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Grouping patterns of rainfed winter wheat test locations and the role of climatic variables

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Abstract Crop cultivar performance is a result of combined effects of genotype, environment and genotype × environment (G × E) interaction. To effectively generate reliable estimates of crop yield the magnitude and patterns of G × E in regional yield trials should be specified. This research aimed to (1) investigate existing possible mega-environments (ME) and suitability of test locations for winter wheat zoning, and (2) determine the role of climatic factors in clustering patterns of G × E. Winter wheat yield data from a three-year nationwide yield trial consisting of 24 genotypes grown in 24 test environments supplemented with 37 climatic factors were subjected to empirical and analytical analyses. Standard deviation-scaled genotype main effect and G × E interaction (SD-GGE) biplot methodology, factorial regression and partial least square regression were applied to both analyses. The combined ANOVA showed that the environmental effect was the main source of variation (83%), and the magnitude of

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G × E interaction was sixfold greater than genotype alone. The SD-GGE biplot confirmed non-repeatable patterns for grouping of test locations across years, indicating significant ($P < 0.01$) rank-change location-by-year interactions and existence of strong "crossover" G × E interactions. This led to the conclusion that the winter wheat growing region in Iran consists of a single but complex ME for grain yield, suggesting that high-yielding-and stable winter wheat genotypes should be developed for the entire region rather than genotypes adapted to specific agro-ecological regions. Precipitation (monthly and total) and temperature (minimum, maximum and average) accounted for 25.4% and 56.8% of total G × E.

Keywords Climatic factors · Crossover G × E interaction · Mega-environment · SD-GGE biplot

Introduction

Wheat (*Triticum* spp.) as the most diverse and widely consumed crop is the mainstay of global food security. Global demand for wheat is expected to grow rapidly in developing countries over the next decades due to high rates of population increase and income enhancement (Mohammadi 2018). Unpredictable environmental conditions in dryland areas caused by fluctuations in rainfall and temperature lead to highly variable yields and food insecurity (Sánchez-García et al. 2013; Hawkesford et al. 2013; Lobell and Gourdji 2012; Del Pozo et al. 2016). The most reliable way to address environmental variation is to choose promising genotypes over multiple locations and years (Malosetti et al. 2013; Yan 2015; Yan et al. 2000; Chairi et al. 2020). However, large yield trials and appropriate statistical methods are required for selection of promising lines, yield-based grouping of test locations and correct zoning of targeted regions (Navabi et al. 2006; Yan and Tinker 2006; Rozeboom et al. 2008).

Several empirical and analytical (biological) approaches are suggested for clustering of test environments in multi-environment trials (MET), including environmental factors (such as precipitation, temperature and soil) and genotypic trait information (Vargas et al. 2001; Motzo et al. 2001; Ramburan et al. 2012; Mohammadi et al. 2015).

Recently, the SD-GGE biplot has received increasing attention as it is an efficient method to fully explore MET data. The SD-GGE biplot is a standard deviation-scaled GGE biplot that explains variation due to G (genotype) and G × E interaction in more detail than the AMMI model and provides an easy and comprehensive solution for MET data analysis (Yan et al. 2007). It provides graphical displays of test environments, genotypes and their interaction based on principal component analysis (PCA) and presents a "which-wins-where" pattern for detecting mega-environment and crossover G × E interactions (Yan 2015). It allows investigation of test environments for selection of genotypes most adapted to target environments. The power of a test location for a representing target region (representativeness) and its ability to discriminate genotypes (discrimination ability) are the most important aspects of an ideal test location to be evaluated through multi-year and multi-location yield trials and outcomes must be repeatable across years (Yan et al. 2000).

Analytical models are required for enhancing the value of yield trials and understanding the causes of G × E interactions (Voltas et al. 2005; Yan and Hunt 2001). These models include some properties of trial sites regarding environmental factors such as precipitation, temperature, altitude, and latitude. Such models including factorial regression (FR; Denis 1988; van Eeuwijk et al. 1996) and partial least square (PLS) regression (Vargas et al. 2001) are based on a generalization of constrained-PCA (C-PCA) and are useful for studying G × E data with integration of some external factors (Amenta and D'Ambra 2001). The C-PCA integrates explanatory variables such as environmental factors into the G × E matrix data. For utilizing these methods, first the data matrix for the explanatory data is decomposed (external analysis) and then applied in PCA is to decompose the matrices (internal analysis).

The SD-GGE biplot methodology was applied to investigate G × E in grain yield data of winter wheat regional yield trials in Iran. The trials involved 24 winter wheat breeding lines and cultivars and 24 rainfed test environments across eight provinces that account for more than 60% of the rainfed winter wheat production area. Grouping of test environments through representativeness and discrimination ability was undertaken to explore the ecological grouping of test locations. Further analyses investigated the effects of climatic factors on G × E. The analysis presented in this research provides a basis for selection of superior winter wheat genotypes for cultivation in wide or narrow agro-ecological regions.

Materials and methods

Winter wheat genotypes and ecological regions

Twenty-four rainfed winter wheat genotypes consisting of 21 promising breeding lines and three current cultivars (Table 1) were evaluated at eight test locations (provinces) over three cropping seasons (2016–2017, 2017–2018, 2018–2019) (Table 2 and Fig. 1). The lines were representative of the national winter wheat breeding program for rainfed areas in Iran and were entries in the 24th Elite Regional Bread Wheat Yield Trial (ERBWYT).

Experimental design

The experimental design was a randomized complete blocks design with four replications at each location. The plot size was 7.2 m^2 (6 rows, 6 m long, and 20 cm row spacing). The sowing density was 380 seeds per m^2. The fertilizers used were 50 kg N ha^{-1} and 50 kg P_2O_5 ha^{-1} as basal application at planting. Herbicides were applied as a tank mixture of 2, 4-D and clodinafop-propargyl at tillering followed by hand weeding as required. No pest or disease control was necessary for the duration of the trials. Grain yields were measured as kg per plot, converted to yield per hectare (kg ha^{-1}) for statistical analyses.

Climatic data collections

The climatic data collected from weather stations at each location included 37 parameters including monthly and total precipitation, and monthly temperature recordings on minimum, maximum and average during the growing period (October–June).

Data analysis

The yield data of 24 genotypes grown in 24 test environments were analyzed. Combined analysis of variance (ANOVA) and phenotypic and genetic correlations among test locations were conducted using the Meta-R package (Alvarado et al. 2015). The GEA-R package (Pacheco et al. 2015) was used in SD-GGE biplot analysis. The general model for the GGE biplot is:

$$\overline{Y}ij - \mu_i - \beta_j = \sum_{k=1}^{N} \lambda_k \alpha_{ik} \eta_{jk}$$

where Y_{ij} is the grain yield of genotype *i* in environment *j*, μ is the grand mean, β_j is the main effect of environment *j*, *k* is the number of principal components (PC); λ_k is the singular value of the *k*th PC; and α_{ik} and η_{jk} are the scores of genotype *i* and environment *j*, respectively, for the kth PC; and ε_{ij} is the residual associated with genotype *i* in environment *j*.

In the SD-GGE biplot the cosine of the angle between vectors of two test locations indicates correlation; an acute angle shows a strong positive correlation whereas an obtuse angle indicates a negative correlation, and a right angle means no correlation. The projection of genotype or environment on the average tester coordinate (ATC) indicates average performance of genotype or desirability of test location (Yan et al. 2000). The distance between genotype and ATC is used to judge the genotype stability, whereas the angle between location vector and ATC assesses the representativeness of a test location. An acute angle shows more representativeness. A long vector for a test location shows greater discrimination. In SD-GGE biplot, the "which-wins-where" pattern shows a polygon view of G × E, in which the environments and genotypes are divided into several sections. The vertex genotype in each section is the one with the best mean performance across locations in that section.

