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THE USE OF AMMI MODEL FOR INTERPRETING GENOTYPE × ENVIRONMENT INTERACTION IN DURUM WHEAT

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SUMMARY

Durum wheat (*Triticum durum*) is one of the most important cereal crops in the Mediterranean region; however, its cultivation suffers from low yield due to environmental constrains. The main objectives of this study were to (i) assess genotype × environment (GE) interaction for grain yield in rainfed durum wheat and to (ii) analyse the relationships of GE interaction with genotypic/meteorological variables by the additive main effects and multiplicative interaction (AMMI) model. Grain yield and some related traits were evaluated in 25 durum wheat genotypes (landrace, breeding line, old and new varieties) in 12 rainfed environments differing in winter air temperature. The AMMI analysis of variance indicated that the environment had highest contribution (84.3% of total variation) to the variation in grain yield. The first interaction principal component axis (IPCA1) explained 77.5% of GE interaction sum of squares (SS), and its effect was 5.5 times greater than the genotype effect, indicating that the IPCA1 contributed remarkably to the total GE interaction. Large GE interaction for grain yield was detected, indicating specific adaptation of genotypes. While the postdictive success method indicated AMMI-4 as the best model, the predictive success one suggested AMMI-1. The AMMI biplot analysis confirmed a rank change interaction among the locations, indicating the presence of strong and unpredictable rank-change location-by-year interactions for locations. In contrast to landraces and old varieties, the breeding lines with high yield performance had high phenotypic plasticity under varying environmental conditions. Results indicated that the GE interaction was associated with the interaction of heading date, plant height, rainfall, air temperature and freezing days.

INTRODUCTION

Durum wheat (*Triticum turgidum* L. var. durum Desf.) is grown on 10% of the world's wheat area and occupies about 11 million ha in the Mediterranean basin. However, its cultivation suffers from variable yields due to limiting environmental conditions. Rainfall and air temperature in Mediterranean dryland areas show large and unpredictable fluctuations within and among cropping seasons. In Iran, durum wheat is cultivated across diverse environments, ranging from warm lowlands to cold

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highlands. The improvement of a crop's productivity under stress conditions requires genotypes with stress tolerance and yield stability (Mohammadi *et al.*, 2011). If relative performances of the genotypes grown in different environments are highly different, then genotype × environment (GE) interaction becomes a major challenging factor as well as potentially useful for breeding crops in specific geographical areas. In such cases, the breeder is faced either with developing specific breeding populations for each environment and/or with selecting genotypes that generally perform well across many environments (Isik and Kleinschmit, 2005).

Grain yield is a very complex quantitative trait, and its expression is the result of genotype, environment and the GE interaction. Complexity of this trait results from different reactions of genotypes on variable environmental conditions during plant development. To optimize growers' yields, despite GE interactions that cause no single genotype to win everywhere all the time, the growing region must be subdivided into relatively homogeneous mega-environments and appropriate genotypes must be targeted for each of these mega-environments. A mega-environment is defined as a group of environments that consistently share the same best genotype(s), (Gauch and Zobel, 1997; Yan and Hunt, 2001). With no subdivision, only broad adaptation can be exploited, but with subdivision, narrow adaptations can also be exploited. Historically, breeders have understood the importance of GE interactions in plant breeding programmes (Allard and Bradshaw, 1964; Gauch, 1992; Yan *et al.*, 2000; Yang *et al.*, 2009). The existence of significant crossover GE interactions can be a serious constraint to crop improvement, leading to reduced genetic gains from selection and a waste of valuable resources. Most of the common statistical techniques available to analyse GE interactions are empirical in nature, focusing on quantification of GE interaction effects, identifying stable cultivars and identification of mega-environments. These include techniques such as ANOVA, joint linear regression, restricted maximum likelihood (REML), AMMI and GGE biplots.

In several cases, AMMI analysis appeared to be able to extract a large part of the GE interaction and is thus more efficient in analysing GE interaction pattern, as demonstrated by earlier reports (Gauch, 1992; Gauch and Zobel, 1997; Ebdon and Gauch, 2002). The AMMI model uses analysis of variance (ANOVA, an additive model) to characterize genotype and environment main effects and principal components analysis (a multiplicative model) to characterize their interactions. Among multivariate methods, AMMI analysis is widely used for GE interaction investigation. This method has been shown to be effective because it captures a large portion of the GE interaction SS, it clearly separates main and interaction effects and may provide agronomically meaningful interpretation of the data (Ebdon and Gauch, 2002). The results of AMMI analysis are useful in supporting breeding programme decisions, such as specific adaptation and selection of environment. Usually, the results of AMMI analysis shown in common graphs are called biplot. The biplot shows both the genotypes and the environments values and relationships using singulars vectors technique (Gauch and Zobel, 1997). For the accurate analysis of multi-environment trials (MET), the AMMI model is a valuable tool due to the accuracy that it provides in GE interaction studies (Ebdon and Gauch, 2002; Gauch, 2006; Li *et al.*, 2006).

