Heliyon 10 (2024) e39599

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Identification of high-yielding and stable cultivars of wheat under different sowing dates: Comparison of AMMI and GGE-biplot analyses

Majid Taherian [a], Fatemeh Saeidnia [a,*], Rasmieh Hamid [b], Seyyed Mahmood Nazeri [a]

[a] Agricultural and Horticultural Science Research Department, Khorasan Razavi Agricultural and Natural Resources Research and Education Center, Agricultural Research, Education and Extension Organization, Mashhad, 91769-83641, Iran

[b] Plant Breeding Department, Cotton Research Institute of Iran, Agricultural Research, Education and Extension Organization, Gorgan, 49166-85915, Iran

ARTICLE INFO

Keywords:
Additive main effects and multiplicative interactions
GGE biplot
GE interaction
Gene action
Interaction principal component axis (IPCA)
Sowing date
Triticum aestivum

ABSTRACT

Evaluating the adaptability and yield stability of wheat varieties across different sowing dates is crucial for the success of breeding programs. In this study, we used Additive Main Effects and Multiplicative Interactions (AMMI) and Genotype × Genotype–Environment (GGE) biplot analyses to evaluate the performance of 13 wheat varieties across eight sowing dates. The main objective was to compare varieties and sowing dates to identify the most stable varieties for cultivation. Both AMMI and GGE biplot analyses showed significant effects of genotype, environment and genotype-environment (GE) interaction on grain yield. The interaction patterns identified by AMMI and GGE-biplots categorized Mihan, Oroom and Pishgam as the most stable, high yielding and early maturing wheat varieties. Furthermore, while the GGE biplot method proved to be more efficient than the AMMI model for stability analysis, our results indicate considerable overlap between the results of these two approaches. These results provide a valuable basis for optimizing genetic improvement strategies in wheat breeding programs.

1. Introduction

Bread wheat (*Triticum aestivum* L.) is a vital staple food, with global production exceeding 700 million tons [1,2]. It supplies a substantial proportion of the energy and caloric intake for approximately one-fifth of the world's population, equating to about 4.5 billion people [3]. Beyond its nutritional significance, wheat plays a critical economic role in developing countries and stands out among cereals as a rich source of fiber, carbohydrates, B-complex vitamins, and essential minerals [4,5]. Durum wheat (*Triticum turgidum* ssp. durum), a tetraploid species ($2n = 4x = 28$) and one of the earliest crops domesticated by farmers in the Fertile Crescent, represents a valuable genetic resource, potentially contributing alleles for traits such as high protein content, drought tolerance, and other economically desirable characteristics [6,7].

Any changes in the growth stages of crops inevitably affect various yield components and ultimately affect the final harvest. Effective management and adaptation of these growth stages offer new opportunities to increase yield. Of particular importance is the

* Corresponding author.
E-mail addresses: majidtaherian1@gmail.com (M. Taherian), fatemeh.saeednia@yahoo.com (F. Saeidnia), rasihamid@gmail.com (R. Hamid), smnazeri56@yahoo.com (S.M. Nazeri).

https://doi.org/10.1016/j.heliyon.2024.e39599
Received 18 June 2024; Received in revised form 15 October 2024; Accepted 17 October 2024
Available online 18 October 2024
2405-8440/

timing of sowing, which has a profound effect on the growth and development throughout the growing season. Adjustments to the growing date can significantly change the duration of the growth phases [8]. Sowing wheat at an inappropriate time, either too early or too late, can have various detrimental effects. In contrast, an optimal sowing date promotes high germination rates, robust tillering, timely phenological development and the establishment of vigorous plants with a well-developed root system, all of which contribute to higher grain yields [9,10].

The evaluation of genotypes poses two main challenges. Firstly, the genotype-environment (GE) interaction for important traits and secondly, the negative correlations between these traits [11]. The GE interaction results from the different responses of genotypes in different environments and is an important source of variability in plant performance. This interaction reduces the correlation between genotypic and phenotypic values, introduces bias in heritability estimation and reduces selection efficiency [12]. Therefore, understanding the extent of GE interactions is crucial for the development of high-yielding varieties that perform consistently under different environments [13].

Various methods have been used to explore and understand genotype-environment (GE) interactions, ranging from simple ANOVA to more specialised assessments of genotype performance. These include univariate linear regression models [13] as well as multivariate models such as the Additive Main Effects and Multiplicative Interactions (AMMI) model [14] and the Genotype × Genotype-Environment Interaction (GGE) biplot method [15]. In their study on bread wheat (*Triticum aestivum* L.), Ahmadi et al. [16] emphasized the utility of AMMI and GGE biplots to facilitate visual comparisons and to select optimal genotypes for specific target environments. Both AMMI and GGE-biplot analyses are represented by biplots showing genotypic response patterns across different environments [15].

Purchase et al. [17] developed the AMMI Stability Value (ASV) based on the IPCA1 and IPCA2 scores of the AMMI model for each genotype, which accounts for most of the variation in the GE interaction. Another AMMI statistic is the sum of the absolute values of the IPCA scores (SIPC). Genotypes with the lowest ASV and SIPC scores are considered as the most stable. However, approaches that incorporate both mean yield and stability into a single criterion are still needed, as the most stable genotypes do not necessarily have the best yield performance. In this context, the rank of ASV (RASV) and the mean yield (RY) are combined into a single selection index called the genotype selection index (GSI), with the lowest GSI indicating the most stable, high yielding genotype [18].

Effective genotype improvement requires a comprehensive understanding of genetic variation, GE interactions, variance components, heritability and the ability to predict genetic progress through selection [19]. Variance component estimation is essential to determine the proportion of phenotypic variance attributable to genetic effects (broad-sense heritability) and the proportion of total genetic variance attributable to additive genetic effects (narrow-sense heritability). This understanding is crucial for assessing genetic progress through selection in segregating populations, which is essential for the development of effective breeding strategies [20].

The selection of plant material that is both ecologically suitable and genetically diverse, particularly those that are native to the target environments, is a crucial aspect of any breeding program [21]. Given the significant influence of sowing dates on crop production, different bread and durum wheat varieties at eight sowing dates were analyzed in our study. The aim was to determine the optimal sowing date for the specific conditions in our region to maximize yield and crop quality. In addition, understanding GE interactions can help breeders achieve this goal while reducing the costs associated with genotype evaluation by avoiding redundant test sites [22]. This study represents the first application of the AMMI model and GGE-biplot analysis to investigate the interaction between genotype and sowing date in wheat. The aims of this study were: (i) to evaluate genetic variability, estimate variance components and assess heritability in terms of grain yield, canopy temperature drop and selected phenological traits over eight sowing dates for wheat varieties; (ii) visually assess the adaptability and stability of grain yield in wheat varieties across these eight sowing dates; and (iii) identify wheat varieties that exhibit consistent response patterns across all sowing dates while maintaining high grain yield using the AMMI model and GGE-biplot analysis.

