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Multi-environment evaluation of winter bread wheat genotypes under rainfed conditions of Iran-using AMMI model

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ABSTRACT

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Genotype × environment interaction is an important and challenging issue for plant breeders in developing new improved varieties. This study aimedto estimate the impact of genotype × environment interactions for grain yield in winter wheat under rainfed conditions using the additive main effects and multiplicative interaction (AMMI) model, and to select genotypes with high grain yield, yield stability, and adaptation for cold rainfed environments in Iran. Twenty-two breeding lines and two commercial winter wheat cultivars, representing winter wheat-growing cold rainfed areas of Iran, were tested in eight locations over three crop cycles (2011-14). Environment was the pre dominant source of variation, accounting for 84.8% of the total sum of squares, with the remainder due to the genotype × environment interaction effect (which was almost four times that of the genotype effect). Average grain yield varied from 1125 to 1608 kg ha^{-1} across the 24 environments, with an average of 1385 kg ha^{-1}. The AMMI biplots identified genotypes with wide and specific adaptation as well as environments with high and low genotype discrimination and characterization. Relative humidity, freezing days, and plant height were among the environmental factors and genotypic co-variables that contributed highly to genotype × environment interactions for grain yield. These findings could identify breeding lines as potential genetic resources for improving and stabilizing grain yield in winter bread wheat breeding programs for cold rainfed areas of Iran, through exploitingand minimizing thegenotype × environment interaction.

Keywords: genotypic and environmental co-variables, grain yield improvement, specific adaptation, wide adaptation, winter wheat.

INTRODUCTION

Bread wheat (*Triticum aestivum* L.) is one of the world's major food crops and has great economic and political importance. Annually, Iran produces about 14 million tons of wheat, of which 90% is bread wheat (FAO, 2012). Average grain yields are approximately 2 tons ha^{-1}. Within Iran, wheat is grown under both irrigated and rainfed conditions. Rainfed wheat covers two-thirds of the total wheat growing area, but accounts for just one-third of total production (Mohammadi and Amri, 2013). Developing new bread wheat varieties with higher grain yield potential, tolerance to drought, and adaptation to rainfed conditions is a major objective for improving bread wheat grain yield and yield stability across Iran.

Multi-environment trials (METs) are used to determine sites representing the target environment and can identify superior cultivars for recommendation to farmers. Data collected from

METs are needed for precise estimation of genotypic value and yield stability (Yan and Hunt, 2001). These trials facilitate quantification of the environment and genotype × environment (GE) interactions. Differences in environmental conditions may cause large GE interactions, especially under drought-prone environments. Large GE interactions would invalidate recommendations of a cultivar with the highest average yield across all tested environments.

Quantification of GE interactions isnecessary for developing new superior cultivars for different environments (Vargas *et al.,* 2001; Thomason and Phillips, 2006). The presence of GE interaction in METs is expressed either as inconsistent responses of some genotypes relative to others (due to changes in genotypic rank) or as changes in the absolute differences between genotypes without rank change (i.e. heterogeneity of within-site variance). Measuring GE interaction is very important in determining an optimum breeding strategy for releasing genotypes with an adequate adaptation to target environments (Fox *et al.*, 1997). Consequently, breeders will always be faced with significant GE interactions, which complicate the identification of superior genotypes.

The interpretation of GE interactions can be facilitated using several statistical models. These models can use linear joint-regression (Yates and Cochran, 1938; Finlay and Wilkinson, 1963; Eberhart and Russell, 1966; Tai 1971; Becker and Leon, 1988), multivariate clustering techniques (Lin and Butler, 1990), or multiplication approaches such as additive mean effects and multiplicative interaction (AMMI; Zobel *et al.,* 1988; Gauch, 1992) and genotype plus GE (GGE) biplot analysis (Yan *et al.,* 2000). Modeling GE interaction in METs helps to determine phenotypic stability of genotypes, but this concept has been defined in different ways and therefore large number of stability parameters have been developed (Gauch and Zobel, 1997).

Statistical methods of analysis of variance (ANOVA), principal component analysis (PCA), and linear regression are often not effective for understanding and evaluating complex data from METs. In contrast to the standard statistical analyses, the AMMI model incorporates the ANOVA with additive parameters and the PCA with multiplicative parameters into a single model. The AMMI biplot simultaneously displays both main and interaction effects for genotypes and environments and enables a single analysis of the GE interaction. AMMI is usually constructed from the first two interaction principal component axes (IPCA; Gauch and Zobel, 1990; Gauch, 1992; Gauch and Zobel, 1997) and can have several models: AMMI0 estimates the additive main effect of genotypes and environments and does not include any IPCA; AMMI1 combines the additive main effects from AMMI0 with the GE interaction effects estimated from IPCA 1; AMMI2, and so forth, up to the full model with all IPCA (Gauch, 1988).

Knowledge on the GE interaction structure may be helpful in determining effective strategies for developing new superior cultivars. The AMMI model, which considers additive effects for genotypes and environments and multiplicative terms for GE interaction, has been very useful for analyzing the GE interaction and stability analysis in crop species in METs (Gruneberg *et al.,* 2005; Samonte *et al.,* 2005; Caliskan *et al.,* 2007). The combination of ANOVA and PCA in the AMMI model – along with the prediction assessment – is an important tool in understanding GE interaction and identification of genotypes with higher yields.

It has recently become popular to use statistical models whose parameters relate better to physiological knowledge and that permit varying degrees of integration between statistical and physiological approaches for description and prediction of genotypic responses across environments (van Eeuwijk *et al.,* 2005). Numerous methods have been used in the search for an understanding of the causes of GE interaction (van Eeuwijk *et al.,* 1996); these can be categorized into two major strategies. The first involves factorial regression analysis of the GE matrix against environmental factors, genotypic traits, or combinations of both (Baril *et al.,* 1995). The second strategy involves the correlation of genotypic or environmental scores derived from AMMI analysis togenotypic or environmental covariates. While differing in approach, both strategies have been shown to produce similar results (Vargas *et al.,* 1999).

This study used AMMI to understand complex GE interactions in winter wheat MET data, characterization of test environments, and selection of genotypes to exploit specific adaptations, as well as enhancing accuracy in recommending new cultivars, repeatability, and genetic gains. Specifically, the study aimed to: (i) assess GE interaction for grain yield in cold rainfed areas of Iran using the AMMI model; (ii) identify high yielding genotypes with yield stability to recommend as new winter bread wheat varieties adapted to cold rainfed areas of Iran; and (iii) investigate the environmental and genotypic causes of GE interaction in winter bread wheat MET data in

Iran.

MATERIALS AND METHODS

Plant materials and experimental layout

Table 1 details the 24 winter wheat genotypes (22 breeding lines from winter bread wheat breeding programs of Iran and two commercial winter bread wheat cultivars) that were evaluated across eight dryland research stations in Iran. Each location was evaluated across three cropping seasons (2011-12, 2012-13, and 2013-14), resulting in a total of 24 environments. The experimental sites (Table 2) represent major rainfed winter wheat-growing areas in Iranand were comprised of Maragheh (Mrg), Ghamlo (Gml), Zanjan (Zan), Ardabil (Ard), Arak (Ark), Uromieh (Urm), Sararood (Sar), and Shirvan (Shr).

