Parameters of AMMI Model for Yield Stability Analysis in Durum Wheat

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Summary

The improvement of new genotypes with acceptable yield stability in different environments is an important issue in breeding programs. In order to study genotype × environment (GE) interaction and to determine the most stable durum wheat genotypes, field experiments were conducted with 20 genotypes for three years (2007-2009). Results showed highly significant GE interaction indicating the possibility of selection for the most stable genotypes. The AMMI (additive main effect and multiplicative interaction) analysis indicated that the first five axes were significant based on F-test of Gollob while the other tests (FGH1 and FGH2) identified first three axes as significant AMMI model components. Furthermore, according to F_{Ratio} test and cross validation results, only first two axes were significant. According to these distinct numbers of significant axes, sixteen AMMI stability parameters plus ASV (AMMI stability value) were computed. Our results showed that EV- and D-based parameters, displayed G7 and G8, SIPC-based parameters indicated G3 and G4 and AMGE-based parameters identified G15 as the most stable genotypes. Genotypes G15 and G7 were the highest mean yielding genotypes and so they could be regarded as the most favorable durum wheat genotypes. The results of this investigation proved that the most of AMMI stability parameters are suitable indices for discriminating stable genotypes and AMGE-based parameters can detect highly seed yield genotypes with good stability.

Key words

AMMI, durum wheat, genotype × environment interaction, multi-environment trial

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Introduction

Considering different unpredictable environmental factors differential genotypic responses known as genotype × environment (GE) interaction are observed from the improved genotypes that are tested in multi-environment trials. These interaction effects result in inconsistent genotype ranking across test environments and too large to be ignored in the plant breeding programs. The GE interaction effects tend to be large when there is a wide variation among genotypes for abiotic stress tolerance such as soil salinity or drought as well as climatic variation among test environments (Kang, 1998; Annicchiarico et al., 2011).

In most of the plant breeding programs, GE interaction effects are of special interest for identifying the most stable genotypes, mega-environments and other adaptation targets. Various methods for yield stability analysis are based on different stability concepts and can be classified accordingly (Flores et al., 1998). Univariate methods such as stability variance (Shukla, 1972) and joint regression (Eberhart and Russell, 1966) have some limitations that can be overcomed by using the multivariate statistical methods.

Gauch (1988) and Zobel et al. (1988) proposed the Additive Main effects and the Multiplicative Interaction (AMMI) model for analyzing multi-environment trials. The AMMI model is comprised of additive main effects of genotype and environment, and the multiplicative effect of GE interaction, and thus can explain more information compared to other methods. The first interaction principal component analysis (IPCA1) is usually superior to linear regression in accounting for the GE sum of squares (Gauch and Zobel, 1996). Gauch et al. (2008) claimed that AMMI model frequently performs much better than linear regression model and some other multivariate procedures such as GGE biplot (Yan et al., 2000) in GE interaction investigation.

Essential feature of AMMI model is detection of number of axes to be retained in the model. The F-test cannot be applied straightforwardly, because the number of degrees of freedom attached to each IPCA (interaction principal component axis) is unknown. Therefore, some special F-tests are introduced by different authors (Gollob, 1968; Cornelius et al., 1992; Cornelius 1993). Also, a cross validation approach was introduced for verifying of the fitted AMMI model versus simulated AMMI model using magnitude of RMSPD (root mean square predicted difference). The RMSPD values detect the best AMMI model and identify suitable numbers of interaction PCAs in AMMI model (Gauch and Zobel, 1997). Additional AMMI stability parameters were introduced by Zobel (1994), Sneller et al. (1997), Purchase (1997), and Annicchiarico (1997). Although some authors (Sabaghnia et al., 2008; Dehghani et al., 2010) used some of the mentioned AMMI stability parameters, the effect of different F-tests on these parameters have not been investigated.

The objectives of this study were to: (i) compare different F-tests for testing the AMMI model interaction axes, (ii) use different AMMI model stability parameters to estimate yield stability of improved durum wheat genotypes, and (iii) explore the advantages and disadvantages of AMMI stability parameters in selecting more stable durum wheat genotypes.