2. Materials and methods

2.1. Plant materials and field experiments

The genetic material used in this study were consisted of thirteen wheat varieties, including one tetraploid durum wheat variety (*Triticum turgidum*) and twelve bread wheat varieties (*T. aestivum*) (Supplementary Table S1). The seeds for these varieties were obtained from the gene bank of the Khorasan Razavi Agricultural and Natural Resources Research and Education Centre. The experimental design followed a split-plot arrangement within a randomized complete block design (RCBD) with three replicates. The main plots were assigned to eight sowing dates (6th September, 6th October, 6th November, 6th December, 6th January, 6th February, 6th March, and 6th April), while the thirteen wheat varieties were allocated to sub-plots over three consecutive growing seasons.

Over the three-year period, each plot comprised four rows, each 300 cm long with a 30 cm row spacing and a within-row spacing of 10 cm. Cultural practices, including irrigation, weed control and fertilization, were applied throughout the year for each sowing date. Weed control was carried out manually, and no chemical herbicides were used during the experiment. Prior to sowing, the seeds were treated with a fungicide and no further pest control program was implemented. Soil fertility was maintained by applying 80 kg N/ha and 90 kg P/ha before sowing, supplemented by an additional 70 kg N/ha at the early stage of stem elongation.

During the three-year study, comprehensive evaluations were carried out on each plot, assessing traits such as days to double ridge (DDR), days to heading (DH), days to physiological maturity (DM), canopy temperature drop (CTD), thousand grain weight (TGW; g) and grain yield (GY; g/m^2). The average data collected over the three-year period was then used for the analysis.

2.2. Experimental site

This study was conducted over three years at the Mashhad Agricultural and Natural Resources Research Station in Torqabeh, Mashhad, Iran (2° 36′ N, 6° 59′ E, 1630m amsl). The station is located on silty clay soil with a pH value of 7.8. According to meteorological records spanning the last 40 years, the region received an average annual precipitation of 230 mm and had a mean temperature of 14.7 °C (www.havairan.com). According to the Koppen climate classification, this region had a tropical and subtropical steppe cool climate. Supplementary Table S2 shows the monthly mean values of climate variables recorded at the study site, including minimum temperature, maximum temperature, mean temperature, and precipitation.

2.3. Statistical analysis

Before analysis of variance (ANOVA), the normality of the data distribution and the homogeneity of the residual variance were tested using the Kolmogorov-Smirnov test and the Bartlett test, respectively. Subsequently, a combined ANOVA was performed using PROC MIXED in SAS (SAS Institute, Cary, NC, USA), version 9.4, to examine the differences between genotypes, years, sowing dates (environments) and all possible interactions, and also to estimate the variance components. For the combined analysis of data collected over three years and eight sowing dates, a split-plot experiment within a randomized complete block design (RCBD) was used, with sowing dates as the main plots and genotypes as subplots. The genotype and sowing date were considered as fixed factors, while year was considered as a random effect. The mean trait values were compared using the Least Significant Difference (LSD) test at $P \leq 0.05$ [23]. Variance components for the assessed traits were estimated using PROC MIXED in SAS. Broad-sense heritability (h_b^2) was calculated based on the phenotypic mean basis averaged over replicates, years and environments using equation (1) [24]:

$$h_b^2 = \frac{\sigma_g^2}{\sigma_g^2 + \frac{\sigma_{gs}^2}{s} + \frac{\sigma_{gy}^2}{y} + \frac{\sigma_{gsy}^2}{sy} + \frac{\sigma_{\gamma}^2}{rs} + \frac{\sigma_{\varepsilon}^2}{rsy}} \quad \text{(Eq. 1)}$$

In the provided equation, h_b^2 represents the broad-sense heritability; σ_g^2 denotes to the genotype variance; σ_{gs}^2 represents the genotype × sowing date variance; σ_{gy}^2 signifies the genotype × year variance; σ_{gsy}^2 indicates the genotype × sowing date × year variance; σ_{δ}^2 and σ_{ϵ}^2 stand for the error variance and the residual variance, respectively; g, s, y, and r symbolize the number of genotypes, sowing dates, years, and replications, respectively. Additionally, the level of genetic variation can be estimated by calculating the phenotypic coefficient of variation (PCV) and the genotypic coefficient of variation (GCV) using equations (2) and (3), respectively.

$$PCV = (\sigma_p / \mu) 100 \quad \text{(Eq. 2)}$$

$$GCV = (\sigma_g / \mu) 100 \quad \text{(Eq. 3)}$$

In the given context: σ_p represents the standard deviation of the phenotypic variance; σ_g denotes to the standard deviation of the genotypic variance; and μ signifies the phenotypic mean [25].

2.4. Stability analysis

2.4.1. Regression method

The stability analysis for grain yield was performed using the stability parameters proposed by Eberhart and Russell [26]. These stability parameters were included the regression coefficients of the variety means (b_i) on the environmental indices (calculated as the average of all varieties in each environment) and the mean squares of deviations from regressions (S_{di}^2). These stability parameters were calculated according to equations (4) and (5) as follows:

$$b_i = 1 + \frac{\sum_j \left(X_{ij} - \overline{X}_{i.} - \overline{X}_{.j} + \overline{X}_{..}\right)\left(\overline{X}_{.j} - \overline{X}_{..}\right)}{\sum_j \left(\overline{X}_{.j} - \overline{X}_{..}\right)^2} \quad \text{(Eq. 4)}$$

$$S_{di}^2 = \frac{1}{E-2}\left[\sum_J \left(\left(X_{ij} - \overline{X}_{i.} - \overline{X}_{.j} + \overline{X}_{..}\right)\right)^2 - (b_i - 1)^2\left(\overline{X}_{.j} - \overline{X}_{..}\right)^2\right] \quad \text{(Eq. 5)}$$

In the provided equations: X_{ij} represents the grain yield of variety *i* in environment (sowing date) *j*; $\overline{X}_{i.}$ denotes to the mean grain yield of variety *i*; $\overline{X}_{.j}$ signifies the mean grain yield of environment (sowing date) *j*; $\overline{X}_{..}$ represents the grand mean and *E* stands for the number of environments (sowing dates).

2.4.2. AMMI model analysis

Following the confirmation of a GE interaction, an analysis of adaptability and phenotypic stability was conducted by the AMMI method, as outlined by Zobel et al. [14]. The results derived from the AMMI model were subsequently interpreted through AMMI1 and AMMI2 biplot analyses. In this evaluation, the main effect of the variety was considered as fixed, while the main effect of the sowing date was treated as random.

The AMMI stability value (ASV) was calculated using equation (6) [17]:

$$ASV = \sqrt{\frac{SS_{IPCA1}}{SS_{IPCA2}}(IPCA1score)^2 + (IPCA2score)^2} \quad \text{(Eq. 6)}$$

where SSIPCA1/SSIPCA2 is the weight given to the IPC1 value by dividing the IPC1 sum of squares on the IPC2 sum of squares and IPCA 1 and IPCA 2 scores are the genotypic scores in AMMI model.

