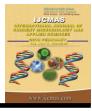


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### **Original Research Article**

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## Parametric vis-à-vis Non Parametric Measures to Describe G × E Interactions for Fodder Yield of Dual Purpose Barley Genotypes Evaluated under MET

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## ABSTRACT

#### Keywords

Dual purpose barley, Parametric and nonparametric measures of G x E interaction, Hierarchical clustering

**Article Info** 

Accepted: 04 January 2018 Available Online: 10 February 2018 estimate GxE by parametric and non-parametric measures. Highly significant differences among genotypes, environments and G x E interaction were observed. Wide variation seen genotypes average yield and G10, G12, and G4 were high yielder genotypes. Value of  $b_i > b_i$ 1 resulted for G12, G10, G11, G5, and G8 besides  $b_i < 1$  for G12. Measures  $W_i^2$  and  $\sigma_i^2$ pointed towards G15, G13, G6, G4 as desirable genotypes. GAI identified G10, G4, G13, G12 while Pi marked G12, G4, G13 genotypes with stable performance. Lower values of Environmental variance favored G15, G13, and G6. Coefficient of variation observed consistent performance of G15, G13, G9, G6.  $S_i^{(1)}$  and  $S_i^{(2)}$  measures marked G15, G13 genotypes whereas  $S_i^{(3)}$  and  $S_i^{(6)}$  found G15 followed by G13, G7 and G14 were stable performance. NP<sub>i</sub><sup>(1)</sup> recognized G10 followed by G1 and G5 were stable as compared to other.  $NP_i^{(2)}$ ,  $NP_i^{(3)}$  and  $NP_i^{(4)}$ , observed stable yield of G7 followed by G14, G9, and G15. Kang's rank-sum measure indicated lower values for G13, G4, and G15. Non-parametric measures isolated G10, G1 and G2 for unstable yield realization. Significant positive correlation of yield with GAI,  $P_i$  & Kang's rank-sum while negative with  $S_i^{(3)}$ ,  $S_i^{(6)}$ ,  $NP_i^{(2)}$ ,  $NP_i^{(3)}$ ,  $NP_i^{(4)}$ . Positive relation maintained  $S_i^{(s)}$ , among themselves.  $NP_i^{(s)}$  explained both type of relationships with each other. Biplot analysis based on first two principal components clustered measures of G x E into 3 major groups by. Larger group comprised of CV<sub>i</sub>, Kang,  $S_i^{(1)}$ ,  $S_i^{(2)}$ ,  $W_i^2$  and  $\sigma_i^2$  while GAI along with P<sub>i</sub> separated in other group. Ward's method clustered Yield, GAI, Pi and Kang measures together. Non parametric  $NP_i^{(2)}$ ,  $NP_i^{(3)}$ ,  $NP_i^{(4)}$  bonded with  $S_i^{(3)}$ ,  $S_i^{(6)}$ . Parametric measures of  $CV_i$ ,  $W_i^2$ ,  $\sigma_{i}^2$ ,  $S_{xi}^2$  joined hands with  $S_i^{(1)}$ ,  $S_i^{(2)}$ .

Fifteen dual purpose barley genotypes were evaluated at ten major growing locations to

### Introduction

Number of approaches has been proposed to understand genotype x environment interaction (Vaezi *et al.*, 2017). Common method is to simplify the environment component of the GxE and characterize the environments as by the average yield of the genotypes (Dehghani *et al.*, 2016). Linear regression models can then be fitted with the yield of every genotype at each environment and the average yield of the set of genotypes at each environment. This method, called Finlay–Wilkinson regression (Finlay and Wilkinson, 1963), is widely used to characterize the yield response to good environments of a set of genotypes. However, it allows only one type of environment characterization based on average yield.

The mostly used, classical parametric approaches for an analysis of genotype x environment interaction are based on several assumptions: normality of the distribution, homogeneity of variances and additive nature of effects (Khalili and Pour-Aboughadareh, 2016). If some of mentioned assumptions are not fulfilled, the validity of these methods may be questionable (Ahmadi et al., 2016). By use of nonparametric methods, which are simple and easy for analysis, all of the mentioned assumptions are avoided (Sisay and Sharma, 2016).

