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Hamid Dehghani

Department of plant Breeding Faculty of Agriculture, Tarbiat Modares University Tehran, P.O. Box 14115-336, Iran E-mail: dehghanr@modares.ac.ir or dehghanirh@yahoo.com

ESTIMATING YIELD STABILITY BY NONPARAMETRIC STABILITY ANALYSIS IN MAIZE (*ZEA MAYS* L.)

ABSTRACT

Assessment of the stability of a genotype to different environments is useful for recommending genotypes for known conditions of cultivation and should be a requirement in plant breeding programs. Nonparametric models do not require parametric assumptions and are good alternatives for parametric measurements to genotypes × environments (GE) interaction study.Twelve maize (*Zea mays* L.) genotypes were tested at eleven locations in for two years (22 environments). The experiments involved a randomized complete block design in which twelve nonparametric procedures were used to analyze genotype stability. Results of nonparametric tests of GE interaction and combined ANOVA showed there were both noncrossover and crossover GE interaction in this research and interactions influenced significantly the genotypes performance for yield. In this study, high value of Top nonparametric statistic was associated with high mean yield, but the other nonparametric methods were not positively correlated with high mean yield and showed statistic stability concept. Genotype G3 was the most stable genotype and was considered the best in terms of favorable genotype (the most stable and high mean yield). As a consequence, the nonparametric stability methods are similar in concept to the GE interaction measures in that they define stability in the ability of the genotype to stabilize itself in different environments and so can be used widely to study and interpret GE interaction of different field crops in every where of world.

Key words: Genotype × Environment Interaction, Multi-environment trials, *Zea mays*

INTRODUCTION

The genotype by environment (GE) interaction structure is an important aspect in both plant breeding programs and the introduction of new crop commodities. GE interaction can occur when specified genotypes are grown across diverse environments (Zobel, 1990). For this reason, multi-environment trials (MET) are conducted throughout the world for major crops every year. However, effective interpretation and utilization of the MET data in making selection decisions remain a major challenge to researchers. Plant breeders use yield trials to identify promising genotypes, and agronomists use them to make recommendations for farmers.

Numerous methods have been used in the search for an understanding of the causes of GE interaction (Flores *et al.*, 1998). These methods can be catego-

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rized into three major strategies. The first strategy involves univariate parametric procedures such as simple linear regression analysis (Finlay and Wilkinson, 1963; Eberhart and Russell, 1966) of the GE matrix (i.e., the yield matrix after the environment and genotype main effects are removed). Univariate parametric methods for estimating GE interactions and phenotypic stability (stability of genotypes over environments) are widely used in plant breeding. The second strategy involves multivariate parametric procedures such as AMMI analysis (Gauch, 1988; Zobel *et al.*, 1988) which has been used to partition the GE interaction effects (remaining after accounting for environment and genotype main effects from multi-environment yield trial data) with a principal components analysis.

All procedures of the above strategies are parametric methods. When using parametric statistics for stability, assumptions are made about the distribution of data and the homogeneity of variance. On the contrary, nonparametric stability procedures as the third strategy, are largely unaffected by data distribution. As these methods are based on ranks and not on values, a genotype is considered stable if its ranking is relatively constant across environments. Several nonparametric procedures proposed by Hühn (1979), Kang (1988), Fox *et al.* (1990) and Thennarasu (1995) are based on the ranks of genotypes in each environment and most of them use the idea of homeostasis as a measure of stability.

Nonparametric procedures for stability based on ranks provide a valuable alternative to existing parametric procedures. Procedures based on ranks are distribution-free. One need not make assumptions about the distribution of the phenotypic values for the measurement under consideration. Although many phenotypic characters may be analyzed by parametric techniques, it is not always true that a given character or its transformed value may be assumed to have a normal distribution. Stability measures based on ranks are easy to use and are not expected to be as sensitive to errors of measurements as are parametric measures. Furthermore, addition or deletion of one or a few observations is not as likely to cause great variations in the estimates as would be the case for parametric stability measures.

Hühn (1979) proposed as stability measures the nonparametric statistics, S_i^1, S_i^2, S_i^3, S_i^4, S_i^5, S_i^6, based on the classification of the genotypes in each environment, and defined stable genotypes as those whose position in relation to the others remained unaltered in the set of environments assessed. The statistical properties and significance for measures of nonparametric stability analysis (S_i^1 and S_i^2) were given by Nassar and Huhn (1987). These nonparametric approaches can be used for other purposes, such as selection in competition and breeding programs, when the order of genotype classification is of fundamental importance (Huehn, 1990a).

