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Naser SABAGHNIA, Mohtasham MOHAMMADI, Rahmatollah KARIMIZADEH¹

INTERPRETING GENOTYPE × ENVIRONMENT INTERACTION OF BEARD WHEAT GENOTYPES USING DIFFERENT NONPARAMETRIC STABILITY STATISTICS

SUMMARY

Evaluation of yield stability is essential in multi-environment trials which can be performed through various statistical methods. The stability of 18 bread wheat (Triticum aestivum L.) genotypes was determined using several nonparametric stability statistics across 11 environments. Highly significant genotype \times environment (GE) interaction suggested differential performance of genotypes across three seasons for four test locations. Results of five distinct nonparametric tests verified combined ANOVA and showed that there were both crossover and non-crossover GE interactions. According to S₁, S₂, S₃, S₄, S₅ and S₆ nonparametric stability statistics, genotypes G10 and G14 were the most stable genotypes while based on NP₁, NP₂ and NP₄ nonparametric stability statistics, genotypes G5, G10 and G14 were the most stable genotypes. In this investigation, high values of Top measure was associated with high mean yield, but the other nonparametric stability statistics were not positively correlated with mean yield and instead characterized a static concept of stability. Clustering of the genotypes according to mean yield and nonparametric stability statistics indicated that there were three genotypic groups with different characteristics. The results of principal component analysis of nonparametric stability statistics and mean yield indicated that only nonparametric superiority index would be useful for simultaneously selecting for high yield and stability. Finally, genotypes G5 (3065.59 kg ha⁻¹) and G9 (3027.27 kg ha⁻¹) were found to be the most favorable genotypes and are thus recommended for commercial release in semiarid areas of Iran.

Key words: adaptation, multi-environmental trials, yield stability

INTRODUCTION

Worldwide wheat production is approximately 685.43 million tons and covers a total area of 227.61 million hectares. The main producers are the Economic European Community, 20% (138.82); China, 17% (115.12); India, 12% (80.68); and Canada, 4% (26.85). The total area of wheat in Iran in the 2009-2010 seasons was 6.65 million ha which produced 13.49 million tons (FAS,

¹ Naser Sabaghnia (corresponding author: sabaghnia@maragheh.ac.ir), Department of Agronomy and Plant Breeding, Faculty of Agriculture, University of Maragheh, Iran; Mohtasham Mohammadi, Rahmatollah Karimizadeh, Dryland Agricultural Research Institute (DARI), Gachsaran, Iran.

2012). The yield performance of cultivated genotypes is very low (typically about 2030 kg ha⁻¹) compared with the average global yields (3010 kg ha⁻¹) and the highest global yields (7670 kg ha⁻¹, produced in United Kingdom; FAS, 2012). Increasing the genetic potential of yield is an important objective of both bread and durum wheat breeding programs in Iran and other countries. Iran has had important wheat breeding program in recent years, supported by the CIMMYT (International Maize and Wheat Improvement Center) and national improvement programs. The improved bread wheat genotypes are evaluated in multi-environment trials to test their performance across different test environments and to select the best genotypes in specific environments. In most cases, genotype \times environment (GE) interaction is observed, complicating selection for improved yield.

The GE interaction is a confounded of the genotype observed performance and its true value. The GE interaction is the result of the yield response of a genotype to the variations in environmental factors such as soil, water availability and temperature or differences in crop management, and other (Crossa et al., 1991). Thus, the resulting yield expression of a cultivated genotype will vary among environments due to their diversity of growth resources. The GE interaction has been one of the important subjects of study in plant breeding, allowing the generation of different methodologies for improvement. This permits plant breeders to select the location to which the genotype is adapted (Romagosa and Fox, 1993; Adugna and Labuschagne, 2003). Also, it has been a worry for plant breeders, especially when the magnitude of GE is large, since this impedes the selection of stable genotypes, as well as slowing selection advancement (Rodriguez et al., 2002).

