World Journal of Agricultural Sciences 3 (4): 444-450, 2007
ISSN 1817-3047

Comparison Study Using Rank Based Nonparametric Stability Statistics of Durum Wheat

K.F. Solomon, H.A. Smit, E. Malan and W.J. Du Toit

Agricultural Research Council, Small Grain Institute, Private Bag X29,
Bethlehem 9700, Free State, Bethlehem, South Africa

Abstract: More than 10 rank based stability analysis methods were applied to durum wheat grain yield performance data obtained from the evaluation of 23 lines across 12 environments. Spearman's rank correlation and cluster analyses were used to investigate the relationships among stability parameters and yield performance. Analysis of variance across environments showed that more than 90% of the total sum of squares was attributed to the effects of environment and genotype by environment interactions. Global χ^2 test based on Huehn's $S_i^{(1)}$ and $S_i^{(2)}$ stability statistics showed that there was significant variability in yield stability among genotypes. Spearman's correlations and cluster analysis showed that rank sum (R_sum) (sum of ranks of mean yield and Shukla's stability variance), TOP and LOW (proportion of environments in which a genotype ranked in the top and bottom third ranks, respectively) were found to define stability in dynamic concept. In this study, high values of TOP were strongly associated with high mean yield across environments. Thus, TOP, LOW and R_sum would be the preferable nonparametric methods that would allow identifying high yielding and stable genotypes.

Key words: Cluster analysis · correlation · grain yield · GXE interaction · phenotypic stability

INTRODUCTION

Due to the diverse nature of the durum wheat growing areas, improved or advanced durum wheat lines are evaluated in multiple environmental trials to test their performance across different environments and to identify the best genotypes with relatively wider adaptation. Different statistical models have been proposed and employed to interpret genotype by environment (GE) interaction. These models can be broadly categorized as parametric and nonparametric methods based on their statistical properties.

The parametric stability methods have good properties under certain statistical assumptions, like normal distribution of errors and interaction effects [1, 2]. However, erroneous interpretation could be resulted from violations of the assumptions [3]. Thus, it is wise to search for alternative approaches that are more robust to departures from underlying assumptions of parametric methods. Stability estimates from nonparametric models based on the relative classification of the cultivars in a given set of environments do not require previous assumptions and are good alternatives for parametric measurements [4, 5]. Unlike parametric measurements, addition or removal of one or few cultivars in nonparametric procedures causes less variation in estimates of the stability parameters [6]. Moreover, nonparametric models, reduces or avoids biases caused by outliers and the stability parameters are easy to interpret and use. In a plant-breeding program, when the order of a genotype classification is of paramount importance, nonparametric stability statistics could be valuable selection tools [3]. Several nonparametric procedures proposed by [3, 4, 7-9] are based on ranks of genotypes in each environment and genotypes with similar rankings across environments are classified as stable. Nassar and Huehn [4] proposed four nonparametric measures of phenotypic stability. $S_i^{(1)}$ represents the mean of the absolute rank differences of a genotype over *n* environments. $S_i^{(2)}$ is the variance among the ranks over *n* environments. $S_i^{(3)}$ and $S_i^{(6)}$ are the sum of the absolute deviations and sum of squares of ranks, respectively. Kang [7] developed an index based on the yield of a genotype in an environment and ranks for stability variance of Shukla [10]. In this method, the genotype with the highest yield receives the rank of one. Rank of one is

Corresponding Author: Dr. K.F. Solomon, Agricultural Research Council, Small Grain Institute, Private Bag X29, Bethlehem 9700, Free State, Bethlehem, South Africa

assigned to the lowest estimated stability variance. The sum of these two ranks provides a final index, in which the genotype with lowest rank sum (R_sum) is regarded as the most stable. Fox *et al.* [8] suggested nonparametric superiority measures for general adaptability. Stratified ranking of cultivars are used and ranking was done at each environment separately. In these methods, the proportion of localities at which the cultivar occurred in the top, middle and bottom third of the ranks was computed to estimate the nonparametric stability measures, TOP, MID and LOW, respectively. A genotype with high value TOP is considered as a widely adapted genotype. Thennarasu [9] proposed stability measures, $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ based on the ranks of adjusted means of the genotypes in each environment and defined stable genotypes as those whose position remained unchanged in the range of environments considered.