The AMMI biplots is the most well-known and appealing component of AMMI analysis. The AMMI1 provides a means of visualizing the mean effects and the stability (IPCA1) of the genotypes simultaneously, while AMMI2 shows its IPCA1 on the abscissa and IPCA2 on the ordinate (Gauch and Zobel, 1997). In addition, the use of AMMI stability estimates (Purchase *et al.*, 2000; Sneller *et al.*, 1997) would be useful as another application of AMMI model.

Understanding the causes of GE interaction would reveal the genotypic characteristics that contribute to a superior genotype and the environmental factors that can be manipulated to facilitate selection of such genotypes (Yan *et al.*, 2000). Numerous methods have been used for understanding the causes of GE interaction (van Eeuwijk, 1995). These methods can be categorized into two major strategies. The first strategy involves factorial regression analysis of the GE interaction matrix (i.e., the yield matrix after the environment and genotype main effects are removed) against environmental factors, genotypic traits or combinations thereof (Baril *et al.*, 1995). The second strategy is associated with the use of the AMMI model in multi-environment trials (MET) data analysis. However, both strategies, although different in approaches, have been shown to produce similar results (Vargas *et al.*, 1999). By relating the PC1 and PC2 scores to environmental conditions and genotypic traits, the environmental and genotypic basis of the GE interactions can be assessed (Yan and Hunt, 2001). Accordingly, van Eeuwijk and Elgersma (1993) showed that the AMMI IPCA1 and IPCA2 scores of environments can be regressed against measured meteorological variables to investigate the causes of GE interactions in ryegrass.

The main objectives of this investigation were to (i) analyse GE interaction in durum wheat multi-environment trials and (ii) investigate the relative influence of genotypic and meteorological variables on the GE interactions of durum wheat under rainfed conditions.

MATERIALS AND METHODS

Twenty-five wheat genotypes (Table 1) including seven durum wheat landraces (G1-G7), 15 durum wheat breeding lines (G8−G22), one modern durum cultivar (G23, Saji), one old durum variety (G24, Zardak), along with one popular old bread wheat cultivar (G25, Sardari) were tested in uniform yield trials across four rainfed research stations representative of the major rainfed durum wheat-growing areas in Iran, during four cropping seasons (2006 to 2010), resulting in 12 environments (combinations of locations and years, with missing some combinations due to crop failure). Information on test environments is given in Table 2.

In each environment, the experimental layout was a randomized complete block design with three replications. Plot size was 7.2 m^2 (6 rows, 6-m long, with 20-cm row spacing). Management practices (e.g., planting date before effective rainfall, seeding rate, row spacing, weed control, crop rotation) recommended for each environment were followed in all environments. The traits recorded were days to 50% flowering (DH) and maturity (DM), plant height (PLH), grain filling period (GFP), 1000-kernel weight (TKW) and grain yield (YLD), which were measured for each genotype in

Table 1. Code, name, origin and type of tested genotypes.

Code	Name	Type	Origin
G1	54-17-3-1	Landrace	Iran
G2	65-12-3-3	Landrace	Iran
G3	19-17-1-4	Landrace	Iran
G4	45-2-2-4	Landrace	Iran
G5	13	Landrace	Iran
G6	48-17-2-5	Landrace	Iran
G7	28-18-2-1	Landrace	Iran
G8	ICAMOR-TA04-62	Breeding line	ICARDA
G9	ICAMOR-TA04-63	Breeding line	ICARDA
G10	ICAMOR-TA04-68	Breeding line	ICARDA
G11	ICAMOR-TA04-1	Breeding line	ICARDA
G12	ICAMOR-TA04-2	Breeding line	ICARDA
G13	Gidara-2	Breeding line	ICARDA
G14	ICAMOR-TA04-23	Breeding line	ICARDA
G15	ICAMOR-TA04-5	Breeding line	ICARDA
G16	Ammar-6	Breeding line	ICARDA
G17	Ammar-8	Breeding line	ICARDA
G18	Icasyr-2	Breeding line	ICARDA
G19	Bcr/Gro1//Mgnl1	Breeding line	ICARDA
G20	Bcr/Gro1//Mgnl1	Breeding line	ICARDA
G21	Azeghar-2//Ch1/F113	Breeding line	ICARDA
G22	Lahaucan	Breeding line	ICARDA
G23	Saji	Durum new cultivar	Iran
G24	Zardak	Durum old variety	Iran
G25	Sardari	Wheat old variety	Iran