To better understand the biological causes of G × E, multivariate partials least squares (PLS) regressions were performed as described by Aastveit and Martens (1986). The general model of PLS is based on the latent variable decomposition:

$$X = TP^T + E,$$
$$Y = TQ^T + F,$$

where T is a $n \times c$ matrix which giving the latent variable (also called scores) for the *n* observations; *P* and *Q* are, respectively, ($p \times c$) and ($l \times c$) orthogonal loading matrices; E and F are error terms assumed to be independent with random normal distributions.

Table 1 Code, name/pedigree, type and origin of genotypes included in trials

Code	Genotype	Type of material	Origin
G1	Baran	Cultivar	Iran
G2	Hashtrood	Cultivar	Iran
G3	Sardari	Cultivar	Iran
G4	ALTAY//JUN/BOMB IRW 05-06-36-0MAR-0MAR-0MAR-1MAR-0MAR	Breeding line	Iran
G5	ALTAY//JUN/BOMB IRW 05-06-36-0MAR-0MAR-0MAR-8MAR-0MAR	Breeding line	Iran
G6	PAVON (dwarf)/KAUZ (tall) IRW 05-06-84-0MAR-0MAR-0MAR-5MAR-0MAR	Breeding line	Iran
G7	CROC-1/AE.SQUARROSA (205)//KAUZ/3/SASIA/4/CHEN/AEGILOPS SQUARROSA (TAUS)//BCN/3/VEE#7/… IRW 05-06-221-0MAR-0MAR-0MAR-6MRA-OMRA	Breeding line	Iran
G 8	ZARGANA-3//JUN/BOMB IRW 05-06-333-0MAR-0MAR-0MAR-10MAR-0MAR	Breeding line	Iran
G9	SOROCA//SAULESKU #44/TR810200 IRW 05-06-171-0MAR-0MAR-0MAR-3MAR-0MAR	Breeding line	Iran
G10	SOROCA//SAULESKU #44/TR810200 IRW 05-06-171-0MAR-0MAR-0MAR-7MAR-0MAR	Breeding line	Iran
G11	SERI 82/SHUHA'S'//GRU90-204782/3/SARDARI/KAU"s"/NAO IRW 05-06-210-0MAR-0MAR-0MAR-4MAR-0MAR	Breeding line	Iran
G12	ALTAY/GAHAR IRW 05-06-41-0MAR-0MAR-0MAR-5MAR-0MAR	Breeding line	Iran
G13	NGDA146/4/YMH/TOB//MCD/3/LIRA/5/F130L1.12/ 6/PELSART /3/DONG87//TJB368.251/BUC/4/RSK/NAC IRW 05-06-138-0MAR-0MAR-0MAR-11MAR-0MAR	Breeding line	Iran
G14	NGDA146/4/YMH/TOB//MCD/3/LIRA/5/F130L1.12/ 6/PELSART /3/DONG87//TJB368.251/BUC/4/RSK/NAC IRW 05-06-138-0MAR-0MAR-0MAR-2MAR-0MAR	Breeding line	Iran
G15	P8-8/LLFN/3/BEZ/NAD//KZM/4/BB//CC/CNO*2/3/TOB156/BB/5/ PF8215/6/F134.71/NAC/7/SARDARI-HR86 IRW 05-06-355-0MAR-0MAR-0MAR-4MAR-0MAR	Breeding line	Iran
G16	GAHAR/3/SKAUZ/PASTOR//PASTOR*2/OPATA IRW 05-06-145-0MAR-OMA-0MAR5-MAR-0MAR	Breeding line	Iran
G17	GAHAR/3/SKAUZ/PASTOR//PASTOR*2/OPATA IRW 05-06-145-0MAR-OMA-0MAR-12MAR-0MAR	Breeding line	Iran
G18	KOHDASHT//37032 TURKEY/DARI-8 IRW 05-06-149-0MAR-0MAR-0MAR-5MAR-0MAR	Breeding line	Iran
G19	BEZ/ALTAY IRW 05-06-14-0MAR-0MAR-0MAR-11MAR-0MAR	Breeding line	Iran
G20	BEZ/ALTAY IRW 05-06-14-0MAR-0MAR-0MAR-2MAR-0MAR	Breeding line	Iran
G21	Azar-2/Ardabil 82-33 IRBW07-23-54-20-0SAR-0SAR-0MAR-8MAR-0MAR	Breeding line	Iran
G22	Sardari/Ardabil 82-33 IRBW07-23-54-36-0SAR-0SAR-0MAR-9MAR-0MAR	Breeding line	Iran
G23	ATTILLA//VORONA/TR810200 TCI02-679-0AP-0AP-1AP-0AP-2AP-05AP	Breeding line	TCI
G24	MV14-2000//SHARK/F4105W2.1 TCI041047-0SE-0E-050YA-050E-1E-0E	Breeding line	TCI

TCI Turkey-CIMMYT-ICARDA nursery

Table 2 Agro-ecological information for the 24 test environments

Environments	Coordinates				Latitude	Altitude (masl)	Temperature (°C)			Rainfall (mm)
Test location	Cropping season	Code	Province	Longitude			MIN	MAX	AVG	
Maragheh	2016–2017	MH7	East Azerbaijan	46°15′ N	37°15′ E	1725	− 11.4	2.1	4.6	263
	2017–2018	MH8					− 5	25.8	7.7	423
	2018–2019	MH9					− 6.6	27.4	6.0	494
Kermanshah	2016–2017	KH7	Kermanshah	47°17′ N	37°19′ E	1351	− 4.8	34.3	11.3	492
	2017–2018	KH8					− 3.6	30.8	12.5	521
	2018–2019	KH9					− 3	33.7	11.9	783
Qamloo	2016–2017	QO7	Kurdistan	47°30′ N	35°10′ E	1860	− 6.8	32	5.4	298.5
	2017–2018	QO8					− 5.4	28.5	7.8	337.5
	2018–2019	QO9					− 4.2	32.8	7.8	444.5
Zanjan	2016–2017	ZN7	Zanjan	48°49′ N	36°13′ E	1850	− 7.8	29.5	7.6	317.3
	2017–2018	ZN8					− 4.4	28.3	8.9	390
	2018–2019	ZN9					− 4.4	30	7.9	430
Urmieh	2016–2017	UH7	West Azerbaijan	44°58′ N	37°52′ E	1350	− 8.9	28.8	7.7	339.7
	2017–2018	UH8					− 1.8	29.0	10.4	531.6
	2018–2019	UH9					− 3.8	31	9.9	578.5
Ardabil	2016–2017	AL7	Ardabil	48°20′ N	38°15′ E	1350	− 12.5	23.5	5.9	189.7
	2017–2018	AL8					− 3.3	21.1	8.5	258
	2018–2019	AL9					− 15	25.9	8.3	274.1
Hamedan	2016–2017	HN7	Hamedan	48°32′ N	34°52′ E	1730	− 7.3	31.7	8.8	252.7
	2017–2018	HN8					− 5.6	31.1	9.8	337.1
	2018–2019	HN9					− 4.5	32.7	8.7	506.1
Arak	2016–2017	AK7	Markazi	49°42′ N	34°05′ E	1775	− 2.4	34.2	11.6	359.8
	2017–2018	AK8					− 5.3	32.4	10.2	293.2
	2018–2019	AK9					− 5.7	32.6	10.1	343.3

To estimate the contribution of climatic variables to G × E, a factorial regression (FR) model was used as described by Denis (1988). The general model for FR is:

$$E(Y_{ij}) = \mu + \alpha_i + \beta_j + \sum_{k+1}^{K} \xi_{ik} Z\gamma_{jk}$$

where μ, αi and βj are grand mean, G and E effects, respectively; zjk is kth climatic factor for environment j; and ξik represents the sensitivity of genotype i to kth climatic factor. The heterogeneity in the ξi's for successive $z1$, zK variables account for G × E interaction, and the sum of multiplicative terms $\sum_{k+1}^{K} \xi_{ik} Z\gamma_{jk}$ shows the interaction. The required number of climatic factors to optimally approximate the dimensionality can be detected using the Fischer F-test and Akaike's information criterion (AIC, Akaike 1974).

