.975	0.143	0.131	0.538	0.687	0.00	1.04

ns, *, **, ***, and **** indicate no significant difference, significant at $p \leq 0.05$, $p \leq 0.01$, $p \leq 0.001$, and $p \leq 0.0001$, respectively. σ^2_p , Phenotypic variance; H², broad sense heritability; h²_{mg}, Heritability of mean genotype; H²_{Piepho} and H²_{Cullis}, Piepho and Cullis heritability; r², coefficient of determination of the GEI interaction; AS, Selection accuracy; rge, correlation of GEI interaction; CVg, genotypic coefficient of variation (%); CVr, residual coefficient of variation (%); and CV ratio, ratio between the coefficient of genotypic and residual variation (%).



preferred over the originally proposed WAASB index method. According to Table 4, three factor components (FA) were identified, explaining 68.61%, 63.87%, and 69.55% of the total variance for S^2_{di} , R^2 , and RMSE, respectively, in durum wheat traits.

In our factor analysis, we evaluated the communality (h^{2i}) and uniqueness (u^{2i}) of each variable to understand how well they are represented by the common factors. Communality indicates the proportion of a variable’s variance explained by these factors, while uniqueness shows the variance not explained by them. The average h^{2i} values were 0.69 for S^2_{di} , 0.64 for R^2 , and 0.70 for RMSE. For S^2_{di} , all durum wheat traits had h^{2i} values greater than 0.5 except for TGW and Cb. For R^2 and RMSE, all traits had h^{2i} values above 0.5 except for Alt and TGW. This indicates that most traits are well represented by the common factors in our analysis.

The nine durum wheat traits were grouped into three factors (FA) for each stability parameter. For S^2_{di} , the first factor (FA1) showed a strong positive correlation with important quality traits, such as the gluten index (0.92) and protein content (0.90), and a moderate correlation with bleached wheat grain (0.61). The second factor (FA2) included traits related to plant productivity, like grain yield (0.94) and ears per m² (0.84), and some quality traits such as thousand-grain weight (0.50) and hectoliter weight (0.48). The third

factor (FA3) had a strong negative correlation with the quality trait shriveled wheat grain (−0.88) and a significant positive correlation with the morphological trait of plant height (0.70).

For R^2 and RMSE parameters, FA1 was associated with quality traits, including protein content (−0.92), gluten index (−0.91), and thousand-grain weight (−0.59) for R^2 , and gluten index (−0.92), protein content (−0.89), bleached wheat grain (−0.61), and thousand-grain weight (−0.50) for RMSE. The second factor (FA2) grouped productive traits (grain yield (−0.80) and ears per m² (−0.83)) and the morphological trait of plant height (0.62) for R^2 , and productive traits (grain yield (−0.86) and ears per m² (−0.91)) for RMSE. Finally, FA3 showed a high correlation with quality traits (bleached wheat grain (0.67) and shriveled wheat grain (−0.80)) for R^2 , and with the morphological trait plant height (−0.58), and quality traits such as shriveled wheat grain (0.83) and protein content (0.72) for RMSE.

3.4 Correlations between agronomic and quality traits

Figure 6 illustrates Pearson’s correlation coefficients between various agronomic and quality traits. These correlations illustrate