The next AMMI statistic is sum of the absolute values of the IPC scores (SIPC) which is calculated by equation (7) [27]:

$$SIPC = \sum_{1}^{n} |IPCA| \quad \text{(Eq. 7)}$$

Based on the rank of mean yield of varieties (RYi) across environments (sowing dates) and rank of AMMI stability value (RASVi), a selection index called GSI was calculated for each genotype using from equation (8) as follows [18]:

$$GSI_i = RASV_i + RY_i \quad \text{(Eq. 8)}$$

The AMMI analysis for grain yield data was conducted using GEA-R version 4.1 [28].

2.4.3. GGE-biplot analysis

Similar to the AMMI model analysis, after confirming the presence of a significant genotype-environment (GE) interaction, the adaptability and stability of grain yield was assessed using GGE biplot analysis as described by Yan [15]. To identify stable and adaptable varieties, the GE interaction was analyzed graphically. For this purpose, the first two components resulting from the singular value decomposition (SVD) were used to generate the biplots using GEA-R version 4.1, with the remaining principal components considered as residuals.

3. Results

3.1. Analysis of variance and genetic analysis

The combined analysis of variance revealed significant differences ($P < 0.05$) between the sowing dates for all measured traits (Table 1). In particular, the effect of genotype was significant for all traits, indicating considerable genotypic variation among the selected varieties. Moreover, the genotype-environment (GE) interaction, which accounted for 18.33 % of the total variation in grain yield (GY), was highly significant for all traits except for canopy temperature drop (CTD). This pronounced GE interaction emphasizes the different responses of the varieties to the different sowing dates. The presence of GE interaction complicates the selection process by minimizing the association between genotypic and phenotypic values [29], thus reducing the predictive value of genotypes. Therefore, stability analysis is crucial to effectively manage these complex relationships.

Mean comparisons of measured traits among the wheat varieties based on the average of three years showed that Mihan was the late maturing variety, followed by Pishgam and Oroom, while Baz and Bezostaya were the early maturing varieties (see Supplementary Table S3). The results also showed that the mean grain yield (GY) ranged from 2.78 to 5.11 t/ha. Pishgam, Mihan and Pishtaz exhibited the higher yields, with values of 5.11, 5.05 and 4.99 t/ha, respectively; while Behrang had the lowest grain yield (2.78 t/ha). Pishgam recorded the highest value of CTD, while Bezostaya had the lowest value for this trait. It is noteworthy that, Pishtaz and Mihan as well as Chamran, Sirvan and Oroom showed no significant differences in CTD (Supplementary Table S3).

Table 2 shows the phenotypic and genotypic coefficients of variation (PCV and GCV) for the evaluated traits. PCV ranged from 4.45 % for days to heading (DH) to 23.50 % for canopy temperature drop (CTD), while GCV ranged from 4.07 % for DH to 19.06 % for CTD. Broad-sense heritability estimates and variance components for all measured traits are also shown in Table 2. For days to double ridge (DDR) and DH, genotype variance accounted for the largest proportion of phenotypic variance. In contrast, for days to maturity (DM), CTD and GY, the interaction of genotype × year had the highest proportion of phenotypic variance. Over the three years and eight sowing dates, heritability estimates ranged from 31.39 % for GY to 83.77 % for DH (Table 2).

3.2. Stability analysis

Application of the AMMI model to partition the genotype-environment (GE) interaction yielded significant results, as shown by the statistical significance of the first five terms of the AMMI model based on an approximate F-statistic. The AMMI5 model analysis explained 99.06 % of the GE sum of squares and effectively partitioned the interaction. Among the identified factors, IPCA1 to IPCA5 were highly significant, contributing 70.47 %, 20.26 %, 4.34 %, 2.35 %, and 1.64 % of the GE sum of squares, respectively (Table 3). These results emphasize the significant differences between sowing dates, varieties, and the interaction effects between sowing date and variety revealed by the AMMI analysis. The pronounced influence of sowing date on GE interaction, genetic variability between varieties and the potential for selection of stable varieties is evident. The model showed that 72.21 % of the total sum of squares was due to environmental effects, while only 6.94 % was due to genotypic effects and 18.33 % to genotype-environment (GE) interaction effects (Table 3). The significant environmental effects emphasize the significant differences between sowing dates. In addition, the considerable proportion of GE effects compared to G indicates the existence of different mega-environments with various high-yielding varieties [30].

Fig. 1 shows the IPCA1 values of the varieties and environments (sowing dates) plotted against the main effects (variety mean and

Table 1
Combined analysis of variance for measured traits in 13 varieties of wheat in eight sowing dates during three years (2012–2014).

Source of variation	Year (Y)	Replication/Y	Sowing date (S)	Y × S	S × rep/Y	Genotype (G)	S × G	Y × G	Y × S × G	Error
d.f	2	6	7	14	42	12	24	84	168	576
Traits	Mean squares									
DDR	2635.40**	102.43$^{n.s}$	78215.32**	103.80**	3.80$^{n.s}$	823.03**	7.40**	138.70**	1.76**	0.19
DH	8188.01**	321.00$^{n.s}$	167938.26**	1193.45**	48.38$^{n.s}$	2315.32**	134.20**	282.08**	40.60**	2.20
DM	2667.60**	106.63$^{n.s}$	394291.08**	726.05**	30.70$^{n.s}$	38321.53**	95.40**	14345.50**	30.40**	1.70
CTD	40.83**	1.70$^{n.s}$	1243.59**	3.01**	1.31$^{n.s}$	67.15**	0.84$^{n.s}$	22.50**	0.38$^{n.s}$	0.50
GY	16.10$^{n.s}$	21.03$^{n.s}$	781.10**	2.75**	0.85$^{n.s}$	36.60**	10.57**	14.80**	0.26$^{n.s}$	0.33
TGW	2.40$^{n.s}$	13.77$^{n.s}$	10314.73**	86.40$^{n.s}$	2.80$^{n.s}$	1113.25**	24.58**	401.17**	15.70**	3.20

n.s: not significant.
d.f, degree of freedom.
CTD, canopy temperature drop; DDR, days to double ridge; DH, days to heading; DM, days to physiological maturity; GY, grain yield; TGW, thousand grain weight.
** show significance at the 0.01 probability level.

Table 2
Genetic parameters including variance components, broad-sense heritability (h_b^2), phenotypic coefficient of variation (PCV), and genetic coefficient of variation (GCV) for measured traits in 13 varieties of wheat in eight sowing dates during 2012–2014.

Traits	Variance components				h_b^2	GCV	PCV
	σ_g^2	σ_{gy}^2	σ_e^2	σ_p^2			
DDR	9.43	5.71	0.19	11.93	79.00	4.41	4.96
DH	26.94	10.06	2.20	32.16	83.77	4.07	4.45
DM	332.10	596.46	1.70	532.24	62.39	11.24	14.23
CTD	0.61	0.92	0.50	0.93	65.81	19.06	23.50
GY	0.16	0.61	0.33	0.51	31.39	12.01	16.89
TGW	9.77	16.06	3.20	15.46	63.17	8.88	11.18

σ_g^2, genotype variance; σ_{gy}^2, genotype × year variance; σ_e^2, error variance; σ_p^2, phenotypic variance; h_b^2, broad-sense heritability; GCV, genetic coefficient of variation; PCV, phenotypic coefficient of variation.
CTD, canopy temperature drop; DDR, days to double ridge; DH, days to heading; DM, days to physiological maturity; GY, grain yield.