Kang (1988) and Kang and Pham (1991) proposed Rank-sum as another nonparametric stability statistics where both yield and Shukla's (1972) stability variance are used as selection criteria. This statistics assigns a weight of one to both yield and stability and enables the identification of high-yielding and stable variety. The genotype with the highest yield is given a rank of 1 and a genotype with the lowest stability variance is assigned a rank of 1. All genotypes are ranked in this way and the ranks by yield and by stability variance are added for each genotype. The genotype with the lowest Rank-sum is the most desirable one.

Fox *et al*. (1990) proposed a superiority measure statistics based on nonparametric procedure for general adaptability. They used stratified ranking of the genotypes. Ranking was done at each environment separately and the number of sites at which the genotype occurred in the top, middle, and bottom third of the ranks was computed. A genotype that occurred mostly in the top third was considered as a widely adapted cultivar. Thennarasu (1995) proposed as stability measures the nonparametric statistics NP_i^1, NP_i^2, NP_i^3 and NP_i^4 based on ranks of adjusted means of the genotypes in each environment, and defined stable genotypes as those whose position in relation to the others remained unaltered in the set of environments assessed.

Two concepts of interaction are available: the usual statistical concept of an interaction (deviations from additivity of main effects in the linear model) and a modified concept of interaction (crossover interaction). A crossover interaction exists if the rankings of the genotypes are not identical in different environments. If these rankings are identical, crossover interaction is said not to exist (de Kroon and van der Laan 1981, de Kroon 1986). Not all the interaction effects in the usual sense are of such a magnitude as to cause changes in the rankings of genotypes in different environments. In this concept of crossover interaction, the usual interactions are only utilized in so far as they lead to different rankings of the genotypes.

Nonparametric statistical procedures for the test of crossover interactions have been developed in the field of medicine and can be applied to GE interactions in MET (Truberg and Huehn, 2000). Nonparametric measures for the test of interactions provide a useful alternative to parametric methods such as the ANOVA currently used, which is based on original data values. Huehn and Leon (1995) and Truberg and Huehn (2000) compared several nonparametric analyses of interactions and grouped them into two different concepts of interactions (crossover and noncrossover interactions). In this paper, four non-parametric statistical procedures were applied to test of GE interactions: Bredenkamp method (1974), Hildebrand method (1980), de Kroon-van der Laan method (1981) and Kubinger method (1986).

The objectives of this study were (1) to identify maize genotypes that have high yield and stable performance across different environments of Iran by nonparametric stability procedures (2) to study the relationships among nonparametric stability statistics.

MATERIALS AND METHODS

Data source

Data from two years late maize (*Zea mays* L.) hybrids performance trials were used in this investigation. Each year 11 genotypes with a check cultivar (G12) tested at 11 different field crop stations: Arak, Esfahan, Ghaemshahr, Hamedan, Kermanshah, Karaj, Khoramabad, Rasht, Sanandaj, Shiraz and Varamin. The range of environmental conditions represented by these sites is presented in Table 1. The trial at each site and each year (environment) was planted using the randomized complete block design (RCBD) with 4 replications. The plot size was 3.75 meters long consisting of 4 rows spaced 48 cm apart (7.2 m^2).

Table 1

Climatic characteristics of testing environments.

Trial Sites	Location		Altitude [m]	Rainfall [mm]	
				Year 1	Year 2
Arak	34°06'N	49°46'E	1708	400.9	429.5
Esfahan	32°37'N	51°40'E	1590	198.9	212.3
Ghaemshahr	36°27'N	52°53'E	14.7	673.9	845.3
Hamedan	35°12'N	48°41'E	1679.7	327.4	662.4
Kermanshah	34°19'N	47°07'E	1322	587.9	702.6
Karaj	35°56'N	50°58'E	1312.5	251.1	339.1
Khoramabad	33°29'N	48°22'E	1125	771	706.1
Rasht	37°15'N	49°36'E	-6.9	1895.3	1446.4
Sanandaj	35°20?N	47°00'E	1373.4	524.9	645.2
Shiraz	29°33'N	52°36'E	14.91	341.5	371
Varamin	35°28'N	51°44'E	1180	165.1	213

Plantings were done following the optimal dates for each site in every year and all the recommended agronomic practices were done. Appropriate pesticides were used to control insects, weeds and disease, and appropriate fertilizers were applied at the recommended rates as usual in the environment. Evaluations were conducted for several agronomic traits, but complete data were obtained only for grain yield in all the site × year combinations, hereafter referred to as environments. The value of grain yield trait was determined from the 2nd central rows of each plot (3.12 m^2). Upon harvested grain yield was determined for each genotype at each test environment; the average yield was computed in accordance with the experimental design.