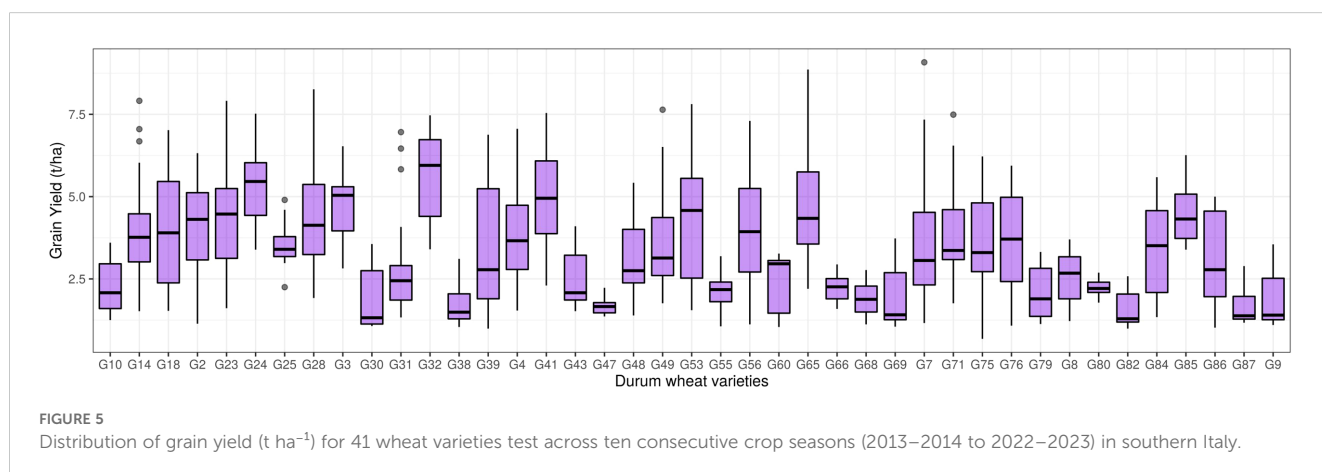


TABLE 4 Factorial analysis of 9 durum wheat traits: assessing regression deviations (S^2_{di}), regression determination coefficient (R^2), and square root mean square error (RMSE) with a weighted emphasis of 70% on performance and 30% on stability.

Trait	S^2_{di}					R^2					RMSE				
	FA1	FA2	FA3	Communality	Uniquenesses	FA1	FA2	FA3	Communality	Uniquenesses	FA1	FA2	FA3	Communality	Uniquenesses
GY	-0.09	0.94	-0.07	0.89	0.11	-0.11	-0.80	-0.12	0.66	0.34	0.15	-0.86	0.24	0.82	0.18
Sp	0.07	0.84	0.04	0.71	0.27	0.14	-0.83	0.3	0.80	0.20	0.016	-0.91	-0.10	0.84	0.16
Pro	0.90	0.15	-0.17	0.85	0.15	-0.92	0.017	0.05	0.85	0.15	-0.89	0.124	0.12	0.83	0.17
Alt	-0.07	-0.09	0.70	0.50	0.50	-0.04	0.63	0.16	0.42	0.58	0.001	0.33	-0.58	0.44	0.56
Pe	0.480	0.482	-0.42	0.64	0.36	-0.53	-0.40	-0.42	0.62	0.38	-0.44	-0.17	0.72	0.74	0.26
Glu	0.92	0.13	-0.13	0.89	0.11	-0.91	-0.001	0.12	0.84	0.17	-0.92	0.12	0.02	0.85	0.15
TGW	0.39	0.50	0.09	0.41	0.59	-0.59	0.06	-0.09	0.36	0.64	-0.50	-0.21	0.33	0.40	0.60
Cb	0.61	-0.15	0.30	0.48	0.52	-0.23	-0.07	0.67	0.51	0.49	-0.62	0.08	-0.36	0.52	0.48
Cs	-0.04	-0.15	-0.88	0.80	0.20	-0.21	-0.15	-0.80	0.70	0.30	0.15	0.32	0.83	0.82	0.18
Eigenvalue	2.96	1.70	1.51	-	-	2.51	1.89	1.35	-	-	2.59	2.12	1.55	-	-
Relative variance (%)	32.89	18.93	16.79	-	-	27.88	21.01	14.99	-	-	28.80	23.52	17.23	-	-
Cumulative variance (%)	32.89	51.82	68.61	-	-	27.88	48.89	63.87	-	-	28.80	52.32	69.55	-	-

Boldface factor loadings indicate the most relevant traits for each factor component. See Table 3 for the complete trait description.