Materials and methods

In this investigation, twenty durum wheat genotypes (18 new improved lines and two commercial cultivars 'Kouhdasht' and 'Seimareh') were studied at five locations during growing seasons 2007-2008, 2008-2009, and 2009-2010, except location Ilam where the trials were not carried out in the season 2008-2009. In each environment (location × year combination), the trials were carried out using a randomized complete block design with four replications. The soil types were Regosols in Gachsaran, Gonbad, Khoramabad and Ilam, and Cambisols in Moghan. Details of soil properties and geographical characteristics for the five locations are given in Table 1. Each plot consisted of six rows spaced 17.5 cm apart. Row length was 7 m in all locations during all years. Seeding rate was adjusted to obtain ≈20 plants m^{-1} row^{-1}. Fertilizer application was 30 kg nitrogen ha^{-1} and 70 kg P_2O_5 ha^{-1} at planting and 40 kg nitrogen ha^{-1} at stem elongation stage. Central area of 4.2 m^2 (four rows 6 m long) was harvested and yield (kg ha^{-1}) was obtained by converting the seed yields obtained from plots to hectares.

Table 1. Geographical properties of test locations

Location	Longitude Latitude	Altitude (m)	Soil Texture	Soil Type	Rainfall (mm)
Gachsaran	50° 50´E 30° 20´N	710	Silty Clay Loam	Regosols	460.8
Gonbad	55° 12´E 37° 16´N	45	Silty Clay Loam	Regosols	367.5
Khoramabad	23° 26´E 48° 17´N	1148	Silt-Loam	Regosols	433.1
Ilam	46° 36´E 33° 47´N	975	Clay-Loam	Regosols	502.6
Moghan	48° 03´E 39° 01´N	1100	Sandy-Loam	Cambisols	271.2

A combined analysis of variance was carried out to test the main effects of environments and genotypes as well as GE interactions. Different F-tests including F-Gollob (1968), F_{Ratio} (Cornelius et al., 1992), F_{GH1} and F_{GH2} tests (Cornelius, 1993) were used to determine significant numbers of IPCAs in AMMI model. The Gollob's F-test indicates more AMMI IPCAs significant than cross validation and has more Type I error rate while F-tests known as F_{GHI} and F_{GH2} were controlled Type I error rates. These statistical methods were described in detail by the mentioned authors. The RMSPD values of AMMI model for cross validation were computed by MATMODEL Version 3.0 (Gauch, 2007). Three replications were used for modelling and one replication was used for testing. The EV stability parameter of AMMI (Zobel, 1994) was calculated according to this expression:

$$EV = \sum_{n=1}^{N} \gamma_{in}^2 / n$$

In this formula γ_{in} is the genotype eigenvector for axis n and N is the number of IPC that were retained in the AMMI procedure via different F-tests or cross validation procedure. The AMGE and SIPC (Sneller et al., 1997) parameters are expressed as:

$$AMGE = \sum_{n=1}^{N}\sum_{g=1}^{M}\lambda_n\gamma_{in}\delta_{jn}$$

$$SIPC = \sum_{n=1}^{n}\lambda_n^{0.5}\gamma_{in}$$

where λ_n is the eigenvalue of the IPC analysis axis n; δ_{jn} is the environment eigenvector for axis n; M is the number of environments, and N is the number of significant IPCAs. The D parameter of AMMI model was proposed by Annicchiarico (1997):

$$D = \sqrt{\sum_{n=1}^{N}(\lambda_n\gamma_{in})^2}$$

where N is the number of IPCs that were significant. AMMI's stability value (ASV) was calculated using as suggested by Purchase (1997):

$$ASV = \sqrt{\frac{SSIPC\ 1}{SSIPC\ 2}(IPCA\ 1)^2 + (IPCA\ 2)^2}$$

where ASV is the AMMI's stability value; SS, sum of squares; IPCA1, interaction principal component axis 1, IPCA2, interaction principal component axis 2. Each one of the AMMI stability parameters produced a unique genotype ranking. This ranking matrix was subjected to PCA and a plot of first two PCs scores was drawn.