Table 1. Genotype code, name/cross name, origin, and type.

Code	Name	Origin	Type
1	Azar-2 (Check)	Iran	Cultivar
2	Ohadi (Check)	Iran	Cultivar
3	KSK46/BUC//DARI-16	IWWIP	Breeding line
4	ZHETISU//PYN/BAU/3/338-K1-1//ANB/BUC	IWWIP	Breeding line
5	WRM/4/FN/3*TH//K58/2*N/3/MY54/N10B//AN/5/PEL 72380/ATR71/6/KVZ/CGN// GLE /7/AGRI/NAC//MLT	IWWIP	Breeding line
6	F9.70/MAYA//4105W/3/PLK70/LIRA/4/88 ZHONG 257//CNO79/ PRL/5/SB-360-1	IWWIP	Breeding line
7	Azar-2/4/T.AEST./SPRW'S'// CA8055 /3/BACANORA86-IRBW01-23-54-29-0SAR-0SAR-0SAR-0SAR-4SAR-0SAR	Iran	Breeding line
8	Boema/116 Yrrgp IRW2000-01 - 082-0MA	Iran	Breeding line
9	M374/Sx//2897/Porsuk/3/Plk70/Lira/5/ Jup/4/Cllf/3/li14.53/Odin//Ci1/ 6/Pvn"A"/ Bow"S7/ Lira"S"/3/Shahi IRW2000-01 -091-0'MA	Iran	Breeding line
10	M374/Sx//2897/Porsuk/3/Plk70/Lira/5/Jup/4/Cllf/3/li14.53/Odin//Ci1/6/Yamhill/A12/32438/3 /Sardari/…	Iran	Breeding line
11	Ebvd99-1/3/Heng-Sxl-7004/Bow//Ks794681/Sxl IRW2000-01 -110-0MA	Iran	Breeding line
12	Lov26//Lfn/Sdy(Es84-24)/3/Seri/4/Seri/4/1 -32-1317A12/32-438/3/ Sabalan IRW2000-01-114-0MA	Iran	Breeding line
13	Ghafghaz//F9.10/Maya"S"/3/Ebvd99-1 IRW2000-01 - 141-0MA	Iran	Breeding line
14	Sabalan/Shanghai 5//4848 Mashad/Tui"S" IRW2000-01 - 147-0MA	Iran	Breeding line
15	Sabalan/1-27-5614/4/ Ne83407/3/Fln/Acc//Ana IRW2000-01-299-0MA	Iran	Breeding line
16	ARWYT-TC-1	IWWIP	Breeding line
17	ARWYT-TC-1	IWWIP	Breeding line
18	ARWYT-TC-1	IWWIP	Breeding line
19	NOVO ZVESDA	IWWIP	Breeding line
20	NE96644(=ODESSKAYA P./CODY)/PAVON//*3SCOUT66/3/ NE94653 (=ARAPAHOE/ABILENE//ARAPAHOE)	IWWIP	Breeding line
21	Azar-2/78Zhong29-38	Iran	Breeding line
22	Azar-2/78Zhong291-64	Iran	Breeding line
23	Azar-2/78Zhong291-115	Iran	Breeding line
24	Azar-2/78Zhong291-118	Iran	Breeding line

IWWIP: International Winter Wheat Improvement Program

Each environment used a randomized complete block design with 24 genotypes and four replications. Plot size was six rows × 7 m long × 0.20 m row spacing. Trials were sown in October using a Winter steiger plot planter with a sowing rate of 400 seeds m^{-2}. Land preparation and other cultivation practices were conducted according to the technical guidelines for wheat cultivation under rainfed conditions released by the Dryland Agriculture Research Institute (DARI, Iran).

Measurements and observations were made throughout the cropping seasons and focused on specific agronomic characteristics including phenological stages, morphological traits, and grain characteristics related to adaptation and yield performance. Moreover, grain yield data were collected by harvesting the entire area of each experimental plot using a Winter steiger plot combine. Grain yields per plot were measured and converted to kg ha^{-1} for the statistical analyses.

Statistical analyses

AMMI analysis was used to analyze two-way experimental data, withthe main effects as additive and the interaction effect as multiplicative. The two-way fixed effect model was fitted to determine the magnitude of the main effects of variation and their interaction on grain yield. Genotype main effect (G), environment main effect (E), and GE interaction were analyzed by the AMMI model (Gauch and Zobel, 1990):

$$Yge = « + G_i + E_j + \sum_{k=1}^{n} ª_k ¥_{ik} ¢_{jk} + °_{ij} + £_{ijk}$$

where Yge is the yield of genotype G in environment E; « is the grand mean; G_i is the genotype effect and E_j is the environment effect; $ª_k$ is the singular value for IPCA; $¥_{ik}$ is the genotype G eigenvector value for IPC axis N; $¢_{jk}$ is the environment E eigenvector value for IPC axis N; $°_{ij}$

is the interaction residual; and $£_{ijk}$ is the random error.

The number of significant terms in the AMMI model was evaluated usingthe method of Gollob (1968) andthe AMMI analysis was performed using Genstat statistical software. AMMI results were graphically presented in the form of a biplot (Gabriel, 1971), where genotype and environment scores of the first two bi-linear terms are represented by vectors, with their starting points at the origin (0, 0) and end points (markers) determined by their scores (Zobel *et al.*, 1988; Gauch and Zobel, 1996; Crossa 1990).

The results of the AMMI analysis were interpreted on the basis of the AMMI-1 graph, which shows the adaptation map as the predicted yields (expected yield from the AMMI model equation without environmental deviations) of genotypes across environmental IPCA1 scores (Gauch and Zobel, 1997), and the AMMI-2 biplot, which shows its IPCA1 on the abscissa and IPCA2 on the ordinate.

A correlation analysis between genotypic/ environmental IPCA1 and IPCA2 scores from AMMI analysis and genotypic/environmental co-variables was performed to interpret major causes of GE interaction in rainfed winter bread wheat MET data.

RESULTS

Climatic conditions

Environments differed in climate (mostly rainfall amount and distribution), thus providing contrasting growing conditions that led to a range of grain yields. Annual rainfall varied by location, from 197.1-275.8 mm at Ard; 199.4-267.8 mm at Shr; 215-337.4 mm at Ark; 219.9-512.9 at Zan; 251.0-351.1 mm at Mrg; 256.1-313.3 mm at Gml; 290.3-400.1 mm at Urm; to302.9-401.3 mm at Sar. Environments also varied in winter temperatures, from an average of3.3 °C at Mrg to 13.4 °C at Sar (Table 2). Genotypes were therefore exposed to both cold and drought stresses, which are limiting factors in cold and moderately-cold rainfed wheat growing areas of Iran.

Table 2. The 24 test environments and their main climatic characteristics.