ICARDA: International Center for Agricultural Research in the Dry Areas.

each environment. The grain yields were measured on a plot basis and converted to kg ha^{-1} for the statistical analyses. The AMMI analysis was performed using the raw data from 12 environments through the Gen Stat Release 15 statistical software (Payne *et al.*, 2012). The model first fits additive effects for the main effects of genotypes and environments followed by multiplicative effects for GE interaction by principal component analysis (PCA, Zobel *et al.*, 1988). The AMMI model is as follows:

$$Yij = \mu + G_i + E_j + \sum_{k=1}^{n} \lambda_k \gamma_{ik} \delta_{jk} + \rho_{ij} + \varepsilon_{ijk},$$

where Yij is the yield of genotype i in environment j; μ is grand mean; G_i is the main effect of genotype i (i = 1, ... ,n) and E_j is the main effect of environment j (j = 1, ... ,m); λ_k is the singular value for IPCA; γ_{ik} is the genotype i eigenvector value for kth PC; δ_{jk} is the environment j eigenvector value for kth PC, ρ_{ij} is the interaction residual and ε_{ijk} is the random error.

The number of significant terms in the AMMI model was evaluated with the method of Gollob (1968). The results of the AMMI analysis were interpreted on the basis of AMMI biplots, integrating genotypic and environmental mean yields and stability (Gauch and Zobel, 1997). In ANOVA, the SS for genotypes (G), GE

Table 2. The test environments and their main climatic characteristics in the study.

Code	Season	Location	Latitude (N)	Longitude (E)	Altitude (m)	Rainfall (mm)	AT (°C)	FD (day)	RH (%)	Eva (mm)
KH07	2006–07	Kermanshah	34°12′19″	47°16′48″	1351	551.8	10.8	84	58.3	919.9
KH08	2007–08	Kermanshah	34°12′19″	47°16′48″	1351	159.2	11.3	95	43.7	1201.5
KH09	2008–09	Kermanshah	34°12′19″	47°16′48″	1351	288.3	11.0	84	48.7	1030
KH10	2009–10	Kermanshah	34°12′19″	47°16′48″	1351	453.9	11.8	57	56.8	823.9
MH07	2006–07	Maragheh	37°22′12″	46°15′0″	1400	418	4.7	148	57.0	678.4
MH08	2007–08	Maragheh	37°22′12″	46°15′0″	1400	137.6	5.0	118	39.7	1001.4
MH10	2009–10	Maragheh	37°22′12″	46°15′0″	1400	487.3	7.2	79	60.9	716.2
SN08	2007–08	Shirvan	37°1348″	58°7′12″	1131	127	9.0	81	55.6	799.7
SN09	2008–09	Shirvan	37°1348″	58°7′12″	1131	239	9.7	95	43.7	1201.5
IM07	2006–07	Ilam	33°40′48″	46°34′48″	975	470.3	13.9	41	64.4	721
IM09	2008–09	Ilam	33°40′48″	46°34′48″	975	277	14.1	36	55.7	944.6
IM10	2009–10	Ilam	33°40′48″	46°34′48″	975	508.8	15.2	11	57.9	950.5

AT: annual average air temperature; FD: freezing days (number of days below zero degree) in a year; RH: annual average relative humidity; Eva: annual evaporatranspiration (Mahmoudi, 2010).

signal (GE_S) and GE noise (GE_N) provide a preliminary indication whether AMMI analysis will be worthwhile. The SS values for G and GE are direct outputs from ANOVA. To estimate SS for GE interaction, the error mean square (from replication) was multiplied by the number of degrees of freedom (df) for GE (Gauch, 1992; 2013). Then, GE_S was obtained by subtracting GE_N from GE. AMMI analysis is appropriate for datasets having substantial G and GE_S. Especially when SS for GE is as large as that for G, as happens frequently, AMMI analysis will probably be worthwhile (Gauch, 2013). We used this criterion, as suggested by Gauch (2013), for the model diagnosis in AMMI. The IPCA1 score of a genotype in the AMMI analysis was used as indicator of the stability of a genotype over environments (Grausgruber *et al.*, 2000).