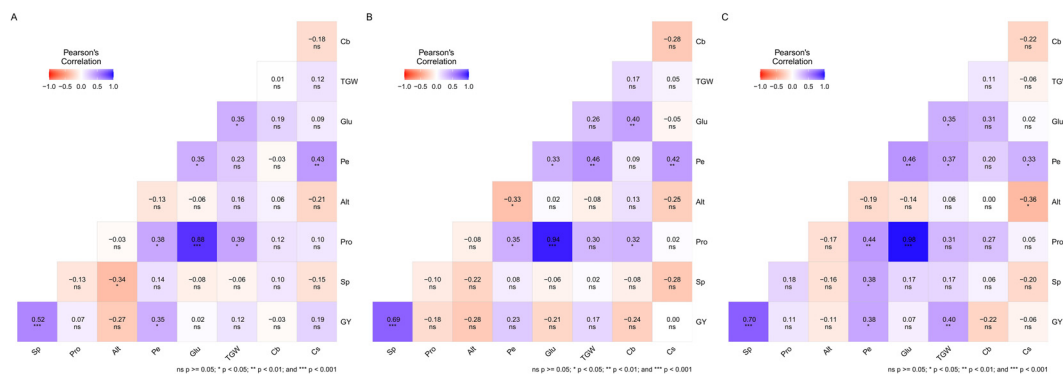


FIGURE 6 Pearson's correlation coefficients between agronomic and quality traits for the mean performance and stability (MPS) index, with a 70% emphasis on performance and 30% on stability, for regression parameters R^2 (A), RMSE (B), and S^2_{di} (C). Refer to Table 3 for the complete trait description.

the relationships among traits using the mean performance and stability (MPS) index, which was established based on three stability parameters (S^2_{di} , R^2 , and RMSE). Approximately 25% of the correlations were significant for both R^2 and RMSE, while 30.56% were significant for S^2_{di} . Traits show varying degrees of correlation depending on the stability parameter considered. Notably, protein content and gluten index exhibited a highly positive correlation (>0.88) across all stability parameters. Additionally, grain yield and spike per square meter (Sp) demonstrated a moderate positive correlation, with coefficients ranging from 0.52 to 0.70. There was a low positive correlation between shriveled wheat grain (Cs) and hectoliter weigh (Pe), with values ranging from 0.33 to 0.43. Conversely, plant height showed a low negative correlation with Cs for S^2_{di} (-0.36), Pe for RMSE (-0.33), and Sp for R^2 (-0.34). Thousand-grain weight (TGW) exhibited low positive correlations with several traits: grain yield (0.40), Pe (0.37), and gluten index (0.35) for S^2_{di} . For RMSE, TGW was positively correlated with Pe (0.46), and for R^2 , it correlated positively with protein content (0.39) and gluten index (0.35). Pe also had low positive correlations with grain yield (0.35) and protein content (0.38) for R^2 , with protein content (0.35) for RMSE, and with grain yield (0.38), Sp (0.38), and

protein content (0.44) for S^2_{di} . Additionally, a low but significant positive correlation between bleached wheat grain (Cb) and both protein content and gluten index (0.32 and 0.40, respectively) was observed for the RMSE parameter.

3.5 Identifying superior genotypes with the MTMPS index

The ranking of the 41 durum wheat varieties based on the Multi-Trait Index (MTMPS) analysis, with a 15% selection intensity, is illustrated in Figure 7. Among the 41 varieties evaluated, six were selected for each of the three regression variance parameters (S^2_{di} , R^2 , and RMSE). Regarding the R^2 parameter, the varieties with lower MTMPS values were Core (G18), Furio Camillo (G31), Antalis (G4), Bering (G9), Dylan (G24), Gibraltar (G32), and Anco Marzio (G3) (Figure 7A). For the RMSE parameter, Core (G18), Aureo (G7), Svevo (G76), Antalis (G4), Bering (G9), and Marco Aurelio (G49) were selected (Figure 7B). In the S^2_{di} parameter, the varieties with lower MTMPS values were Core (G18), Aureo (G7), Marco Aurelio