Statistical analysis

Bartlett test for variance homogeneity was significant and therefore square root transformation was applied on primary data which these data had homogenous variances and the transformed data of grain yield was subjected to combined analyses of variance to see the effects of genotypes, sites and years as well as their first and second order interactions. Years were considered as random variables while the genotypes and sites were treated as fixed variables. Different nonparametric stability measures were applied on original (untransformed) dataset.

In this research, four nonparametric procedures were applied to test the significance of GE interaction. The methods of Bredenkamp (1974), Hildebrand (1980), and Kubinger (1986) are based on the usual interactions (noncrossover) and the procedure of the de Kroon-van der Laan (1981) was used for test of crossover interactions. These statistical procedures have been described in detail by Huehn and Leon (1995) and Truberg and Huehn (2000).

Hühn (1979) proposed six nonparametric stability measures that combine mean yield and stability. For a GE matrix data 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 $\bar{r}_{ij}$ 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:

$$S_i^1 = 2 \times \sum_{j}^{n-1} \sum_{j'=j+1}^{n} \frac{\left| r_{ij} - r_{ij'} \right|}{n(n-1)}$$

$$S_i^2 = \sum_{j=1}^{n} \frac{\left(r_{ij} - \bar{r}_{i.} \right)^2}{(n-1)}$$

$$S_i^3 = \frac{\sum_{j=1}^{n} \left(r_{ij} - \bar{r}_{i.} \right)^2}{\bar{r}_{i.}}$$

$$S_i^4 = \sqrt{\frac{\sum_{j=1}^{n} \left(r_{ij} - \bar{r}_{i.} \right)^2}{n}}$$

$$S_i^5 = \frac{\sum_{j=1}^{n} \left| r_{ij} - \bar{r}_{i.} \right|}{n}$$

$$S_i^6 = \frac{\left| r_{ij} - \bar{r}_{i.} \right|}{\bar{r}_{i.}}$$

Kad stability and enables the identification of high-yielding and stable genotype. Ranks were assigned for mean yield with the genotype with the highest yield receiving the rank of 1. Similarly, ranks were assigned for the stability variance of Shukla (1972), with the lowest estimated value receiving the rank of 1. The ranks by yield and by stability variance are added for each genotype and were named Rank-sum. The genotype with the lowest Rank-sum is the most favorable one. Fox *et al.* (1990) suggested a nonparametric superiority measure for general adaptability. They used stratified ranking of the cultivars. Ranking was done at each site separately and the number of sites at which the cultivar occurred in the top, middle, and bottom third of the ranks was computed. A genotype that occurred mostly in the top third was considered as a widely adapted cultivar.

Thennarasu (1995) proposed the use of the parameters NP_i^1, NP_i^2, NP_i^3 and NP_i^4 as stability measurements based on the classification of genotypes in various environments, where:

$$NP_i^{(1)} = \frac{1}{n} \times \sum_{j=1}^{n} \left| r_{ij}^* - M_{di}^* \right|$$

$$NP_i^{(2)} = \frac{1}{n} \times \left[\sum_{j=1}^{n} \frac{\left| r_{ij}^* - M_{di}^* \right|}{M_{di}} \right]$$

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

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

Determining the ranks of genotypes in each environment according adjusted phenotypic values ($x_{ij}^* = x_{ij} - \bar{x}_{i.}$) is another strategy in nonparametric analysis of GE interaction (Thennarasu, 1995). In the formula, the quantities $\bar{x}_{i.}$ and M_{di} are the mean and median ranks respectively of the i^{th} genotype, obtained from the original (unadjusted) grain yield (x_{ij}) while $\bar{r}_{i.}^*$ and M_{di}^* are the same parameters computed from the adjusted grain yield data (x_{ij}^*). In these methods, genotypes with low NPs values are considered as stable genotypes and genotypes with high NPs are not stable genotypes.