The predicted nominal yields estimated on the basis of the AMMI model equation without the environmental deviation across environmental IPCA1 scores, which indicates that the adaptability of each genotype (Gauch and Zobel, 1997) was applied. This information allows the evaluation of the effects of genetic improvement on yield stability and adaptability and the identification of the highest yielding genotypes in specific environment. A correlation analysis between genotypic/environmental lPCAs scores from the best AMMI model and genotypic and meteorological variables was applied to identify most sources of GE interaction in rainfed durum wheat MET data.

RESULTS

The AMMI analysis of variance for grain yield of durum wheat genotypes across environments showed highly significant main effects (p <0.01) of genotypes, environments and GE interaction (Table 3). Of the total variation, 84.3% contributed by the environment and GE interaction contributed for 9.7% of the total variation. Genotypic main effect accounted for 1.4% and the residual variance (i.e., error variance) captured for 4.2% of the total variation. The partitioning of GE interaction matrix constitutes the multiplicative term. The first four significant IPCAs were

Table 3. Analysis of variance of main effects and interactions for grain yield of 25 wheat genotypes across 12 environments.

Source	df	Sum of squares	Mean squares	Gollob's F-test	GE Sum of squares		Variability explained	
					Noise	Signal	(%TSS)	(%GE)
Treatments	299	2,240,414,845	7,493,026	44.01**			95.3	
Genotypes (G)	24	31,749,118	1,322,880	7.8**			1.4	
Environments (E)	11	1,980,753,444	180,068,495	384.9**			84.3	
Block/E	24	11,228,283	467,845	2.7**			0.5	
GE interactions	264	227,912,283	863,304	5.1**	44,951,808	182,960,475	9.7	
IPCA1	34	176,673,725	5,196,286	30.5**	176,673,725			77.5
IPCA2	32	15,115,128	472,348	2.8**	191,788,853			6.6
IPCA3	30	11,300,604	376,687	2.2**	203,089,457			5.0
IPCA4	28	8,629,580	308,199	1.8**	211,719,037			3.8
GE residuals	140	16,193,247	115,666	0.7^{ns}				7.1
Error	576	98,076,934	170,272					
Total	899	2,349,720,062	2,613,704					

**Significant at 1% level of probability; ns: non-significant; TSS: total sum of squares; GE: genotype × environment interaction.

accounted for 77.5%, 6.6%, 5.0% and 3.8% of the total GE interaction, respectively. The residual effect contributed 7.1% of the total GE interaction (Table 3). The first interaction principal component axis (IPCA 1) alone captured 77.5% of the GE interaction SS using 12.8% of the GE interaction df. The postdictive success through the multiplicative terms indicated four significant IPCAs, which indicated AMMI-4 as the best model, while the predictive success method suggested AMMI-1 as the best model.

The breeding line G20, followed by G23 (new cultivar), G18, G17 and G8 had the highest mean yield productivity across environments, while the genotype G25 (bread wheat old variety) followed by G7, G6, G24 and G2 had the lowest yield productivity across environments (Table 4).

To characterize GE interaction, an AMMI-1 biplot was plotted using the genotype and environment mean yields and their IPCA1 scores (Figure 1). The biplot accounted for 97.7% of the treatment SS and is thus suitable for interpreting the GE interaction and main effects. Environments with scores near zero have little GE interaction across genotypes and provide low discrimination among genotypes. This pattern was observed for some test environments, i.e., IM09, IM07 and MH10. In contrast, the environments of IM10, KH10 and KH07 with high interaction across genotypes provided highest discrimination among genotypes. The environment KH08 with lowest yielding productivity had the low IPCA1 score and led to low interaction, whereas the environments IM10, KH10 and KH07 with high-yielding performance tended to have the highest contribution to GE interaction (Figure 1).

The lowest IPCA1 as indicator of stability was observed for breeding line G22 followed by G19, landraces of G2 and G4 and breeding line G8. In contrast, the

Table 4. Mean yields (kg ha^{-1}) for 25 wheat genotypes across 12 environments. In each column, bold values indicate the winner genotype for each environment.