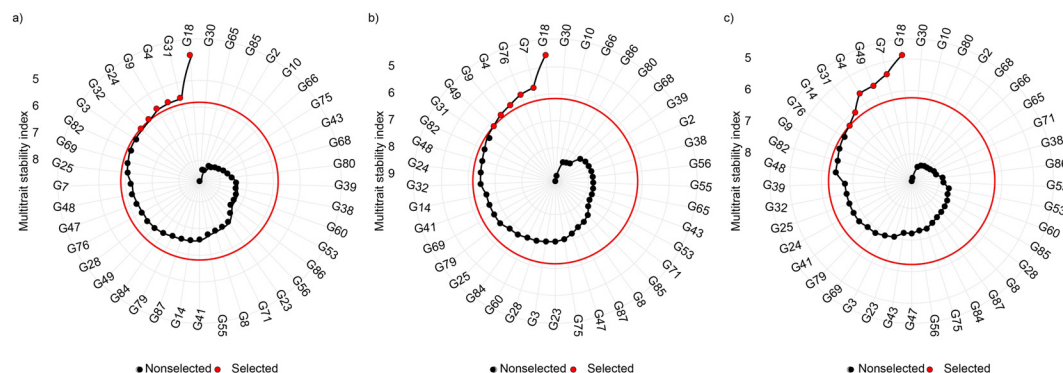


FIGURE 7 Multi-trait index (MTMPS) analysis of durum wheat varieties with 15% selection intensity (red circle), emphasizing 70% performance and 30% stability for regression parameters: R^2 (A), RMSE (B), and S^2_{di} (C). Based on the Eberhart and Russell (1966) model. See Supplementary Table S1 for the complete variety description.

(G49), Antalis (G4), Furio Camillo (G31), Claudio (G14), and Svevo (G76) (Figure 7C). These six varieties selected across three regression parameters demonstrated satisfactory mean grain yield performance. Specifically, their yields ranged from 3.41 t/ha in R^2 , to 3.91 t/ha in RMSE, and 3.61 t/ha in S^2_{di} . Additionally, these varieties exhibited better stability in grain yield across different growing seasons, highlighting their resilience and consistency under varying environmental conditions.

The multi-trait mean performance and stability index (MTMPS) proved highly effective in selecting traits with selection gain (SG) for all durum wheat traits, achieving a success rate of 77.77% (7 out of 9 traits) based on RMSE and R^2 , and 88.89% (8 out of 9 traits) based on S^2_{di} , with a few exceptions. Notably, the trait Cb showed reductions of 4.95%, 10.17%, and 13.55% for S^2_{di} , RMSE, and R^2 , respectively, indicating its favorable desirability as a wheat trait in this context. Specifically, the trait Cb exhibited reductions of 4.95%, 10.17%, and 13.55% for S^2_{di} , RMSE, and R^2 , respectively, which is desirable wheat trait in this context. Additionally, Cs showed a slight reduction of 0.04% for S^2_{di} . Conversely, the trait Alt experienced increased gains of 0.33%, 1.21%, and 1.50% for RMSE, S^2_{di} , and R^2 , respectively, which are not suitable for mechanized harvesting. For the parameters R^2 and RMSE, Cs increased by 1.92% and 4.46%, respectively, which negatively impacts durum wheat quality. Regarding S^2_{di} , the selection gain percentages for traits with desirable values ranged from 0.70% for Pe to 3.65% for TGW (Table 5). Similarly, the MTMPS index gains for the R^2 and RMSE parameters followed a comparable pattern, with increases in selection gains for six desirable wheat traits. For R^2 , the gains ranged from 1.28% for Pe to 6.08% for Sp, while for RMSE, the gains ranged from 0.19% for Pe to 3.67% for Glu (Table 5).

Figure 8 illustrates the strengths and weaknesses of selected durum wheat varieties identified over ten consecutive growing seasons. Based on the R^2 parameter, the “G31” variety exhibits strengths in FA1, indicating high performance in quality wheat traits such as protein (Pro), gluten (Glu), thousand-grain weight (TGW), and plant height (Pe). The variety “G4” shows strengths associated with FA2, which includes grain yield (GY), ears per m^2 (Sp), and plant height (Alt), while the variety “G9” excels in FA3, encompassing traits like shriveled wheat grain (Cs) and bleached wheat grain (Cb) (Figure 8A). For the RMSE parameter, FA1, which primarily relates to Pro, Glu, TGW, and Cb, significantly influences the deviation of the “G49” variety from the ideotype, suggesting areas for improvement in these traits. Meanwhile, the “G4” variety demonstrates strengths in both FA2 (GY and Sp) and FA3 (Alt, Pe, and Cs), indicating a well-rounded performance across these factors (Figure 8B). Regarding the S^2_{di} parameter, the “G18” variety performs very well in FA1, showing strong traits in protein (Pro), gluten (Glu), and bleached wheat grain (Cb). The “G14” variety shows robustness in FA2, associated with GY, Sp, and Pe. On the other hand, the “G31” variety presents a positive gain in traits related to Alt and Cs (Figure 8C).