Table 3
Results of additive main effects and multiplicative interaction (AMMI) analysis of variance for grain yield of 13 wheat varieties evaluated at eight sowing dates.

Source of variation	d.f	SS	MS	Total variation (%)
Total	311	2348.374		
Sowing date (S)	7	1695.752	242.250**	72.21
Variety (V)	12	162.867	13.572**	6.94
S × V	84	430.408	5.124**	18.33
PC1	18	303.328	16.852**	70.47
PC2	16	87.213	5.451**	20.26
PC3	14	18.683	1.335**	4.34
PC4	12	10.098	0.842**	2.35
PC5	10	7.041	0.704**	1.64
PC6	14	4.05	0.290$^{n.s}$	0.17
PC7	6	1.252	0.209$^{n.s}$	0.29
Residual	208	59.280	0.285$^{n.s}$	13.77

n.s: not significant.
d.f, degree of freedom; SS, sum of squares; MS, mean squares; PC, principal component.
** significant at 0.01 probability level.

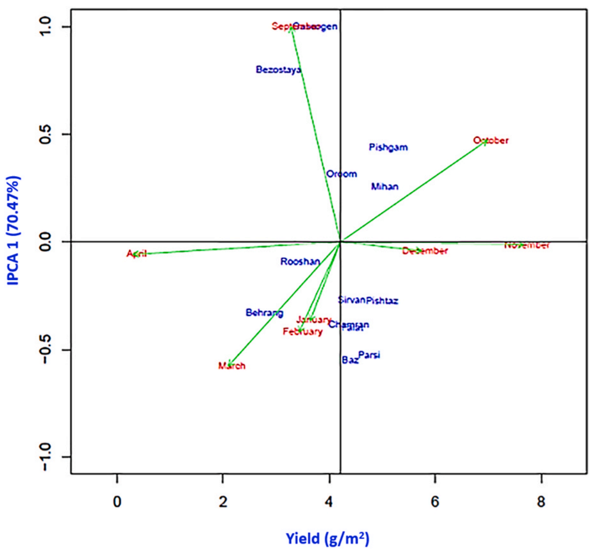

Fig. 1. AMMI1 biplot with the main effects vs. first principal component axis of interaction (IPCA1) for grain yield of 13 wheat varieties in eight sowing dates.

environment mean). The AMMI biplot captures 92.07 % of the variation, with 6.94 % due to the genotypic sum of squares (GSS), 72.21 % due to the environmental sum of squares (ESS) and 12.92 % due to IPCA1. According to the AMMI model, genotypes with a high mean performance (which is above the average yield) and IPCA values close to zero show general adaptability in different environments. Conversely, genotypes with high mean yields and elevated IPCA values indicate specific adaptation to certain environments [31]. The AMMI1 biplot shows that regardless of the direction of IPCA1 values, a group of varieties, including Mihan, Oroom, Pishgam, Pishtaz, and Sirvan consistently achieve high yields with IPCA1 values close to zero (Fig. 1; Supplementary Table S4). Consequently, these varieties exhibit high stability and are only minimally affected by genotype-environment interactions. Within this group, Oroom, Pishgam and Pishtaz show positive interactions with the September and October sowing dates (environments), while Mihan and Sirvan show positive interactions with the remaining sowing dates, as shown by similar signs of their interaction scores [14]. In contrast, Bezostaya and Gascogen were identified as the most unstable varieties, with grain yields below the grand mean and the highest IPCA1 values, but they were identified as specifically adapted to the September sowing date. Rooshan and Behrang, with relatively low IPCA1 values, are categorized as moderately stable varieties (Fig. 1; Supplementary Table S4).

Among the sowing dates (environments) examined in this study, September and March mostly cotributed to the genotype-environment (GE) interaction, as evidenced by their highest IPCA1 values and their positions far from the origin in the AMMI1 biplot. In contrast, the sowing dates in November, December, April, and October had the lowest IPCA1 values, indicating their minimal contribution to the GE interaction (Fig. 1). These sowing dates, characterized by IPCA1 values close to zero and negligible interaction effects, proved to be the most stable, indicating that all varieties performed well under these specific sowing dates.

Fig. 2 presents the AMMI-2 biplot illustrating the IPCA1 and IPCA2 for grain yield. This biplot compares the relative magnitude and sign of the GE interaction for each genotype and environment. Genotypes and environments close to the origin are considered as the most stable, indicating minimal contribution to the GE interaction, while those positioned farther from the origin are considered as unstable and show significant interaction. The AMMI2 biplot accounted for 90.73 % of the total sum of squares of the GE interaction for grain yield (Fig. 2). The results show that varieties such as Behrang, Chamran, Falat, Mihan, Oroom, Pishgam, Pishtaz, and Sirvan are clustered near the origin of the biplot, indicating their stability. Among these varieties, Mihan, Oroom and Pishgam showed particularly stable performance. In contrast, Gascogen, Bezostaya and Rooshan were far from the origin and exhibited a highly interactive behavior that classified them as unstable and specifically adapted to the September sowing date (Fig. 2).

The Average Environment Coordination (AEC) method (Fig. 3) graphically represents the average grain yield and stability of the varieties. In this biplot, the single arrow line passing through the origin of the biplot and the average environment marker and extending to higher values denotes to the AEC abscissa. The projections of the varieties onto this AEC abscissa correspond approximately to their mean grain yield, with longer projections indicating less stability [15]. As shown in Fig. 3, the varieties are divided into two groups. The first group, which has above-average performance, includes Mihan, Pishgam, Pishtaz, Parsi, Oroom, Chamran, Falat, and Baz. The order of their stability, from the most stable to the least stable, is as follows: Pishtaz, Mihan, Parsi, Oroom, Chamran, Falat, Baz, and Pishgam. The second group, consisting of Sirvan, Gascogen, Rooshan, Bezostaya, and Behrang, had below-average performance. An ideal variety would combine high average performance with absolute stability in a wide range of environments [32]. Consequently, Pishtaz, Mihan and Oroom are identified as the most stable and relatively high-yielding varieties, which makes them the most favorable varieties (Fig. 3).