Results

ANOVA and variation in grain yield

The combined ANOVA for grain yield data showed that the effects of genotype, environment and G × E were highly significant (Table 3). The relative contribution of each treatment effect on variation in grain yield was determined according to the percentage of each treatment effect over the total effect. Environment (Y, L and Y × L) had the greatest impact on

Table 3 Combined analysis of variance for grain yield of 24 winter wheat genotypes across eight test locations and three cropping seasons

Sources	df	Mean square	F value	VE%
Environment (E)	23	61,140,365	922.4**	83.0
Genotype (G)	23	896,648	3.72**	1.2
G × E	529	240,749	3.6**	7.5
R/E	72	420,810	6.3	1.8
(R × G)/E	1656	66,287.2		6.5
Total	2303			
Year (Y)	2	234,927,934	3544.1**	27.7
Location (L)	7	70,231,750	2.21	29.0
Y × L	14	31,767,878	479.2**	26.3
G	23	896,648	3.16**	1.2
G × Y	46	283,432	1.38	0.8
G × L	161	302,196	4.56**	2.9
G × L × Y	322	203,929	3.1**	3.9
R/E	72	420,811	6.3483	1.8
(R × G)/E	1656	66,287		6.5
Total	2303			

**Significant at $P < 0.01$; VE%: Percentage of variance explained

grain yield, accounting for 83% (27.7%, 29.0% and 26.3% corresponding to Y, L and Y × L effects) of the variation. G × E accounted for 7.5% of grain yield variability, whereas genotype contributed only 1.2%. The contribution of G × E was therefore about sixfold that of genotype alone, indicating a high G × E in these yield trials. The impact of each factor on grain yield variability could be ranked from high to low as: L (29%) > Y (27.7%) > Y × L (26.3%) > G × Y × L (3.9%) > G × L (2.9%) > G (1.2%) > G × Y (0.8%).

Genotypic mean yields varied from 1789 to 2181 kg/ha across environments. In the case of locations the yield levels ranged from 1346 (Arak) to 2553 kg/ha (Kermanshah). The mean yield in each cropping season was 2419 kg/ha (2016–2017), 1936 kg/ha (2017–2018) and 3303 kg/ha (2018–2019). The grain yield of genotypes varied among environments showing high G × E interaction. In addition to fixed environmental properties such as latitude, altitude and soil type that may influence G × E there were also the effects of climatic variables such as rainfall (amount and monthly pattern) and temperature which can be highly variable from year to year and location to location under dryland Mediterranean conditions. However, the poor temporal and spatial distribution of rainfall in the region (Fig. 2) is the main challenge for winter wheat productivity.

The rainfall across environments during the growing period (October-June) varied from 189.7 mm at Ardabil in 2016–2017 (with a mean of 241 mm across years of study) to 782.5 mm at Kermanshah in 2018–2019 (mean of 599 mm rainfall). Given that about 400 mm of rainfall is required for successful crop production only 11 of 24 environments exceeded that level and consequently water stress conditions prevailed in more than of 50% of environments. Thus, some test environments were under severe drought conditions in different years.

Winter wheat mega-environments

Graphic analysis using the SD-GGE biplot for grain yield trials in single and multiple years provided an opportunity to identify possible mega-environments across the region. The which-wins-where pattern of the SD-GGE biplot showed several clustering patterns in the regional yield trials. A group of test locations sharing the same winner genotype is considered as a mega-environment (Gauch and Zobel 1997; Yan et al. 2000). Based on yearly SD-GGE biplots, the test locations were placed into groups, ranging from three in 2017–2018 and 2018–2019 to four in 2016–2017 (Fig. 3a–c).

In 2016–2017, the eight test locations were divided into four clusters with the four best performers (Fig. 3a). The best genotype was G3 at Maragheh (MH7), Qamloo (QO7) and Arak (AK7). The second cluster included Kermanshah (KH7) and Zanjan (ZN7) with G7 as winner. The locations of Hamedan and Urmieh clustered in the same section with G9 as the best yielder. The Ardabil (AL7) location tended to separate in a single cluster with G21 as winner.

In the second year (2017–2018; Fig. 3b) there were three location clusters with three performer genotypes. G20 performed the best at Zanjan (ZN8), Qamloo (QO8), Arak (AK8) and Urmieh (UH8). G7 was winner at Kermanshah (KH8), Maragheh (MH8) and Hamedan (HN8). As in the first year Ardabil (AL8) clustered in a separate group with G24 being the winner.

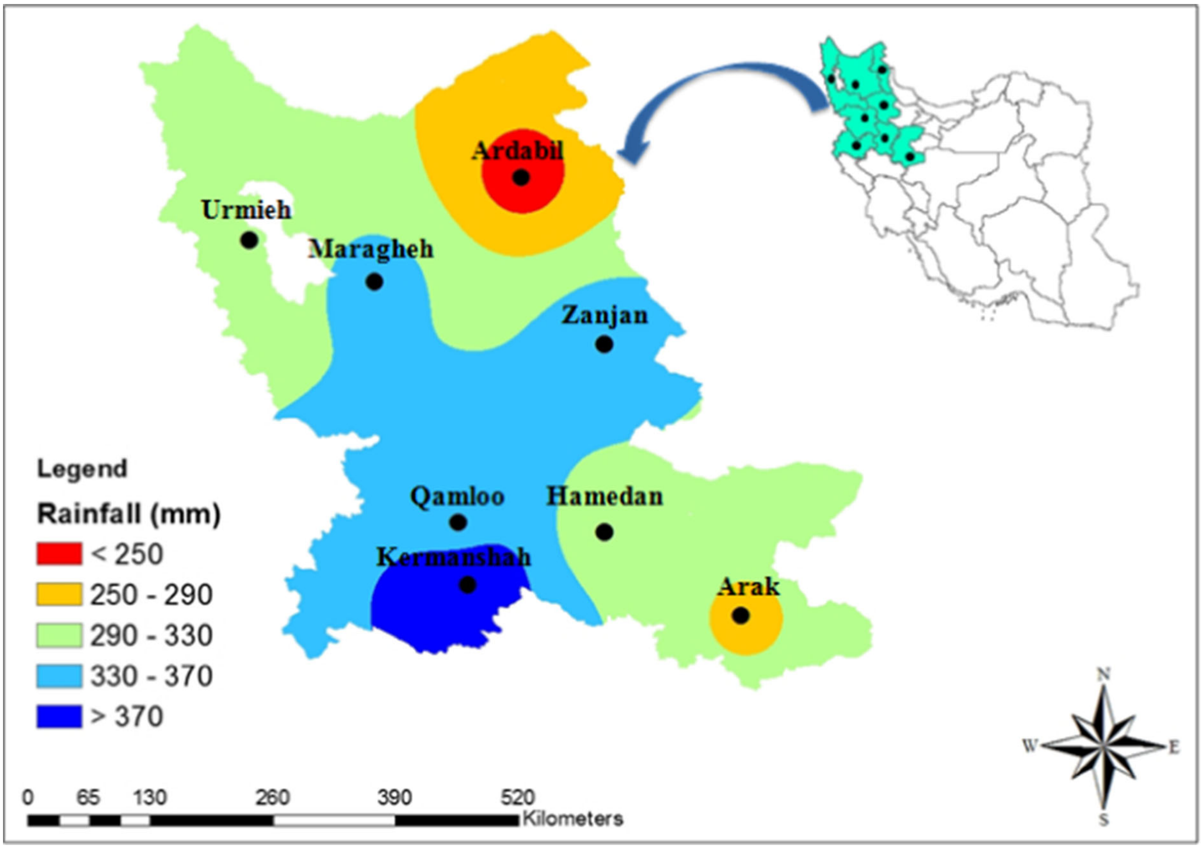

Fig. 1 Map of Iran showing winter wheat test locations and area grouping based on long-term rainfall using the geographical information system