The level of association among stability estimates of different models is indicative of whether one or more estimates should be obtained for reliable predictions of cultivar behaviors and also helps the breeder choose the best adjusted and most informative stability parameter (s) to fit the static and dynamic concepts of stability [2, 11].

The objective of this study was to determine the phenotypic stability of grain yield in durum wheat lines and evaluate the relationships among different nonparametric stability measurements.

MATERIAL AND METHODS

Data source: The data set involves 23 durum wheat genotypes tested in 12 environments (year-location combinations during 2003 and 2004), extracted from Small Grain Institute cultivar evaluation trials. One check and 22 experimental lines were evaluated for their yield performance at six localities namely at Loskop, Marydale, Prieska, Upington and Reitriver (two planting dates). In all the test localities, yield trials were performed for two years in Randomized Complete Block Design (RCBD) with three replications. Plots were planted with a Wintersteiger Plotman. Experimental plots were 5.1 m^2 with six rows each, 5 m long and 0.17 m interrow spacing. The seeding rate was fixed according to thousand kernel masses with a seeding rate of 120 kg/ha being used. Weed control was applied when necessary and foliar diseases were not controlled. Fertilization practices were according to individual recommendations based on previously analyzed soil samples. Harvesting was done using a Walter Wintersteiger Plot Combine harvester. Plot yield was converted to ton/ha and used for the analysis.

Statistical analysis: The yield data were subjected to combined analysis of variance. Replications and environments were considered random while genotypes were assumed fixed using PROC GLM procedure of SAS [12]. Nassar and Huehn [4] proposed four nonparametric stability statistics that combine mean yield and stability. Accordingly, for two-way data with *k* genotypes and *n* environments, the rank of the $_i$th genotypes in the $_j$th environment can be denoted as r_{ij}. The mean rank across all environments for the $_i$th genotype is $\bar{r}_i$. The stability statistics based on yield ranks of genotypes in each environment are expressed as follows:

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

$$S_i^{(3)} = \frac{\sum_{j=1}^{n}\left(r_{ij} - \bar{r}_{i.}\right)^2}{\bar{r}_i}; \quad S_i^{(6)} = \frac{\sum_{j=1}^{n} /r_{ij} - \bar{r}_{i.}/}{\bar{r}_{i.}}.$$

The significance tests for $S_i^{(1)}$ and $S_i^{(2)}$ were determined according to Nassar and Huehn [4]. χ^2 values associated with $S_i^{(1)}$ and $S_i^{(2)}$ were obtained by the expression $\chi^2 = \sum_{i=1}^{g} Z_i^m$, where m=1, 2, $Z_i^m = \left[S_i^m - E(S_i^m)\right]^2 / V(S_i^m), E(S_i^m) =$ expected value (=mean) of S_i^m and $V(S_i^m) = S_i^m$ variance. The significance test for the null hypothesis that all the genotypes were equally stable was done using a χ^2 distribution with *g* degrees of freedom. Thennarasu's [9] non-parametric stability statistics are based on ranks of adjusted yield of genotypes within each locality. The adjusted rank, r_{ij}^*, is determined from adjusted phenotypic values as: $x_{ij}^* = x_{ij} - \bar{x}_i$, where $\bar{x}_i$ is the mean performance of the *i*th genotype. The ranks obtained from adjusted values (x_{ij}^*) depend only on genotype by environment interaction and error effects. Using the adjusted rank values, Thennarasu [9] defined the following stability parameters: $Np_i^{(1)} = \frac{1}{n}\sum_{j=1}^{n} /r_{ij}^* - M_{di}^*/$; $Np_i^{(2)} =$

$$\frac{1}{n}\left(\sum_{j=1}^{n} \left| r_{ij}^* - M_{di}^* \right| \Big/ M_{di}\right); NP_i^{(2)} = \frac{\sqrt{\sum\left(r_{ij}^* - \overline{r_{i.}^*}\right)^2 \Big/ n}}{\overline{r_{i.}}};$$

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

Where, r_{ij}^* is the rank of x_{ij}^*, $\overline{r}_{ij*}$ and M_{di}^* are the mean and median ranks for adjusted values, while $\overline{r_i}$ and M_{di}^* are the mean and median ranks for unadjusted (original) values.