For selection of the most favorable genotype(s) in multi-environment trials usually various stability statistics are used. Several univariate versus multivariate statistics as well as parametric statistics nonparametric statistics, have been proposed to asses the GE interaction and stability analysis (Annicchiarico, 2002). An interesting stability and adaptation strategy as nonparametric procedures were discussed at first time by Huehn (1979). The concept of selecting a genotype based on high mean yield and stability was later given the rank-sum method (Kang, 1988). Considering both mean yield and standard deviation of mean yields (σ_{mv}) as well as both mean yield and standard deviation of ranks (σ_r) for all genotypes were proposed by Ketata et al. (1989). In these procedures a genotype is regarded as the most stable if its σ_{my} or σ_r values are relatively consistent in all the test environments.

Another nonparametric adaptation procedure was discussed by Fox et al. (1990) which is consists of ranking of genotypes in each environment, by which one derives on the proportion of environments in which a genotype occurred in the Top, Middle and Lower thirds of the ranks. Thennarasu (1995) proposed some improved nonparametric stability indices that are free from all the aforesaid drawbacks. The important characteristics of these indices are that the levels of achievement of genotypes and their stability are quantified by expressing the

individual achievements relative to the mean performance in the set of genotypes evaluated (Bajpai and Prabhakaran, 2000). According to Huehn (1996), the nonparametric stability statistics have the some advantages over the other conventional methods. These statistics reduce the bias caused by outliers, no assumptions are needed about the distribution of the dataset, they are easy to use and interpret, and additions or deletions of one or few genotypes do not cause much variation of results (Huehn, 1990a).

Although many conventional statistical methods have been used to investigation GE interactions (Crossa, 1990; Ceccarelli et al., 2000), most of them fail to distinguish between significant crossover and non-crossover interactions (Baker, 1990). As an alternative strategy, nonparametric methods for the test of crossover interactions have been proposed to test of GE interactions in multi-environment trials (Truberg and Huehn, 2000). Bredenkamp (1974), Hildebrand (1980), and Kubinger (1986) proposed nonparametric tests based on the usual linear model for interactions or non-crossover interactions. de Kroon and van der Laan (1981), and Azzalini and Cox (1984) introduced nonparametric tests for evaluation of crossover GE interactions. If some of the necessary assumptions are violated, the validity of the inferences obtained from the conventional procedures such as ANOVA, may be questionable or lost and so the results of nonparametric procedures can be more reliable (Truberg and Huehn, 2000).

The objectives of this investigation were (i) to apply nonparametric tests to investigate the crossover and non-crossover GE interaction in multi-environment trials, (ii) to identify bread wheat genotypes that have both high yield and stable performance across test environments of Iran's semiarid areas, and (iii) to study the relationships among different nonparametric stability statistics.

MATERIAL AND METHODS

The plant material for the investigation comprised of 17 newly improved genotypes along with one check cultivar, which were evaluated in three seasons 2006-2008 by following randomized complete block design with four replications in the experiment plots of the four test locations Gachsaran, Gonbad, Khoramabad and Moghan. Due to the high drought condition of Moghan in the year 2008, there were not acceptable mean yield for the studied genotypes and so only 11 location × year combinations (environments) were analyzed. The test locations vary in latitude, rainfall, soil types, temperature and other agro-climatic factors and some of these characteristics are given in Table 1. Sowing was done with an experimental drill in 1.05 m × 7.00 m plots (6 rows with 17.5 cm space). According to local need, appropriate pesticides were used to control insects, weeds and diseases and appropriate fertilizers were applied at recommended rates usual for the environment. Seed yield of each plot was determined from 3.6 m² from the centre of each plot.

Location	Longitude Latitude	Altitude (m)	Soil Texture	Soil Type¶	Rainfall (mm)
Gachsaran	50° 50´ E 30° 20´ N	710	Silty Clay Loam	Regosols	431
Gonbad	55° 12´ E 37° 16´ N	45	Silty Clay Loam	Regosols	350
Khoramabad	23° 26´ E 48° 17´ N	1125	Silt-Loam	Regosols	523
Moghan	48° 03′E 39° 01′N	32	Sandy-loam	Cambisols	271