The above twelve nonparametric stability measures were computed for 11 maize genotypes, in which planted in different environmental conditions. The stability parameters were compared using Spearman's rank correlation (Steel and Torrie, 1980). Lu (1995) developed an SAS-based computer program that computes $S_i^{(1)}$ and S_i^2 nonparametric measures. A comprehensive SAS program has become available, which calculate different parametric and nonparametric stability statistics (Hussein *et al.*, 2000). SAS software (1996) was used to perform analysis of nonparametric stability statistics on the mean values of yield (kg × ha^{-1}) obtained over environments by using above mentioned programs.

RESULTS

Analysis of ge interaction

Analysis of variance was conducted to determine the effects of year (Y), site (S), genotype (G) and all possible interactions among these factors. The results of combined analysis of grain yield across sites and years are given in Table 2.

Table 2

Analysis of variance of maize late hybrids performance trial yield data.

Source	df	Type III SS	MS	F	% of total
Year (Y)	1	14001.9	14001.9	3.37ns	8.4
Site (S)	10	59176.3	5917.6	1.41ns	35.8
Y S	10	41479	4147.9	26.3**	25.1
Error A (R/YS)	66	8213.7	124.4		
Genotype (G)	11	3184.1	289.4	2.77*	1.9
Y G	11	640	58.2	0.95ns	0.3
S G	110	11736.9	106.6	1.75**	7.1
Y S G	110	6680.5	60.7	2.19**	4
Error B	726	20099.9	27.6		
Total	1055	165212.3			

**,* Respectably significant at 0.01 and 0.05 level of probability.
ns Non significant.

However, the interaction effects of Y×S, G×S and G×Y×S (GE) are all highly significant at the $p<0.01$ levels for grain yield and genotype main effect (G) is significant at the $p<0.05$ levels. The main effect of year, site and Y×G interaction are not significant at the $p<0.05$ level.

Table 3

Analysis of GE interaction using different non-parametric tests on 12 maize genotypes grown in 22 environments.

Nonparametric tests	df	Statistic X^2	P-value
Bredenkamp	231	406.47	0.00
Hidebrand	231	397.74	0.00
Kubinger	231	386.23	0.00
de Kroon-van der Laan	231	754.32	0.00

The values of the test statistics for the different nonparametric statistical procedures for GE interaction are presented in Table 3. The null hypothesis for Hildbrand and Kubinger is no non-crossover GE interactions and for de Kroon-van der Laan is no crossover G+E interaction. Results of these indicated that both significant non-crossover and crossover interactions were found in this MET according to Hildbrand and Kubinger procedures (for non-crossover) and the van der Laan-de Kroon test (for crossover). This result is in agreement with the ANOVA, but provides more specific information about the nature of GE interactions.

Measures of stability

For each genotype, Z1 and Z2 values were calculated based on the ranks and summed over genotypes to obtain Z values (Table 4). It is seen that $\sum_{i=1}^{k} Z_i^1 = 128.16$ and $\sum_{i=1}^{k} Z_i^2 = 111.62$. Since both of these statistics were more than the critical value $X^2_{0.01,11} = 26.8$, significant differences in rank stability were found among the 12 genotypes grown in 22 environments (Nassar and Huehn, 1987). On inspecting the individual Z values, it was found that some genotypes were significantly unstable relative to others, because they showed larg Z values, compared with the above critical value X^2.

Table 4

Estimation and test of nonparametric stability measures for 12 maize genotypes across 22 environments.

Genotype	Mean yield (root transformed)	Mean yield [kg × ha-1]	S_i^1	Z1	S_i^2	Z2
G1	105.3	11238.21	4.56	8.77	15.4	7.5
G2	104.54	11082.07	3.34	10.28	8.25	8.32
G3	105.69	11342.13	4.17	1.03	12.87	0.57
G4	100.56	10240.34	3.81	0.64	10.92	0.62
G5	100.73	10281.95	2.84	32.49	6.85	15.91
G6	103.36	10893.16	5.12	33.45	19.83	38.78
G7	103	10728.11	4.27	2.24	13.39	1.35
G8	102.54	10654.9	3.26	12.8	8.07	9.17
G9	102.99	10757.25	3.78	0.91	10.64	1.01
G10	104.68	11102.67	4.12	0.57	12.74	0.42
G11	104.77	11147.97	4.96	24.97	18.63	27.95
G12	106.09	11412.26	3.95	0.01	11.73	0.02
Sum				128.16		111.62