Code	Location	Season	Longitude	Latitude	Altitude	Rainfall (mm)	AT (°C)	RH (%)	FD	Evap.
Mrg0	Maragheh	2011-12	46°15'0"	37°22'12"	1400	251.0	3.9	61.5	142	778.5
Gml0	Ghamlo	2011-12	47°13'48"	35°22'48"	1850	313.3	6.5	51.6	131	937.2
Znj0	Zanjan	2011-12	48°5'4"	36°32'28"	1875	512.9	6.6	57.8	128	815.4
Ard0	Ardabil	2011-12	48°22'12"	38°10'48"	1500	275.8	6.1	69.2	125	491.4
Ark0	Arak	2011-12	49°41′20″	34°05′30″	1748	269.1	9.84			
Urm0	Uromieh	2011-12	45°1'48"	37°19'48"	1332	290.3	7.2	61.5	137	
Sar0	Sararood	2011-12	47°16'48"	34°12′19"	1351	302.9	11.0	46.7	98	978.6
Shr0	Shirvan	2011-12	58°7′12"	37°1348"	1131	267.8	8.9	67.1	118	
Mrg1	Maragheh	2012-13	46°15'0"	37°22'12"	1400	351.1	6.4	59.7	103	837.6
Gml1	Ghamlo	2012-13	47°13'48"	35°22'48"	1850	256.1	8.4	60.8	107	868.0
Znj1	Zanjan	2012-13	48°5'4"	36°32'28"	1875	311.2	8.6	54.9	76	764.0
Ard1	Ardabil	2012-13	48°22'12"	38°10'48"	1500	233.4	8.7	67.3	70	607.2
Ark1	Arak	2012-13	49°41′20″	34°05′30″	1748	215.0	11.13			
Urm1	Uromieh	2012-13	45°1'48"	37°19'48"	1332	400.1	10.1	61.4	104	
Sar1	Sararood	2012-13	47°16'48"	34°12′19"	1351	394.3	13.4	45.9	58	1257.4
Shr1	Shirvan	2012-13	58°7′12"	37°13'48"	1131	235.5	10.6	60.4	75	
Mrg2	Maragheh	2013-14	46°15'0"	37°22'12"	1400	288.6	9.6	56.3	120	877.3
Gml2	Ghamlo	2013-14	47°13'48"	35°22'48"	1850	294.0	6.6		127	
Znj2	Zanjan	2013-14	48°5'4"	36°32'28"	1875	219.9	7.3	58.3	96	914.1
Ard2	Ardabil	2013-14	48°22'12"	38°10'48"	1500	197.1	7.0	69.8	117	677.4
Ark2	Arak	2013-14	49°41′20″	34°05′30″	1748	337.4	10.1			
Urm2	Uromieh	2013-14	45°1'48"	37°19'48"	1332	314.5	8.9	59.2	91	
Sar2	Sararood	2013-14	47°16'48"	34°12′19"	1351	401.3	11.6	40.7	68	860.9
Shr2	Shirvan	2013-14	58°7′12"	37°13'48"	1131	199.4	10.4	61.1	87	

AT =average temperature; RH =relative humidity; FD =number of freezing days; Evap. = evaporation

Partitioning variance for grain yield

Table 3 shows the results of partitioning variance for genotype yield using the AMMI model and related Gollob's F-test. The three sources of variation were highly significant (P<0.01). In the ANOVA, the sum of squares for environment main effect explained 84.8% of the grain yield total variation, showing the highest environmental effect on grain yield. The differences between genotypes explained 1.2% of the total variation, while the effects of GE interaction explained 5.5% of total variation.

The significance of the GE interaction effect suggests that there are significant differences in responses of genotypes to environments, and hence sensitivity and instability. The greater GE interaction relative to genotype effect suggests significant environmental groups with different top-yielding genotypes.

Table 3. Analysis of variance of main and interaction effects for grain yield of 24 winter bread wheat genotypes across 24 environments.

Source	df	Sum squares	Mean squares	F-value	Pr(>F)	Total variation explained (%)	GE interaction explained (%)
Environment (E)	23	1066481295	46368752	179.4**	0.00000	84.8	
Block/E	72	18606384	258422	4.9**	0.00000	1.5	
Genotype (G)	23	15149626	658679	12.4**	0.00000	1.2	
G x E	529	68748327	129959	2.5**	0.00000	5.5	
IPCA1	45	14289980	317555	6.4**	0.00000		20.8
IPCA2	43	8536005	198512	4.0**	0.00000		12.4
IPCA3	41	7961461	194182	3.9**	0.00000		11.6
IPCA4	39	7070274	181289	3.7**	0.00000		10.3
IPCA5	37	5447623	147233	3.0**	0.00000		7.9
IPCA6	35	4633992	132400	2.7**	0.00000		6.7
IPCA7	33	4295730	130174	2.6**	0.00000		6.2
IPCA8	31	3932786	126864	2.5**	0.00000		5.7
IPCA9	29	2881589	99365	2.0**	0.00320		4.2
Residual	196	9698887	49484				14.1
Pooled Error	1656	87928498	53097			7.0	
Total	2303	1256914130					

** Significant at the 1% probability level.

The large variation due to environment confirms that the testing environments were different, with large differences among environmental means causing most of the variation observed for genotypes (Yan and Kang, 2002; Fan *et al.,* 2007). Genotypic rank differences over environments showed the existence of crossover GE interaction (Crossa, 1990), which emphasized the necessity to assess the response of the genotypes to environmental variations.

The partitioning of the GE interaction matrix results (in the multiplicative terms) led to nine significant IPCAs (P<0.01). Based on the results, the best model – called AMMI9 – is built from nine significant IPCAs. Table 3 shows the singular value and its percentage; the first singular value, as the largest, recovers 20.8% of the variation. The AMMI9 model used the first nine singular values in the model, so it recovered 85.8% variation of the GE interaction.

Environment effects on grain yield

Environment was the main cause of variations observed ingrain yield. Studies have shown that the environmental portion in METcan be the largest among all sources of variation (Samonte *et al.,* 2005; Caliskan *et al.,* 2007). In this study, average yieldsby environment ranged from 289 kg ha^{-1}(Shr2) to 3019 kg ha^{-1}(Sar2). Genotypic mean yield productivity was highest in Sar (2014 kg ha^{-1}) and lowest in Urm (634.1 kg ha^{-1}) (Table 4).

There was a difference of 59.4% in grain yield between environments, owing to the significant (P<0.01) effect of favorable versus unfavorable conditions, which yielded 1970 kg ha^{-1} and 790 kg ha^{-1},respectively. Low-yielding environments consisted of Gml0, Sar0, Ark0, Ark1, Ard0, Ard1, Ard2, Zan0, Uro0, Uro1, Uro2, and Shr2, while the high-yielding environments were Sar1, Sar2, Mrg0, Mrg1, Mrg2, Gml1, Gml2, Ark2, Zan1, Zan2, Shr0, and Shr1.