Table 1. Geographical properties of four test locations

For a two-way dataset with k genotypes and n environments, we denote the phenotypic value of *i*th genotype in *j*th environment as x_{ij} , where i = 1, 2, ..., k, j = 1, 2, ..., n, r_{ij} as the rank of the *i*th genotype in the *j*th environment, and $\overline{r_{ij}}$ as the mean rank across all environments for the *i*th genotype. The statistics based on yield ranks of genotypes in each environment are expressed as follows (Huehn, 1979):

$$S_{i}^{(1)} = 2\sum_{j}^{n-1} \sum_{j'=j+1}^{n} |r_{ij} - r_{ij'}| / [n(n-1)]$$

$$S_{i}^{(2)} = \sum_{j=1}^{n} (r_{ij} - \overline{r_{i.}})^{2} / \sum_{j=1}^{n} |r_{ij} - \overline{r_{i.}}|$$

$$S_{i}^{(3)} = \frac{\sum_{j=1}^{n} (r_{ij} - \overline{r_{i.}})^{2}}{\overline{r_{i.}}}$$

$$S_{i}^{(4)} = \sqrt{\frac{\sum_{j=1}^{n} (r_{ij} - \overline{r_{i.}})^{2}}{n}}$$

$$S_{i}^{(5)} = \frac{\sum_{j=1}^{n} |r_{ij} - \overline{r_{i.}}|}{n}$$

$$S_{i}^{(6)} = \frac{\sum_{j=1}^{n} |r_{ij} - \overline{r_{i.}}|}{\overline{r_{i.}}}$$

Kang's (1988) rank-sum is another nonparametric stability statistics where both the mean yield and Shukla's (1972) stability variance are used as selection criteria. Ketata et al. (1989) proposed plotting mean rank across environments against standard deviation of ranks for all genotypes (σ_r) or plotting mean yield across environments against standard deviation of yields for all genotypes (σ_{my}). The formula for calculating both standard deviations are expressed as:

$$\sigma_r = \sqrt{\frac{\sum\limits_{j=1}^{n} (r_{ij} - \overline{r}_{i.})^2}{n-1}}$$
$$\sigma_{my} = \sqrt{\frac{\sum\limits_{j=1}^{n} (r_{ij} - \overline{x}_{i.})^2}{n-1}}$$

Nonparametric stability statistics as Top, Mid and Low were introduced by Fox et al. (1990) as nonparametric superiority index (SI) using stratified ranking of the genotypes and their ranking was done at each environment separately and the number of environment at which the genotype occurred in the top, middle, and lower third of the ranks was computed.

Thennarasu (1995) proposed the use of the four nonparametric statistics based on the corrected ranks. In other word, the ranks of genotypes in each environment were determined according adjusted values $(x_{ij}^* = x_{ij} - \overline{x_{i.}})$. Thennarasu's (1995) nonparametric stability statistics are:

$$NP_{i}^{(1)} = \frac{1}{n} \sum_{J=1}^{n} \left| r^{*}_{ij} - M^{*}_{di} \right|$$

$$NP_{i}^{(2)} = \frac{1}{n} \left[\sum_{J=1}^{n} \left| r^{*}_{ij} - M^{*}_{di} \right| / M_{di} \right]$$

$$NP_{i}^{(3)} = \frac{\sqrt{\sum \left(r^{*}_{ij} - \overline{r^{*}}_{i.} \right)^{2} / n}}{\overline{r}_{i.}}$$

$$NP_{i}^{(4)} = \frac{2}{n(n-1)} \left[\sum_{j=1}^{n-1} \sum_{j'=j+1}^{n} \left| r^{*}_{ij'} - r^{*}_{ij'} \right| / \overline{r}_{i.} \right]$$

Lu (1995) developed a program that computes the first two nonparametric measures of Huehn (1990b). A comprehensive SAS program called SASG \times ESTAB (Hussein et al., 2000) has become available, which calculates some nonparametric stability statistics. Both of these programs and Microsoft Excel were used to calculate nonparametric stability statistics.

RESULTS AND DISCUSSION

The combined analysis of variance indicated that the main effects of genotypes and environments were highly significant (Table 2). Also the GE interaction effect was significant (P < 0.01). The bread wheat seed yield was affected by environment, which accounted for 96% of sum of squares

Table 2. ANOVA analysis	s of bread whea	at performance trial y	ield data
SOV	DF	Mean Squares	% of G+E+GE†
Environment (E)	10	161572682.5 ^{**}	96
Replication/E	33	1271585.7	<i>y</i> 0
Genotype (G)	17	609621.1**	1
GE	170	302985.5**	3
Error	561	140808.5	

(E+G+GE), whereas G and GE captured 1% and 3% of sum of squares (E+G+GE), respectively.