Results

The combined analysis of variance was conducted to determine the effects of environment (location × year combination), genotype, and their interactions on seed yield of durum wheat genotypes (Table 2). The main effect of environment (E) was highly significant (*P < 0.01*), while the main effect of genotypes (G) was only significant at 5% probability level (*P < 0.05*). The GE interaction was highly significant at 1% probability level (*P < 0.01*). Environments had the largest effect, explaining 96.43% of total variability, while genotypes and GE interaction explained only 0.43 and 3.14% of total sum of squares, respectively (Table 2).

The high significance of GE interactions for seed yield of durum wheat genotypes and its large magnitude of genotype main effect (about seven times) are indicating thatthe studied genotypes exhibited complex GE interaction. Seed yield is a quantitative trait; its expression is the result of genotype, environmental factors and GE interaction. Cooper et al. (1995) mentioned that the large magnitude of GE interaction causes more dissimilarity in the genetic systems that are controlling the physiological processes that are conferring yield stability in different environments. The relative contributions of GE interaction effects for seed yield found in this study are similar to those found in other studies in rain-fed environments (Bertero et al., 2004; Sabaghnia et al., 2006). Therefore, GE interaction makes it difficult to select the best performing and most stable genotypes (Yau, 1995).

The PCA based on GE interaction showed that the cumulative contributions of the first five components accounted for over 86% of the total variation in seed yield (Table 3). Similar to the results obtained using AMMI models for the analysis of multi-environment trials of different crops such as soybean, citrus and lentil (Zobel et al., 1988; Iwata et al., 2002; Sabaghnia et al., 2008), the AMMI model used in the present investigation exhibited complex interaction requiring as many as five IPCAs. The application of different F-test verified this hypothesis and indicated that, according to Gollob's F-test (1968), first five IPCs were significant. Also, based on F_{Ratio} (Cornelius et al., 1992),

Table 2. Combined analysis of variance of durum wheat performance yield trial data

Source of Variation	DF	Mean Squares	% of G+E+GE
Environment (E)	13	177747550.3**	96.43
Replication within E	42	826660.4	
Genotype (G)	19	544937.2*	0.43
G × E	247	304181.0**	3.14
Replication × G within E	798	133065.7	

** and * significant at the 0.01 and 0.05 probability level, respectively

Table 3. Eigenvalues and contributions of the first five principal components

Components	Eigenvalue	Proportion	Cumulative
IPC1	$5.81 \times 10^{+6}$	31.0	31.0
IPC2	$4.40 \times 10^{+6}$	23.4	54.4
IPC3	$2.45 \times 10^{+6}$	13.0	67.4
IPC4	$1.93 \times 10^{+6}$	10.3	77.7
IPC5	$1.65 \times 10^{+6}$	8.8	86.5
Total variance	$18.78 \times 10^{+6}$		

Table 4. Computation of different F-tests and cross validation for interaction principal components of AMMI mode

Components	U_1	U_2	V_1	V_2	F_{GH1}	F_{GH2}	F_{Ratio}	F_{Gollob}	RMSPD
IPC1	25.40	5.70	20845	27152	6.863^{**}	6.880^{**}	1.805^{**}	4.557^{**}	458.16
IPC2	50.36	7.16	42570	45850	2.618^{**}	2.625^{**}	1.378^{*}	3.685^{**}	451.65
IPC3	46.50	6.96	39132	42921	1.579^{*}	1.583^{*}	1.150^{ns}	2.205^{**}	457.69
IPC4	42.65	6.76	35725	40017	1.355^{ns}	1.359^{ns}	0.934^{ns}	1.874^{**}	460.63
IPC5	38.79	6.55	32348	37125	1.277^{ns}	1.280^{ns}	0.683^{ns}	1.745^{*}	460.44

U_1, U_2, V_1 and V_2 are computed by approximations for calculating F_{GH1} and F_{GH2} according to Cornelius (1980) and Cornelius (1993); RMSPD, the root mean square prediction differences in cross validation

Table 4. Computation of different F-tests and cross validation for interaction principal components of AMMI mode