Kang's [7] rank sum (R_sum) and Fox *et al.* [8] nonparametric stability parameters were computed using a comprehensive SAS program called SASG X ESTAB [1]. The stability parameters associations were determined from Spearman's rank correlation analysis. To further understand the relationships among stability parameters, genotypes were assigned ranks for yield and each of the stability parameters separately. Euclidean distance was computed for every pair wise stability statistics. Cluster analysis was performed on Euclidean distance using the unweighted pair group with arithmetic averages (UPGMA) method.

RESULTS

The effects of Environment (E), Genotype (G) and GE interaction on grain yield of durum wheat were highly significant (P<0.01) (Table 1). Environment and GE interaction effects accounted for most of the sum of squares (Table 1). The results of nonparametric stability measures and genotypes mean grain yield are shown in Table 2. Ranks of genotypes based on the various stability parameters are also given in Table 3. Global χ^2 tests $Z_1^{(1)} = 35.22$ and $Z_2^{(2)} = 36.91$ for $S_i^{(1)}$ and $S_i^{(2)}$, respectively were significant ($P<0.05$; $df=23$), indicating that there was a difference in stability among genotypes. Based on the individual $Z_i^{(m)}$ χ^2 tests with 1*df*, genotypes can be tested as significantly more or less stable than the average stability. The χ^2 tests for individual $Z_i^{(1)}$ were only significant for G12 ($Z_i^{(1)} = 6.71$; P<0.01) and G22 ($Z_i^{(1)} = 4.10$; P<0.05). The genotypes, G12 and G22, also had the lowest values for $S_i^{(1)}$ suggesting that they were the most stable. The maximum $S_i^{(2)}$ value recorded for G1 (Table 2) was significant ($Z_i^{(2)} = 4.688$; P<0.05), indicating G1 was the least stable genotype. The minimum value obtained for G12 was also significant ($Z_i^{(2)} = 5.468$; P<0.05) suggesting G12 was the most stable one. The pattern of genotypes ranking based on $S_i^{(1)}$ and $S_i^{(2)}$ was similar (Table 3). The two other statistics, $S_i^{(3)}$ and $S_i^{(6)}$ were developed to combine yield and stability based on yield ranks of genotypes in each environment. The lowest value for each of these statistics indicates maximum stability. Like $S_i^{(1)}$ and $S_i^{(2)}$, G1 had the highest values for both $S_i^{(3)}$ and $S_i^{(6)}$ (Table 2) and hence was the most unstable (Table 3). On the basis of $S_i^{(3)}$ G14 was the most stable while G5 was the most stable according to $S_i^{(6)}$ (Table 3). The nonparametric superiority measure of Fox *et al.* [8], consists of scoring the percentage of environments in which each genotypes ranked in the top, middle and bottom third of trial entries. According to this measures, a genotype that appear in the top third of entries across localities can be considered as relatively well adapted and stable. On the basis of this measurement, G1 had the highest top value while G5 and G14 had the lowest top values (Table 2). Accordingly, G1 was the most stable while G5 and G14 were the most unstable (Table 3). Kang's [7] R_sum is another non-parametric stability statistics where both yield and Shukla's 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 manner. The ranks by yield and by stability variance are added for each genotype. The genotype with the lowest R_sum is the most desirable (Table 2). According to this measurement, G12 and G21 were the most stable while G8 was the least stable (Table 3). Values of Thennarasu's [9] nonparametric stability parameters, computed from ranks adjusted yield, are shown in Table 2. Like Nassar and

Table 1: Analysis of variance for grain yield performance of 23 durum wheat genotypes evaluated across 12 environments

Source	DF	MS	% of total SS
Genotype (G)	22	4.4613 **	1.99
Environment (E)	11	375.784 **	84.01
GE	242	1.569 **	7.72
Replication (E) (Error 1)	24	2.700	
Replication (GE) (Error 2)	528	0.462	
Total	827		
R^2(%)	95		
CV(%)	8.85		

**P<0.01(F-test)

Table 2: Mean grain yield and nonparametric stability parameters for 23 durum wheat genotypes evaluated across 12 environments