Genotype effect on yield

There were significant differences among genotypes for grain yield. The low effect of genotype may be explained by the fact that the tested genotypes were selected as top yielding genotypes from the national regional bread wheat yield trials. Genotypic average yield across environments varied from 1235 kg ha^{-1}(breeding line No. 16) to 1608 kg ha^{-1} (cultivar Azar-2), with a mean of 1385 kg ha^{-1} (Table 4). Genotypic mean yield across cropping seasons varied with location, from 565 kg ha^{-1} (breeding line No. 8) to 761 kg ha^{-1} (breeding line No. 11) at Ard; from 1004 kg ha^{-1} (breeding line No. 10) to 1730 kg ha^{-1} (cultivar Azar-2) atArk; from 1335 kg ha^{-1} (breeding line No. 16) to 2326 kg ha^{-1} (breeding line No. 21) at Gml; from 1701 kg ha^{-1} (breeding line No. 16) to 2277 kg ha^{-1} (cultivar Azar-2) at Mrg; from 1808 kg ha^{-1} (breeding line No. 15) to 2290 kg ha^{-1} (breeding line No. 21) at Sar; from 912 kg ha^{-1} (breeding line No. 15) to 1335 kg ha^{-1} (cultivar Ohadi) at Shr; from 477 kg ha^{-1} (breeding line No. 20) to 859 kg ha^{-1} (cultivar Ohadi) at Urm; and from 1173 kg ha^{-1} (breeding line No. 4) to 1768 kg ha^{-1} (cultivar Azar-2 cultivar) at Zan.

Thousand grain weight (TGW) was more important (r = 0.505*, P <0.05) than other traits in terms of explaining of the grain yield differences across environments. These results concur with other studies carried out across Mediterranean environments that have reported a positive relationship between TGW and grain yield (Moghaddam *et al.,* 1997; Kanatti *et al.,* 2014). Days to heading, days to maturity, and plant height were found to be more variable in their contribution to

Table 4. The mean values for 24 winter wheat genotypes in 24 test environments. Underlined values indicate the highest

Env. Code	Genotypes																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	
ARD0	1205	1198	1135	1078	1250	1343	1010	995	958	1058	1510	1195	990	1418	1230	1088	1188	1175	1
ARD1	428	368	428	421	333	365	398	356	370	545	411	336	371	475	343	208	490	630	3
ARD2	633	240	503	333	253	438	380	343	548	650	363	598	488	328	700	430	595	403	3
ARK0	1249	1014	942	751	893	991	1054	871	853	857	1111	945	739	954	1126	877	645	960	7
ARK1	1569	1681	1195	1171	1328	1189	1193	891	1017	703	1291	1233	1360	955	1377	1047	1295	1440	1
ARK2	2373	2093	2154	1839	2048	1781	1749	1673	1981	1454	2175	2005	1735	2068	2271	1821	2023	1923	2
GML0	1661	1520	1307	1116	1066	1081	1426	1123	1603	1217	1074	1115	1208	1254	1039	713	1025	1208	1
GML1	2677	2849	2068	1932	2023	1685	2164	2277	2223	1975	2138	1990	2231	2013	1673	1636	1995	1804	1
GML2	2309	2071	1747	1738	1906	1678	2106	1915	1998	1903	1791	1926	2114	2136	1776	1656	1810	1772	1
Mrg0	2381	2474	2128	2262	2309	2094	2098	2144	2224	2232	2296	2182	1986	2113	2067	1966	2010	2000	1
Mrg1	1990	2050	1809	1898	1804	2010	1969	1835	1755	1821	2290	2189	2186	1679	1984	1910	1931	1842	2
Mrg2	2461	2105	1865	2000	2358	2081	2014	2013	1613	2013	1995	2184	1700	2138	2022	1226	2245	1773	2
SAR0	1245	1214	1062	1111	1192	1324	946	1165	1371	1078	931	1206	1228	1085	1119	1193	1142	1324	1
SAR1	2105	1742	2129	2002	1857	1605	1992	1563	1971	2057	2163	1640	1959	1793	1631	1791	1928	1704	1
SAR2	3312	3112	3464	3085	3436	2798	2630	2732	3191	3091	2774	2933	3400	2914	2674	3105	2603	2692	3
Shr0	1593	1738	1676	1411	1682	1693	1605	1573	1457	1634	1545	1424	1399	1518	1355	1423	1596	1653	1
Shr1	1557	1897	1667	1297	1583	1727	1657	1587	1383	1674	1594	1410	1459	1547	1281	1407	1666	1607	1
Shr2	420	370	210	263	333	380	340	353	340	360	437	247	307	267	100	327	127	123	2
Uro0	604	673	453	526	531	462	457	455	462	533	563	547	478	443	612	537	462	469	6
Uro1	556	932	533	1058	730	645	719	768	513	546	800	843	488	443	1013	421	543	809	8
Uro2	969	972	934	538	601	507	688	747	608	649	483	639	938	625	750	669	913	538	8
Zan0	1215	1065	820	595	790	620	770	615	930	970	715	730	875	555	735	555	530	715	1
Zan1	1935	2115	2035	1410	1770	2075	1850	1800	1990	1755	2010	1955	1730	1895	2150	1820	1590	1860	1
Zan2	2155	1875	1485	1515	1545	1540	1665	1900	1670	1705	2095	1830	1575	1460	1825	1820	1415	1645	1
Mean	1608	1557	1406	1306	1401	1338	1370	1321	1376	1353	1440	1388	1373	1336	1369	1235	1324	1336	1
Favorable environments (> Grand mean)																			
Unfavorable environments (<Grand mean)																			

final grain yield.

The influence of TGW on grain yield in irrigated conditions seems to arise from the fact that wheat grains yield is frequently sink limited (Fischer, 1985). For this reason, TGW has also been reported as a promising trait in increasing wheat grain yield under rainfed conditions. It was concluded that high grain weight is an important component of grain yield under a range of environments, and that improving this trait would benefit yield improvement in winter bread wheat under drought prone environments.

Genotype × environment interaction effect on grain yield

The GE interaction had a strong impact on grain yield ($P<0.01$), which explained 5.5% of the model sum of squares (about four times that of the genotype effect). METs have often shown that yield variation due to GE interaction exceeds that due to genotype (Bidinger *et al.*,1996). This is supported by the fact that the GE mean yield varied from 100 kg ha^{-1} (breeding line No.15in environment Shr2) to 3464 kg ha^{-1}(breeding line No. 3 in environment Sar2), indicating a considerable variation in yield of 24 genotypes in 24 test environments (Table 4). However, the strong GE interaction for quantitative traits such as grain yield can severely limit genetic gain in selecting superior genotypes for developing new improved cultivars.

AMMI biplot analysis

AMMI-1 biplot

To characterize GE interaction, an AMMI-1 biplot was plotted using the genotype and environment mean yields and their IPCA 1 scores (Fig. 1). The biplot accounted for 87.2% of the total sum of squares, making it reasonable for interpreting the GE interactions and main effects. Interactions in the biplot are identified from relative IPCA signs of the genotype and the environment points. The clustering of the tested genotypes according to their IPCA 1 values and average yield on the biplot (Fig. 1) also explains their similarities in yield performance (Shafii *et al.*, 1992).

In general, environments with scores near zero have little interaction across genotypes and provide low genotype discrimination (Anandan *et al.*, 2009). This pattern was observed for sometest environments i.e., Shr2, Sar0, Zan2, Mrg0, and Ar1. In contrast, the environments of Gml1, Gml0, Sar2, Gml2, and Mrg2 had high interaction across genotypes and providedthe highest genotype discrimination.