	MY	EV1	EV2	EV3	EV5	D1	D2	D3	D5
G1	2520	0.062	0.064	0.263	0.395	601	606	943	1036
G2	2697	0.019	0.023	0.024	0.197	334	360	199	674
G3	2452	0.050	0.180	0.198	0.204	538	928	1074	957
G4	2635	0.195	0.212	0.257	0.330	1064	1098	582	1200
G5	2509	0.001	0.190	0.190	0.433	91	914	1247	1136
G6	2528	0.052	0.151	0.203	0.456	548	858	1025	1152
G7	2644	0.003	0.004	0.007	0.031	141	156	144	265
G8	2580	0.006	0.014	0.014	0.015	180	262	261	265
G9	2564	0.009	0.094	0.199	0.502	226	654	1081	1093
G10	2637	0.023	0.038	0.108	0.272	366	446	656	803
G11	2513	0.076	0.096	0.284	0.290	662	727	998	1000
G12	2493	0.003	0.027	0.036	0.172	121	352	492	630
G13	2397	0.002	0.060	0.075	0.089	110	518	740	573
G14	2562	0.020	0.063	0.063	0.151	338	551	598	679
G15	2680	0.263	0.273	0.345	0.416	1236	1254	634	1372
G16	2376	0.011	0.024	0.058	0.154	257	351	503	623
G17	2564	0.001	0.032	0.110	0.201	76	374	773	710
G18	2641	0.036	0.043	0.060	0.130	457	488	364	640
G19	2745	0.155	0.397	0.415	0.438	950	1401	1441	1433
G20	2470	0.015	0.017	0.092	0.124	293	305	587	580

Table 6. The AMMI stability parameters based on SIPC and AMGE equations

	SIPC1	SIPC2	SIPC3	SIPC5	AMGE1	AMGE2	AMGE3	AMGE5	ASV
G1	-12.23	-10.42	7.24	20.74	0.00047	0.00047	-0.00023	-0.00009	14.18
G2	6.80	9.77	8.51	14.34	-0.00022	0.00040	0.00044	0.00052	8.36
G3	-10.96	-27.46	-22.08	-25.94	-0.00094	0.00016	0.00050	0.00049	20.76
G4	-21.66	-15.70	-24.11	-36.96	-0.00030	0.00027	0.00072	0.00105	25.61
G5	-1.86	-21.72	-21.93	-14.33	-0.00007	-0.00187	-0.00187	-0.00277	19.98
G6	11.15	25.58	16.53	42.26	0.00050	0.00140	0.00153	0.00117	19.30
G7	2.87	4.32	2.22	7.59	0.00042	0.00056	0.00050	0.00017	3.60
G8	-3.67	0.48	0.17	-0.42	0.00008	0.00030	0.00033	0.00032	5.92
G9	4.60	-8.80	-21.61	4.21	-0.00016	-0.00077	-0.00142	-0.00162	14.40
G10	7.46	13.03	2.58	-7.79	0.00051	0.00063	-0.00030	-0.00070	10.23
G11	13.49	20.02	37.20	39.53	0.00050	0.00096	0.00126	0.00118	16.83
G12	-2.47	-9.70	-13.31	-18.16	-0.00050	-0.00073	-0.00080	-0.00060	7.76
G13	2.24	-8.81	-3.96	-9.74	0.00012	0.00088	0.00108	0.00094	11.35
G14	6.88	-2.64	-2.75	-18.08	0.00015	0.00041	0.00041	-0.00041	12.38
G15	25.17	29.82	40.43	27.20	-0.00270	-0.00245	-0.00260	-0.00327	29.31
G16	5.24	10.44	3.22	-4.12	-0.00017	-0.00016	-0.00056	-0.00158	7.96
G17	1.55	9.54	-1.55	-15.73	0.00013	0.00075	0.00014	-0.00023	8.19
G18	-9.30	-13.07	-18.28	-21.22	-0.00109	-0.00105	-0.00120	-0.00071	11.34
G19	-19.34	3.16	8.50	12.63	0.00080	0.00100	0.00089	0.00082	31.64
G20	-5.96	-7.87	2.98	3.98	0.00016	0.00019	0.00075	0.00078	7.11

the first two components were significant while according to F_{GH1} and F_{GH2} tests (Cornelius, 1993), three IPCs were meaningful (Table 4). Only Gollob's F-test result verified the complex GE interaction that could be associated with the nature of the crop, environmental conditions or diverse genetic background obtained from different sources. In contrast other F-test results showed relatively simple GE interaction nature. Applying cross validation procedure for the fitted AMMI model of durum wheat dataset, indicated similar to F_{Ratio}, only the first two components were sufficient for interpreting this dataset (Table 4).