	Environments*												
	Moderate				Warm			Cold					
Genotype	KH07	KH08	KH09	KH10	IM07	IM09	IM10	MH07	MH08	MH10	SN08	SN09	Mean
G1	2921	528	**1581**	5070	3013	1656	2219	1879	1837	2093	1011	**1057**	2072
G2	3922	604	996	5025	2814	1625	3063	819	1617	2161	891	983	2043
G3	3219	473	1233	5254	3351	2078	2948	827	1932	2068	944	780	2092
G4	4307	718	1326	5062	3159	1448	3151	1756	1920	2236	900	939	2244
G5	2816	576	1421	4627	3470	2198	3005	964	2077	2164	898	838	2088
G6	2601	630	1101	4348	3181	1474	2391	**1926**	2167	1820	1069	826	1961
G7	2491	701	1571	4406	2705	1677	2177	1765	1809	1922	887	751	1905
G8	4330	721	905	5982	2961	**2234**	4948	1072	1949	2281	798	876	2421
G9	4498	568	802	6251	2655	1932	4498	1325	1920	1842	704	964	2330
G10	4481	497	1158	6134	3114	1776	4616	1585	1743	1190	804	921	2335
G11	4322	719	1064	6311	3264	2057	4462	740	1417	1751	718	897	2310
G12	4608	651	999	6222	3032	1573	4930	1462	1894	1867	887	876	2417
G13	4293	550	1127	5912	2950	1683	4784	1266	1341	1810	664	790	2264
G14	4802	510	800	6042	3186	1463	4535	728	1065	2410	613	962	2260
G15	4128	486	1099	6064	3072	1599	4935	951	1700	2117	522	894	2297
G16	4557	667	855	5892	3478	1600	5170	901	1499	2119	696	602	2336
G17	4624	810	716	5768	3231	2104	5154	1060	2174	1923	824	861	2437
G18	**5005**	552	951	6569	3476	1562	4545	1556	1445	2074	834	846	2451
G19	3990	839	811	5717	3576	1589	4540	1001	1943	1760	991	1021	2315
G20	4810	598	1317	**6828**	3554	1849	5100	1229	2279	1970	1045	953	**2628**
G21	3821	716	824	5878	3442	1943	**5365**	873	1441	1973	920	811	2334
G22	3969	800	897	5430	3562	1719	4311	1061	989	2254	836	942	2231
G23	4640	842	1312	5579	3311	2115	5289	1235	2073	2133	592	883	2500
G24	2426	764	1040	4112	**3598**	1755	3052	1681	1853	2160	1089	651	2015
G25	2732	**1161**	1519	2595	2796	1552	1125	1646	**2478**	**2623**	**1544**	1036	1901
Mean	3933	3198	1252	667	1783	867	1097	1771	878	5483	4012	2029	2248

*For environments code see Table 2.

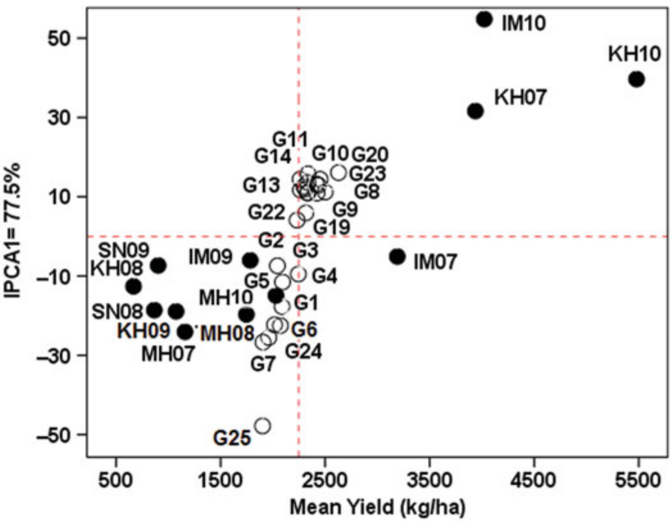

Figure 1. The AMMI-1 biplot for 25 wheat genotypes (open circles) evaluated for grain yield across 12 rainfed environments (solid circles) during 2006–10 cropping seasons. G1–G7 durum landraces, G8–G22 durum breeding lines, G23 durum new cultivar, G24 durum old variety, G25 bread wheat old variety. For details on genotype and environment codes see Tables 1 and 2.

highest IPCA1 was found for bread wheat old variety (G25) followed by landraces G7, G6, G1 and durum old variety of G24 (Zardak) (Figure 1).