4 Discussion

In recent years, Italy a country that suffers from drought for most of the year and where agriculture requires large amounts of

water, especially for wheat cultivation, has been working for many years on developing new varieties of durum wheat that can resist drought and high temperatures due to the phenomenon of global warming, which has become a global concern.

In this study, the grain yield, agronomic traits, and quality parameters of 41 durum wheat varieties were assessed over ten consecutive growing seasons in Southern Italy, particularly in the foothills of the Apennine Mountains. The likelihood-ratio test indicated a significant effect of genotype by environment interaction (GEI) for all traits, demonstrating that the performance of these varieties was strongly influenced by different growing conditions. GEI significantly impacts grain yield in wheat, highlighting the complexity of breeding programs aimed at improving yield stability across diverse environments. Studies have consistently shown that wheat genotypes exhibit variable performance under different environmental conditions, underscoring the necessity of multi-environment trials to accurately assess their yield potential (Eltaher et al., 2021; Gupta et al., 2022; Khare et al., 2024).

The contrasting environmental conditions during warm and cooler years had a significant impact on wheat grain yield, agronomic traits, and quality parameters. The observed differences can be attributed to the interplay between various climatic factors and their effects on wheat development stages.

In warm and dry environments like those in 2021 and 2022, high temperatures, high vapor pressure deficit (VPD), and water deficit had profound impacts on agronomic and quality traits. Water stress, occurring on more than 20% of days during the tillering stage, reduced the number of tillers by 21%, flag leaf area by 43%, plant height by 12%, and dry matter by 19% compared to control treatments, highlighting the sensitivity of this stage to water deficits (Zabn and Alsajri, 2022). High temperatures and water stress during the jointing stage accelerated the development process, leading to shorter periods for biomass accumulation and potentially reducing overall plant height and yield (Djanaguiraman et al., 2020). The combination of high temperatures (Tmax ranging from 22.4°C to 35.9°C) and high vapor pressure deficit (VPD up to 2.83 kPa day^{-1}) during the critical heading and maturity stages created significant heat and drought stress. During the grain-filling stage, high temperatures accelerated the process, resulting in shorter maturation times and smaller grains, leading to higher concentrations of proteins, including gluten-forming proteins like gliadins and glutenins (Gagliardi et al., 2020; Djanaguiraman et al., 2020; Yang et al., 2023; Sihag et al., 2024). Elevated temperatures and high VPD can alter the balance of protein fractions in the grain, increasing the proportion of gliadins relative to glutenins, which enhances the gluten index and overall protein content (Torbica and Mastilović, 2008). These environmental stresses also influence the synthesis and assembly of glutenin polymers, crucial for dough strength and elasticity (Torbica and Mastilović, 2008; Wehrli et al., 2021). Additionally, studies have shown that high VPD can activate nitrogen metabolism, as indicated by increased expression of nitrogen transporter genes and higher concentrations of amino acids such as glutamine, aspartate, and serine in the leaves (Fakhet et al., 2021). These amino acids play crucial roles in regulating nitrate reductase gene expression and overall nitrogen assimilation,

TABLE 5 Durum wheat traits, selection differential (SD), heritability (h²), and selection gain (SG) of selected varieties for the MPS index using three regression variance parameters (S²_{di}, R² and RMSE).