According to EV1 which benefits only IPC1 scores, genotypes G5, G13 and G17 were the most stable genotypes and based on EV2 (IPCA1 and IPCA2), genotypes G7, G8 and G20 were the most stable genotypes (Table 5). The EV3 (using first three IPCAs) introduced genotypes G2, G7 and G8 as the most stable genotypes while the EV5 (using five IPCAs) identified genotypes G7, G8 and G13 as the most stable genotypes. Using different numbers of IPCAs in EV computation results in achieving relatively different conclusions in identification of the most stable genotypes. It is important to notice that EV1 parameter is based on only 31% of GE interaction variability while EV2, EV3 and EV5 are based on AMMI models that explain 54.4, 67.4 and 86.5% of GE interaction sum of squares, respectively. The stability evaluation based on parameters D1, D2, D3 and D5 was similar to EV and identified same genotypes as the most stable ones (Table 5). Generally, regarding all EV and D parameters, genotypes G7 and G8 could be recognized as the most stable ones.

According to SIPC1 (using IPCA1 scores), genotypes G1, G4 and G19 were the most stable genotypes and based on SIPC2 and

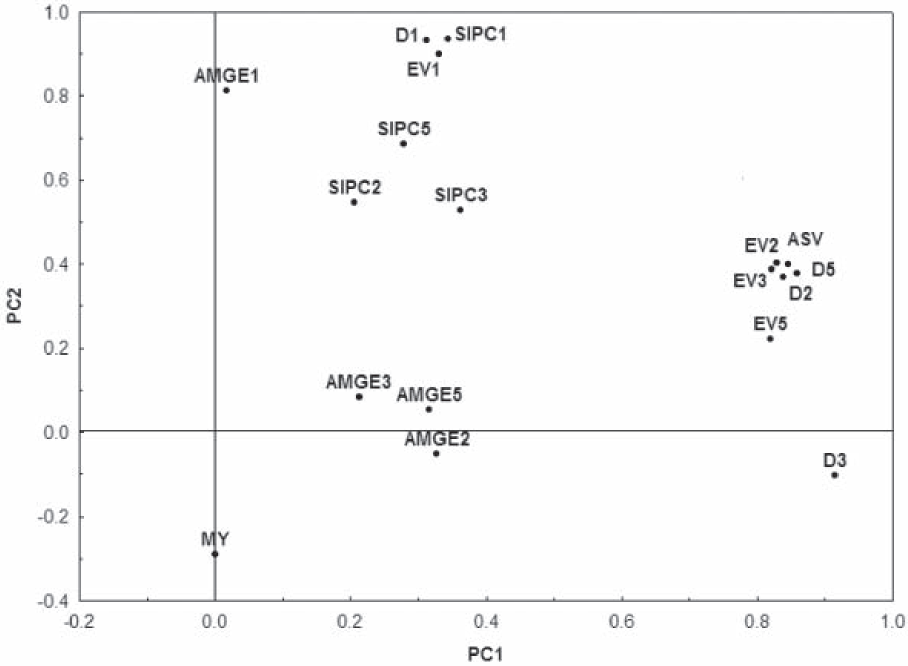

Figure 1.
Plot of the PC1 versus PC2 of mean yield and AMMI stability parameters using yield data from 20 durum wheat genotypes grown in 14 environments

SIPC3, genotypes G3, G4 and G5 were the most stable (Table 6). The SIPC5 (using first five IPCAs) identified genotypes G3, G4 and G18 as the most stable genotypes. It is interesting that most of these stable genotypes had low mean yield except G19 (Table 5). AMGE1 identifies genotypes G3, G15 and G18, and AMGE2 genotypes G5, G9 and G15 as the most stable ones (Table 6). Also, according to AMGE3 and AMGE5 parameters, genotypes G3, G4 and G5 were the most stable. In general, according to all SIPC stability parameters, genotypes G3 and G4 were detected as the most stable genotypes while according to all AMGE stability parameters, genotype G15 was identified as the most stable genotype. The mean yield performance was high for genotype G15, and relatively high for genotype G4.