Most widely used measures are regression coefficient (b<sub>i</sub>) (Finlay and Wilkinson 1963), Environmental variance  $(S_{xi}^2)$  (Becker and Leon 1988; Lin et al., 1986), Shukla variance  $\sigma_{i}^{2}$  (1966), Wricke's ecovalence ( $W_{i}^{2}$ ) (Wricke 1962) and the Coefficient of variability  $(CV_i)$ (Francis and Kannenberg 1978), Superiority Measure P<sub>i</sub> (Lin and Binns 1988) and Geometric adaptability index GAI (Mohammadi and Amri, 2008). Several nonparametric procedures proposed by Hu"hn (1990), Nassar and Huehn (1987), Kang (1988) and Thennarasu (1995) measures based on the ranks of genotypes in each environment and genotypes with similar ranking across environments were classified as stable. Objectives of the present study were (1) use parametric and nonparametric methods to analyze genotype x environment interaction (2) identify better adaptive dual purpose barley genotypes for fodder yield across environments, and (3) to point out similarities/ dissimilarities among the parametric and nonparametric measures.

## Materials and Methods

Promising fifteen dual purpose barley genotypes were evaluated in field trials at ten major growing locations of the country i.e. Hisar. Durgapura, Ludhiana, Varanasi, Kanpur, Faizabad, Rewa, Kota, Udaipur and Jabalpur during the cropping seasons of 2016-Experiments were laid 2017. out as randomized complete block design with four Recommended agronomical replications. practices were followed to harvest the good crop. The fodder yield of genotypes were further analysed to describe gxe interactions by parametric and non-parametric measures.

SASGESTAB (Hussein et al.. 2000) employed to calculate nonparametric measures. Rank correlation was calculated to study the relationship among the measures using SAS software version 9.3 and principal component analysis (PCA) were performed by JMP version 9 (2016) software to comprehend the relationships in much detailed. Ward's (1963) method was exploited for hierarchical classification of genotypes and measures via Euclidean distance.

## **Results and Discussion**

Analysis of variance showed the highly significant effects of genotypes, environments and G x E interaction. Wide variation observed among yield from 120 to 174 g/ha and seven genotypes had realized yield more than average yield of 147.48 g/ha as G10, G12, and G4 were higher yielder while G5 and G7 observed as lowest vielder across ten environments (Table 2). Genotypes G12, G10, G11, G5 and G8 with  $b_i > 1$  had the yield performance more than average yields and were adapted to the favorable environments; while G12 with  $b_i < 1$  and the lower yields were poorly adapted to the environments. Wricke's ecovalance  $(W_i^2)$  and Shukla's variance  $(\sigma^2_i)$  pointed towards G15, G13, G6,

G4 as desirable genotypes. GAI similar to yield identified G10, G4, G13, G12 while  $P_i$  marked G12, G4, G13 genotypes with stable performance. More over lower values of Environmental variance ( $S_{xi}^2$ ) selected G15, G13 and G6. Consistent performance of G15, G13, G9, G6 judged by lower values of CV<sub>i</sub>.

Significant tests of non-parametric measures based on ranks of genotypes  $S_i^{(1)}$  and  $S_i^{(2)}$  were conducted as suggested by Nassar and Huehn (1987). Individual  $Z_1$  and  $Z_2$  for genotypes were calculated and summed over to obtain  $Z_1$ = 26.68 and  $Z_2$  = 21.27 (Table 2). These values were less than the significant value of  $\chi^2$  (0.01, 15) = 30.6.