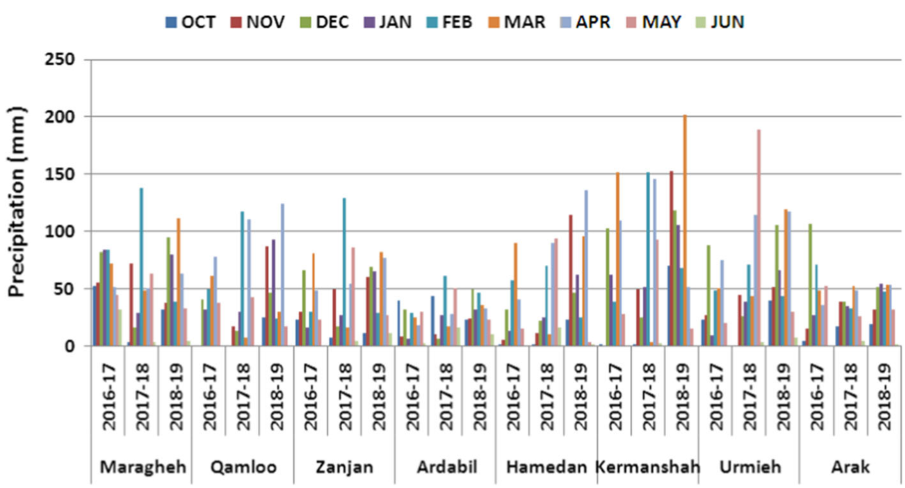

Fig. 2 Monthly patterns of rainfall in eight test locations over three cropping seasons

The eight locations were divided by three winner genotypes in the third year (Fig. 3c); G5 was highest yielding at Kermanshah (KH9), Zanjan (ZN9) and Qamloo (QO9), whereas the best performers at Hamedan (HN9), Maragheh (MH9) and Ardabil

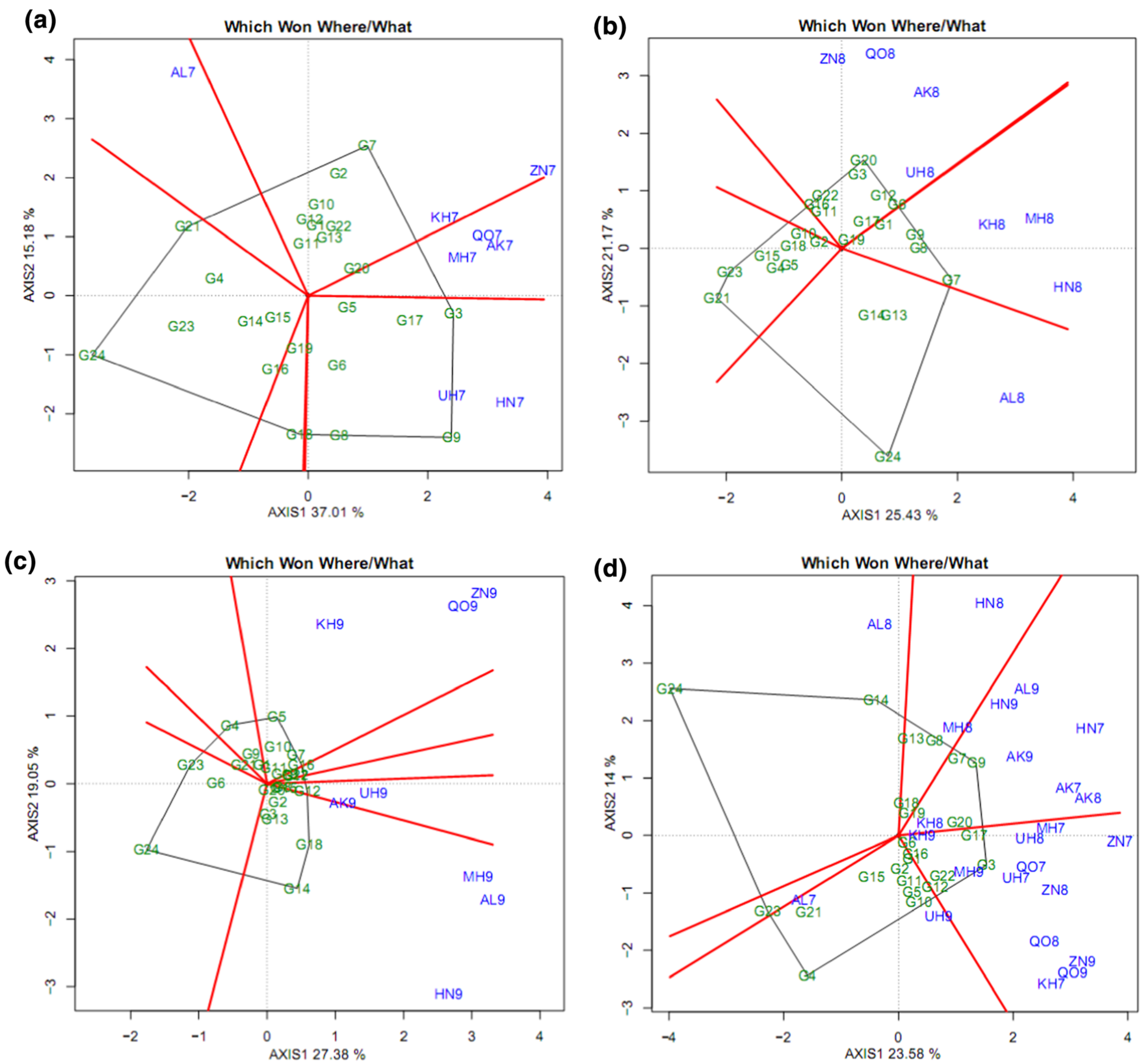

Fig. 3 SD-GGE biplot showing "which-wins-where" patterns of G × E interaction for 24 winter wheat genotypes in single-year (**a** 2016–2017; **b** 2017–2018; **c** 2018–2019) and multiple-year (**d**) trials

(AL9) were G14 followed by G18; and G12 was the highest at Arak (AK9) and Urmieh (UH9).

Based on all data for 24 genotypes across 24 test environments (Fig. 3d), G3 performed the best in Kermanshah (KH7, KH9), Qamloo (QO7, QO8, QO9), Zanjan (ZN7, ZN8, ZN9), Maragheh (MH7, MH9) and Urmieh (UH7, UH8); G9 was first at Arak (AK7, AK8, AK9), Hamedan (HN7, HN9) and Ardabil (AL9); G8 performed well at Maragheh (MH8) and Hamedan (HN8), G4 at Urmieh (UH9) and Ardabil (AL7), and G14 at Ardabil (AL8). However, the grouping patterns varied from year to year reflecting large G × E interaction effects, leading to the conclusion that the GGE biplot analyses did not detect repeatable G × L interaction patterns across years. Thus, the winter wheat growing region in Iran appears to be a single but complex mega-environment.

Discrimination *vs*. representativeness of test locations

Discrimination power and representativeness of test locations are components of an ideal test location. Discriminative power was evaluated through vector length at each location whereas the representativeness was determined by the angle between the location vector and average tester coordinate (ATC). The ATC is the axis that passes from the biplot origin to the point representing the average of all locations (Yan et al. 2007). Thus, an ideal test location is a location with the longest vector (most discriminating) and the smallest angle with ATC (most representative). Among the eight locations in 2016–2017, the locations QO, AK, MH, KH, ZN were found as ideal test locations, and characterized as informative locations (Fig. 4a). Ardabil was identified as a non-informative location. In 2017–2018 the ideal test locations were MH, KH and UM (Fig. 4b); AL and ZN were not informative test locations. In 2018–2019, MH and AL showed relatively strong representativeness and discriminating ability (Fig. 4c). From the location positions on the biplot, no repeatable grouping pattern across years were observed, and the same locations in different years showed positive and negative PC1 scores, indicating crossover G $\times$ E interaction. Similar observations in the case of discrimination and representativeness of test location could be observed, as the same locations in different years expressed differences in discriminating ability and representativeness (Fig. 4d).