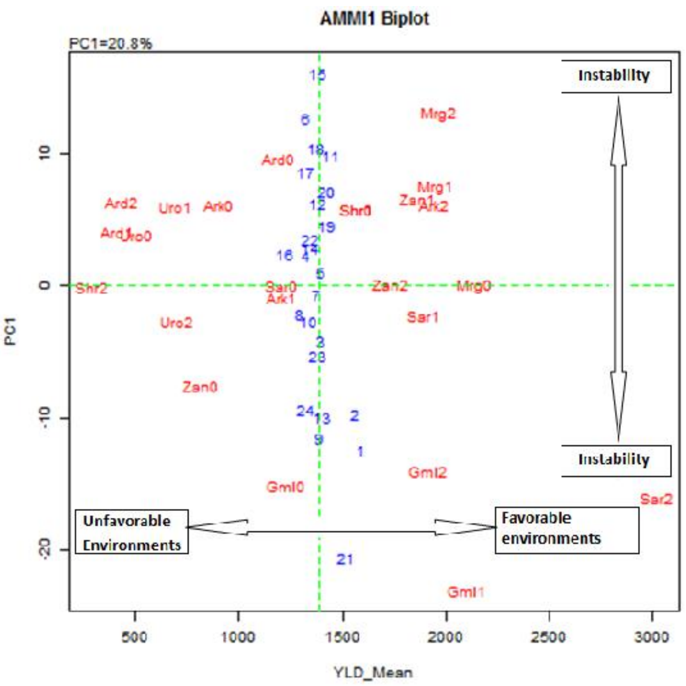

Fig. 1. Biplot for the primary component of interaction (IPCA 1) and meanyield (kg ha^{-1}) of 24 winter wheat genotypes in 24 test environments. The vertical line at the center of the biplot represents the general grand mean.

A negative interaction was observed in breeding lines No. 15, 6, 18, and 11 with positive IPCA in environments Gml1, Gml0, Sar2, Gml2, and negative IPCA in Zan0. Grain yield of three genotypes No. 15, 6, 18 at these environments were low. The yield performance of genotypes No. 15, 6, and 18 was as follows: Gml1 –1673, 1685, and 1804 kg ha^{-1}, respectively; Gml0 –1039, 1081, and 1208 kg ha^{-1};Sar2 –2674, 2798, and 2692 kg ha^{-1}; Gml2 – 1776, 1678, and 1772 kg ha^{-1}; and Zan0– 733, 620, and 715 kg ha^{-1}, respectively. The mean yields of these three genotypes across the24 environments were 1369, 1338, and 1336 kg ha^{-1}, respectively.

These three breeding lines (No. 15, 6, and 18) had positive interactions with the high-yielding environments Mrg2 and Ard0. They yielded 2022, 2081, and 1773 kg ha-1, respectively, in Mrg2 and 1230, 1363, and 1175 kg ha^{-1}, respectively,in Ard0. Breeding lines No. 15, 6, 18 (positive IPCA scores) and No. 21, 1, and 9 (negative IPCA scores) had the highest contribution to GE interactions, whereas breeding lines No.5, 7, 4, 16, 14, 8, and 10 made the lowest contribution. Remaining genotypes had moderate contributions to GE interactions.

The environment with lowest yields (Shr2) had the minimum IPCA 1 and led to zero interaction, whereas the high yielding environments Mrg0 and Zan2 had the least contribution to GE interactions. Environments Sar2, Gml1, Mar2, and Gml2 – with the highest yields – had the highest contributions to GE interactions (Fig. 1).

Yield stability of the genotypes was evaluated using an AMMI-1biplot. Genotypes interacted differently with weather conditions in the test environments. Breeding lines No. 15, 6, 18, 11, 17, 20, and 12 interacted positively with environments Mrg2, Ard0, Mrg1, Zan1, Ark2, Shr0, Ark0, Uro1, Ard2, Ard1, and Uro0,but negatively with environments Gml1, Gml0 and Gml2, and Sar2 (Fig. 1). In contrast, the breeding lines No.21, 1, 9, 2, 13, and 24 interacted positively with environments Gml1, Gml0 and Gml2, and Sar2, but negatively with the environments from Mrg, Ard, and Ark. Accordingly breeding lines No. 21, 15, 6, 18, 11, 17, 20, 12, 9, 13, 24, and check cultivars (1, 2) with the highest IPCA1 values were found to be instable genotypes when all environments were considered. In contrast, some genotypes such as breeding lines No. 5 and 7 had stable, but average yield performance, with the IPCA 1 values closest to zero. This type of genotype is considered highly desirable for wide adaptabilities in winter wheat breeding under variable rainfed conditions. However, in analyzing MET data, some genotypes tend to show wide adaptation while most of them have specific adaptability (Yan and Hunt 1998; Atanasova *et al*. 2009). These findings suggest breeding line No. 21 (with highest average yield after the check cultivars) shows a high specific adaptability to environments representing Kurdistan and Kermanshah provinces.

Similar IPCA 1 values were also found in environments Mrg0, Zan2, Sar0, Shr2, and Ark1, with yield productivity ranging from lowest (Shr2) to highest (Mrg0) values. Environments that contributed most to total GE interaction were Mrg2 followed by Gml1, Shr0, Sar2, Gml0, and Gml2, while there was nearly no contribution from environments Shr2, Mrg1, Shr1, Ur02, and Uro0 (Fig. 2). Differences across all the environments were mainly summarized by the IPCA1, while the IPCA2 essentially captured the dissimilarities between Zan2, Shr0, and Sar1 with the other environments.

Adaptation to environmental change

Fig. 2. shows the adaptation map indicating the predicted mean yields of 24 winter wheat genotypes as a function of the score on the environment IPCA1. The mean yields predicted usingthe AMMI model equation – without the environmental deviation across environmental IPCA1 scores – indicatedthe adaptability of each genotype (Gauch and Zobel, 1997). This information enablesthe evaluation of the effects of genetic improvement on yield stability and adaptability and the identification of the highest yielding genotypes in specific environment IPCA1 ranges.

The lines in Fig. 2. resulted from the projection of the predicted yield of each genotype versus the environmental IPCA1 scores. The order of the environments along the IPCA1 axis suggested that climatic conditions (mainly rainfall and temperature) have a greater impact on the occurrence of GE interaction. The slope of the lines reflects the adaptation patterns of the genotypes across environments. The results show that these interactions led to different rankings of the genotypes across environments.

Breeding lines No. 15 and 11 (with sharp slopes) were found to have instable yield; they exhibited the lowest yields in environments with a large negative IPCA1 and the highest yields in environments with large positive IPCA1 scores. In contrast, cultivar Ohadi (2)with a high sharp slope exhibited the highest yields in environments with large negative IPCA1 and the lowest yields in environments with a large positive IPCA1. Breeding lines No. 5, 7, 22, 12, and 18, with high yield performance across the test environments, were found to be widely adapted genotypes.