This proved the non-significant difference in rank stability among the 15 genotypes grown in 10 environments. Two out of fifteen genotypes showed significantly large values as compared to  $\chi^2$  (0.05, 1) = 3.84 this proved the unstable behavior of G13, G15. S<sub>i</sub><sup>(1)</sup> and S<sub>i</sub><sup>(2)</sup> measures marked G15, G13 genotypes with lower rank. S<sub>i</sub><sup>(3)</sup> and S<sub>i</sub><sup>(6)</sup> found line G15 followed by G13, G7 and G14 were stable, while G10, G2, and G12 would be with lower stability.

Thennarasu's non-parametric measures calculated from the ranks of adjusted yield are given in table 2 and their ranks presented in table 3.  $NP_i^{(1)}$  recognized G10 followed by G1 and G5 were stable as compared to other at the same times G2, G12 and G15 with the higher values.

As per NP<sub>i</sub><sup>(2)</sup>, NP<sub>i</sub><sup>(3)</sup> and NP<sub>i</sub><sup>(4)</sup>, G7 followed by G14, G9, and G15 had the lower values for stable behaviour. The unstable performance of G10 followed by G12 and G1 based on these measures. Kang's rank-sum measure indicated G13, G4, G15 with the lower values and G5, G7 with higher values for unstable yield. All non-parametric measures identified G10, G1 and G2 for unstable yield realization.

### Association among measures

Spearman's rank correlation (Piepho and Lotito, 1992) values were depicted in table 4. Significant positive correlation of yield with GAI,  $P_i$  and Kang's rank-sum while negative with  $S_i^{(3)}$ ,  $S_i^{(6)}$ ,  $NP_i^{(2)}$ ,  $NP_i^{(3)}$ ,  $NP_i^{(4)}$  (Sisay and Sharma 2016). GAI showed similar behavior as positive with  $P_i$ , Kang's rank-sum while negative with  $S_i^{(3)}$ ,  $S_i^{(6)}$ ,  $NP_i^{(2)}$ ,  $NP_i^{(3)}$ ,  $NP_i^{(4)}$ .  $W_i^2$  and  $\sigma_i^2$  maintained the positive values of correlation with most of measures except  $b_i$  and  $NP_i^{(1)}$ .

Worth to mention, the positive correlation of  $S_{xi}^2$  with all measures except negative with  $b_i$ and  $NP_i^{(1)}$ .  $CV_i$  exhibited inverse with  $b_i$  and NP<sub>i</sub><sup>(1)</sup> only. Regression coefficient bi maintained negative correlation with all measures though the degree varies. P<sub>i</sub> showed positive correlation with  $S_i^{(1)}$ ,  $S_i^{(2)}$ , Kang. Nassar and Huehn's measures S<sub>i</sub><sup>(s)</sup>, maintained positive relation among themselves. Thennarsu's measures NP<sub>i</sub><sup>(s)</sup> explained both type of relationships with each other (Dehghani et al., 2016).

## Ward's hierarchical analysis

Multivariate hierarchical cluster analysis based on the ranks of fodder yield and gxe measures was performed by Ward's methods. Genotypes were separated into three clusters as depicted in Dendrogram generated by this analysis (Figure 2).

The first cluster (I) comprised the higher yielding RD2035, RD2715, RD2954 as well as relatively unstable genotypes as per non parametric measures (Vaezi *et al.*, 2017). Second cluster included the lower yielder with stable performance UB1064, UPB1066 and KB1527. Finally, UPB1065, RD2952, RD2552, Azad, and KB1530 with moderate yields and good level of adaptability were placed into the third cluster.