Fig. 4 shows a polygon view of the GGE biplot, illustrating the "which-won-where" pattern of interaction between the varieties and the sowing dates. In this biplot, the varieties located at the vertices of the polygon (i.e. Behrang, Bezostaya, Gascogen, Pishgam, Parsi, and Baz) are either the best or the worst at one or more sowing dates, based on their maximum distance from the origin in their

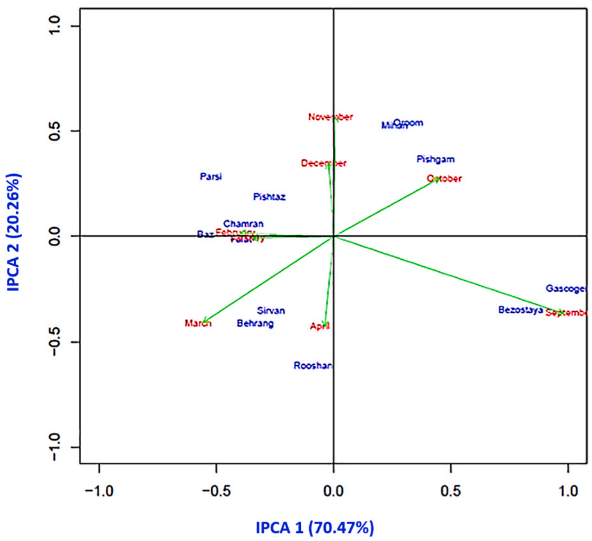

Fig. 2. AMMI 2 biplot (IPCA1 *vs.* IPCA2) for grain yield of 13 wheat varieties evaluated at eight sowing dates.

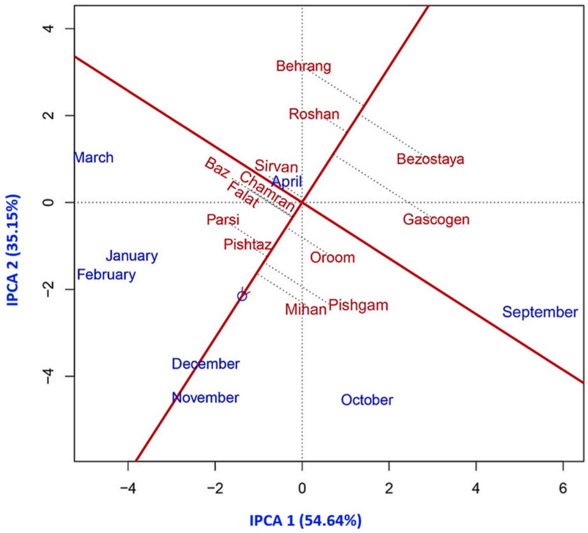

Fig. 3. GGE biplot showing the ranking of wheat varieties based on grain yield and stability.

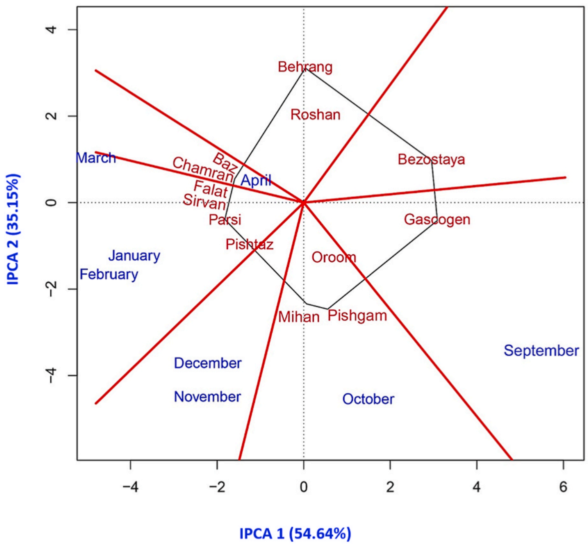

Fig. 4. 'Polygon' view of the GGE biplot to show which variety of wheat performed better in which sowing date in terms of grain yield.

respective directions, and are therefore considered to be specifically adapted. As shown in Fig. 4, Gascogen produced the highest yield on 6th September, Pishgam on 6th October, Parsi on 6th January, 6th February and 6th March and Baz on 6th April. The two apex varieties of Behrang and Bezostaya did not achieve the highest yield on any of the sowing dates and therefore were the poorest performing varieties on all or some sowing dates (Fig. 4).

The results of the regression stability parameters (b_i, S^2_{di}) (Table 4) showed the variability of the studied wheat varieties in terms of stability. Their b_i values ranged from 0.629 to 1.377 (Rooshan and Oroom, respectively). For the standard deviation of the regression (S^2_{di}), the varieties showed a wide range of values, with S^2_{di} ranging from 0.179 to 5.508 (Rooshan and Gascogen, respectively).

4. Discussion

In order to meet the food demand of growing world population, a significant increase in agricultural production is essential. Given the central role of wheat as a staple food for the growing world population, understanding the contributions of genetic factors, environmental conditions and genotype-environment interactions is crucial for effective wheat breeding. In this study, significant genetic variability was observed among wheat varieties for all measured traits, indicating a considerable genetic potential for trait improvement through targeted selection in breeding programs. The pronounced genotype-environment (GE) interaction shows

Table 4
Regression method parameters and AMMI-based stability parameters for grain yield of 13 wheat varieties grown in eight sowing dates.

Varity name	Regression method parameters		AMMI- based parameters		
	b_i	S^2_{di}	ASV	SIPC	GSI
Pishgam	1.294	1.035	6.35	2.42	14.00
Gascogen	1.075	5.508	9.19	3.41	21.00
Falat	0.907	0.718	22.02	4.30	8.00
Chamran	0.967	0.803	19.59	4.44	13.00
Rooshan	0.628	0.179	17.15	5.73	17.00
Parsi	1.049	1.695	22.73	5.82	6.00
Pishtaz	1.077	0.486	15.74	3.83	12.00
Sirvan	0.744	0.371	17.07	4.01	13.00
Mihan	1.365	0.339	16.90	2.99	10.00
Oroom	1.377	0.479	7.53	2.54	21.00
Bezostaya	0.972	3.871	10.67	4.05	22.00
Behrang	0.650	0.518	20.63	5.38	17.00
Baz	0.896	1.626	25.23	4.45	8.00

ASV: AMMI stability value; SIPC: sum of the absolute values of IPC scores; GSI: genotype selection index.

considerable differences in the performance of the varieties across the eight sowing dates and facilitates a robust assessment of phenotypic stability in the subsequent analyses. It is noteworthy that the GE effect was significantly larger and almost three times greater than the genotype (G) effect of the total variation, which suggested the possible existence of different mega-environments with different top-yielding varieties and indicated the need for stability analysis [32].

In addition, the study showed considerable genetic variation in all assessed traits, indicating significant potential for genetic improvement through selection within the studied germplasm. The relatively low difference between the phenotypic coefficient of variation (PCV) and the genotypic coefficient of variation (GCV) indicates a greater potential gain through selection, as this indicates a lower environmental influence and higher heritability. In this context, smaller differences between these coefficients were observed for traits such as days to double ridge (DDR) and days to heading (DH), suggesting that selection for these traits could lead to significant improvements. These results were in agreement with the findings of Saeidnia et al. [33] in wheat, who reported lower differences between PCV and GCV for phenological traits compared to yield and its components.