**, * and ^{ns}, respectively significant at the 0.01 and 0.5 probability level and non-significant

Nonparametric tests	df	statistic χ^2	P-value
Bredenkamp	170	425.4	< 0.001
Hidebrand	170	364.5	< 0.001
Kubinger	170	377.0	< 0.001
de Kroon-van der Laan	170	261.2	< 0.001
Azzalini-Cox	170	236.8	< 0.001

Table 3. Analysis of GE interaction using different nonparametric tests on 18 bread wheat genotypes grown in 11 environments

The large seed yield variation due to environment was the main source of variation in most of the multi-environment trials (Gauch and Zobel, 1997). The test statistics of the different nonparametric statistical procedures including Bredenkamp (1974), Hildebrand (1980), and Kubinger (1986) for non-crossover GE interaction indicated the presence of this interaction type in bread wheat dataset (Table 3). Also, based on de Kroon and van der Laan (1981), and Azzalini and Cox (1984) procedures, there was crossover GE interaction type. Results of the above mentioned nonparametric tests showed that there were both significant non-crossover and crossover interactions in this investigation. Although these results are in agreement with the conventional ANOVA, but provide more specific information about the nature of GE interactions.

The relatively large magnitude of GE interactions for grain yield of 18 bread wheat genotypes tested across five locations were larger than that of genotypic main effect (three times), but smaller than that of environment main effect (Table 2). The studied genotypes showed both crossover and non-crossover types of GE interaction. The relative contributions of G and GE interaction effects to the total variation for grain yield found in this study are similar to those found in other crop adaptation studies such as cereals or food legumes in rain-fed environments (Alagarswamy and Chandra, 1998; Berteroa et al., 2004; Sabbaghnia et al., 2008). Therefore, it would be very difficult to achieve an indirect response to selection over all of the bread wheat target population of environments from selection in a few environments, ignoring the observed GE interactions.

According to Table 4, genotypes G1, G4 and G16 were the highest yielding genotypes with 3310.23, 3147.11 and 3132.30 kg ha⁻¹, respectively. Based on Top measure, genotypes G1, G4 and G16 were the most favorable genotypes while according to Mid measure, genotypes G10, G11, G12 and G14 were detected the most favorable genotypes (Table 4). Considering all three Top, Mid and Low values as the nonparametric superiority index (SI) of Fox et al. (1990), genotypes G1, G4 and G16 were the most favorable genotypes G1, G4 and G16 were the favorable genotypes from both stability and mean yield aspects. Among different nonparametric stability statistics, only Top measure and rank-sum procedure were related to the agronomic concept of yield stability (Flores et al., 1998; Sabaghnia et al., 2012). Our results are in a good agreement with the finding of the other researchers who used various nonparametric stability statistics in different crops. Traditionally, stability has been divided into distinct concepts including dynamic and static concepts (Becker, 1981). For many decades, most plant breeders used the static or biological stability concept to explain a genotype which indicates a relatively constant mean yield, independent of various environmental conditions. However, this stability concept is not acceptable to most plant researchers, who would prefer a dynamic concept of stability. In this concept of stability, it is not needed that the genotypic response to environmental conditions should be equal for all genotypes (Becker and Leon, 1988). In recent decades, most plant breeders prefer to use dynamic or agronomic concept of yield stability for GE interaction investigation and identification of the most stable genotype(s).