Associations among test locations

The test locations Zanjan, Kermanshah, Qamloo, Maragheh and Arak were closely correlated in the 2016–2017 cropping season, as can be seen through the acute angles between their vectors. A similar pattern also observed between Hamedan and Urmieh. The Ardabil location was not associated with any other test location. In 2017–2018 the locations Zanjan, Qamloo and Arak as in the previous year kept their association in genotype ranking, and this pattern also occurred for Kermanshah and Maragheh as they showed consistent correlations. These two locations showed a positive correlation with Hamedan. Like the previous year, Ardabil did not associate with any other location.

The locations Zanjan and Qamloo were closely correlated in 2018–2019 and also showed a positive correlation with Kermanshah. Maragheh, Ardabil and Hamedan were also associated with each other in genotype rankings. Due to short vectors, Arak and Urmieh were not associated with other locations. In all three years a repeatable correlation was observed between Zanjan and Qamloo but this pattern was not observed between other locations.

Genetic and phenotypic correlation analyses (Fig. 5) between locations confirmed the relationships reported for test locations through the SD-GGE biplot. The most prominent genetic and phenotypic correlations were observed between Maragheh, Zanjan, Qamloo, Kermanshah, and Arak in the first cropping season. In second cropping season, positive relationships were observed among Qamloo, Zanjan, Urmieh and Arak. Similarly, significantly genetic and phenotypic correlations were observed between Maragheh and Kermanshah as well as between Ardabil and Hamedan. In the third cropping season Maragheh, Hamedan and Ardabil were positively associated, and a similar trend was observed between Qamloo and Zanjan.

Mean yield and stability performance

The test locations that formed a mega-environment tended to change from year to year, thus leading to a conclusion that a grouping pattern was not consistent across years. This suggests that genotypes should be developed for high yield and stability across all environments rather than to breed genotypes with specific adaptation. Figure 6 shows the SD-GGE biplot ranking the 24 winter wheat genotypes for mean yield and stability performances across 24 test environments. Genotypes G3 and G9 produced the highest mean yield, followed by G17, G7 and G2; G8 ranked sixth followed by G22, G12, G13 and G9. All these genotypes expressed mean yields higher than the grand mean. Among them, G17 and G20 showed the highest stability as they were placed near to the ATC abscissa and had PC2 scores near to zero. Genotypes G24, G14 and G4 with highest contributions to G $\times$ E had yields less than the grand mean (Tables 4 and 5).

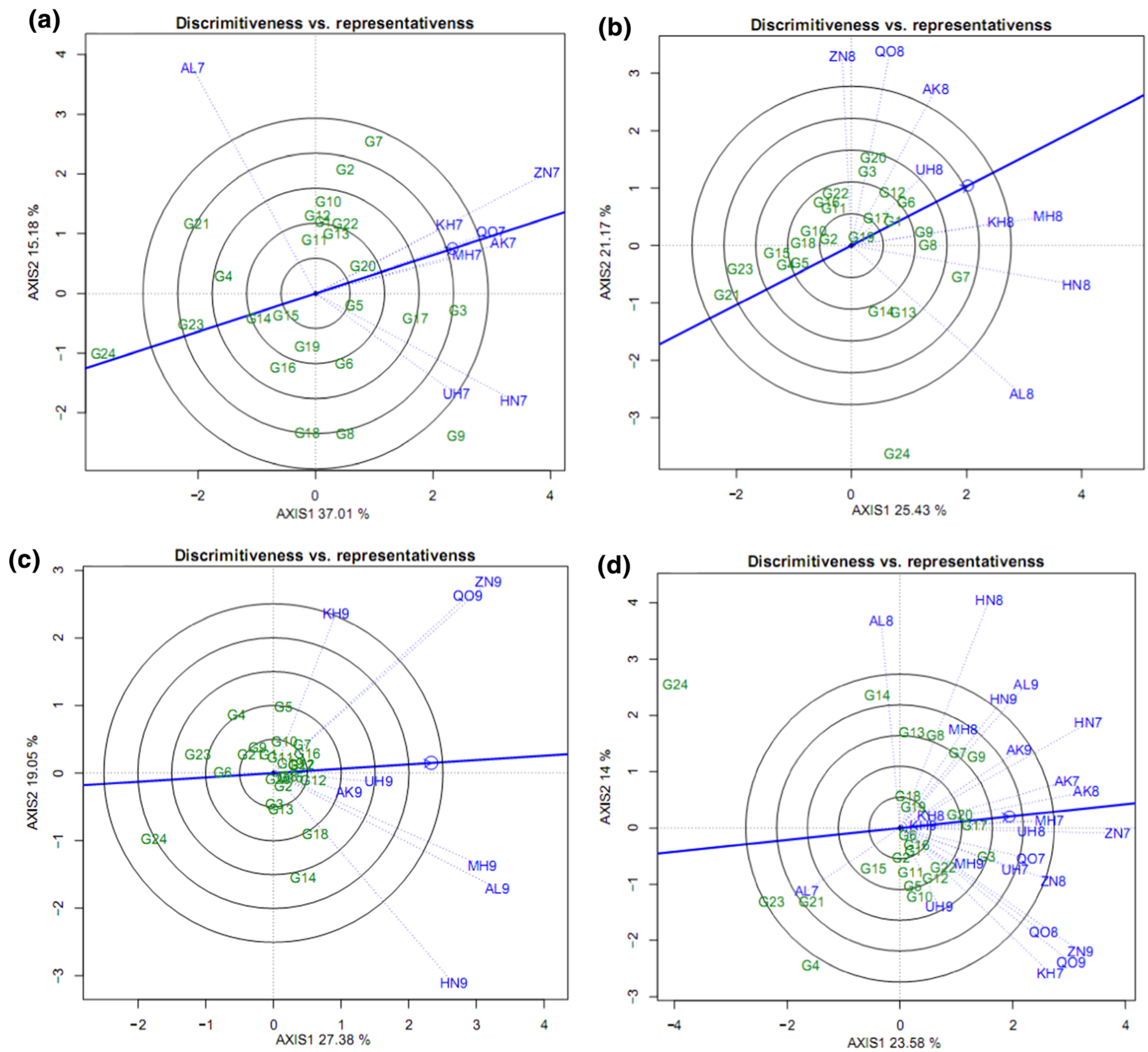

Fig. 4 SD-GGE biplot showing representativeness and discrimination ability of test locations in single-year (**a** 2016–2017; **b** 2017–2018; **c** 2018–2019) and multiple-year (**d**) trials

Climatic factors contributing to G × E interaction

Analytical methods FR and PLS regression were applied to investigate important environmental factors affecting G × E and grouping of test locations. Of 37 climatic variables applying to monthly rainfall and minimum, maximum and average temperatures, 23 were significantly ($P < 0.01$) influenced G × E according to F-tests. The validity of entered variables in the RF model was also confirmed by AIC (Table 6). These variables together explained 82.2% of total G × E interaction. Rainfall, and maximum, minimum and average temperatures accounted for 25.4%, 20.6%, 20.0%, and 16.2% of total G × E, respectively.