## **Parametric measures**

Finlay and Wilkinson (1963) linear regression coefficient bi	$b_{i} = 1 + \frac{\sum_{j} (X_{ij} - X_{i}, -X_{j} + X_{i}) (X_{i} - X_{i})}{\sum_{j} (X_{i} - X_{i})^{2}}$	bi > 1 are better adapted to favourable environmental condi- tions. bi < 1, perform better in low yielding environments. bi = 1, for average adaptability to environments.
Lin <i>et al.</i> , (1986) Environmental variance	$S_{xi}^{z} = \frac{\sum (X_{ij} - X_{i})^{z}}{(E-1)}$	Genotype with minimum variance considered to be more stable
Shukla's variance (1966) $\partial_i^*$	$\hat{\sigma}_{i}^{z} = \frac{1}{(G-1)(G-2)(E-2)} \left[ G(G-1) \sum_{j} (X_{ij} - X_{i} - X_{j} + \overline{X}_{j})^{z} - \sum_{i} \sum_{j} (X_{ij} - \overline{X}_{i} - \overline{X}_{j} + \overline{X}_{j})^{z} \right]$	Large value associated with instability of genotype
Lin and Binns (1988) Superiority index (P <sub>i</sub> )	$P_i = \frac{\sum_{j=1}^{n} (X_{ij} - M_j)^2}{2E}$	Genotypes with the largest yield difference in comparison to the reference genotype would have the highest Pi-value
Wricke's ecovalence (1962) W <sup>2</sup> <sub>i</sub>	$W_{i}^{z} = \sum (X_{ij} - \bar{X}_{i} - \bar{X}_{i} + \bar{X}_{i})^{z}$	$\begin{array}{ll} \text{Greatest} & \text{stability} \\ \text{associated with } W^2_i = 0. \end{array}$
FrancisandKannenberg(1978)Coefficientofvariation (CV <sub>i</sub> )	$CV_i = (S_{Xi} / \overline{X}_i) \ge 100$	Low CVs and high average yields were considered as the most desirable one
Mohammadi and Amri (2008) Geometric adaptability index (GAI)	$GAI = \sqrt[n]{\prod_{i=1}^{n} \overline{X}_{i}}$	Genotypes with high GAI will be desirable

# Non-parametric measures

Nassar and Huehn (1987)	$S_{i}^{(0)} = \frac{z z_{i}^{(-1)} z_{i}^{(-1)} z_{i}^{(-1)} z_{i}^{(-1)} z_{i}^{(-1)}}{(-())!}$	S <sub>i</sub> <sup>(1)</sup> mean of the absolute rank differences of a genotype over the n environments,
	$S_{i}^{(2)} = \frac{z_{i}^{m_{2}} (\tau_{i} - \tau_{i})^{-1}}{(m^{-1})}$	$S_{i} \ ^{\left( 2 \right)}$ variance among the ranks over the n environments
	$S_i^{(2)} = \frac{\sum_{j=1}^m (r_{ij} - \bar{r}_i)^2}{\bar{r}_i}$	$S_i^{(3)}$ sum of the absolute deviations for each genotype relative to the mean of ranks and
	$S_i^{(\bullet)} = \frac{\Sigma_{i=1}^m [\tau_{ij} - \tilde{\tau}_i]}{\tau_i}$	S <sub>i</sub> <sup>(6)</sup> sum of squares of rank for each genotype relative to the mean of ranks
Thennarasu's (1995)	$NP_i^{(1)} = \frac{1}{m} \sum_{j=1}^m  r_{ij}^* - M_{di}^* $	$r_{ij}^*$ was the rank of $Y_{ij}^*$ , and $\overline{r}_a$ and $M_{di}$ were the mean and median ranks for original, where $\overline{r}_a^*$ and $M_{di}^*$ were the same parameters computed from the corrected yield values.
	$NP_i^{(2)} = \frac{1}{m} \left( \frac{\Sigma_{i=1}^m  \pi_{i}^* - M_{2i}^* }{M_{2i}} \right)$	
	$NP_i^{(2)} = \frac{\sqrt{1}(\tau_{ij}^* - \tau_i^*)^{2/m}}{\tau_i}$	
	$NP_{i}^{(4)} = \frac{z}{m(m-1)} \left[ \sum_{j=1}^{m-1} \sum_{j=j+1}^{m} \frac{ \tau_{ij}^{*} - \tau_{ij}^{*} }{\tau_{i}} \right]$	
Kang's rank sum (1988)	Combines yield and Shukla's stability variance into one statistic.	Highest yielder assigned rank of 1, lowest variance got rank of 1. Ranks for yield and variance are summed as genotype with lowest rank would be desirable