The first tow Hühn's (1979) nonparametric measures of stability ($S_i^{(1)}$ and S_i^2) for grain yield of 12 maize genotypes evaluated in 22 environments of Iran are presented in Table 4. The $S_i^{(1)}$ and S_i^2 statistics are based on ranks of the genotypes across environments and they give equal weight to each environment. Genotypes with fewer changes in rank are considered to be more stable (Becker and Leon, 1988). As shown in Table 4, the two overall chi-square stabilities (Z1 and Z2) were significant and there was sufficient evidence for differences in stability among genotypes. Hence, G5 had the smallest changes in ranks and thus regarded as the most stable genotype unlike G11, which was unstable. The next most stable genotype was G8, followed by G2 that gave the mean yield above the general mean for this research (Tables 4 and 6).

The genotype with the lowest $S_i^{(3)}$ value was G5, followed by G4, G8, and G2, all except G2 had not mean yields above the general mean for the experiment. On the other hand, G2 had mean yields above the general mean but relatively high $S_i^{(3)}$ values and, consequently, showed relatively low stability. According to Scapim et al (2000), $S_i^{(1)}$, S_i^2 and $S_i^{(3)}$ nonparametric measures of stability introduced the same genotypes as the most stable genotype and the same genotypes as the most unstable genotypes.

Nonparametric statistic $S_i^{(4)}$ is one of the nonparametric methods of Hühn (1979) used to determine the stability of genotypes depending on the ranks. According to this method, genotypes with low $S_i^{(4)}$ are considered more stable than the others. Accordingly, the G5, G2, G8 and G4 genotypes of maize were identified as stable genotypes (Table 5). The computed $S_i^{(5)}$ statistics and the rank of genotypes based on these values are given in Table 5 and 6. According to this stability parameter, genotypes with minimum $S_i^{(5)}$ are considered more stable. Hence, the G5, G2, G8 and G9 genotypes were the most stable genotypes, whereas G6, G11 and G1 were classified as the least stable ones.

The genotypes with the lowest $S_i^{(6)}$ value were G5, G4, G8, and G9, all of these genotypes except G2 had mean yields under the general mean. On the other hand, G2 had mean yields above the general mean and relatively low $S_i^{(6)}$ values and, consequently, showed relatively high stability. It is worth noting that G5 was judged as the most stable genotype and G1 and G11 were judged as the most unstable genotypes according to six nonparametric methods of Hühn (1979). Sabaghnia *et al.* (2006) pointed out that the four nonparametric procedures $S_i^{(1)}$, S_i^2, $S_i^{(3)}$ and $S_i^{(6)}$ are associated together and introduced relatively the same genotypes as the most stable genotype and the most unstable genotypes.

In an alternative nonparametric procedure for assessing the stability of genotypes in MET proposed by Fox *et al.* (1990), the nonparametric superiority statistic of a genotype may be consists of scoring the percentage of environments in which each genotype ranked in the top, middle, and bottom third of trial entries. A genotype usually found in the top third of entries across environments can be considered relatively well adapted and stable. Therefore, G3 was stable because it ranked in the top third of genotype in a high percentage of environments (63.6%), and was followed by G12 that were the high yield genotypes in this study with 11412.26 and 11342.13 kg ha^{-1}, respectively (Tables 5 and 6). The undesirable genotypes in this method were G5 and G4 genotypes with 0 and 4.5% Top value, respectively.

Rank-sum nonparametric stability statistic of Kang (1988) and Kang and Pham (1991) uses both yield and stability variance of Shukla (1972). The lowest value for this statistics indicates maximum stability for a certain genotype. According to the Rank-sum statistic, G2 and G12 had the minimum value for Rank-sum and therefore were the most stable genotypes (Table 5). Further-

Table 5

Nonparametric stability statistics for grain yield of 12 maize genotypes evaluated under 22 environments