Code	Genotype	Y Ton/ ha	$S_i^{(1)}$	$S_i^{(2)}$	$S_i^{(3)}$	$S_i^{(6)}$	TOP	MID	LOW	R_sum	$NP_i^{(1)}$	$NP_i^{(2)}$	$NP_i^{(3)}$	$Np_i^{(4)}$
G1	KRONOS	8.03	9.89	77.66	97.63	10.57	58	8	33	25	7.92	1.979	1.011	1.224
G2	DBSP00/1	7.57	7.52	40.79	36.38	5.30	33	33	33	34	5.75	0.411	0.549	0.679
G3	DBSP00/2	7.94	8.86	58.27	61.53	7.89	42	25	33	27	7.08	0.545	0.775	0.921
G4	DBSP02/6	7.09	6.52	35.18	22.11	3.31	8	17	75	34	6.17	0.308	0.389	0.480
G5	DBSP02/7	7.19	5.68	22.99	14.95	2.79	0	33	67	25	5.08	0.290	0.350	0.433
G6	DBSP02/8	8.27	8.02	49.48	70.23	8.90	50	33	17	23	7.50	1.071	1.062	1.294
G7	DBSP02/9	7.97	6.94	37.27	45.56	6.22	50	42	8	25	5.33	0.667	0.702	0.855
G8	DBSP02/10	7.01	7.12	39.45	25.53	3.53	8	25	67	40	7.25	0.382	0.470	0.580
G9	DBSP02/11	7.79	8.47	50.81	46.26	6.21	33	33	33	26	6.75	0.587	0.605	0.744
G10	DBSP02/13	7.66	8.27	49.09	41.54	5.54	25	33	42	28	5.58	0.385	0.497	0.612
G11	DBSP02/19	7.79	6.65	32.75	32.02	5.02	33	50	17	25	4.67	0.359	0.525	0.628
G12	DBSP02/22	7.91	4.67	15.97	19.16	3.93	33	58	8	11	3.33	0.351	0.480	0.579
G13	DBSP03/02	7.48	6.77	34.45	28.24	4.48	25	25	50	22	4.83	0.312	0.430	0.529
G14	DBSP03/03	7.17	5.52	21.70	14.32	2.84	0	42	58	24	4.83	0.302	0.360	0.436
G15	DBSP03/04	7.95	8.32	49.72	49.35	6.42	33	33	33	23	6.33	0.667	0.644	0.798
G16	DBSP03/10	7.71	7.14	36.57	35.76	5.11	25	50	25	23	5.42	0.516	0.585	0.718
G17	DBSP03/11	7.48	8.45	52.00	40.86	5.43	33	17	50	35	7.00	0.438	0.545	0.669
G18	DBSP03/12	7.91	5.89	28.45	35.09	5.25	50	42	8	17	4.42	0.589	0.595	0.726
G19	DBSP03/16	7.92	5.74	23.90	30.63	5.61	42	58	0	14	4.33	0.542	0.601	0.748
G20	DBSP03/17	7.24	6.12	27.00	19.16	3.29	8	33	58	30	5.17	0.304	0.408	0.500
G21	DBSP03/18	7.99	6.38	29.36	35.55	6.07	50	33	17	11	5.58	0.744	0.670	0.816
G22	DBSP03/19	7.54	5.32	21.30	17.68	3.28	17	42	42	18	4.17	0.321	0.365	0.453
G23	DBSP03/20	8.03	7.06	35.70	45.31	6.69	42	33	25	12	4.67	0.549	0.665	0.822

Y= mean grain yield across 12 environments, $S_i^{(1)}$, $S_i^{(2)}$, $S_i^{(3)}$ and $S_i^{(4)}$ are Nassar and Huehn [4] nonparametric stability statistics, TOP, MID and LOW are parameters of Fox *et al.* [8], R_sum is Kang's [7] parameter, $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ are parameters of Thennarasu [9]

Table 3: Ranks of 23 durum wheat genotypes for grain yield and various nonparametric stability statistics across 12 environments