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Code	Genotype	Parentage	Code	Environments	Latitude	Longitude	Altitude (m)
G 1	RD2953	RD2552/RD2786	E 1	Hisar	29°10'N	75° 46'E	215.2
G 2	JB348	DL88/BG105	E 2	Durgapura	26°51'N	75°47' E	390
G 3	AZAD	K12/K19	E 3	Ludhiana	30°54' N	75°52' E	247
G 4	RD2951	RD2552/RD2743	E 4	Varanasi	25° 20' N	83°03'E	75.5
G 5	UBP1066	IBYT-HI-11 (2013-14)	E 5	Kanpur	26°29'N	80°18'E	125.9
G 6	RD2552	RD2035/DL472	E 6	Faizabad	26°47' N	82°12' E	113
G 7	UPB1064	1st GSBSN-80 (2013-14)	E 7	Rewa	24° 31' N	81° 15' E	365.7
G 8	NDB1660	1st GSBSN-19 (2013-14)	E 8	Kota	25° 21' N	75° 86' E	259.7
G 9	KB1530	EIBGN-68 (2014-15)	E 9	Udaipur	24° 34' N	70°42'E	582
G 10	RD2715	RD387/BH602//RD2035	E 10	Jabalpur	23°90' N	79° 58' E	394
G 11	RD2954	RD2808/ RD2743					
G 12	RD2035	RD103/PL101					
G 13	UPB1065	IBYT-HI-16 (2012-13)					
G 14	KB1527	PL 816/K 551					
G 15	RD2952	RD2552/RD2743					

## Table.1 Parentage details and environmental conditions

## Table.2 Parametric vis-à-vis non - parametric measures of G x E interactions

		Yield	GAI	W <sub>i</sub> <sup>2</sup>	$\sigma^{2}_{i}$	S <sup>2</sup> <sub>xi</sub>	CVi	b <sub>i</sub>	Pi	S <sub>i</sub> <sup>(1)</sup>	Ζ1	<b>S</b> <sub>i</sub> <sup>(2)</sup>	Ζ2	S <sub>i</sub> <sup>(3)</sup>	S <sub>i</sub> <sup>(6)</sup>	NP <sub>i</sub>	NP <sub>i</sub> <sup>(2)</sup>	NP <sub>1</sub> <sup>(3)</sup>	NP <sub>i</sub> <sup>(4)</sup>
																			ı
G 1	RD2953	154.18	140.60	20256.94	2497.84	2300.73	31.11	1.00	2553.19	6.11	1.7999	28.32	3.0148	35.90	6.65	6.40	1.42	0.7453	0.9264
G 2	JB348	138.03	129.20	7941.63	918.95	981.71	22.70	1.02	2929.25	5.62	0.5820	25.88	1.6815	25.59	4.68	11.50	1.00	0.4965	0.5690
G 3	AZAD	142.90	132.93	6959.92	793.09	796.61	19.75	1.02	2260.29	4.60	0.2000	15.43	0.3381	15.26	3.21	7.00	0.78	0.4584	0.5763