of Fo	ox et al. (199	90) for <u></u>	grain yiel	ld of 18	bread wł	neat gen	otypes ev	valuated	in 11
envir	onments								
	MY	•	Τc	op	М	id	Lo	W	SI
	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Rank
G1	3310.23	1	72.73	1	18.18	17	9.09	1	1
G2	2986.00	12	36.36	9	36.36	10	27.27	9.5	8.5
G3	3045.11	7	36.36	9	36.36	10	27.27	9.5	8.5
G4	3147.11	2	54.55	2.5	27.27	14.5	18.18	3.5	2
G5	3065.59	4	45.45	4.5	36.36	10	18.18	3.5	4
G6	2953.18	14	45.45	4.5	27.27	14.5	27.27	9.5	5
G7	3047.20	6	36.36	9	36.36	10	27.27	9.5	8.5
G8	2831.23	17	9.09	16.5	45.45	6	45.45	17.5	16.5
G9	3027.27	9	36.36	9	45.45	6	18.18	3.5	6
C10	2021 55	0	10.10		10 11	•	10.10	~ -	

Table 4. Mean values (Y), Top, Mid and Low nonparametric stability measures

G2	2986.00	12	36.36	9	36.36	10	27.27	9.5	8.5
G3	3045.11	7	36.36	9	36.36	10	27.27	9.5	8.5
G4	3147.11	2	54.55	2.5	27.27	14.5	18.18	3.5	2
G5	3065.59	4	45.45	4.5	36.36	10	18.18	3.5	4
G6	2953.18	14	45.45	4.5	27.27	14.5	27.27	9.5	5
G7	3047.20	6	36.36	9	36.36	10	27.27	9.5	8.5
G8	2831.23	17	9.09	16.5	45.45	6	45.45	17.5	16.5
G9	3027.27	9	36.36	9	45.45	6	18.18	3.5	6
G10	3034.55	8	18.18	14	63.64	2	18.18	3.5	13
G11	2992.07	11	18.18	14	54.55	3.5	27.27	9.5	14.5
G12	2948.02	15	18.18	14	54.55	3.5	27.27	9.5	14.5
G13	2953.50	13	36.36	9	27.27	14.5	36.36	15	11.5
G14	2916.41	16	0.00	18	72.73	1	27.27	9.5	18
G15	2782.20	18	9.09	16.5	45.45	6	45.45	17.5	16.5
G16	3132.30	3	54.55	2.5	9.09	18	36.36	15	3
G17	3047.52	5	36.36	9	27.27	14.5	36.36	15	11.5
G18	3014.18	10	36.36	9	36.36	10	27.27	9.5	8.5

Genotypes G5, G10 and G14 were the most stable genotypes based on both first two nonparametric stability statistics of Huehn (1979) which are known as S_1 and S_2 (Table 5). Genotypes G8, G14 and G15 based on S_3 and S_6 statistics; and genotypes G8, G10 and G14 based on S_4 and S_5 statistics were identified as the most stable genotypes (Table 5). Among these the most stable genotypes, genotype G5 had relatively high mean yield following to genotype G10 which had relatively moderate mean yield (Table 4). According to Flores et al. (1998), S_1 and S_2 nonparametric stability statistics; based on Sabaghnia et al. (2006), S_3 and S_6 nonparametric stability statistics had static concept stability concept.

	S	1	S	2	S	3	S	4	S	5	S	6
	Value	Rank										
G1	7.02	14	24.77	14	73.48	17	4.13	9.5	2.03	9.5	12.86	18
G2	6.47	10	21.48	11	36.38	8	4.35	12	2.08	12	6.40	9
G3	6.73	13	22.91	13	35.01	7	4.13	9.5	2.03	9.5	6.56	10
G4	7.16	15	26.32	15	55.01	16	4.68	14.5	2.16	14.5	9.41	16
G5	5.09	2	13.01	2	42.03	13	4.12	8	2.03	8	7.99	15
G6	6.18	9	20.18	9	40.64	12	4.73	16	2.17	16	7.09	12
G7	7.35	16	27.73	16	48.14	15	4.81	17	2.19	17	7.94	14
G8	5.93	5	17.55	5	18.54	2	3.44	2.5	1.85	2.5	4.23	2
G9	5.42	4	16.12	4	37.92	10	3.85	4	1.96	4	6.91	11
G10	5.16	3	13.75	3	27.67	4	3.44	2.5	1.85	2.5	5.56	4
G11	6.15	8	19.26	8	33.27	6	4.00	5.5	2.00	5.5	6.00	5.5
G12	6.69	12	22.21	12	37.14	9	4.31	11	2.08	11	6.19	7
G13	6.55	11	21.47	10	38.92	11	4.53	13	2.13	13	6.33	8
G14	4.62	1	10.69	1	12.94	1	2.68	1	1.64	1	3.51	1
G15	7.45	17	28.04	17	24.85	3	4.02	7	2.00	7	4.70	3
G16	8.04	18	35.01	18	78.93	18	6.05	18	2.46	18	12.03	17
G17	6.11	7	18.87	7	44.53	14	4.68	14.5	2.16	14.5	7.42	13
G18	6.00	6	18.35	6	30.82	5	4.00	5.5	2.00	5.5	6.00	5.5