The estimation of heritability, which quantifies the genetic variance in relation to the total phenotypic variance, is of utmost importance for crop improvement. It facilitates the evaluation of environmental and genetic influences on trait expression and helps to determine the selection efficiency for the development and implementation of breeding programs [13,34]. In this study, high heritability estimates were observed for all traits except for grain yield, indicating the presence of important genes or quantitative trait loci (QTLs) influencing these traits. Traits with high heritability can be effectively improved by recurrent or mass selection [35]. These results are consistent with the previous studies in wheat (e.g. Ref. [36]), which identified major QTLs affecting agronomic traits. Despite its economic importance, grain yield showed low heritability, which is a challenge for phenotypic selection. In such cases, indirect selection for traits with high heritability and strong correlations with grain yield can be an advantageous alternative [37]. Numerous studies have investigated the heritability of important economic traits affecting wheat yield (e.g. Ref. [38]), contributing to a deeper understanding of trait inheritance in wheat breeding programs.

Accurate estimation of the magnitude and relative proportions of the different components of genetic variance is essential for understanding the underlying gene actions that control the traits of interest. This knowledge forms the basis for devising targeted breeding strategies to effectively improve the desired traits. However, the interaction between genotype and environment remains a major challenge for plant breeders, geneticists and agronomists in performance testing, as biases in the estimation of variance components can lead to flawed breeding methods and hinders variety development [39]. Plant breeding researchers are constantly searching for genotypes with high yield potential and minimized GE interactions. Evaluation of genotypes in different environments is crucial for the accurate assessment of their performance. Hassani et al. [40] have shown that performing GE analyses improves the selection of genotypes suitable for specific target environments.

According to the methodology proposed by Eberhart and Russell [26], a genotype is considered stable if it has a high yield, a regression coefficient close to one and a minimum deviation from the regression. The stability analysis using the regression approach showed that certain varieties had stable grain production, while others were only productive at certain sowing dates. It is noteworthy that some varieties had regression coefficients close to 1, indicating high stability. Pishtaz, for example, had a regression coefficient of approximately 1.0, combined with a low S^2_{di} value, indicating high adaptability across the eight sowing dates. Although regression approaches provide valuable insights into the stability of individual genotypes, a major limitation is that they cannot provide a comprehensive representation of the overall response pattern [41]. This limitation arises from the fact that the responses of genotypes to changing environmental conditions are inherently multivariate, whereas stability parameters often remain univariate [29].

Among the various statistical methods developed for analyzing GE interactions, the AMMI model is particularly effective in the capturing of substantial proportion of GE sums of squares [6]. The AMMI model is widely recognized for its efficiency and has been successfully used to describe GE interactions in several crops, including wheat [16,42], barley [43], and lupine [44]. In this study, we used this multivariate technique to evaluate the stability of grain yield of wheat varieties across eight sowing dates.

AMMI analysis revealed that environmental factors were the main source of variability and significantly affected grain yield. The significant contribution of GE interaction to the total sum of squares emphasizes the considerable variation in wheat genotypic response across sowing dates [45], justifying an estimate of phenotypic stability. Using the AMMI model, we partitioned the GE interactions into interaction principal components (IPCA) and noise. Principal component analysis revealed that the first five IPCAs accounted for the majority of GE sums of squares, which is consistent with the results of Dehghani et al. [31]. However, this is in contrast to the recommendations of Yan and Rajcan [46], who argued in favor of using the first two IPCAs to predict the most accurate AMMI model. These results show that determining the optimal number of terms for an AMMI model requires a thorough predictive assessment [30]. Factors like the type of crop, germplasm diversity and environmental conditions contribute to the complexity of the optimal predictive model [32]. IPCA1 reflects the non-crossover interactions, while IPCA2 considers the crossover interactions. This means that varieties with high IPCA1 values, such as Gascogen, Bezostaya and Baz, show greater non-crossover interactions with the environments (sowing dates), while varieties with higher IPCA2 values, such as Rooshan, Oroom, and Mihan, show more pronounced crossover interactions.

Differences in stability and adaptability to environments can be qualitatively assessed using the biplot graphical representation that scatters the genotypes according to their principal component values [47]. In addition, the AMMI1 biplot provides valuable insights into the patterns of GE interaction. Pattern analysis within the AMMI model facilitates the grouping of genotypes and environments that show similar responses [31]. The results of the AMMI2 biplot analysis divided the wheat varieties into four distinct groups. The first group, consisting of Chamran, Falat, Mihan, Pishgam, Pishtaz, Oroom, and Sirvan, showed high demand due to their relatively high yield and stability, with Mihan, Oroom, and Pishgam showing higher stability within this group. The second group, characterized by high yield but low stability, includes Baz and Parsi, while the third group compromises Behrang and Rooshan, which have low yield but moderate stability. The fourth group, represented by Gascogen and Bezostaya, showed a relatively low yield and low stability. The AMMI2 biplot results showed that only three varieties, namely Mihan, Oroom, and Pishgam, had above-average yields and general adaptability, as indicated by their IPCA scores close to zero. In general, environments with scores close to zero have minimal interaction with genotypes and provide limited discrimination [48]. Consistent with this observation, the environments in November, December, April, and October had lower scores and contributed less to the overall GE interaction.

The estimates of three AMMI-based stability parameters for grain yield of wheat varieties are shown in Table 4. Among the varieties with the lowest ASV values, Pishgam, Oroom, Mihan, and Pishtaz had mean grain yields above the overall mean, characterizing them as the most stable varieties. Based on the SIPC score, varieties Pishgam, Oroom, Mihan, and Pishtaz, which exhibited suitable grain yields, were also identified as the most stable. Conversely, the varieties Parsi, Behrang, and Baz had the highest ASV and SIPC values for grain yield. These findings are consistent with the results of the biplot analysis. The genotype selection index (GSI) identified Mihan, Pishtaz, and Pishgam as possessing general adaptation (stable variety) and high grain yield.

As the AEC abscissa approximates the contributions of genotypes to G, the AEC ordinate must approximate the genotype contributions to GE, offering a measure of stability or instability [15]. In this respect, Pishtaz, Mihan, and Oroom (the varieties exhibiting high grain yield) were also the most stable varieties, demonstrating consistent ranks across all sowing dates. In contrast, Gascogen, one of the high-yielding varieties, followed by Behrang, Bezostaya, and Pishgam, exhibited the least stability and tended to be specifically adapted to certain sowing dates. The varieties of Pishtaz, Mihan, and Oroom, which showed above-average performance, exhibited superior performance across all sowing dates, emphasizing their potential for stable performance across different sowing dates. In contrast, other varieties such as Pishgam, Chamran, Falat, and Baz, which had high yield but low stability, are more suitable for specific sowing dates.

According to the GGE biplot, an ideal genotype should have the highest mean performance and absolute stability and demonstrate broad adaptability across a wide range of environments [32]. In this context, Pishtaz was identified as the ideal variety, while Mihan, Parsi, Pishgam, and Oroom were considered as the most desirable varieties, because they were closest to the ideal genotype. Among these five varieties, Pishgam, Mihan, and Oroom, which had above-average performance, were close to the AEC abscissa and had short projections on the AEC ordinate. These varieties could be considered as the most stable and optimal ones.