G 4	RD2951	159.96	146.94	5347.90	586.42	767.23	17.32	1.02	1213.92	4.71	0.0997	16.00	0.2300	20.57	4.86	8.50	1.31	0.6459	0.8190
G 5	UBP1066	120.70	111.09	32926.27	4122.11	4455.24	55.30	0.98	5521.39	5.73	0.8000	24.67	1.1641	22.20	4.20	6.46	0.59	0.5815	0.7000
G 6	RD2552	143.24	132.31	5291.29	579.17	607.92	17.21	1.03	2401.89	5.00	0.0007	17.88	0.0201	17.68	3.63	9.00	0.95	0.4559	0.5788
G 7	UPB1064	121.50	109.58	9778.59	1154.46	1836.20	35.27	0.99	3973.54	4.49	0.3349	16.00	0.2300	13.09	3.09	8.00	0.62	0.4111	0.5111
G 8	NDB1660	143.43	135.58	6069.43	678.93	692.60	18.35	0.98	2414.61	4.69	0.1170	15.39	0.3474	16.29	3.76	8.00	0.89	0.4682	0.5908
G 9	KB1530	147.26	138.99	5694.57	630.87	632.78	17.08	1.02	2183.56	4.36	0.5425	13.38	0.9045	14.33	3.67	7.00	0.88	0.4437	0.5582
G 10	RD2715	174.00	161.49	20745.07	2560.42	3086.55	31.93	0.98	1888.91	3.56	2.8345	18.18	0.0077	51.13	7.88	5.80	2.90	1.2283	1.4514
G 11	RD2954	155.08	140.86	14137.03	1713.23	1634.95	26.07	0.98	2067.67	4.13	0.9993	14.62	0.5290	22.69	4.76	6.56	1.46	0.6624	0.8199
G 12	RD2035	167.81	146.48	15113.79	1838.46	2138.77	27.56	0.96	1044.99	5.82	0.9993	24.27	1.0141	33.09	6.36	9.50	1.73	0.7509	0.9293
G 13	UPB1065	154.95	146.82	2946.68	278.57	389.45	12.74	1.02	1487.75	2.53	8.3734	5.78	5.3719	7.43	2.00	9.00	1.29	0.4686	0.5714
G 14	KB1527	139.87	132.30	7938.75	918.58	946.36	21.99	1.01	2944.93	4.31	0.6228	14.00	0.7042	14.00	3.11	7.50	0.75	0.4310	0.5358
G 15	RD2952	149.27	139.28	1348.01	73.62	153.34	8.30	1.01	1587.99	2.53	8.3734	5.38	5.7105	5.63	1.86	9.50	1.12	0.2408	0.2972
										Sum =	26.68		21.27		$\chi^2$	=3.84	$\chi^2$	=6.63	
															(0.05,1)		(0.01,1)		
E(s1) =		4.98		V(s 1) =	0.7136										$\chi^2$	=25.0	$\chi^2$	=30.6	
															(0.05,15)		(0.01,15)		
E(s 2) =		18.67		V(s 2) =	30.92														