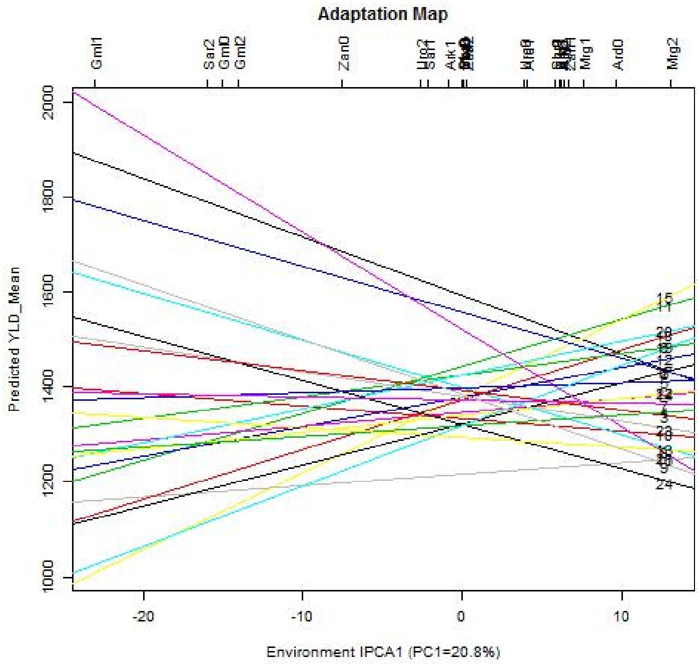

Fig. 2. Adaptation map showing the predicted mean yields of 24 winter wheat genotypes as a function of the score on the environment IPCA1 scores of 24 test environments. Lines are the responses of genotypes to different environments and the environments are ranked based on their IPCA1 scores.

These results show that the genotypes contrastedin adaptation, yield performance, and stability. However, the results revealed that – compared to the check cultivars – the breeding lines were better adapted to the majority of environments tested. Some genotypes were found with wide adaptability to all environments, showing a good combination of yield and its stability.

AMMI-2 biplot

In order to clearly determine the which-won-where pattern and sensitivity degree between the genotype and environment, the AMMI-2 biplot was constructed based on the IPCA1 and IPCA2 scores (Fig. 3). The AMMI-2 biplot accounted for 33.2% of total GE interaction sum of squares. The low goodness of fit reflects the complexity of the GE interactions for grain yield of 24 genotypes grown in 24 tested environments in cold and drought-prone environments. Nevertheless, according to Kroonenberg (1995), the fundamental patterns of GE interactions should be captured by the biplots. In our investigation, environments Gml1, Gml2, Gml0, Sar2, and Zan0 tended to be separate from the other environments and were effective genotype discrimination environments for selecting genotypes No. 21, 2, and 9. This indicates that these three genotypes had negligible GE interactions in Gml1, Gml2, Gml0, Sar2, and Zan0, but higher GE interactions inthe remaining environments.

In contrast, genotypes No. 15, 11, 6, 20, 12, and 19, located on the right side of the biplot, showed the least interaction with the majority of environments and were identifiedas widely adapted genotypes. These results indicate that these promising breeding lines are suited to cultivation in different environments in cold and drought-prone environments of Iran. The interaction of other breeding lines and checks are also displayed in the AMMI-2 biplot. The check cultivars (1 and 2) were poorly adapted to the majority of the environments tested. This confirms the genetic improvement in the adaptation of promising winter bread wheat lines, compared to checks, in the rainfed winter bread wheat breeding program of Iran.

In the AMMI-2 biplot (Fig. 3), the longer environmental vectors for environments Mrg2, Gml1, and Sar2 indicate that these environments had greater influence on determining GE interaction. The short vectors corresponding to environments Shr2, Ark1, Uro2, and Uro0 showed that they tend to contribute less to GE interaction, resulting in their poor genotype discrimination (Fig. 3). The angles between the environmental vectors in the biplot represent the phenotypic correlation between environments. The cosine of angle between two environmental vectors approximates the correlation between them (Yan and Kang, 2002; Yan and Rajcan, 2002). An acute angle (<90 degrees) indicates a positive correlation; an angle close to 90

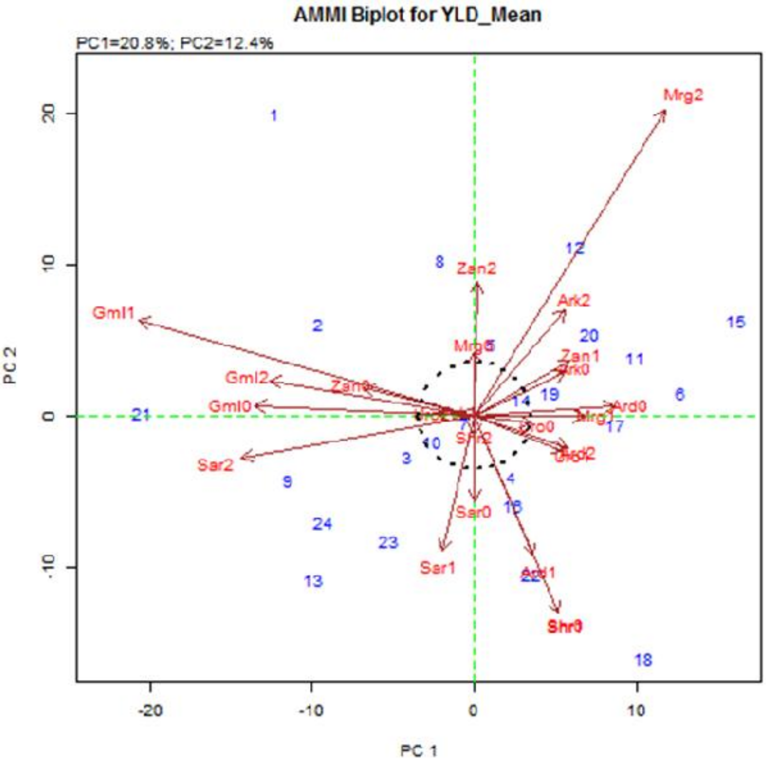

Fig. 3. AMMI 2 biplot derived from the first two IPCAs showing the interaction effect between 24 winter wheat genotypes tested in the 24 dryland environments. Vectors represent test environments and numbers corresponds to the genotypes.

degrees indicates that the environments were not correlated; whereas an obtuse angle (close to 180 degrees) represents a strong negative relationship.

The angles between environments Gml1, Gml2 and Gml0, Sar2 and Zan0 were well below 90 degrees, indicating that these environments tend to have similar genotype discrimination. The best adapted genotype to these environments was the breeding line No. 21. These environments made an obtuse angle with the second group of environments including Mrg2, Ark2, Zan1, Ark0, Ard0, Mrg1, Ard2, Uro1, Ard1, Shr0, and Shr1, indicating that these two groups of environments differed in genotype discrimination. Breeding lines No. 15, 6, 11, 17, 20, and 12 performed successfully in the second group of environments (Fig. 3).

There was wide variation between environments Zan0, Zan1, and Zan2 in three years, as shown by the obtuse angle between the corresponding vectors, which indicates the profound effect of cropping season in this location for genotype discrimination. A similar pattern was observed in Ark. Gml environments were highly associated in ranking of genotypes and had a strong tendency to separate from the other environments.