Genotype	$S_i^{(3)}$	$S_i^{(4)}$	$S_i^{(5)}$	$S_i^{(6)}$	Top	Mid	Low	R-sum	$N_i^{(1)}$	$N_i^{(2)}$	$N_i^{(3)}$	$N_i^{(4)}$
G1	53.12	3.54	3.11	13.19	45.5	27.3	27.3	14	3.500	0.700	0.273	0.711
G2	24.79	2.5	2.06	8.16	45.5	36.4	18.2	9	2.318	0.464	0.341	0.521
G3	58.11	3.45	2.91	14.22	63.6	13.6	22.7	12	3.091	1.03	0.278	0.665
G4	18.67	2.78	2.38	5.74	4.5	31.8	63.6	18	2.591	0.259	0.297	0.595
G5	9.9	1.99	1.5	3.75	0	36.4	63.6	12	1.864	0.207	0.378	0.457
G6	52.25	4.01	3.68	11.96	40.9	18.2	40.9	19	4.091	0.629	0.221	0.816
G7	28.81	3.04	2.69	8.39	31.8	31.8	36.4	12	3.182	0.455	0.277	0.626
G8	21.66	2.71	2.27	6.71	18.2	45.5	36.4	12	2.364	0.315	0.371	0.499
G9	27.75	3.01	2.32	7.11	18.2	54.5	27.3	14	2.545	0.364	0.329	0.578
G10	35.33	3.03	2.69	10.32	36.4	40.9	22.7	12	3.000	0.500	0.280	0.630
G11	55.79	3.93	3.46	12.51	40.9	27.3	31.8	13	3.818	0.636	0.243	0.728
G12	43.44	3	2.41	11.68	54.5	36.4	9.1	9	2.818	0.705	0.308	0.587

Table 6

Ranks of the genotypes according to 12 different nonparametric stability statistics

Genotype	Y	$S_i^{(1)}$	$S_i^{(2)}$	$S_i^{(3)}$	$S_i^{(4)}$	$S_i^{(5)}$	$S_i^{(6)}$	Top	Mid	Low	R-sum	$N_i^{(1)}$	$N_i^{(2)}$	$N_i^{(3)}$	$N_i^{(4)}$
G1	3	10	10	10	10	10	11	3.5	9.5	5.5	9.5	10	10	3	10
G2	6	3	3	4	2	2	5	3.5	5	2	1.5	2	6	10	3
G3	2	8	8	12	9	9	12	1	12	3.5	5	8	12	5	9
G4	12	5	5	2	4	5	2	11	7.5	11.5	11	5	2	7	6
G5	11	1	1	1	1	1	1	12	5	11.5	5	1	1	12	1
G6	7	12	12	9	12	12	9	5.5	11	10	12	12	8	1	12
G7	9	9	9	6	8	7.5	6	8	7.5	8.5	5	9	5	4	7
G8	10	2	2	3	3	3	3	9.5	2	8.5	5	3	3	11	2
G9	8	4	4	5	6	4	4	9.5	1	5.5	9.5	4	4	9	4
G10	5	7	7	7	7	7.5	7	7	3	3.5	5	7	7	6	8
G11	4	11	11	11	11	11	10	5.5	9.5	7	8	11	9	2	11
G12	1	6	6	8	5	6	8	2	5	1	1.5	6	11	8	5

Table7

Spearman's rank correlation coefficients between the different nonparametric stability statistics for grain yield of 12 maize genotypes

	Yield	$S_i^{(1)}$	$S_i^{(1)}$	$S_i^{(3)}$	$S_i^{(4)}$	$S_i^{(5)}$	$S_i^{(6)}$	Top	Rank-sum	$N_i^{(1)}$	$N_i^{(2)}$	$N_i^{(4)}$
S1	-0.49											
$S_i^{(1)}$	-0.49	1.00**										
$S_i^{(3)}$	-0.84**	0.83**	0.83**									
$S_i^{(4)}$	-0.49	0.97**	0.97**	0.86**								
$S_i^{(5)}$	-0.53	0.98**	0.98**	0.87**	0.98**							
$S_i^{(6)}$	-0.86**	0.81**	0.81**	0.99**	0.83**	0.84**						
Top	0.93**	-0.45	-0.45	-0.76*	-0.41	-0.45	-0.80**					
Rank-sum	0.30	0.45	0.45	0.12	0.52	0.47	0.07	0.37				
$N_i^{(1)}$	-0.46	0.99**	0.99**	0.82**	0.97**	0.99**	0.80**	-0.41	0.47			
$N_i^{(2)}$	-0.96**	0.66*	0.66*	0.93**	0.66*	0.70*	0.95**	-0.92**	-0.13	0.64*		
$N_i^{(4)}$	0.41	-0.99**	-0.99**	-0.78**	-0.96**	-0.97**	-0.77**	0.38	-0.52	-0.99**	-0.60*	
$N_i^{(4)}$	-0.49	0.97**	0.97**	0.83**	0.96**	0.98**	0.82**	-0.43	0.52	0.97**	0.66*	-0.98**

more, G3, G5, G7, G8 and G10 genotypes showed the same stability performance based on Rank-sum nonparametric stability statistic and thus had the same ranks (Tables 5 and 6). The undesirable genotypes based on the rank-sum statistic were G4 and G6.