Table 5. Nonparametric stability statistic of Huehn (1979) for grain yield of 18 bread wheat genotypes evaluated in 11 environments

According to rank-sum nonparametric stability method (Kang, 1988), genotypes G5, G10 and G18 were detected as the most stable genotypes (Table 6). According to NP₁ nonparametric stability statistic of Thennarasu (1995), genotypes G5, G10 and G14; and according to NP₂ nonparametric stability statistic, genotypes G1, G9 and G10 were the most stable genotypes (Table 6). Based on NP₃ nonparametric stability statistic, genotypes G5, G10 and G14 were the most stable genotypes (Table 6). Based on NP₄ genotypes G5, G10 and G14 were the most stable genotypes (Table 6). Among these most stable genotypes, G1 and G5 were high mean yield and G9 and G10 were moderate mean yield.

Although based on Sabaghnia et al. (2006) and Dehghani (2008), all nonparametric stability statistics of Thennarasu (1995) had static concept stability concept, but some of the most stable genotypes had high mean yield and so reflected dynamic concept of stability. Considering most of the nonparametric stability statistics, genotypes G5, G10 and G14 were the most stable genotypes.

	RS		N	NP1		P2	NP3		NP4	
	Value	Rank								
G1	17	7.5	2.77	15	0.297	1	0.196	6.5	0.735	15
G2	15	4.5	2.57	10.5	0.585	14	0.195	5	0.685	10
G3	16	6	2.57	10.5	0.468	11	0.218	10	0.712	13
G4	20	11	2.68	14	0.348	5	0.240	13	0.829	18
G5	6	1	1.94	3	0.320	4	0.232	12	0.523	2
G6	26	16	2.58	12	0.427	10	0.152	2	0.596	5
G7	21	13.5	2.89	17	0.657	16	0.229	11	0.792	16
G8	23	15	2.21	5	0.669	17	0.242	14	0.604	6
G9	20	11	2.03	4	0.307	3	0.213	9	0.552	4
G10	13	2	1.82	2	0.301	2	0.371	18	0.551	3
G11	18	9	2.27	8	0.376	6	0.280	16	0.669	8
G12	28	17	2.55	9	0.516	13	0.269	15	0.675	9
G13	21	13.5	2.62	13	0.595	15	0.175	3	0.699	11
G14	17	7.5	1.79	1	0.407	7	0.298	17	0.503	1
G15	32	18	2.88	16	0.873	18	0.189	4	0.719	14
G16	20	11	3.46	18	0.420	9	0.115	1	0.826	17
G17	15	4.5	2.26	6.5	0.412	8	0.196	6.5	0.700	12
G18	14	3	2.26	6.5	0.514	12	0.210	8	0.660	7

Table 6. Nonparametric stability statistic of Thennarasu (1995) and rank-sum (Kang, 1988) for grain yield of 18 bread wheat genotypes evaluated in 11 environments

To better reveal associations among studied genotypes, the two-way data of genotypes' ranks based on different nonparametric stability statistics, was analyzed further using a clustering procedure. Ward's hierarchical clustering indicated that the eighteen genotypes could be divided into three major groups (Fig. 1). The first group (G-I) consists on genotypes G1, G3, G4, G5, G7, G16 and G17 which were relatively high mean yield and unstable or semi-stable genotypes. The second group (G-II) consists on genotypes G2, G6, G13 and G18 which were relatively moderate or low mean yield and unstable or semi-stable genotypes. The third group (G-III) consists on genotypes G8, G9, G10, G11, G12, G14 and G15 which were relatively moderate or low mean yield and stable genotypes (Fig. 1). Although the most favorable genotype (G5) was belong to group G-I, but it seems that genotype G9 of group G-III as one of the most stable genotypes which had acceptable mean yield and so could be regarded for commercial release.