Regression variance index	Traits	Factor	SD	SD (%)	h ²	SG	SG (%)	Sense	Goal
S ² _{di}	Pro	FA 1	1.11	8.54	0.21	0.23	1.78	increase	100
	Glu	FA 1	1.17	11.86	0.25	0.30	2.99	increase	100
	Cb	FA 1	-2.09	-10.01	0.49	-1.03	-4.95	decrease	100
	GY	FA 2	0.29	9.28	0.24	0.07	2.26	increase	100
	Sp	FA 2	14.18	4.93	0.31	4.38	1.53	increase	100
	Pe	FA 2	0.72	0.92	0.76	0.55	0.70	increase	100
	TGW	FA 2	1.92	4.20	0.87	1.67	3.65	increase	100
	Alt	FA 3	1.96	2.75	0.44	0.86	1.21	decrease	0
	Cs	FA 3	-0.01	-0.22	0.20	0.00	-0.04	decrease	100
R ²	Pro	FA 1	1.29	9.95	0.21	0.27	2.07	increase	100
	Pe	FA 1	1.32	1.68	0.76	1.01	1.28	increase	100
	Glu	FA 1	1.32	13.31	0.25	0.33	3.35	increase	100
	TGW	FA 1	0.98	2.13	0.87	0.85	1.85	increase	100
	GY	FA 2	0.56	18.08	0.24	0.14	4.41	increase	100
	Sp	FA 2	56.47	19.66	0.31	17.47	6.08	increase	100
	Alt	FA 2	2.41	3.39	0.44	1.07	1.50	decrease	0
	Cb	FA 3	-5.71	-27.40	0.49	-2.83	-13.55	decrease	100
	Cs	FA 3	0.42	9.57	0.20	0.08	1.92	decrease	0
RMSE	Pro	FA 1	1.36	10.48	0.21	0.28	2.18	increase	100
	Glu	FA 1	1.44	14.55	0.25	0.36	3.67	increase	100
	TGW	FA 1	1.54	3.37	0.87	1.34	2.93	increase	100
	Cb	FA 1	-4.29	-20.56	0.49	-2.12	-10.17	decrease	100
	GY	FA 2	0.16	5.11	0.24	0.04	1.25	increase	100
	Sp	FA 2	11.08	3.86	0.31	3.43	1.19	increase	100
	Alt	FA 3	0.53	0.75	0.44	0.24	0.33	decrease	0
	Pe	FA 3	0.20	0.25	0.76	0.15	0.19	increase	100
	Cs	FA 3	0.98	22.22	0.20	0.20	4.46	decrease	0

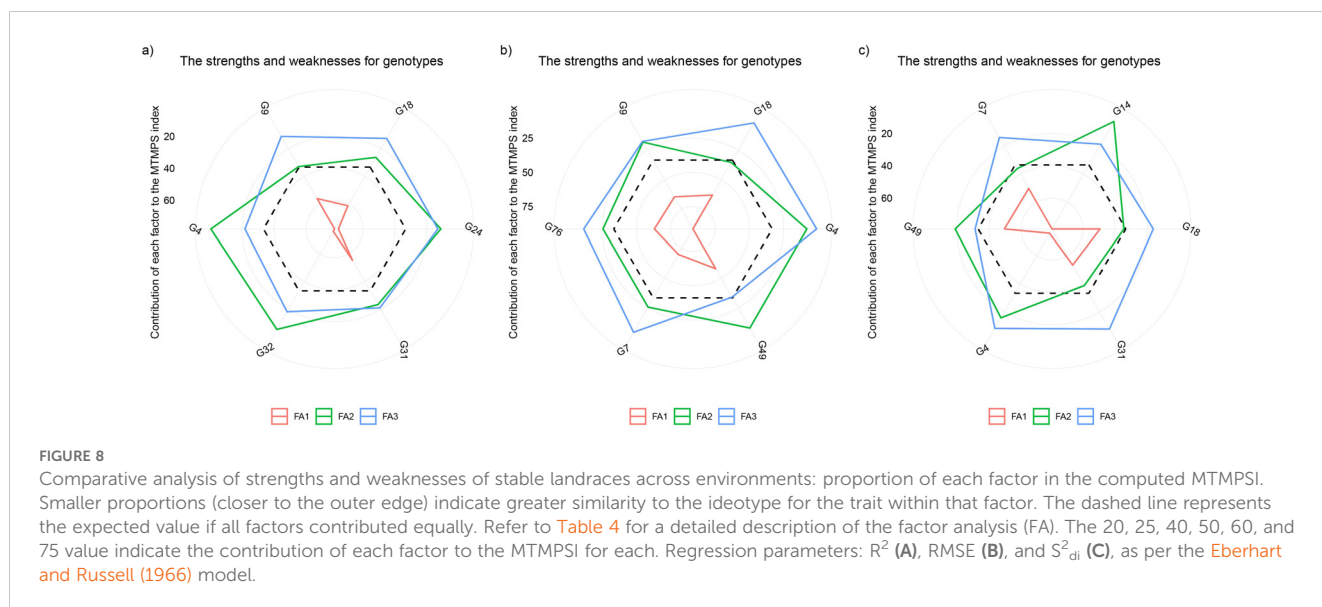
See Table 3 for the complete trait description.