Code	Genotype	Y	$S_i^{(1)}$	$S_i^{(2)}$	$S_i^{(3)}$	$S_i^{(6)}$	TOP	LOW	R_sum	$NP_i^{(1)}$	$NP_i^{(2)}$	$NP_i^{(3)}$	$Np_i^{(4)}$
1	KRONOS	2	23	23	23	23	1	10	12	23	23	22	22
2	DBSP00/1	15	16	16	14	12	9	10	20	15	11	12	12
3	DBSP00/2	6	22	22	21	21	6	10	17	20	15	21	21
4	DBSP02/6	22	9	11	6	5	19	23	20	16	4	4	4
5	DBSP02/7	20	4	4	2	1	22	21	12	9	1	1	1
6	DBSP02/8	1	17	18	22	22	2	5	8	22	22	23	23
7	DBSP02/9	5	12	14	18	18	2	2	12	11	19	20	20
8	DBSP02/10	23	14	15	7	6	19	21	23	21	9	7	8
9	DBSP02/11	11	21	20	19	17	9	10	16	18	17	16	15
10	DBSP02/13	14	18	17	16	14	15	15	18	13	10	9	9
11	DBSP02/19	11	10	9	10	9	9	5	12	5	8	10	10
12	DBSP02/22	10	1	1	4	7	9	2	1	1	7	8	7
13	DBSP03/02	18	11	10	8	8	15	17	7	7	5	6	6
14	DBSP03/03	21	3	3	1	2	22	19	11	7	2	2	2
15	DBSP03/04	6	19	19	20	19	9	10	8	17	19	17	17
16	DBSP03/10	13	15	13	13	10	15	8	8	12	13	13	13
17	DBSP03/11	17	20	21	15	13	9	17	22	19	12	11	11
18	DBSP03/12	9	6	7	11	11	2	2	5	4	18	14	14
19	DBSP03/16	8	5	5	9	15	6	1	4	3	14	15	16
20	DBSP03/17	19	7	6	4	4	19	19	19	10	3	5	5
21	DBSP03/18	4	8	8	12	16	2	5	1	13	21	19	18
22	DBSP03/19	16	2	2	3	3	18	15	6	2	6	3	3
23	DBSP03/20	2	13	12	17	20	6	8	3	5	16	18	19

Y= mean grain yield across 12 environments, $S_i^{(1)}$, $S_i^{(2)}$, $S_i^{(3)}$ and $S_i^{(4)}$ are Nassar and Huehn [4] nonparametric stability statistics, TOP, MID and LOW are parameters of Fox *et al.* [8], R_sum is Kang's [7] parameter, $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ are parameters of Thennarasu [9]

Table 4: Spearman's rank correlation coefficients between the different nonparametric stability parameters for grain yield of 23 durum wheat genotypes evaluated across 12 environments. Significance probability levels are given in brackets

	Y	$S_i^{(1)}$	$S_i^{(2)}$	$S_i^{(3)}$	$S_i^{(6)}$	TOP	LOW	R_sum	$Np_i^{(1)}$	$Np_i^{(2)}$	$Np_i^{(3)}$
$S_i^{(1)}$	-0.33										
$S_i^{(2)}$	-0.33	0.99**									
$S_i^{(3)}$	-0.74**	0.87**	0.87**								
$S_i^{(6)}$	-0.87**	0.72**	0.73**	0.95**							
TOP	0.91**	-0.36	-0.39	-0.73**	-0.85**						
LOW	0.79**	0.05	0.06	-0.38	-0.53**	0.79**					
R_sum	0.52*	0.47*	0.50*	0.09	-0.13	0.38	0.63**				
$Np_i^{(1)}$	-0.11	0.83**	0.86**	0.63**	0.49*	-0.17	0.31	0.61**			
$Np_i^{(2)}$	-0.87**	0.57**	0.59**	0.86**	0.91**	-0.89**	-0.63**	-0.25	0.43*		
$Np_i^{(3)}$	-0.91**	0.61**	0.62**	0.90**	0.96**	-0.91**	-0.65**	-0.21	0.43*	0.95**	
$Np_i^{(4)}$	-0.90**	0.61**	0.63**	0.89**	0.96**	-0.90**	-0.64**	-0.20	0.43*	0.95**	99**