The breeding lines G20, G18, G8, G10 and new cultivar (G23) interacted positively with the KH10, KH07 and IM10, belonging to moderate and warm locations, but negatively with the cold locations and some moderate and warm environments (Figure 1). All landraces (G1–G7) along with old durum (G24) and bread wheat (G25) varieties adapted to the cold environments. The breeding lines G19, G8 and G10 had high yield and stable performance, with the IPCA1 value closest to zero. Similar IPCA1 values were found for the landrace G4.

Adaptation map which shows the predicted nominal yields of 25 wheat genotypes as a function of the score on the environment IPCA1 scores of 12 test environments is presented in Figure 2. Lines resulted from the projection of the mean yield of each genotype versus the environmental IPCA1 scores. The order of the environments along the IPCA1 axis suggested that the climatic conditions, mainly rainfall and air temperature, have a greater impact on the occurrence of GE interaction. The slope of the lines reflects the adaptation patterns of the genotypes across the environmental IPCA1 scores. The results show that these interactions lead to different rankings of the genotypes across environments. From Figure 2, the breeding lines G21, G23, G20, G17, G16, G15 and G12 showed a sharp slope (highest instability) and exhibited the lowest yield productivity in cold environments (low IPCA1 values) and the highest mean yield at warm environments (high IPCA1 values). In contrast, the landraces and old variety with low slope had general stability and low to moderate yield productivity. The landraces G1 and G6 with average yield performances found

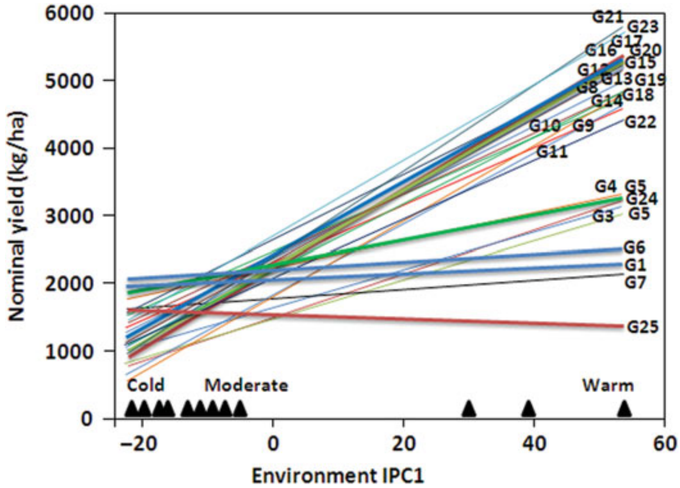

Figure 2. Yield estimates of the winning genotypes, as related to the AMMI1 score of the environments (IPCA1). The lines are the responses of genotypes to different environments and the black triangles are the environments which are ranked based on their IPCA1.

Table 5. Correlation coefficients between the first two IPCAs from AMMI analysis and various genotypic/environmental variables.

Variables	IPCA1	IPCA2
Genotypic variables		
Days to heading	− 0.46*	0.09
Plant height	− 0.83**	0.13
Days to maturity	− 0.26	− 0.18
1000-kernel weight	− 0.03	− 0.34
Grain filling period	0.42	− 0.23
Meteorological variables		
Rainfall	0.63*	− 0.12
Average air temperature	0.58*	0.46
Freezing days	− 0.62*	− 0.60*
Relative humidity	0.39	0.08
Evaporatranspiration	− 0.06	0.11

*, **Significant at 5% and 1% level of probability, respectively.

to be the most stable genotypes. The correlation coefficients of genotypic and meteorological variables with the first two IPCA scores from AMMI model are presented in Table 5. IPCA1 scores were positively correlated with meteorological variables of rainfall (p <0.05), average air temperatures (p <0.05) and freezing days (p <0.05). IPCA1 showed negative correlations with plant height (p <0.01) and heading date (p <0.05), indicating that shorter plants and those with late in flowering tended to contribute to GE interaction. IPCA2 scores were not correlated with various genotypic variables and among the meteorological variables only correlated with freezing days (p <0.05), indicating that the contribution of most variables can be defined in relation to IPCA1 scores.