 $S_i^{(1)}$  average absolute rank dispersion of a genotype over environments,  $S_i^{(2)}$  variance among the ranks over environments,  $Z_1$  and  $Z_2$  the standard values of  $S_i^{(1)}$  and  $S_i^{(2)}$  respectively, for  $\chi^2$  test,  $S_i^{(3)}$  and  $S_i^{(6)}$  the sum of absolute deviations and sum of squares of ranks for each genotype relative to the mean of ranks respectively, NP nonparametric stability parameters

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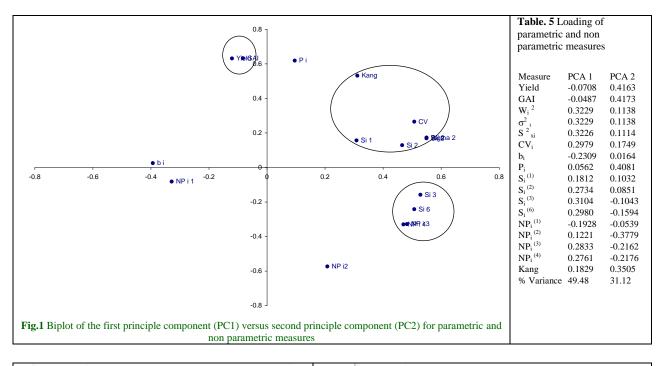
		Yield	GAI	$W_i^2$	$\sigma^{2}_{i}$	S <sup>2</sup> <sub>xi</sub>	CVi	b <sub>i</sub>	Pi	S <sub>i</sub> <sup>(1)</sup>	S <sub>i</sub> <sup>(2)</sup>	S <sub>i</sub> <sup>(3)</sup>	S <sub>i</sub> <sup>(6)</sup>	NP <sub>1</sub> <sup>(1)</sup>	NP <sub>i</sub> <sup>(2)</sup>	NP <sub>i</sub> <sup>(3)</sup>	NP <sub>i</sub> <sup>(4)</sup>	Kang	SRT
G 1	RD2953	6	6	13	13	13	12	7	11	15	15	14	14	2	12	13	13	11	190
G 2	JB348	13	13	9	9	9	9	13	12	12	14	12	10	15	8	9	5	13	185
G 3	AZAD	11	10	7	7	7	7	10	8	8	7	6	5	6	4	6	7	10	126
G 4	RD2951	3	2	4	4	6	5	12	2	10	9	9	12	10	11	11	11	2	123
G 5	UBP1066	15	14	15	15	15	15	4	15	13	13	10	9	3	1	10	10	15	192
G 6	RD2552	10	11	3	3	3	4	15	9	11	10	8	6	12	7	5	8	5	130
G 7	UPB1064	14	15	10	10	11	14	6	14	7	9	3	3	9	2	2	2	14	145
G 8	NDB1660	9	9	6	6	5	6	5	10	9	6	7	8	9	6	7	9	9	126
G 9	KB1530	8	8	5	5	4	3	11	7	6	3	5	7	6	5	4	4	5	96
G 10	RD2715	1	1	14	14	14	13	2	5	3	11	15	15	1	15	15	15	9	163
G 11	RD2954	4	5	11	11	10	10	3	6	4	5	11	11	4	13	12	12	9	141
G 12	RD2035	2	4	12	12	12	11	1	1	14	12	13	13	14	14	14	14	6	169
G 13	UPB1065	5	3	2	2	2	2	14	3	2	2	2	2	12	10	8	6	2	79
G 14	KB1527	12	12	8	8	8	8	9	13	5	4	4	4	7	3	3	3	12	123
G 15	RD2952	7	7	1	1	1	1	8	4	2	1	1	1	14	9	1	1	3	63

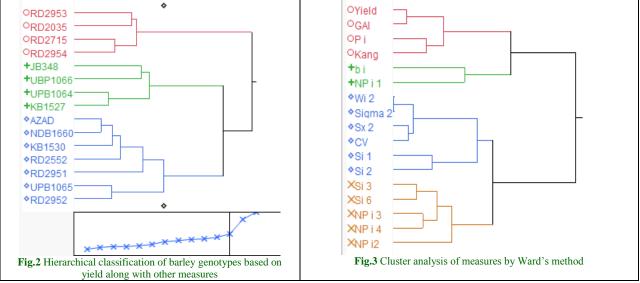
## Table.3 Ranking of genotypes by parametric vis-à-vis non parametric measures