For better understanding of the association among the AMMI stability parameters, a PCA based on the rank correlation matrix was performed. When applying the PC analysis, the two first PCs explained 62.8% (39.8 and 23.0% by PC1 and PC2, respectively) of the variance of the original variables. The relationships among the different AMMI stability parameters are graphically displayed in a graph by plotting the first two PCs scores (Fig. 1). In this scatter plot, the PC1 axis did not distinguish the mean yield and AMMI stability parameters. The PC2 axis separated AMGE2 and D3 stability parameters from the other parameters that mean yield (MY) also groups near these parameters. It is clear that most similar parameters were grouped near each other. For example, EV2, EV3 and EV5; AMGE2, AMGE3 and AMGE5; and SIPC2, SIPC3 and SIPC5 were grouped together. Also, EV1, AMGE1, SIPC1 and D1 parameters are grouped near each other.

Discussion

This study demonstrated that GE interaction was highly significant and had remarkable effect on genotypic performance in different environments. Its magnitude was seven times larger than genotype main effect. Seed yield is the net effect of G, E and GE interaction, and although E is responsible for about 80% of the total variability, only G and GE interaction are relevant to the evaluation of genotypes in multi-environment trials (Yan and Kang, 2002). The multivariate procedures such as AMMI model can display several aspects of multi-dimensionality of GE interaction phenomenon (Iwata et al., 2002).

The AMMI parameters based on EV and D formulas displayed genotypes G7 and G8 as the most stable genotypes. Also, SIPC-based stability parameters indicated genotypes G3 and G4 as the most stable genotypes, while AMGE-based stability parameters identified genotype G15 as the most stable genotype. The applied parameters of adaptability and stability presented some incongruence, since they identified the different genotypes as stable. The mean yield performance of genotypes G15 and G7 were the highest mean yielding genotypes and so could be regarded as the most favorable durum wheat genotypes. But it was clear that the most of the stable genotypes according to seventeen AMMI stability parameters had moderate or low mean yield. Our findings are in agreement with this idea of adaptation that says that the least stable genotypes have the highest economic production in rein-fed conditions or dry land areas (Ceccarelli, 1996).

According to graphic analysis of the AMMI stability parameters and mean yield, the most of these parameters indicated static concept of stability. Most stability statistics relate to either static (biological) or dynamic (agronomical) concept of stability (Becker and Léon, 1988). Static stability is analogous to environmental buffering while dynamic stability is related to environmental sensitivity. The dynamic stability depends on the specific tested genotypes in spite of the static. Static stability concept may be more useful than dynamic concept of stability in a wide range of environmental changes, especially in developing countries (Simmonds, 1991). Sabaghnia et al. (2008) and Dehghani et al. (2010) have reported static concept of stability for EV, SIPC and AMGE parameters that were calculated for significant numbers of the Gollob's F-test (1968). In contrast there is not any report for the stability nature of AMMI stability parameters based on the other F-tests. However, it seems that the AMMI stability parameters have both static and dynamic concepts of stability regarding crop nature, experiments conditions and etc.

Finally, the AMMI model analysis was as an effective tool in understanding complex GE interactions in multi-environment trials of durum wheat. Also, besides differences in crops and regions (climatic conditions, soil properties etc), the observed GE interactions may be partly explained by the structure of the dataset that was considered and by the selection of the genotypes. The AMGE approach was a good procedure in detecting the most favorable genotypes. Genotype G15 can be considered as the most stable genotype with regard to both good stability (based on AMGE-based parameters) and high yield (2680 kg ha^{-1}). Therefore it is recommended for release as a cultivar by the Dry Land Agricultural Research Institute of Iran.

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