The analysis of genotype response in the AMMI-2 biplot (Fig. 3) indicated that the genotypes could be evaluated based on both concepts of specific adaptation and yield stability. Breeding lines No. 7, 10, and 16 (with the smallest IPCA1 and IPCA2 scores) had the lowest contribution to GE interaction and showed high stability across the environments. Conversely, breeding lines No. 1, 21, 18, and 15 (with the highest values of IPCA1 or IPCA2, or both) had the highest contribution to GE interaction and therefore specific adaptation to certain environments.

Genotype recommendation and yield improvement

Table 5 presents the environments grouped by the high yielding genotypes and the expected yield improvement using the first four AMMI recommended wheat genotypes. Breeding line No. 21 ranked in the top four genotypes in 10 of 24 environments and was the superior genotype in seven environments (Shr0, Shr1, Sar0, Ark1, Gml2, Gml0, and Gml1). Cultivar Azar-2 (No. 1) ranked in the top four genotypes in 17 of 24 environments and was the superior genotype in five environments (Ark2, Uro0, Mrg0, Uro2, and Zan0). Breeding line No. 15 performed well in three environments (Zan1, Ard2, and Ark0) and ranked in the top four genotypes in 7 of the 24 environments. Breeding line No. 11 was the best performing genotype in two environments (Mrg1 and Zan2) and ranked among the top four in nine environments, while breeding line No. 20 was also the leading genotype in two environments (Mrg2 and Ard0) and ranked in the top four genotypes in six environments.

Table 5. Grouping of environments using the higher yielding genotypes and the expected yield improvement using the first four AMMI recommended wheat genotypes.

Environment			First four AMMI genotypes recommended per environment								Yield improvement (Kg ha^{-1})			
Code	Mean	Score	1st	Yield	2nd	Yield	3rd	Yield	4th	Yield	1st	2nd	3rd	4th
Ard1	414	3.5	22	568	10	551	17	498	7	488	154	137	84	74
Shr0	1565	1.3	21	1728	6	1681	2	1676	22	1642	163	116	111	77
Shr1	1565	0.0	21	1820	2	1728	22	1685	6	1684	255	163	120	119
Sar0	1208	-0.2	21	1559	20	1398	19	1394	6	1352	351	190	186	144
Ark1	1206	-1.1	21	1689	2	1654	1	1455	15	1383	483	448	249	177
Gml2	1912	-13.6	21	2389	1	2330	2	2322	9	2052	477	418	410	140
Gml0	1231	-15.3	21	1711	2	1655	1	1639	9	1433	480	424	408	202
Gml1	2100	-22.6	21	2726	1	2718	2	2712	7	2306	626	618	612	206
Uro0	507	4.5	1	630	15	614	2	607	11	591	123	107	100	84
Mrg0	2136	0.9	1	2437	2	2317	11	2203	10	2200	301	181	67	64
Uro2	703	-2.2	1	979	3	861	2	851	5	809	276	158	148	106
Ark2	1941	7.1	1	2400	15	2263	11	2159	3	2134	459	322	218	193
Zan0	820	-7.4	1	1166	20	1147	21	1099	19	1017	346	327	279	197
Zan1	1860	7.4	15	2140	1	2062	6	2036	20	2021	280	202	176	161
Ard2	435	7.3	15	596	3	584	10	573	1	556	161	149	138	121
Ark0	900	7.2	15	1207	1	1165	11	1082	2	1010	307	265	182	110
Mrg2	1965	14.0	20	2521	1	2427	5	2367	17	2250	556	462	402	285
Ard0	1189	9.7	20	1424	6	1358	19	1313	11	1309	235	169	124	120
Sar2	3019	-15.3	13	3418	3	3413	1	3358	21	3340	399	394	339	321
Mr1	1951	8.2	11	2342	19	2219	21	2098	23	2080	391	268	147	129
Zan2	1736	1.9	11	2110	1	2089	20	2034	19	1965	374	353	298	229
Shr2	288	0.7	10	442	1	425	11	365	2	351	154	137	77	63
Uro1	693	6.2	4	1025	2	1003	15	952	24	908	332	310	259	215
Sar1	1894	-2.1	23	2230	11	2132	22	2115	1	2088	336	238	221	194
Average	1385	0		1719		1658		1608		1540	334	273	223	155

A grain yield improvement of 334 kg ha^{-1} could be achieved across the 24 environments if only the superior genotype for each environment was grown. If the second, third, and fourth recommended genotypes were planted across the 24 environments, yield improvements of 273, 223, and 155 kg ha^{-1}, respectively, could be achieved.

Suitable environments for thefour top genotypes were identified. Breeding line No. 21 was highly adapted to Gml in all three cropping seasons and was consistently the top genotype. At Mrg, breeding lines No. 1, 11, and 20 were the top genotypes and some fluctuations in genotype responses were observed under rainfed conditions. At Sar, breeding lines No. 21, 13, and 23 were the top yielding genotypes; at Shrbreeding lines No. 21 and 10 ranked as top genotypes; and at Urm breeding lines No. 1 (Azar2) and 4 were the highest yielding genotypes. At Zan, breeding lines No. 1, 15, and 11 were the highest yielding under rainfed conditions, while breeding lines No. 20, 22, yielded the highest under rainfed conditions at Ard. The best adapted genotypes for Ark were breeding lines No. 15, 21, and 1. However, in most locations, breeding line No. 21 (followed by cultivar Azar-2) emerged as widely adapted genotypes as they were the superior genotypes in contrasting environments with “+” and “-“ IPCA scores (Table 5).

Causes of GE interaction in the MET data

Table 6 presents the Pearson's correlation coefficients between IPCA scores from the AMMI analysis, with some genotypic and environmental co-variables. Both genotypic and environmental IPCA1 and IPCA2 scores included positive and negative coefficients. Therefore, both IPCA1 and IPCA2 summarized the most important part of the cross over GE interaction in data collected from rainfed winter bread wheat MET trials. IPCA1 scores were positively correlated with relative humidity (P<0.05), suggesting that environments with higher relative humidity tend to have greater IPCA1 scores. The IPCA1 showed a negative correlation (P<0.05) with plant height, indicating that genotypes with shorter stature tend to contribute more to GE interactions.

IPCA2 scores were negatively correlated with freezing days (P<0.05). This significant correlation indicated that there were large differences among genotypes in response to low temperatures in different environments. Thus, these traits caused some genotypes to perform relatively better in some environments but poorer in the others.

Table 6. Correlation coefficients between the first two IPCAs of pattern analysis and various environmental/genotypic co-variables.