## Table.4 Association analysis among measures

	Yield	GAI	$W_i^2$	$\sigma^{2}_{i}$	S <sup>2</sup> <sub>xi</sub>	CVi	bi	Pi	S <sub>i</sub> <sup>(1)</sup>	S <sub>i</sub> <sup>(2)</sup>	S <sub>i</sub> <sup>(3)</sup>	Si <sup>(6)</sup>	NP <sub>i</sub> <sup>(1)</sup>	<b>NP</b> <sup>(2)</sup>	$NP_i^{(3)}$	<b>NP</b> <sup>(4)</sup>
GAI	0.9750															
$W_i^2$	0.0286	0.0929														
σ <sup>2</sup> ι	0.0286	0.0929	1.0000													
S <sup>2</sup> <sub>xi</sub>	0.0250	0.0821	0.9857	0.9857												
CVi	0.1714	0.2393	0.9536	0.9536	0.9714											
bi	0.2643	0.1643	-0.7250	-0.7250	-0.6857	-0.6679										
Pi	0.8679	0.8679	0.3714	0.3714	0.3536	0.4786	0.0107									
<b>S</b> <sub>i</sub> <sup>(1)</sup>	0.2339	0.2875	0.4268	0.4268	0.4554	0.4304	-0.0339	0.3125								
<b>S</b> <sub>i</sub> <sup>(2)</sup>	0.0946	0.1482	0.6911	0.6911	0.7375	0.7125	-0.2268	0.3196	0.8214							
S <sub>i</sub> <sup>(3)</sup>	-0.3643	-0.2964	0.7250	0.7250	0.7179	0.6036	-0.4357	-0.0393	0.5696	0.7982						
<b>S</b> <sup>(6)</sup>	-0.5000	-0.4429	0.6607	0.6607	0.6643	0.5286	-0.4607	-0.1643	0.5125	0.6946	0.9571					
NP <sub>i</sub> <sup>(1)</sup>	0.0393	0.0750	-0.6464	-0.6464	-0.6107	-0.5571	0.4214	-0.3286	0.0375	-0.2089	-0.4000	-0.4429				
<b>NP</b> <sup>(2)</sup>	-0.9143	-0.8643	0.1107	0.1107	0.1107	-0.0250	-0.2571	-0.7321	-0.0339	0.1482	0.5607	0.6107	-0.0071			
<b>NP</b> <sup>(3)</sup>	-0.6036	-0.5893	0.6214	0.6214	0.6250	0.4857	-0.4536	-0.3214	0.3839	0.5982	0.8857	0.9000	-0.3821	0.7107		
<b>NP</b> <sup>(4)</sup>	-0.6143	-0.5786	0.5786	0.5786	0.5750	0.4536	-0.5071	-0.3179	0.4089	0.5589	0.8571	0.8821	-0.4679	0.6571	0.9393	
Kang	0.6589	0.6911	0.7375	0.7375	0.7196	0.8018	-0.3232	0.8589	0.3750	0.5250	0.3018	0.1732	-0.3982	-0.4161	0.0696	0.0232

Critical values of correlation at 5% and 1% level of significance are 0.5549 and 0.6978 respectively





#### **Biplot analysis based on ranks**

Principle component analysis (PCA) was performed to study the relationships between the rankings of genotypes proposed from parametric and non-parametric measures. First two PCAs jointly explained 80.6 % (49.48 and 31.12 % by PCA1 and PCA 2, respectively) of the total variations (Table 5). The relationships among different measures were graphically displayed (Figure 1). Parametric and non-parametric measures of GxE interaction clustered into 3 major groups by Biplot analysis. Larger group I included the CV, Kang,  $S_i^{(1)}$ ,  $S_i^{(2)}$ ,  $W_i^2$  and  $\sigma_{i}^2$ , while separate group of GAI and Pi lied in separate quadrant (Khalili and Pour-Aboughadareh, 2016).

The PCAs axes separated the nonparametric of  $NP_i^{(3)}$ ,  $NP_i^{(4)}$ ,  $S_i^{(6)}$  with  $S_i^{(3)}$  in group III and the remaining measures scattered.

## **Clustering pattern of measures**

Ward's method was applied to judge the closeness, if any, among the parametric and non-parametric measures for this study (Figure 3). Yield, GAI, P<sub>i</sub> and Kang measures clustered together while bi combined with NP<sub>i</sub><sup>(1)</sup>. Non parametric based on corrected yield response NP<sub>i</sub><sup>(2)</sup>, NP<sub>i</sub><sup>(3)</sup>. NP<sub>i</sub><sup>(4)</sup> bonded with S<sub>i</sub><sup>(3)</sup>, S<sub>i</sub><sup>(6)</sup>. Parametric measures of CV<sub>i</sub>,  $W_i^2, \sigma_i^2, S_{xi}^2$  joined hands with S<sub>i</sub><sup>(1)</sup>, S<sub>i</sub><sup>(2)</sup>. This type of behavior is very well justified by high as well as significant correlation values (Table 4).

Measures of GxE interaction proved to supplement or complement each other for adaptability behavior of genotypes. Observations based on the correlation matrix and the PCA analysis confirmed the joint use of measures to assess the adaptability behavior. Genotypes G15 G13 showed scope for breeding program due to high fodder yield.

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