Four Thennarasu's nonparametric stability statistics (NP_i^1, NP_i^2, NP_i^3 and NP_i^4), which are calculated from ranks of adjusted yield means, are shown in Table 5, and the ranks of genotypes according to these statistics are given in Table 6. According the first two statistics (NP_i^1 and NP_i^2), genotype G5 was the most stable in comparison with other genotypes These results are in agreement with the Hühn's (1979) nonparametric stability measurements (Table 5). Genotype G6 had the lowest value of NP_i^3 and was the most stable, followed by G11 and G1. Because of the high values for NP_i^2, the stabilities of G5, G8 and G2 were low (Table 5). NP_i^4, like NP_i^1 and NP_i^2 and , identified G5 as the most stable genotype, although it had the lowest mean yield. The flowing most stable genotypes were G8 and G2, which also had relatively low mean yield performances. The unstable genotypes according to NP_i^4 statistics were G6, G11 and G1.

Comparison of the nonparametric stability measures

The correlation among the nonparametric stability estimates of the different procedures may indicate if more estimates should be obtained to improve confidence in the prediction of genotype behavior. According to Table 7 the Spearman's rank correlation between the $S_i^{(3)}$, S_i^6 and NP_i^2 with mean yiel (Y) wre negative and significant (P < 0.01). This estimate indicates that genotypes that are more responsive tended to have lower $S_i^{(3)}$, S_i^6 and NP_i^2 values. In contrast, rank correlation between the Top statistics and mean yield (Y) was positive (r = 0.93) and significant (P < 0.01). We found that $S_i^{(1)}$ and S_i^2, $S_i^{(3)}$ nonparametric statistics of Hühn (1979) were positive related to each other significantly (Table 7).Similar results were obtained in maize (*Zea mays* L.) (Scapim *et al*. 2000), wheat (*Triticum aestivum* L.) (Kara, 2000) and lentil (*Lens culinaris* Medik.) (Sabaghnia *et al. 2006).*

All nonparametric statistics of Hühn (1979) including $S_i^{(1)}$, S_i^2, $S_i^{(3)}$, S_i^4, S_i^5 and S_i^6, were correlate positively with NP_i^1, NP_i^2 and $NP_i^{(4)}$ statistics of Thennarasu (1995) while were correlate negatively with Thennarasu's (1995) NP_i^3 (Table 7). Flores *et al.* (1998) reported high rank correlations between and in faba bean (*Vicia faba* L.) and pea (*Pisum sativum* L.) METs.

None of the Hühn 's (1979) nonparametric statistics except $S_i^{(3)}$, and S_i^6 did not correlate with Top statistics and so introduced low yield genotypes as the most stable genotypes (Table 7). The $S_i^{(3)}$, and S_i^6 statistics of Hühn (1979) were highly associated with Top statistic (r = -0.76 and r = -0.80 respectively). Rank-sum statistic did not correlate with the other nonparametric statistics or mean yield (Y). Sabaghnia *et al.* (2006) also found no significant correlations among Rank-sum and the other nonparametric methods.

The stability parameters NP_i^1, NP_i^2 and $NP_i^{(4)}$ were positively correlated with each other, but the NP_i^1 measure was negatively correlated with other NPs (Table 7). Sabaghnia *et al.* (2006) reported high rank correlations between NP_i^2 and $NP_i^{(4)}$ in lentil (*Lens culinaris* Medik.) METs.

DISCUSSION

Plant breeders aim to select genotypes with stable and high performing yield across different environments. However, the environment and GE interaction affect the phenotype of genotypes, especially if the target environments are different. GE interaction also reduces the association between phenotypes and genotypes, thereby selected genotypes in one environment may exhibit a poor performance in another environment (Romagosa and Fox, 1993). In the Iran region of Middle East, maize breeding has the same objectives, despite the large variation in climate, soil, length of the cropping season and cultural practices and Iranian breeders give high priority to grain yield. GE interactions are important sources of mean yield variation in any crop and anywhere. For example, agronomic performance of maize may be affected by temperature in northern Iran and water supply in southern and dry regions of Iran.