* and ** significant at $P<0.05$ and 0.01, respectively

Y= mean grain yield across 12 environments, $S_i^{(1)}$, $S_i^{(2)}$, $S_i^{(3)}$ and $S_i^{(4)}$ are Nassar and Huehn [4] nonparametric stability statistics, TOP, MID and LOW are parameters of Fox *et al.* [8], R_sum is Kang's [7] parameter, $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ are parameters of Thennarasu [9]

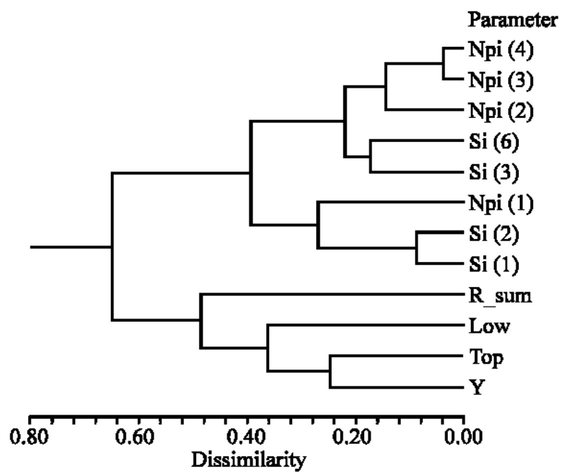

Fig. 1: UPGMA method clustering of nonparametric stability statistics using yield performance data of durum wheat genotypes evaluated across 12 environments. Y= mean grain yield across 12 environments, $S_i^{(1)}$, $S_i^{(2)}$, $S_i^{(3)}$ and $S_i^{(4)}$ are Nassar and Huehn [4] nonparametric stability statistics, TOP, MID and LOW are parameters of Fox *et al.* [8], R_sum is Kang's [7] parameter, $NP_i^{(1)}$, $Np_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ are parameters of Thennarasu

Huehn's [4] parameters, smallest values indicate maximum stability. Based on the estimates of $NP_i^{(1)}$, G12 and G22 had the lowest values (Table 2) and hence, were the most stable (Table 3). G1 on the other hand had the highest value (Table 2) and thus was the most undesirable one (Table 3). On the basis of $NP_i^{(2)}$, however, G5 was the most stable while G1 was still the most unstable one (Table 3). Estimates of $NP_i^{(3)}$ (Table 2) showed that G5, G14 and G22 were the most stable while G6 and G1 were the least stable ones (Table 3). The pattern of classifications of genotypes based on $NP_i^{(4)}$ was more similar to that of $NP_i^{(3)}$ (Table 3). Each one of the nonparametric stability statistics resulted in unique genotype ranking (Table 3). The associations of the different stability statistics were determined from Spearman's rank correlation analysis. The results are shown in Table 4. Mean grain yield performance across localities, was highly and positively correlated to stability parameter of Kang's R_sum ($r = 0.52$; $P<0.05$), as well as the TOP and LOW parameters of Fox *et al.* [8] ($P<0.01$). There were no association between yield and $S_i^{(1)}$, $S_i^{(2)}$ and $NP_i^{(1)}$ ($P>0.05$). However, classifications of genotypes based on $S_i^{(3)}$, $S_i^{(6)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ were significantly ($P<0.01$) but negatively correlated to ranking of genotypes based on mean yield across environments. $S_i^{(1)}$ and $S_i^{(2)}$ were perfectly ($r = 0.99$; $P<0.01$) correlated to each other. Their associations with the rest of stability measures were also significant and positive, except for the correlations with the LOW and TOP stability measures (Table 4). $S_i^{(3)}$ was correlated negatively only to TOP while $S_i^{(6)}$ was correlated negatively to both TOP and LOW. R_sum was positively correlated only to $S_i^{(1)}$, $S_i^{(2)}$ and LOW. The association between grain yield and all Thennarasu's [9] nonparametric measures, except for $NP_i^{(1)}$, were significant but negative (Table 4). Thennarasu's [9] nonparametric measures were positively correlated with each other and all Nassar and Huehns' [4] parameters (Table 4). $NP_i^{(1)}$ was also positively correlated to R_sum. All the other Thennarasu's nonparametric statistics were significantly but negatively associated to both LOW and TOP (Table 4). To better understand the relationships among nonparametric stability measures, cluster analysis were performed on the ranks of 23 genotypes based on the different stability statistics computed. Figure 1 showed three distinct groupings of stability parameters. At the bottom of the dendrogram, yield (Y), TOP, LOW and R_sum were grouped together. In the middle of the dendrogram, $S_i^{(1)}$, $S_i^{(2)}$ and $NP_i^{(1)}$ were grouped together. All the remaining parameters were clustered together at the top of the dendrogram.