The principal component analysis based on rank correlation matrices was performed to understand the relationship among the different nonparametric stability statistics as well as mean yield. For better visualization, the first two principal components (PC1 and PC2) were plotted against each other (Fig. 2). These first two principal components explained 82% (59% and 23% by PC1 and PC2, respectively) approximately of the nonparametric stability statistics. In this plot, both of the Top measure and the nonparametric superiority index (SI) of Fox et al. (1990) were correlated with mean yield. Kaya and Taner (2003) pointed out that the method of Fox et al. (1990) is associated with the dynamic concept of stability. Also, Sabaghnia et al. (2006) and Dehghani (2008) noted that the SI nonparametric measure of stability is similar in concept to GE interaction measures as it defines stability in the sense of agronomical concept of stability.

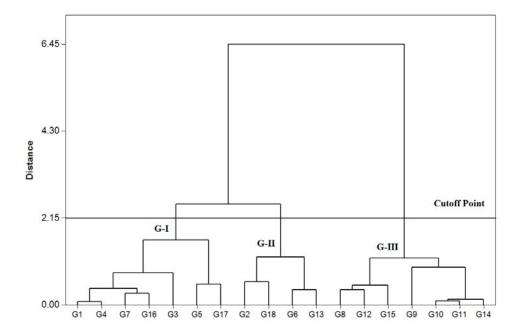


Figure 1. Hierarchical cluster analysis of the 18 bread wheat genotypes based on Ward's method using a GE matrix of mean yields

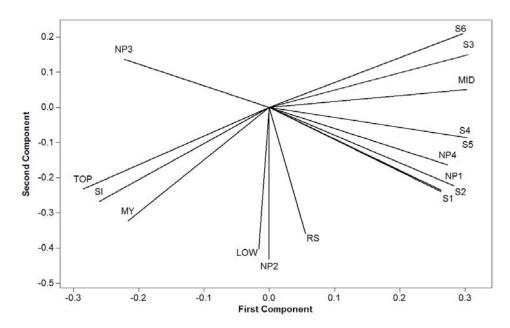


Figure 2. Plot of the two first principal components analysis for mean yield and the several nonparametric stability statistics used to study GE interaction.

Thus, the first principal component separates the methods into two main groups according to the two stability concepts: figure indicates on the left nonparametric statistics corresponding to the agronomical concept and on the right the nonparametric statistics based on the biological concept of stability.

The Low measure of Fox et al. (1990), NP₂ and rank-sum method (Kang, 1988) were correlated with each other (Fig. 2). Although, Kang and Pham (1991) found that the rank-sum method of Kang (1988) would be useful tool for selecting simultaneously for mean yield and yield stability, but we did not observed any relationship between mean yield and rank-sum method. In contrast, Sabaghnia et al. (2006) reported that the Low measure of Fox et al. (1990) and NP₂ are similar in concept to GE interaction measures as it defines stability in the sense of biological concept. The Mid measure of Fox et al. (1990), S_3 and S_6 were positively correlated with each other. Also, S₁, S₂, S₄, S₅, NP₁ and NP₄ were positively associated with each other (Fig. 2). Lin et al. (1986) classified stability into three types which is the Type I stability follows the biological concept. Nassar and Huehn (1987) and Scapim et al. (2000) found that S₁ and S₂ nonparametric stability statistics define stability in the sense of homeostasis. Sabaghnia et al. (2006) and Ebadi-segheloo et al. (2008) reported that NP₁ and NP₄ and Dehghani et al. (2008) pointed out that the S₄ and S₅ nonparametric statistics are associated with the static or biological concept of stability.