Among monthly rainfall variables, precipitation through March (4.1%), January (3.8%), April (3.5%), November (3.1%) and October (3%) significantly contributed to interaction variance. Maximum temperatures in November, February, January, October and April were significant and respectively, captured for 4.5%, 3.9%, 3.0%, 2.8%, and 2.8% of the total variation in G × E. Minimum temperatures in May, February, April, and June also significantly influenced

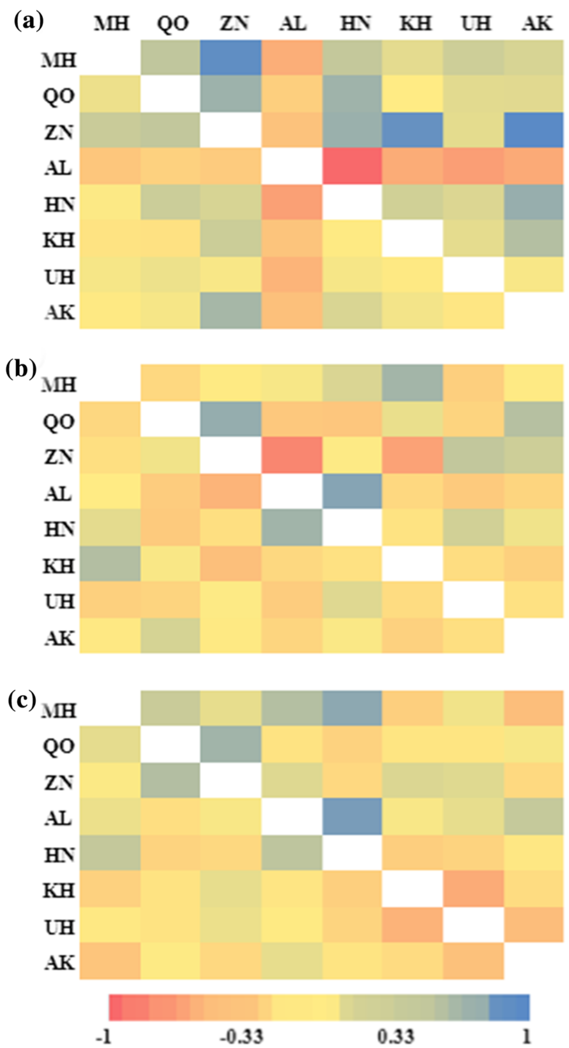

Fig. 5 Heatmap for genetic (above diagonal) and phenotypic (below diagonal) correlations between grain yields observed at different test locations in 2016–2017 (**a**), 2017–2018 (**b**) and 2018–2019 (**c**) cropping seasons

G × E, accounting for 4.3%, 2.6%, 2.4%, 2.1%, and 2.1%, respectively. Average temperatures in November, March, October, January and February significantly contributed for 5.5%, 4.7%, 4.2%, 2.8% and 2.8% of total variation in G × E, respectively.

A biplot based on first and second PLS factors enriched by the 23 climatic factors was constructed (Fig. 7). The explanatory climatic factors that showed the highest contribution to interaction in factorial regression (Table 6) tend to show similar patterns in the PLS biplot, being placed further from the biplot origin indicative of high contributions to G × E. Test

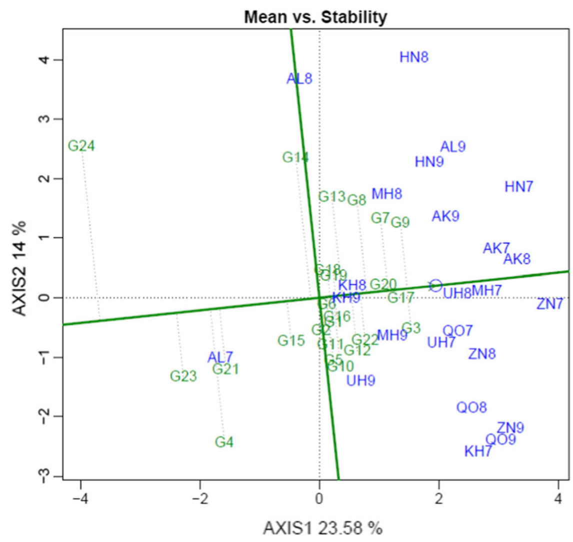

Fig. 6 SD-GGE biplot showing yield and stability analyses for 24 winter wheat genotypes (green) grown in 24 test environments (blue). (Color figure online)

environments (KH9, UH9, KH7, HN9, ZN9, ZN8, MH9, UH7) located at the top of the biplot favored high values for rainfall through April, March, January, November, October and total rainfall, whereas the other environments (KH8, UH8, HN8, ZN8, QO8, QO7, AL7, AL8, AL9) located at the bottom tended to have high rainfall during May and February, and maximum temperatures in March, December and February; as well as minimum and average temperatures in March (Fig. 7).

The genotypes were clearly separated based on the first factor of the biplot, where genotypes G15, G16, G8, G3, G14 and G1 performed better in environments with high rainfall and temperature (corresponding to Kermanshah and Arak in all three years as well as to Hamedan and Urmieh in some years); whereas genotypes G4, G10, G21, G12, G5, G11 and G22 showed better adaptation to environments favored low temperatures (Maragheh and Qamloo in all three years as well as Zanjan and Ardabil in some years).

The PLS biplot clearly separated Maragheh and Qamloo from Karmanshah and Arak, showing differences in adaption of genotypes to these locations in their agro-climatic characteristics such as monthly rainfall distribution. For example, G13, G23, G6, G2, G22, G8, G18, and G3 favored high rainfall in April, March, January, November, October, whereas G14, G1, G9, G17, G15, and G16 favored higher rainfall in

Table 4 Mean yield (kg/ha) and descriptive statistics for 24 winter wheat genotypes grown in 24 test environments

Code	Test environment												
	AK7	AK8	AK9	AL7	AL8	AL9	HN7	HN8	HN9	MH7	MH8	MH9	QO7
G1	1029	1414	1339	2648	2548	2310	877	2190	1510	1505	3305	1692	1156
G2	890	1410	1426	2909	2448	2335	1026	1875	1492	1536	3059	2246	1551
G3	1109	1466	1641	2268	2558	2122	976	2151	1666	1432	3150	1936	1241
G4	711	1211	1455	2623	2194	1758	625	1495	1067	1549	3157	2107	1123
G5	1029	1307	1503	2437	2619	2116	824	1880	1398	1576	2674	1796	1116
G6	890	1739	1909	2200	2471	2045	922	2234	1217	1651	3194	1674	938
G7	1105	1276	1719	2741	2996	2681	882	2557	1452	1523	3336	1873	981
G8	962	1421	1902	2216	2595	2532	1157	2635	1519	1486	3123	1783	1069
G9	963	1947	1728	1950	2726	2174	1130	2557	1480	1628	3243	1647	1363
G10	870	1501	1967	2670	2325	2316	862	2029	1180	1649	2688	2015	1118
G11	913	1760	1332	2540	2334	2417	880	1977	1400	1674	2861	2031	903
G12	996	1724	1213	2648	2690	2288	919	2128	1499	1488	3113	2578	1033
G13	935	1513	1825	2506	3256	2709	849	2583	1293	1764	2958	2069	969
G14	877	1648	1557	2479	3175	2665	873	2542	2033	1656	2849	2391	944
G15	977	1549	1276	2523	2608	2406	827	1789	1419	1679	2645	2303	822
G16	863	1495	1436	2417	2660	2556	994	2174	1515	1349	2882	1982	863
G17	967	1824	1486	2374	2796	2255	1119	2128	1574	1686	2881	2515	1110
G18	835	1809	1910	2461	2277	2465	953	1979	1907	1519	3148	2441	817
G19	894	1786	1829	2358	2527	2480	1003	2076	1379	1514	3017	2193	897
G20	1005	2007	1889	2563	2573	2404	1046	2214	1547	1479	3133	1898	1106
G21	830	1368	1558	2697	2396	2114	681	1966	1315	1424	1975	1884	840
G22	1024	1351	1729	2525	2771	2178	876	2240	1602	1470	2704	2543	981
G23	851	818	1300	2425	1769	1921	755	1829	1021	1189	2834	1693	797
G24	840	921	1293	2675	3659	1979	769	2313	1400	1168	3163	1660	789
Mean	932	1511	1592	2494	2624	2301	909	2147	1454	1525	2962	2040	1022
LSD ($P < 0.05$)	164.7	313.0	198.6	358.8	378.8	419.7	217.0	260.4	265.1	274.7	244.4	476.5	155.2
CV(%)	15.0	17.6	10.6	12.2	12.2	15.5	20.2	10.3	15.5	15.3	7.0	19.8	12.9
H^2b	55.6	79.4	87.8	45.1	82.1	48.0	52.5	85.1	75.2	36.3	87.5	54.8	87.6