Crossa (1990), Gregorious and Namkoong (1986) stated that GE interaction becomes very important in agricultural production, when there are changes in a genotype's rank over environments. These are called crossovers interactions, in contrast to noncrossover interactions (Gail and Simon, 1985). With a crossover interaction, genotype differences vary in direction among environments, whereas with noncrossover interactions, genotypic differences change in magnitude but not in direction. Therefore, it is important to test for crossover interactions (Baker, 1988). The results of different nonparametric tests for GE interactions were equivalent with combined ANOVA in this research. Truberg and Huehn (2000) and Sabaghnia *et al.* (2006), who recommended Hildbrand and Kubinger tests for noncrossover interaction and the de Kroon-van der Laan test for crossover interaction, reported similar results. Therefore, nonparametric tests for GE interactions seem particularly appropriate (for both crossover and noncrossover interactions) to analysis of differences between two genotypes tested in a series of different environments.

Nonparametric measures for stability based on ranks provide a useful alternative to routine parametric (univariate and multivariate) measures currently used in GE interaction analysis which are based on absolute data values. Moreover, nonparametric versus parametric stability statistics exist some advantages such as: reduction or avoidance of the bias caused by outliers; no assumptions are needed about the distribution of the phenotypic values; stability statistics based on ranks are easy to use and to interpret; additions or deletions of one or few genotypes do not cause much variation of results (Huhn, 1990b). Many nonparametric measures of phenotypic stability have been presented and compared in the literature (Becker and Leon, 1988; Flores et al, 1998; Sabaghnia et al, 2006).

The nonparametric stability methods are similar in concept to the GE interaction measures in that they define stability in the sense of homeostasis or the ability of the genotype to stabilize itself in different environments (Hühn, 1979; Huhn, 1990a Thennarasu, 1995). The most of nonparametric measures that are widely applicable are based on the variance of the genotype rank across environments (Hühn, 1990b; Thennarasu, 1995) and so have Type 2 concept of stability. Since Type 2 stability (Lin et al, 1986) implies low GE interaction, nonparametric stability measures could be provided by the ranks of each genotype over the different environments.

According to Huehn (1990a), the use of $S_i^{(1)}$ was preferred to S_i^2 for many practical applications; it was reported to be easy to calculate, interpret and it has an efficient test of significance while $S_i^{(3)}$ and S_i^6, which are the sum of the absolute deviations and sum of squares of rank for each genotype relative to the mean of ranks, respectively. Nevertheless, S_i^4 and S_i^5 not been widely studied. To compute these measures, however, the mean yield data have to be transformed into ranks for each genotype and environment, and the genotypes are considered stable if their ranks are similar across environments. The results of this research indicated that these statistics are strongly positive correlated with the other Huhn's measures. According to Becker and Leon (1988), nonparametric measures of stability are distribution-free and no assumption on the distribution of values is necessary. As a result, they are less sensitive to errors of measurements than the parametric statistics.

As a consequence, for an estimation of the nonparametric stability statistics of genotypes grown in different environments, use of nonparametric statistics $S_i^{(1)}$, S_i^2, $S_i^{(3)}$, S_i^4, S_i^5 and S_i^6 as well NP_i^1, NP_i^2, NP_i^3 and NP_i^4 values, together with ranks, can be recommend to breeders and agronomists who make selection based upon GE interaction and want to use static concept of stability. On the other hand, these ten nonparametric stability statistics introduced low yielding genotypes as the most stable ones (Huhn, 1990b; Thennarasu, 1995; Sabaghnia et al, 2006). This type of stability is not acceptable to most agronomists, who would prefer a dynamic concept of stability (Becker, 1981) where ‘‘for each environment the performance of a stable genotype corresponds completely to the estimated level or the prediction.

Top statistics (Fox *et al*. 1900) is a method based on stratified ranking, which evaluates the proportion of environments where any genotype ranks in the top, middle or bottom third of the entries. There is no doubt that yield level plays a very important role in this method, and it is not surprising that it clearly influenced by yield. Thus this nonparametric statistic has dynamic concept of stability and introduce the high mean yielding genotypes as the most stable genotypes. Only genotype G3 showed stable position according to Top statistics which is positive correlated with mean yield (Y) and had the high grain yield. However genotype G3 was considered the best in terms of favorable genotype (the most stable and high mean yield).

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