DISCUSSION

The significance of the GE interaction suggests that there are significant differences in responses of genotypes to variable environments, and hence sensitivity and instability. The greater GE interaction relative to genotype effect suggests different mega-environments. Pronounced influences of environment on the grain yield compared to the genotype or the GE interaction effects have been documented in many crops (Fan *et al.*, 2007; Ramburan *et al.*, 2011; Yan *et al.*, 2000). The large variation due to environment confirms that the testing environments were different, with large differences among environmental means causing most of the variation in genotypic performances (Fan *et al.*, 2007). Genotypic rank differences over environments showed the existence of crossover GE interaction, which showed the necessity to assess the response of the genotypes to environmental variation.

The GE interaction had a strong impact on grain yield ($p < 0.01$), which explains the 9.7% (about 7-fold the genotype effect) of the model SS. METs have often shown that the yield variation due to GE interaction exceeds that due to genotype (Bidinger *et al.*, 1996). This is supported by the fact that the GE interaction mean yield varied from 473 kg/ha (corresponding to G3 at environment KH08) to 6828 kg/ha (corresponding to G20 at environment KH10) (Table 4), indicating a considerable variation in yield productivity of 25 genotypes in 12 environments. However, the strong GE interaction for quantitative traits such as grain yield can severely limit gain in selecting superior genotypes for improved cultivar development. In the present study, significant yield improvements were observed mostly in environments without stress (moderate and warm environments) rather than those with stress (cold). This agrees with findings reported by others (Ceccarelli, 1996; Muñoz *et al.*, 1998; Voltas *et al.*, 1999b). However, the breeding lines and modern cultivar showed high superiority over bread and durum old varieties and landraces under moderate and warm conditions, whereas the landraces and old varieties showed superiority over the breeding lines under cold stress conditions. The high superiority of landraces over the breeding lines and modern cultivar under cold stress conditions suggested that the evaluation of breeding lines in moderate and warm locations should be continued. These differences could be attributed to differences in the genetic material tested as well as to differences in the testing environments. However, under rainfed conditions, bread wheat cultivation is more profitable than durum wheat due to higher yield production and even the higher price of durum wheat (6% higher than bread wheat) has not encouraged farmers to expand durum cultivation. Thus, in durum wheat breeding programmes, a popular bread wheat cultivar is usually used as a control to test for superior of durum wheat genotypes in Iran. Among the check genotypes, Sardari (bread wheat) is an outstanding landmark bread wheat genotype, which is grown on a large scale in rainfed cold and moderate cold regions for 40 years in the whole country (Mohammadi and Amri, 2013). However, durum breeding in the Mediterranean basin, particularly in Iran, has made little progress in cold regions and most progress was in warm and moderate cold regions, highlighting the difficulty to increase yield of durum wheat under cold conditions.

Predictive accuracy as assessed by the signal and noise GE interaction (Gauch, 2013) showed that AMMI-1 as the best AMMI model for interpreting the variation in the data. This indicates that AMMI-1 estimation is closer to the true value of yield prediction. So, in this dataset, AMMI-1 is better procedure to estimate the mean yield of genotype in each environment. The IPCA1 effect was 5.5 times greater than the genotype effect, indicating the high importance of IPCA1 to contribute in the total GE interaction. However, the first IPCA was accounted for the majority (>77%) of GE interaction in the AMMI analysis, indicating the importance of AMMI-1 model for interpretation of yield data. As the GE interaction noise (GE_N) was larger than genotype effect, it is valuable that AMMI-1 discards this large amount of noise. This was in agreement with Sneller *et al.* (1997), who suggested that GE interaction pattern is collected in the first IPCA. The earlier reports indicate that AMMI analysis is adequate in characterizing GE interaction for grain yield in different crop species (Crossa *et al.*, 1991; Ebdon and Gauch, 2002; Li *et al.*, 2006). A graphically represented AMMI analysis enables selection of stable and high-yielding genotypes for variable environments, as well as genotypes with specific adaptability.

The adaptation pattern of different types of genotypes indicated that the landraces and old variety were different from breeding lines in stability and yield productivity. This indicates that the breeding lines are opposite to the landraces and old varieties in adaptation, yield performance and stability. Despite the relatively low potential of breeding lines at cold areas, majority of breeding lines and new cultivar had the highest mean yield, implying that they had good dynamic stability concept. According to Figure 2, there were two mega-environments including warm environments as breeding lines, especially G21 and new cultivar (G23) were wining genotypes, and cold environments as the landraces and old varieties with wining genotypes G6 and G1. The moderate lactation in some years was correlated with cold and in some years with warm location, indicating that the moderate location as already suggested can be used as a representative location to share breeding materials for both the warm and cold regions of Iran (Mohammadi *et al.*, 2010).