which can shift the balance of protein fractions in the plant. The combined effects of elevated temperatures and high VPD on stomatal conductance, photosynthesis, and nitrogen metabolism lead to significant changes in the balance of protein fractions in wheat, necessitating careful nitrogen management to optimize protein quality and maintain crop productivity in warm environments (Fakhet et al., 2021; El Haddad et al., 2021).

Our study found that the residual variance of quality traits, such as gluten index and protein content, is often higher than other phenotypic variances due to the inherent complexity and variability associated with nitrogen management strategies (Table 2). Environmental variability, measurement errors, genotype by environment interactions, and temporal variability all contribute to this increased residual variance. Understanding and managing these sources of variability is crucial for

improving the accuracy and reliability of field trial results in plant breeding and agronomic research (Geiler-Samerotte et al., 2013; Wang et al., 2023). However, during heading and maturity, these conditions (elevated temperatures and high VPD) also impair photosynthesis and reduce pollen viability, leading to lower grain yield and reduced hectoliter weight due to the production of shriveled grains (Dupont and Altenbach, 2003; Jamieson et al., 2004; Triboi et al., 2003). Water deficit exacerbates these effects by limiting the plant's ability to uptake water, further increasing the relative protein content compared to carbohydrates (Guttieri et al., 2000; 2001; Gulati et al., 2014).

In the cooler years such as 2013, 2014, 2015, 2017, and 2020, characterized by favorable water availability and lower vapor pressure deficit (VPD), wheat plants experience reduced stress across all phenological stages, including emergence, tillering,



jointing, heading, and maturity. These conditions promote better early growth and establishment due to higher relative humidity during the emergence and tillering stages, which enhances seedling vigor and tiller formation ([Farooq et al., 2009](#)). Adequate water availability and moderate temperatures during the jointing stage support robust stem elongation and biomass accumulation, setting a strong foundation for subsequent growth phases ([Shang et al., 2020](#)). During the critical heading and maturity stages, cooler temperatures and sufficient precipitation reduce heat and drought stress, allowing for optimal photosynthesis, pollen viability, and grain setting. This results in higher grain yield, increased hectoliter weight, and more spikes per square meter ([Cetin et al., 2022](#)). The cooler temperatures also lead to a more prolonged grain filling period, enabling the development of plumper, denser grains with lower protein and gluten content. This dilution effect occurs because the grains have more time to accumulate biomass, which dilutes the concentration of proteins within the grain ([Lama et al., 2022](#); [Zhang et al., 2022](#)). Furthermore, the high precipitation and lower VPD conditions in cooler environments enhance plant water status by maintaining higher stomatal conductance and reducing water loss, which supports better growth and biomass accumulation and reduces the incidence of shriveled grains, as the plants were not concentrating their resources on survival but rather on maximizing growth and yield ([Gibberd et al., 2000](#); [Stoddard et al., 2006](#); [Fakhet et al., 2021](#)). The negative correlation between precipitation and grain protein concentration further supports this, as cooler, wetter conditions typically result in lower protein content ([Fowler, 2003](#); [Orlandini et al., 2011](#)).