DISCUSSION

The selection of high yielding genotypes with wider adaptation and stable performance in targeted agro-ecology remains an important goal in breeding programs. Plant breeders rely on stability parameters to assess their breeding lines across environments. According to Huehn [3], nonparametric stability analysis procedures have the following advantages: they reduce the bias caused by outliers, no assumptions are needed about the distribution of observed values, they are easy to use and interpret and additions or deletions of one or a few genotypes do not cause much variation of results. As a result, many researchers applied different nonparametric statistics to evaluate stability [2, 6, 13, 14]. The term stability is sometimes used to define a genotype that shows relatively constant yield, regardless of changes in environmental conditions. This idea of stability is often considered as a biological or static concept of stability [15]. However, most breeders and agronomists prefer genotypes with high mean yields and the potential to respond to improved management practices or environmental conditions. Huehn [3] suggested for a cultivar with maximum stability, $S_i^{(1)} = S_i^{(2} = S_i^{(3)}$. $S_i^{(1)}$ and $S_i^{(2)}$ are based on ranks of the genotypes across environments and they give equal weight to each environment. The $S_i^{(1)}$ estimates are based on all possible pair-wise rank differences across environments for each genotypes, whereas $S_i^{(2)}$ is based on the variance ranks for each genotype across environments [4]. In this experiment, classification of genotypes based on these parameters was similar. This agrees with the earlier findings [2, 6, 14]. According to Huehn [3] $S_i^{(1)}$ and $S_i^{(2}$ are functions only of the stability measurements whereas the numerical values of $S_i^{(3)}$ and $S_i^{(6)}$ combine yield and stability based on yield ranks of genotypes in each environment. The results of this experiment showed that these parameters were significantly (P<0.01) and positively correlated with each other. Flores *et al.*[16] also reported significant and positive association between $S_i^{(1)}$ and $S_i^{(2)}$. Scapim *et al.* [6] also found significantly high correlation among $S_i^{(1)}$, $S_i^{(2)}$ and $S_i^{(3)}$. This suggests that one of the three statistics could be used to assess stability. Nevertheless, none of these statistics were positively correlated to grain yield performance. Nassar and Huehn [4] indicated that $S_i^{(1)}$ and $S_i^{(2)}$ are associated with the static biological concept of stability, as they define stability in the sense of homeostasis. Sabaghnia *et al.* [2] also reported that $S_i^{(1)}$ and $S_i^{(2)}$ represent static concept of stability. Thus, $S_i^{(1)}$ and $S_i^{(2)}$ could be used as a compromise method that select genotypes with moderate yield and yield stability. Distinct clustering of $S_i^{(1)}$ and $S_i^{(2)}$ also confirms that these two nonparametric statistics can define stability in terms of static or biological concept and hence would have little relevance in selecting genotypes that can respond to changing environmental conditions. Stability analysis of genotypes based on $S_i^{(3)}$ and $S_i^{(6)}$ were similar (Table 3). These parameters were strongly correlated to Thennarasu's nonparametric statistics. However, they were found to be inversely related to high yield performance. Moreover, these two statistics were grouped together along the $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ in the cluster analysis, indicating that this group of parameters can define stability in dynamic concept. Sabaghnia *et al.* [2] also found similar association between $S_i^{(3)}$, $S_i^{(6)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ and pattern of grouping based on principal component analysis. Thennarasu's nonparametric stability statistics uses ranks from adjusted yield. According to these procedures, stable genotypes are those whose adjusted ranks remain unaltered in relation to the other in the set of localities assessed. $NP_i^{(3)}$ and $NP_i^{(4)}$ express stability in units of mean ranks, therefore they are very much related to $S_i^{(3)}$ and $S_i^{(6)}$. The correlations between $S_i^{(3)}$, $S_i^{(6)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ were very strong (*P*<0.01). Moreover, these parameters were grouped in the same cluster (Fig. 1). These suggest that Thennarasu's nonparametric stability estimates did not add important information to those statistics obtained by Nassar and Huehn [4]. Thus, the use of Huehn [3] stability parameters could be a method of choice as there is a statistical procedure available to test the significance of $Si^{(1)}$ and $S_i^{(2)}$. However, Thennarasu's [9] nonparametric stability estimates would be important alternatives to parametric models. The association between R_sum, LOW, TOP and yield were positive. Cluster analysis also showed that these parameters were grouped together. This underlines that these statistics could define stability in dynamic (agronomic) concept. Flores *et al*. [16] also pointed out TOP could be used to select genotypes with both high yield and stability. Sabaghnia *et al.* [2] also reported that these parameters were grouped together and thus can be used to define stability in dynamic concept. Kang and Pham [17] noted that the rank sum (R_sum) methods related with high yield performance and therefore this stability parameter defines stability with dynamic (agronomic) concept. In conclusion, nonparametric stability measurements seem to be useful under conditions where the basic assumptions of parametric stability measurements are not met. However, many of the available statistics define stability in its homeostasis term and thus they do not provide information about the genotype adaptability.