The AMMI-1 biplot can be used to identify the appropriate check cultivar for all locations (general check) or for specific locations (specific check). Durum breeders would then compare their promising lines against either the general or specific check cultivar in selecting for the next high-yielding cultivar. For example, results from this study suggest that breeding lines G19 and G22 should be the general check genotypes for all environments because of their high yield and stability performance across environments. In addition, Saji new cultivar (G23) should be included in the MET and serve as an additional check cultivar at the warm and moderate test locations, since it had the highest yield at these locations. Results from AMMI biplot analysis indicated that breeding line G21 and new cultivar (G23) were the best genotypes in terms of better yield mostly at warm and moderate environments. The analyses also indicate that most of breeding lines qualify as check genotypes in moderate and warm environments.

The IPCA1 summarizes the most important part of the crossover GE interaction in rainfed durum wheat yield trials. Any genotypic traits and environmental factors that are highly correlated with the IPCA1 scores can thus be interpreted as possible genotypic and environmental causes of crossover GE interaction (Yan and Hunt, 2001). The correlation of genotypic and environmental factors with IPCA1 indicates again the importance of AMMI-1 as the best model for interpreting these dataset in durum wheat. The results verified that plant height and days to heading are important traits responsible for the observed GE interaction and suggest that GE interaction could be reduced by optimizing the earliness and plant height (i.e., by selecting plants with medium height). This means that extremely tall genotypes can be discarded with confidence even at early stages of breeding. Thus, the phenotypic traits led some genotypes to perform more favourably in some environments but less so in others. In the case of meteorological variables, rainfall and average temperature were significantly (p <0.05) contributed to GE interaction and can be more effective in identifying superior genotypes for different environments. This finding suggests that environments with greater rainfall and higher winter temperature tended to have greater IPCA1 scores. These relatively high correlations indicate that there were large differences among genotypes in response to rainfall and air temperature. By using this approach, van Eeuwijk and Elgersma (1993) in ryegrass, Van Oosterom *et al.* (1996) in pearl millet and Yan and Hunt (2001) in winter wheat identified the major environmental/genotypic causes of GE interaction in different crop species.

The cold environments characterized by low rainfall and temperatures, tend to favour a category of genotypes which are taller (with more susceptible to lodging in favourable years) and generally late in maturity with higher TKW. These genotypes are mainly represented by landraces and old varieties. The relatively short plant height of breeding lines and new cultivar might have allowed these genotypes to took advantage of good water status during grain filling, because it was associated to lower lodging susceptibility (Voltas *et al.*, 1999a; Yan and Hunt, 2001). The heading date of breeding lines, was strongly correlated to GE interaction, may have been important for the specific adaptation, possibly allowing a higher level of yield productivity. On the other hand, the landraces with taller stature performed relatively better when growing conditions were harsher. The lateness of the landraces and the lower temperatures during grain filling period might have exerted an influence on the grain growth, and hence leading to a higher TKW. This reveals a better adaptation of these kinds of genotypes to water limitations during their terminal growth stages, in agreement with previous studies on durum wheat landraces (Moragues *et al.*, 2006).

CONCLUSION

The results have demonstrated the existence of large and complex GE interactions, which imply repressiveness of some entries to different environments but not others, that may be exploited for improved selection and evaluation. However, the environment was the major source of variation in grain yield and accounted for more than 80% of total variation. In addition to the effects of some seasonal variables (rainfall and temperature) on separation of rainfed environments, substantial variation was also observed between environments, which showed variation along IPC axes. This suggests that in addition to GE interaction patterns, grouping of environments based on seasonal variables can be regarded in durum breeding programme. However, the use of genotypic variables to investigate the responses of genotype groups to environmental factors will help better understanding about the variation in test environments and could the facilitate specific breeding objectives. According to AMMI, appropriate check genotypes for all locations or for specific locations were identified, with the breeding lines being qualified as check genotypes in moderate and warm environments, and old varieties and landraces in cold locations. The presence of specific adaptation evidenced by our results is of particular relevance in Mediterranean environments, such as Iran. The breeding line G20 is recommended for further inclusion in the breeding programme due to its highest yield performance among genotypes, and breeding line G19 is recommended because of its stability and high yield. The findings indicated that plant height and heading date were the major genotypic causes of GE interaction, and climatic variables of rainfall, average temperature and freezing days were significantly contributed to the GE interaction.

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