Code	Test environment											
	QO8	QO9	KH7	KH8	KH9	UH7	UH8	UH9	ZN7	ZN8	ZN9	Mean
G1	3475	3582	2551	2132	3407	795	2778	2554	1045	2270	1675	2074
G2	3272	3331	2299	2197	3260	758	2083	2779	1085	2340	1650	2052
G3	3622	3663	2579	1961	2310	1197	2546	2833	1270	2575	1605	2078
G4	3294	3820	2407	2271	3324	989	1852	2389	860	2135	1530	1914
G5	3255	3697	2365	1697	3883	1089	2847	2672	1025	2220	1890	2038
G6	3525	3461	2588	2616	2895	811	2131	2479	995	2300	1340	2009
G7	3052	3528	2392	2354	4079	767	3287	2365	1377	2275	1755	2181
G8	3170	3508	2251	2359	3659	750	2801	2832	945	2345	1510	2105
G9	3183	3426	2402	1942	3448	983	2477	2138	1160	2290	1755	2073
G10	3394	3787	2504	1986	3012	772	2500	2554	1125	2225	1735	2033
G11	3410	3676	2561	2035	3443	622	2569	2473	1040	2215	1610	2028
G12	3616	3619	2571	2100	3068	610	2847	3337	995	2295	1725	2129

Table 4 continued

Code	Test environment											
	QO8	QO9	KH7	KH8	KH9	UH7	UH8	UH9	ZN7	ZN8	ZN9	Mean
G13	2800	3317	2297	1743	2865	683	2523	2781	1220	2370	1495	2055
G14	3031	3209	2170	1472	2809	594	2468	2447	925	2185	1420	2017
G15	3381	3551	2282	1656	3216	883	2018	2809	905	2245	1625	1975
G16	3194	3535	2514	1612	3528	806	2315	2702	930	2720	1890	2039
G17	3292	3530	2542	2169	3445	878	2546	2084	1130	2355	1845	2105
G18	2777	3205	2391	1463	3453	1461	2049	2748	905	2395	1565	2039
G19	3197	3525	2456	2009	3716	643	2639	2339	993	2180	1595	2052
G20	3706	3309	2550	1678	3423	850	2408	2282	1185	2430	1685	2099
G21	3053	3470	2404	1456	3292	566	2574	2502	935	2140	1585	1876
G22	3894	3817	2700	1738	3728	710	2235	2091	1070	2530	1565	2086
G23	2640	2718	2370	1736	3248	506	2709	2815	915	2460	1615	1789
G24	2849	2600	2118	2090	3263	505	1644	1936	578	1875	880	1790
Mean	3253	3453	2428	1936	3324	801	2452	2539	1025	2307	1606	2027
LSD ($P < 0.05$)	432.2	241.9	270.8	253.8	368.5	227.8	362.5	340.8	236.2	352.8	187.0	291.7
CV(%)	11.3	5.9	9.5	11.1	9.4	24.1	12.5	11.4	19.5	13.0	9.9	13.4
H^2b	64.7	88.2	36.6	88.2	83.0	81.4	82.3	78.8	61.4	21.0	85.1	68.6

Table 5 Year and multi-year grouping of test locations and the correspondence winner genotypes based on SD-GGE biplot

Cropping season	Wining genotype	Location grouping[a]	Characterization of location
2016–2017	G9	HN, UH	Ideal: QO, AK, MH, KH, ZN
	G7	KH, ZN	Not informative: AL
	G3	MH, QO, AK	
	G21	AL	
2017–2018	G20	ZN,QO, AK, UH	Ideal: MH, KH, UH
	G7	KH, MH, HN	Not informative: AL, ZN
	G24	AL	KH, MH, UH
2018–2019	G5	KH, ZN, QO	Ideal: MH, AL
	G14, G18	HN, MH, AL	Not informative: KH, HN
	G12	AK, UH	
2016–2019	G3	KH (2), QO (3), ZN (3), MH (2), UH (2)	Ideal: ZN, AK(2), MH, UH
	G9	AK (3) HN (2), AL, KH	Not informative: KH(2), AL(2), UH
	G8	MH (1), HN (1)	
	G4	UH (1), AL (1)	
	G14	AL (1)	

[a]Numbers in parentheses indicate number of times that a location was placed in that section

May and February. This indicated that monthly rainfall and its distribution led to significant G × E under rainfed conditions. Similar trends were observed for sensitivity of genotypes to monthly

Table 6 Factorial regression analysis with 37 environmental factors for grain yield of 24 winter wheat genotypes across 24 test environments

Source	df	Mean square	F-value	Pr(> F)	VE%	AIC
Environment (E)	23	61,140,365	922.4	0.0000	83	
Genotype (G)	23	896,648	3.72	0.0000	1.2	
R/E	72	420,810	6.3	0.0000	1.8	
G × E	529	240,749	3.6	0.0000	7.5	
Rainfall					25.4	
G × RAIN5	23	226,289	3.4	0.0000	4.1	33,257
G × RAIN4	23	209,983	3.1	0.0000	3.8	33,125
G × RAIN7	23	192,522	2.9	0.00001	3.5	32,937
G × RAIN2	23	171,411	2.6	0.00006	3.1	32,847
G × RAIN1	23	163,608	2.5	0.00015	3	33,160
G × RAIN10	23	146,654	2.2	0.0009	2.7	33,209
G × RAIN9	23	149,044	2.2	0.0007	2.7	32,704
G × RAIN6	23	139,596	2.1	0.00182	2.5	32,832
Maximum temperature			20.6			
G × MAXT2	23	300,160	4.5	0.0000	5.4	32,796
GMAXT5	23	261,150	3.9	0.0000	4.7	32,763
G × MAXT4	23	201,927	3	0.0000	3.7	32,685
G × MAXT1	23	190,119	2.8	0.00001	3.4	32,808
G × MAXT7	23	186,506	2.8	0.00001	3.4	33,008
Average temperature			20.0			
G × AVGT2	23	303,729	4.5	0.0000	5.5	32,791
G × AVGT6	23	261,554	3.9	0.0000	4.7	33,308
G × AVGT1	23	231,786	2.9	0.0000	4.2	32,905
G × AVGT4	23	152,321	2.3	0.0005	2.8	32,871
G × AVGT5	23	156,133	2.3	0.00034	2.8	32,820
Minimum temperature			16.2			
G × MINT8	23	284,022	4.3	0.0000	5.1	32,969
G × MINT5	23	174,810	2.6	0.00004	3.2	33,052
G × MINT7	23	161,031	2.4	0.00020	2.9	32,656
G × MINT6	23	137,535	2.1	0.00223	2.5	32,722.9
G × MINT9	23	137,660	2.1	0.00220	2.5	33,083.8
Residuals	1656	66,287			6.5	
AIC critical value = 32,656.16						

Rain Rainfall, *MINT* minimum temperature, *MAXT* maximum temperature, *AVGT* average temperature, Numbers 1, 2, 3, 4, 5, 6, 7, 8, 9 and 10 followed by climatic variable stand for October, November, December, January, February, March, April, May, June and annually (October–June), respectively

minimum and maximum temperatures. Genotypes G15, G16 G3, G18, G8, G14, and G1 were positively favored by higher temperatures, whereas G4, G10, G21, G12, G5, G11, and G22 positioned in the opposite side of the biplot, were negatively affected by higher temperatures. In general, the PLS biplot clearly separated environments in different groups with positively interactions with some specific climatic factors.