5. Conclusions

In summary, considerable and significant differences observed among wheat varieties for the studied traits highlight the substantial genetic diversity within this germplasm. This variation indicates that it is possible to find the most desirable varieties for each sowing date with high stability and performance using targeted selection and stability analysis methods. The remarkably low broad-sense heritability for grain yield, reflects the influence of both genetic and non-genetic factors on the genetic control of this trait. Consequently, in breeding programs for wheat, selection based on an index would be more effective for improvement of grain yield. In addition, the important role of genotype-environment interactions requires the selection of superior varieties through multi-environment trials to improve their performance under different conditions. Although it has been revealed that the GGE biplot method is more efficient than the AMMI model in evaluating GEI, our results showed a high overlap between the results of these two methods. From analysis of GEI in wheat varieties, high-yielding and stable varieties were identified. Both AMMI and GGE biplot analyses consistently identified Mihan, Oroom, and Pishgam as high yielding and stable varieties. To validate and extend the results of this study, future research should focus on conducting AMMI and GGE biplot analyses at different locations and over several years. Such multi-environment studies would allow to provide a deeper understanding of genotype-environment interactions and their impact on wheat breeding. In addition, using from the varieties of Mihan, Oroom and Pishgam with high yield and stable performance across different sowing dates could be recommended for mapping studies in order to identify loci associated with productivity and yield stability.

CRediT authorship contribution statement

Majid Taherian: Visualization, Validation, Software, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Fatemeh Saeidnia:** Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rasmieh Hamid:** Writing – review & editing. **Seyyed Mahmood Nazeri:** Methodology, Investigation, Conceptualization.

Data and code availability statement

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e39599.

References

[1] X. Ye, J. Li, Y. Cheng, F. Yao, L. Long, Y. Wang, et al., Genome-wide association study reveals new loci for yield-related traits in Sichuan wheat germplasm under stripe rust stress, BMC Genom. 20 (2021) 640, https://doi.org/10.21203/rs.2.10187/v1.

[2] A. Sallam, A.M. Alqudah, M.F. Dawood, P.S. Baenziger, A. Borner, Drought stress tolerance in wheat and barley: advances in physiology, breeding and genetics research, Int. J. Mol. Sci. 20 (13) (2019) 1–36, https://doi.org/10.3390/ijms20133137.

[3] S.S. Bilgrami, H. Darzi Ramandi, V. Shariati, Kh Razavi, E. Tavakol, B.A. Fakheri, et al., Detection of genomic regions associated with tiller number in Iranian bread wheat under different water regimes using genome-wide association study, Sci. Rep. 10 (2020) 14034, https://doi.org/10.1038/s41598-020-69442-9.

[4] F. Boukid, M. Dall'Asta, L. Bresciani, P. Mena, D. Del Rio, Phenolic profile and antioxidant capacity of landraces, old and modern Tunisian durum wheat, Eur. Food Res. Technol. 245 (2019) 73–82, https://doi.org/10.1007/s00217-018-3141-1.

[5] N.M. Tshikunde, J. Mashilo, H. Shimelis, A. Odindo, Agronomic and physiological traits, and associated quantitative trait loci (QTL) affecting yield response in wheat (*Triticum aestivum* L.): a review, Front. Plant Sci. 10 (2019) 1428, https://doi.org/10.3389/fpls.2019.01428.

[6] I. Urbanaviciute, L. Bonfiglioli, M.A. Pagnotta, Selection of durum wheat and SSR markers for agronomic farming in central Italy using AMMI analysis, Agron 14 (2024) 458, 1003390/agronomy14030458.

[7] F. Shoormij, A. Mirlohi, G. Saeidi, M. Mohammadi, Concurrent improvement of durum and emmer wheat through reciprocal backcrossing and hybridization, Agron. J. 114 (2022) 3074–3082, https://doi.org/10.1002/agj2.21183.

[8] M.L. Khichar, R. Niwas, Microclimatic profiles under different sowing environments in wheat, J. Agrometeorol. 8 (2006) 201–209.

[9] S. Gupta, R.K. Singh, N.K. Sinha, A. Singh, U.P. Shahi, Effect of different sowing dates on growth and yield attributes of wheat in Udham Singh Nagar District of Uttarakhand, India, Plant Arch 17 (2017) 232–236.

[10] K. Nahar, K. Ahmad, M. Fujita, Phenological variation and its relation with yield in several wheat (*Triticum aestivum* L.) cultivars under normal and late sowing mediated heat stress condition, Not. Sci. Biol. 2 (2010) 51–56, https://doi.org/10.15835/nsb234723.

[11] W. Yan, Crop Variety Trials: Data Management and Analysis, John Wiley and Sons, 2014.

[12] E. Oral, E. Kendal, Y. Dogan, Selection the best barley genotypes to multi and special environments by AMMI and GGE biplot models, Fresenius Environ. Bull. 27 (2018) 5179–5187.

[13] F. Amini, M.M. Majidi, A. Mirlohi, Genetic and genotype × environment interaction analysis for agronomical and some morphological traits in half-sib families of tall fescue, Crop Sci. 53 (2013) 411–421, https://doi.org/10.2135/cropsci2012.05.0277.

[14] R.W. Zobel, M.J. Wright, H.G. Gauch, Statistical analysis of a yield trial, Agron. J. 80 (1988) 388–393, https://doi.org/10.2134/agronj1988.00021962008000030002.

[15] W. Yan, Two types of biplots to integrate multi-trial and multi-trait information for genotype selection, Crop Sci. 64 (2024) 1608–1618, https://doi.org/10.1002/csc2.21231.

[16] J. Ahmadi, A. Mohammadi, T. Najafi Mirak, Targeting promising bread wheat (*Triticum aestivum* L.) lines for cold climate growing environments using AMMI and SREG GGE biplot analyses, J. Agric. Sci. Technol. 14 (2012) 645–657.

[17] J.L. Purchase, H. Hatting, C.S. Van Deventer, Genotype × environment interaction of winter wheat (*T. aestivum*) in South Africa: stability analysis of yield performance, S. Afr. J. Plant Soil 17 (2000) 101–107, https://doi.org/10.1080/02571862.2000.10634878.

[18] E. Farshadfar, N. Mahmodi, A. Yaghotipoor, AMMI stability value and simultaneous estimation of yield and yield stability in bread wheat (*Triticum aestivum* L.), Aust. J. Crop. Sci. 5 (13) (2011) 1837–1844.

[19] J. Puig, G. Pauluzzi, E. Guiderdoni, P. Gantet, Regulation of shoot and root development through mutual signaling, Mol. Plant 5 (2012) 574–583, https://doi.org/10.1093/mp/sss047.

[20] M.M. Majidi, B. Araghi, M. Barati, A. Mirlohi, Polycross Genetic analysis of forage yield and related traits in *Dactylis glomerata*, Crop Sci. 55 (2015) 203–210, https://doi.org/10.2135/cropsci2014.05.0386.

[21] R. Johnson, L. Stitch, P. Olwell, S. Lambert, M. Horning, R. Cronn, What are the best seed sources for ecosystem restoration on BLM and USFS lands? Native Plants J. 11 (2010) 117–130, https://doi.org/10.2979/NPJ.2010.11.2.117.