Co-variables	IPCA1	IPCA2
Climatic variables		
Rainfall	-0.190	0.086
Average Temperature	-0.007	0.228
Relative Humidity	0.480*	0.067
Freezing days	0.014	-0.488*
Evaporation	-0.340	0.077
Genotypic variables		
Days to heading	-0.040	0.232
Days to maturity	-0.072	0.325
Plant height	-0.409*	-0.105
1000-kernel weight	-0.311	-0.378

*** Significant at the 5% probability level.**

DISCUSSION

Considering the highly variable and unpredictable year effect, which results in strong GE interaction, the ranking of genotypes according to grain yield levels varied from location to location and from year to year, so that in each environment (location/year) different genotype(s) was found superior. The large variance accounted for by the environments revealed highly diverse environments (Table 2). Considerable differences among environmental means resulted in significant variations in yield and presented wide variations that need to be understood and explored for effective improvement in winter bread wheat production in cold rainfed areas of Iran. The concurs with several other studies that have reported large effects of the environment on yield stability (Yan *et al.,* 2000; Samonte *et al.,* 2005; Fan *et al.,* 2007; Hristov *et al.,* 2010; Sibiya *et al.,* 2012; Nowosad *et al.,* 2016).

Graphical analysis of the AMMI model enabled selection of high-yielding genotypes with yield stability for target regions, as well as genotypes with specific adaptation. To better characterize GE interaction in winterbread wheat METs, AMMI 1 and 2 biplots were used to assess the relationships among the genotypes and environments, as suggested by earlier reports (Zobel *et al.,* 1988; Gauch, 1992; Vargas *et al.,* 1999; Ebdon and Gauch, 2002; Yan and Rajcan, 2002; Li *et al.,* 2006; Rodriguez *et al.,* 2008; Hristov *et al.,* 2010).

According to the AMMI-1 biplot, environments were clearly separate for both yield and contribution to GE interaction. However, while genotypes were clearly separated for contribution to GE interaction, they did not separate clearly for yield. The IPCA scores of genotypes in the AMMI analysis are indicators of genotypic yield stability over environments. Genotypes that showed high positive interactions with the environments would exploit specific agro-ecological conditions in target environments (Annicchiarico, 1997; Gauch and Zobel, 1997; Grausgruber *et al.,* 2000; Purchase *et al.,* 2000).

The “Ohadi”check cultivar was poorly adapted to most of the test environments, whereas most of the breeding lines showed better adaptation. Breeding lines with positive interactions with the majority of environments had the highest specific adaptation to these environments. The findings of this research indicated that Gml differed from the other test locations.

The results ofthe applied analyses enable better understanding for the development and recommendation of new superior winter bread wheat cultivars for target regions. Such analyses also provide selection criteria and facilitate further genetic improvements in the national rainfed winter bread wheat breeding program (Vargas*etal.,* 1999; Ebdon and Gauch, 2002; Rodriguez *et al.,* 2008; Hristov *et al.,* 2010; Nowosad *et al.,* 2016).

Knowledge of GE interactions facilitates decisions on releasing new cultivars with specific or wide adaptation in crop breeding programs and therefore is important in recommending new cultivars for target regions (Dias and Krzanowski, 2003; Gruneberg *et al.,* 2005). The combined ANOVA for yield across environments and genotypes revealed significant GE interactions that affected grain yield of genotypes in different environments. For some genotypes, significant GE interactions caused yield instability and their ranking changed from year to year. The analysis also identified the four best performing genotypes per environment; breeding line No. 21 (Azar-2/78Zhong29-38), followed by cultivar Azar-2 and breeding line No. 15 (Sabalan/1-27-5614/4/Ne83407/3/Fln/Acc//Ana IRW2000-01-299-0MA) were superior performers in several of the test environments (Table 5). The difference in ranking forthe AMMI selected genotypes in the different environments also implied differential yield performance as a result of the significant GE interaction.

The AMMI genotype recommendation revealed that the superior genotypes had similar responses in different environments, indicating that these genotypes are widely adapted to different environments. The genotypes recommended based on the AMMI model tended to have higher yield in drought-prone environments. Thus selecting breeding lines in variable environments would lead to higher gainsin yield improvement. In particular, the genotype adaptation map indicated breeding lines No. 5 and 7, which have wide adaptation to extreme environments (according totheir IPCA scores) and good combination of yield and its stability. The idea that variable environments can be explored for developing of new superior cultivars is a significant finding (Annicchiarico, 1997; Yan *et al.,* 2000). However, the presence of specific adaptation is of particular importance in rainfed winter bread wheat of Iran, where the extreme environmental constraints limit crop production.

The analyses indicated IPCA1 and IPCA2 scores with either positive or negative values that resulted in crossover GE interactions andled to inconsistent performance of genotypes across test environments (Yan and Hunt, 2001). Our findings confirmed plant height as an important trait contributing to the observed GE interactions, and suggested that GE interactions could be reduced by optimizing plant height in breeding material.

Among the environmental co-variables analyzed, relative humidity andfreezing days were the main environmental contributors to GE interactions and should be considered effective criteria for identifying superior genotypes for different environments. Using similar approaches, major environmental/genotypic causes of GE interaction have been previously identified by van Eeuwijk and Elgersma (1993) in rye grass, van Oosterom *et al.* (1996) in pearl millet, and Yan and Hunt (2001) in winter wheat.

The GE interactions for grain yield detected in this study were significantly affected by climatic/genotypic variables. Moreover, there were crossover interactions between yields of genotypes grown in different environments. This emphasizes the importance of considering both the genotypic traits and the environmental factors involved in the specific adaptation, as shown by our data, in selecting suitable genotypes for each environment. However, genotype evaluation in the presence of unpredictable GE interaction has been a constant constraint in crop breeding (Bramel-Cox, 1996). Thus, to select for superior genotypes, it seems that there is no easier way than to conduct METs and select for both average yield and yield stability (Lin and Binns, 1994; Kang, 1997; Yan and Hunt, 2001).

CONCLUSION

The results of this study indicated the presence of strong GE interactions, suggesting that further efforts are necessary for exploring and/or minimizing GE interaction in MET data. The AMMI model was demonstrated to be an effective tool for quantifying and interpreting GE interactions. Moreover, simultaneous assessment of IPCA scores for genotypes and environments facilitated the interpretation and identification of specific interactions. The AMMI analysis of the data can be summarized as follows: (i) suitable locations for superior genotypes were identified for improving winter bread wheat production in rainfed areas of Iran, (ii) genotypes were identified that differed in adaptation, yield, and yield stability; and (iii) the presence of significant GE interactions causing changes in the ranking of genotypes across environments emphasized the need for data mining strategies that will effectively explore– and at the same time minimize – GE interactions in data derived from winter bread wheat METs.

The application of such a minimization strategy in this study enabled the identification of breeding lines No. 5 (WRM/4/FN/3*TH//K58/2*N/3/…) and 7 (Azar-2/4/T.AEST./SPRW'S'//…) as widely adapted genotypes that may be considered as candidates for commercial release in winter bread wheat growing rainfed areas of Iran. The test environments could also be classified in two major groups. The breeding line 21 (Azar-2/78Zhong29-38) can also be recommended as a highly adapted genotype for target environments.

The results also verified environmental co-variables (including relative humidity and freezing days) as well as genotypic variables (including plant height) that contribute most to GE interactions in winter bread wheat METsin rainfed wheat growing areas of Iran. These variables were the reason for some genotypes performing better in some environments. These findings represent potential gains for yield and its stability in winter bread wheat breeding lines evaluated in this study in rainfed winter wheat growing areas of Iran.

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