REFERENCES

1. Hussein, M.A., A. Bjornstad and A.H. Astveit, 2000. SASG X ESTAB: A SAS program for computing genotype x environment stability statistics. Agron. J., 92: 454-459.
2. Sabaghnia, N., H. Dehghani and S.H. Sabaghpour, 2006. Nonparametric methods for interpreting Genotype X Environment Interaction of lentil genotypes. Crop Sci., 46: 1100-1106.
3. Huehn, M., 1990. Non-parametric measures of phenotypic stability: Part 1. Theory. Euphytica, 7: 189-194.
4. Nassar, R. and M. Huehn, 1987. Studies on estimation of phenotypic stability: Tests of significance for non-parametric measures of phenotypic stability. Biometrics, 43: 45-53.
5. Huehn, M. and R. Nassar, 1989. On tests of significance for non-parametric measures of phenotypic stability. Biometrics, 45: 997-1000.
6. Scapim, C.A., V.R. Oliveira, A.L. Braccini, C.D. Cruz, C.A.B. Andrade and M.C.G. Vidigal, 2000. Yield stability in maize (*Zea mays* L.) and correlations among the parameters of the Eberhart and Russell, Lin and Binns and Huehn models. Genet. Mol. Biol., 23: 387-393.
7. Kang, M.S., 1988. A rank-sum method for selecting high yielding, stable corn genotypes. Cereal Res. Com., 16: 113-115.
8. Fox, P.N., B. Skovmand, B.K. Thompson, H.J. Braun and R. Cormier, 1990. Yield and adaptation of hexaploid spring triticale. Euphytica, 47: 57-64.
9. Thennarasu, K., 1995. On certain non-parametric procedures for studying genotype–environment interactions and yield stability. PhD. Thesis. P.J. School, IARI, New Delhi, India.
10. Shukla, G.K., 1972. Some aspects of partitioning genotype by environmental components of variability. Heredity, 28: 237-245.
11. Duarte, J.B. and M.J. Zimmermann, 1995. Correlation among yield stability parameters in common bean. Crop Sci., 35: 905-912.
12. SAS Institute, 1999. SAS/STAT user's guide. 8 Version. SAS Institute Inc. Cary, NC.
13. Kaya, Y. and S. Taner, 2002. Estimating genotypes ranks by nonparametric stability analysis in bread wheat (*Triticum aestivum* L.). Journal of Central European Agriculture, 4: 47-53.
14. Kaya, Y., S. Taner and S. Ceri, 2003. Nonparametric stability analysis of yield performances in Oat (*Avena sativa* L.) genotypes across environments. Asian Journal of Plant Sciences, 3: 286-289.
15. Becker, H.C. and J. Leon, 1988. Stability analysis in plant breeding. Plant Breed., 101: 1-23.
16. Flores, F, M.T. Moreno and J.I. Cubero, 1998. A comparison of univariate and multivariate methods to analyze environments. Field Crops Res., 56: 57-64.
17. Kang, M.S. and H.N. Pham, 1991. Simultaneous selection for high yielding and stable crop genotypes. Agronomy Journal, 83: 161-165.