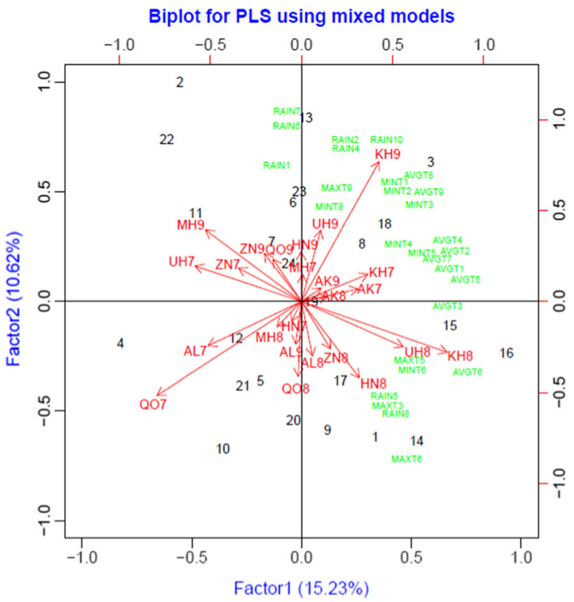

Fig. 7 PLS biplot representing X-scores for 24 winter wheat genotypes (numbers 1–24), Y-loadings of 24 rainfed test environments (red) enriched with the X-loadings of 23 climatic factors (green)s. (Color figure online)

Discussion

Western and north-western Iran is the main region for rainfed winter wheat production. This region accounts for 54.7% of the total rainfed wheat area and 58.9% of total rainfed wheat production in the country. The region is defined as a cold highland area with wide variation in amount and monthly patterns of rainfall and minimum and maximum temperatures during the cropping season. The long-term rainfall in the area is 325 mm ranging from 235 (corresponding to Ardabil in the north) to 420 mm (corresponding to Kermanshah in the west). Cropping seasons with rainfall less than 300 mm are considered unfavorable for wheat production, although the monthly distribution of rainfall in dryland conditions is much more important than total rainfall. Wheat is most sensitive to drought during flowering and grain filling (May and June) and usually there is inadequate rainfall during that period; the period of stem elongation (March and April) is also important.

The highest mean yield in the three years study was recorded in 2018–2019, the year with highest rainfall (3303 kg/ha and 482 mm rainfall). This cropping season can be regarded as a favorable year in respect to rainfall. The 2016–2017 season with lowest rainfall, but with good monthly distribution was a moderate production year (2419 kg/ha and 314 mm rainfall); whereas 2017–2018 with moderate rainfall and the lowest productivity (1936 kg/ha and 386 mm rainfall) was more stressful due to insufficient precipitation at the critical growth stages. The latter two seasons can be regarded as unfavorable. Because of differences in productivity in unfavorable years it is obvious that wheat productivity is affected by climatic variables in addition to total rainfall. Factorial and PLS regression studies highlighted the importance of other climatic variables, especially monthly rainfall distribution. Rainfall during the critical growth stages in February, January, April, November and October contributed more to variation in grain yield than total rainfall. In addition, differences in minimum temperatures during the critical growth stages, particularly in May, February and April; and difference in maximum temperatures in November, February, January, October and April were also important and affected genotypes in different ways. Rainfall and minimum temperatures in June were also significant factors.

Environment accounted for 83% of the variation in grain yield. According to ANOVA and SD-GGE biplot, the G $\times$ E effect was sixfold greater than genotype effect. Such a pattern of interacting variance components indicates that the highest component of variation in dryland winter wheat regional yield trials was the environment. Similar results regarding the relative magnitude of genotype, environment and G $\times$ E were already reported (De Vita et al. 2010; Sánchez-García et al. 2012; Mohammadi et al. 2018). Highly significant interaction among environment (year, location, year $\times$ location interaction) and genotype leads to low yield stability. Thus, wheat breeders are advised to increase the number of genotypes in METs to identify the highest yielding, stable genotypes and minimize negative effects of G $\times$ E.

The "which-won-where" pattern of the SD-GGE biplot clearly showed a "crossover" pattern of location grouping in regional yield trials. Several location groups were distinguished each year. Clustering patterns showed poor repeatability across years, as most (but not all) locations showed changes in grouping across years. This instability in grouping could be due to the random nature of year-dependent factors caused by yearly variation in climatic variables (Navabi et al. 2006; Yan 2014; George and Lundy 2019). Yan (2014) defined this phenomenon as a type

IV classification of regional yield trials. According to this kind of classification, the G × E interaction is dominated by genotype-by-location-by-year (G × L × Y) interaction, thus the target area cannot be meaningfully divided into distinct mega-environments. In our study, G × L × Y accounted for 3.9% of total variation and its size was threefold the genotype effect (1.2%) (Table 3). Furthermore, partitioning of G × E into its components indicated that G × L × Y was the largest source of interaction compared to G × L (2.9%) and G × Y (0.8%).

Based on the present results the target region is best represented as a single but complex mega-environment, suggesting that evaluation of winter wheat genotypes must occur over multiple locations and years. Thus, evaluation and selection of future varieties for dryland conditions must focus on genotypes with wide adaptation rather than genotypes adapted to specific regions. Similar recommendations were made by Navabi et al. (2006) in relation to spring wheat in Alberta when they found a lack of repeatability in the G × E interaction patterns over years. They suggested a single mega-environment with unpredictable "crossover" G × E interaction for spring wheat that did not support the previous classification of wheat growing areas in Alberta. Similarly, our results do not support the traditional classification of the winter wheat growing area in Iran which was based on empirical knowledge of the wheat growing area.

Clustering of locations for a target region has been subjected to several previous studies (George and Lundy 2019; Rakshit et al. 2012; Navabi et al. 2006; Mohammadi et al. 2010). George and Lundy (2019) pointed out that the cereal growing areas in California comprised a single but unstable mega-environment for grain yield in wheat. They concluded that the G × E interaction observed in California was primarily due to non-crossover G × E interaction and seasonal effects (i.e., G × Y and G × L × Y), with genotype effects generally dominating. Due to remarkable fluctuations in climatic conditions that cause unpredictable year effects, the recommended genotypes for the region should have high mean yield and stable performance. Our findings suggest that two outstanding breeding lines (G17 and G20) with the highest mean yield and stability across environments could be released for production in the entire region after further evaluation.

The mean productivity in the region has reached to 1517 kg/ha (Official statistics for Agriculture of Iran, 2019) and potential yield of newly developed winter wheat genotypes in regional yield trials is estimated to be 2100 kg/ha. This shows that wheat production in this region achieves about 70% of genetic yield potential. However, this gap is likely due to non-optimal cropping practices and lack of adoption of new varieties. The test location network included locations that are generally exposed to abiotic stress such as drought and cold that commonly occur in the Mediterranean rainfed conditions of western and north-western Iran.

Conclusion

Highly significant G × E interaction observed in the present trials was mostly explained by variation in monthly rainfall and temperatures from one location to another during critical growth periods. According to SD-GGE biplot analysis no repeatable G × L interaction patterns were identified, leading to the conclusion that the dryland winter wheat growing area in Iran is a single but complex mega-environment for grain yield. Thus, improvement in winter wheat grain yield will be best achieved by selecting genotypes with high mean yield and stable performance across the entire region that accounts for more than 60% of total rainfed wheat production in the country.

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Declarations

Conflict of interest The authors declare no conflicts of interest in the development and execution of this research.

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