[22] H.G. Gauch, H.P. Piepho, P. Annicchiarico, Statistical analysis of yield trials by AMMI and GGE. Further considerations, Crop Sci. 48 (2008) 866–889, https://doi.org/10.2135/cropsci2007.09.0513.

[23] R.G.D. Steel, J.G. Torrie, Principles and Procedures of Statistics, McGraw–Hill, Book, New York, 1980.

[24] A.R. Hallauer, J.B. Miranda, Quantitative Genetics and Maize Breeding, Iowa State University Press, Ames, IA, USA, 1988.

[25] D.S. Falconer, T.F.C. Mackay, Introduction to Quantitative Genetics, Longman, Harlow, UK, 1996.

[26] S.A. Eberhart, W.A. Russell, Stability parameters for comparing varieties, Crop Sci. 6 (1966) 36–40, https://doi.org/10.2135/cropsci1966.0011183X000600010011x.

[27] C.H. Sneller, L. Kilgore-Norquest, D. Dombek, Repeatability of yield stability statistics in soybean, Crop Sci. 37 (1997) 383–390, https://doi.org/10.2135/cropsci1997.0011183X003700020013x.
[28] A. Pacheco, M. Vargas, G. Alvarado, F. Rodríguez, J. Crossa, J. Burgueño, GEA-R (Genotype X Environment Analysis with R for Windows) Version 4.1, CIMMYT Research Data and Software Repository Network, 2015, p. V16. https://hdl.handle.net/11529/10203.
[29] J. Crossa, H.G. Gauch, R.W. Zobel, Additive main effects and multiplicative analysis of two international maize cultivar trials, Crop Sci. 30 (1990) 493–500, https://doi.org/10.2135/cropsci1990.0011183X003000030003x.
[30] F. Ebrahimi, M.M. Majidi, A. Arzani, G. Mohammadi-Nejad, Oil and seed yield stability in a worldwide collection of safflower under arid environments of Iran, Euphytica 212 (2016) 131–144. /s10681-016-1779-y.
[31] M.R. Dehghani, M.M. Majidi, A. Mirlohi, G. Saeidi, Study of genotype by environment interaction in tall fescue genotypes and their polycross progenies in Iran based on AMMI model analysis, Crop Pasture Sci. 67 (2017) 792–799, https://doi.org/10.1071/CP15386.
[32] F. Saeidnia, M.M. Majidi, M.R. Dehghani, G. Saeidi, A. Mirlohi, Drought tolerance and stability of native Iranian tall fescue genotypes: comparison of AMMI and GGE biplot analyses, Agron. J. 114 (2022) 2180–2185, https://doi.org/10.1002/agj2.211217.
[33] F. Saeidnia, F. Shoormij, A. Mirlohi, E. Soleimani Kartalaei, M. Mohammadi, M.R. Sabzalian, Drought adaptability of different subspecies of tetraploid wheat (*Triticum turgidum*) under contrasting moisture conditions: association with solvent retention capacity and quality-related traits, PLoS One 18 (2) (2023) e0275412, https://doi.org/10.1371/journal.pone.0275412.
[34] S. Spanani, M.M. Majidi, N. Hughes, Genetics of inbreeding effects in smooth bromegrass, Crop Sci. 58 (2018) 1899–1906, https://doi.org/10.2155/cropsci2018.01.0019.
[35] L. Mwadzingeni, H. Shimelis, T.J. Tsilo, Variance components and heritability of yield and yield components of wheat under drought-stressed and non-stressed conditions, Aust. J. Crop. Sci. 11 (11) (2017) 1425–1430, https://doi.org/10.21475/ajcs.17.11.11.pne548.
[36] X. Li, X. Xia, Y. Xiao, Z. He, D. Wang, R. Trethowan, et al., QTL mapping for plant height and yield components in common wheat under water-limited and full irrigation environments, Crop Pasture Sci. 66 (2015) 660–670, https://doi.org/10.1071/CP14236.
[37] A. Blum, Plant Breeding for Water Limited Environments, Springer, New York, 2011.
[38] R. Abdolshahi, M. Nazari, A. Safarian, T. Sadathossini, M. Salarpour, H. Amiri, Integrated selection criteria for drought tolerance in wheat (*Triticum aestivum* L.) breeding programs using discriminant analysis, Field Crops Res. 174 (2015) 20–29, https://doi.org/10.1016/j.fcr.2015.01.009.
[39] M. Bantayehu, Analysis and correlation of stability parameters in malting barley, Afr. J. Crop Sci. 17 (2010) 145–153.
[40] M. Hassani, B. Heidari, A. Dadkhodaie, P. Stevanato, Genotype by environment interaction components underlying variations in root, sugar and white sugar yield in sugar beet (*Beta vulgaris* L.), Euphytica 214 (2018) 79, https://doi.org/10.1007/s10681-018-2160-0.
[41] L.K. Bose, N.N. Jambhulkar, K. Pande, O.N. Singh, Use of AMMI and other stability statistics in the simultaneous selection of rice genotypes for yield and stability under direct- selected conditions, Chil. J. Agric. Res. 74 (1) (2014), https://doi.org/10.4067/SO718–58392014000100001.
[42] J. Ahmadi, B. Vaezi, M.H. Fetokian, Graphical analysis of multi-environment trials for barley yield using AMMI and GGE-biplot under rainfed conditions, J. Plant Physiol. Breed. 2 (1) (2012) 43–54.
[43] M. Khalili, A. Pour-Aboughadareh, Parametric and nonparametric measures for evaluating yield stability and adaptability in barley doubled haploid lines, J. Agric. Sci. Technol. 18 (2016) 789–803.
[44] P. Annicchiarico, N. Harzic, A.M. Carroni, Adaptation, diversity, and exploitation of global white lupin (*Lupinus albus* L.) landrace genetic resources, Field Crops Res. 119 (2010) 114–124, https://doi.org/10.1016/j.fcr.2010.06.022.
[45] K.S. Brar, S. Manhas, D.M. Hegde, GGE biplot analysis visualization of mean performance and stability for seed yield in safflower (*Cartamus tinctorus*) at diverse locations in India, Int. J. Agric. Sci. Res. 2 (2012) 77–90.
[46] W. Yan, I. Rajcan, Biplot analysis of test sites and trait relations of soybean in Ontario, Crop Sci. 42 (2002) 11–20, https://doi.org/10.2135/cropsci2002.0011.
[47] P.D. Vita, A.M. Mastrangeloa, L. Matteua, E. Mazzucotellib, N. Virzi, M. Palumboc, et al., Genetic improvement effects on yield stability in durum wheat genotypes grown in Italy, Field Crops Res. 119 (2010) 68–77, https://doi.org/10.1016/j.fcr.2010.06.016.
[48] A. Anandan, T. Sabesan, R. Eswaran, G. Rajiv, N. Muthalagan, R. Suresh, Appraisal of environmental interaction on quality traits of rice by additive main effects and multiplicative interaction analysis, Cereal Res. Commun. 37 (1) (2009) 139–148, https://doi.org/10.1556/CRC.37.2009.1.15.