In the present investigation, interpretation of the GE interaction was based on the nonparametric stability techniques. The conventional univariate methods had shown certain deficiencies for explaining GE interaction patterns. The nonparametric stability statistics do not need any assumptions about the dataset distribution and variance homogeneity. The nonparametric strategy appears to be able to extract a large portion of the GE interaction and is efficient in analyzing GE interaction pattern in different crops such as legumes (lentil, Sabaghnia et al., 2006; chickpea, Ebadi-segheloo et al., (2008) and cereals (maize; Dehghani, 2008). The GE interaction concepts are strongly related to that of selection in which plant breeders are interested and can define static and dynamic concepts of stability. In conclusion, nonparametric stability statistics seem to be useful alternatives to parametric statistics (Yue et al., 1997). For several reasons, some plant breeders prefer the use of nonparametric stability statistics. These statistics avoid the bias caused by outliers and no assumptions are needed about the distribution of dataset. Also, these statistics are easy to use and to interpret and yield stability estimation seems to be a proper strategy.

Many nonparametric statistics of stability have been presented and compared in the literature (Flores et al., 1998; Sabaghnia et al., 2006; Ebadisegheloo et al., 2008). For making practical recommendations, it is essential to study the relationships among these nonparametric statistics with conventional parameters and compare their powers for different stability methods. This interesting topic will be considered in detail in future investigations.

CONCLUSIONS

The following findings can be summarized from the present investigation: (i) genotypes G5 (3065.59 kg ha⁻¹) and G9 (3027.27 kg ha⁻¹) were found to be the most favorable genotypes and are thus recommended for commercial release in semi-arid areas of Iran; (ii) the nonparametric superiority index (SI) of Fox et al. (1990) was found to be useful in detecting the phenotypic stability of the genotypes studied; (iii) some of the most stable genotypes according to nonparametric stability statistics which are using static concept of stability, could be as the most high mean yielding genotypes; and (iv) the significant GE interactions suggest a breeding strategy of specifically adapted genotypes in homogeneously grouped test environments.

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Naser SABAGHNIA, Mohtasham MOHAMMADI, Rahmatollah KARIMIZADEH

INTERPRETRANJE INTERAKCIJE GENOTIP × LOKALITET KOD GENOTIPOVA OBIČNE PŠENICE KORISTEĆI RAZLIČITE NEPARAMTERIJSKE STATISTIČKE TESTOVE STABILNOSTI

SAŽETAK

Evaluacija stabilnosti prinosa je od ključnog značaja u multilokacijskim ogledima koja se može vršiti različitim statističkim metodama. Stabilnost 18 genotipova obične pšenice (Triticum aestivum L.) utvrđena je korišćenjem nekoliko neparametrijskih statističkih testova stabilnosti na 11 lokacija. Veoma značajna interakcija genotip × lokalitet (GE) ukazuje na različite performanse genotipova tokom tri vegetacijska perioda na četiri ogledna lokaliteta. Rezultati pet različitih neparametrijskih testova verifikovani su kombinovanom ANOVA analizom i pokazali da postoje i unakrsne i ne-unakrsne GE interakcije. Prema S1, S2, S3, S4, S5 i S6 neparametrijskom statističkom testu stabilnosti, genotipovi G10 i G14 bili su najstabilniji genotipovi, dok su na osnovu NP1, NP2 i NP4 neparametrijskim statističkim testovima stabilnosti, najstabilnihi genotipovi bili G5, G10 i G14. U ovom istraživanju, visoke vrijednosti najviših vrijednosti povezane su sa visokom aritmetičkom sredinom prinosa, ali ostali neparametrijski statistički testovi stabilnosti nijesu bili u pozitivnoj korelaciji sa aritmetičkom sredinom prinosa, već su odražavali statički koncept stabilnosti. Grupisanje genotipova po aritmetičkoj sredini prinosa i neparametrijskim statističkim testovima stabilnosti ukazuje da postoje tri grupe genotipova različitih odlika. Rezultati glavne komponente analize neparametrijskih statističkih testova stabilnosti i aritmetičke sredine prinosa ukazuju da bi jedino neparametrijski indeks superiornosti bio koristan za simultan odabir visokog prinosa i stabilnosti. Na kraju, genotipovi G5 (3065.59 kg ha-1) i G9 (3027.27 kg ha-1) su najpovoljniji genotipovi i stoga se preporučuju za komercijalnu upotrebu u poluaridnim područjima Irana.

Ključne riječi: adaptacija, multilokacijski ogledi, stabilnost prinosa.