Traditionally, plant breeders have focused on single-trait analysis, primarily yield, due to its direct economic impact, simplicity, and ease of measurement ([Luby and Shaw, 2009](#); [Yan, 2021](#); [Beavis and Mahama, 2023](#)). Yield-focused breeding is less resource-intensive

and easier to implement, particularly in early breeding stages or regions with limited resources. This approach has a strong historical precedent due to the straightforward nature of phenotypic measurement and selection processes ([Luby and Shaw, 2009](#)). However, as the need for crops with multiple desirable traits like disease resistance, drought tolerance, and nutritional quality grows, the limitations of single-trait analysis are becoming clear ([Merrick et al., 2022](#)). Multi-trait analysis, which considers genetic correlations between traits, enhances predictive accuracy and efficiency and offers a more comprehensive and sustainable approach. With advanced statistical tools and computational resources becoming more accessible, multi-trait analysis is increasingly adopted to address the complex challenges of modern agriculture effectively ([Guo et al., 2014](#); [Merrick et al., 2022](#)).

The MTMPS index is a sophisticated quantitative genetic technique used for the selection of suitable varieties across various crop species such as bread wheat ([Farhad et al., 2022](#)), elephant grass ([Rocha et al., 2018](#)), and maize ([Olivoto et al., 2021](#); [Yue et al., 2022](#)) and is free from the multicollinearity problem ([Sampaio Filho et al., 2023](#)). According to the MTMPS results, two varieties, Antalis (G4) and Core (G18), were consistently selected across all regression parameters, indicating their broad adaptability and robust performance across diverse environments, particularly in drier and warmer conditions. Additionally, variety Furio Camillo (G31) was positioned near the selection intensity threshold for the RMSE parameter and ranked among the top six varieties for both R^2 and S^2_{di} , suggesting it possesses valuable traits. Overall, Antalis (G4) and Core (G18) varieties were consistently selected across all regression parameters, showcasing their unique strengths. The Antalis (G4) variety is optimal for grain yield and number of ears per m^2 , making it a top choice for high-yield production. In contrast, the Core (G18) variety excels in protein content and

gluten index, underscoring its potential for producing high-quality wheat. However, both varieties exhibit the undesired trait of high shriveled wheat grain, which should be addressed in future breeding programs to enhance their overall quality.

5 Conclusions

This study underscores the critical influence of environmental factors on the performance of durum wheat varieties in Southern Italy, emphasizing the importance of genotype by environment interaction (GEI) in breeding programs. The significant GEI effects observed highlight the necessity for multi-environment trials to accurately evaluate and enhance yield stability and quality traits across diverse conditions. Our findings indicate that warm years characterized by high temperatures, elevated vapor pressure deficit (VPD), and water deficits adversely affect grain yield and quality, leading to lower yields, reduced hectoliter weight, and increased grain shriveling. Conversely, cooler years with sufficient water availability and lower VPD foster better plant development, resulting in higher yields, increased hectoliter weight, and a greater number of spikes per square meter. The application of the Multi-Trait Mean Performance Selection (MTMPS) index proved to be an effective tool for identifying durum wheat varieties with superior performance and stability, particularly under varying environmental conditions. Varieties such as Antalis (G4) and Core (G18) demonstrated broad adaptability and robust performance, making them valuable candidates for high-yield and quality wheat production. These findings suggest that future breeding efforts should focus on multi-trait analysis to balance yield with other critical traits such as disease resistance. In conclusion, the integration of advanced statistical tools and computational resources in multi-trait selection can significantly improve the resilience and productivity of durum wheat varieties. Addressing undesired traits like high grain shriveling in future breeding programs will further enhance the overall quality and stability of wheat crops, ensuring sustainable agricultural practices in the face of climate change.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

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MHS: Data curation, Formal analysis, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. IDM: Data curation, Formal analysis, Investigation, Project administration, Resources, Writing – review & editing. LO: Data curation, Formal analysis, Investigation, Project administration, Resources, Writing – review & editing. EC: Formal analysis, Investigation, Project administration, Resources, Writing – review & editing. PDV: Conceptualization, Supervision, Writing – review & editing. MM: Conceptualization, Resources, Supervision, Writing – review & editing, Project administration.

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Supplementary material

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fagro.2024.1466040/full#supplementary-material>

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