

Parametric and Non-parametric Procedures for Identifying Stable and Adapted Tropical Maize Genotypes in NLB Disease Infested Environments

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Abstract: Multi-locational trials are critical for establishing stable and adaptable genotypes across different geographic areas prior to considering commercial release. The stability and adaptation of 20 tropical maize hybrids in environments infected with Northern leaf blight disease were assessed using 12 parametric and 14 nonparametric parameters across five environments. The purpose of this research is to estimate the genotype-environment interaction (GEI) for grain yield in selected maize genotypes and to identify associated stability factors to aid in the rationalization of stability analysis in Multi-Environment Trial (MET) data used in breeding programs. Except for De Kroon and Van der Laan (1981), both the combined ANOVA and nonparametric tests of GEI showed significant differences across hybrids, as well as significant crossover and non-crossover interactions. This suggests differential genotypes responses to the test environments. Spearman correlation analysis revealed significant differences between many nonparametric and parametric parameters, indicating that the two may be utilized interchangeably. Additionally, the correlation matrix and principal component analysis results from parametric and nonparametric parameters demonstrated their potential to assess the responses of maize genotypes to changing environments. G13 and G20 appeared most phenotypically stable with associated high mean yield based on the high values expressed by most parametric and nonparametric parameters.

Keywords: Maize, Parametric, Non-Parametric, Genotypes, Environment, Multi-Environment Trial, Spearman Correlation, Principal Component Analysis

1. Introduction

Maize is third most economically important cereal crops after wheat and rice, and most widely cultivated cereal crop in sub-Saharan Africa. The Food and Agriculture Organization [1] reported that maize was cultivated on approximately 197 million hectares of land in the 2017 planting season, with about 1.1 billion tons of maize grain produced the same year. Maize performs well in diverse environments because of its wide genetic and morphological variability due to its cross-pollinated nature. However, maize productivity is being disrupted by pest and disease attack.

Among the major diseases affecting maize productivity is the Northern leaf blight (NLB) disease incited by the fungus *Exserohilum turcicum* (Pass.) Leonard and Suggs (syn. *Helminthosporium turcicum* Pass.). NLB disease infection can cause up to 100% reduction in grain yield depending on the variety and infection stage [2].

The phenotypic expression of a trait is a combined influence of the genotype and environment. A significant genotype-environment interaction (GEI) alters the relationship between phenotypic and genotypic values, resulting in bias in genetic effects and combining ability estimations for characteristics sensitive to environmental

variation. Such characteristics have a negligible response to selection [3]. Because the impacts of genotypes and environments are statistically non-additive, cultivar yield variation is environment dependent [3]. Thus, genotype selection based on average grain production in a particular environment will be less successful. The significance of GEI in cultivar evaluation and breeding programs have been demonstrated in virtually all major crops, including maize [4, 5]. Both parametric and nonparametric statistical techniques have been employed to identify stable and superior genotypes in stability investigations. The three concepts of stability (Type 1, 2, 3) analysis was proposed by [6, 7], they later introduced the type 4 stability analysis. Type 1 concept, also known as the static or biological concept of stability, is used to estimate quality traits and disease resistance and stress characters. Coefficient of determination (R_i^2), coefficient of variability (CV_i) and the genotypic variances across environments (S_{xi}^2) are reported as parameters used to define this kind of stability [8-10]. The Type 2 is called a dynamic or agronomic concept of stability [10]. A stable genotype does not vary from the general response to environments, allowing a predictable response. Stability variance (σ_i^2) and regression coefficient (b_i) can estimate type 2 stability [11, 12]. [10] reported Type 3 as part of the dynamic or agronomic stability concept. [13, 14] methods are used to describe type 3 stability. [13] employed regression coefficient (b_i) and deviation from regression (S^2d_i), and they reported that genotype is more stable if $b_i = 1$. [10] classified the stability techniques as dynamic based on GEI effects estimate. These include Wricke's ecovalence GEI partitioning [15] and Shukla's stability of variance [11] methods utilizing [12, 4] regression algorithms. Cultivar performance measure (P_i) and the within location variance (MSy/l) was proposed as type 4 [7, 16], where P_i of genotype i was defined as the mean square of the distance between genotype i and the genotype with the maximum response. Stability statistics, according to [17], provide an incomplete view of the response pattern. This is because responses of genotype to diverse environments are multivariate [6], while the stability indices are univariate. Cultivars with similar responses can be grouped and analysed easily using multivariate analysis [18, 19]. Additive Main effect and Multiplicative Interaction (AMMI) model is one of the multivariate techniques that combines genotype analysis of variance and the environment's main effects with principal component

analysis of the GEI [20, 21]. Besides parametric methods of stability analysis, nonparametric procedures have been used based on genotype ranking over environment and with environmental resistance as a stability estimate. Stable genotypes are those genotypes with similar rankings across environments. According to [22], stable genotypes are those whose position regarding other genotypes is not altered across test environments. [22] proposed four nonparametric statistics of phenotypic stability ($S_i^{(1)}$, $S_i^{(2)}$, $S_i^{(3)}$, and $S_i^{(6)}$) according to genotypes classification over environment. [23] recommended a nonparametric superiority estimate. Fox *et al.* (1990) employed a stratified ranking approach of the varieties over environment to estimate the percentage of locations where each variety occurred in the top, middle, and bottom third of the ranks, establishing the nonparametric estimates TOP, MID and LOW, correspondingly. As reported by [24, 25], rank-sum and simultaneous selection for yield and stability are the other nonparametric stability statistics that combine both yield and stability variance of [11] as selection criteria. These nonparametric statistics ascribe a weight of one to both yield and stability and facilitates the identification of high-yielding and stable genotypes. [26] suggested nonparametric statistics $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$, and $NP_i^{(4)}$ according to cultivars adjusted means ranking over environment. This study aims to (i) estimate genotype \times environment interaction (GEI) of grain yield in selected maize genotypes, and (ii) identify related stability parameters to rationalize stability analysis in Multi Environment Trial (MET) data in breeding programs.

2. Materials and Methods

2.1. Plant Materials

Twenty maize hybrids were selected based on good specific combining ability (SCA) of grain yield and varying response to NLB disease were selected for this study. (Table 2) [27]. The trial evaluation was carried out at the Teaching and Research Farms of the Federal University of Technology, Akure (FUTA; 7°15'N, 5°15'E, 370m altitude) and Obafemi Awolowo University, Ile-Ife (OAU; lat. 04°33'E, long. 08°28'N, 244m altitude), and an isolated experimental field of the National Cereal and Research Institute (NCRI, outstation) in the 2016 cropping season. In the 2017 cropping season, the evaluation was repeated at FUTA, and OAU.

Table 1. The ten (10) selected inbred lines used.

Number	Pedigree	Response to NLB disease infestation	Maturity group	Source
1	TZEEI 82	Susceptible	Extra-early	IITA
2	TZEEI 9	Susceptible	Extra-early	IITA
3	TZEEI 14	Moderately resistant	Extra-early	IITA
4	TZEEI 108	Resistant	Extra-early	IITA
5	TZEI 134	Susceptible	Early	IITA
6	TZEI 27	Moderately susceptible	Early	IITA
7	TZEI 9	Moderately susceptible	Early	IITA
8	TZEI 16	Moderately resistant	Early	IITA
9	TZEI 14	Resistant	Early	IITA
10	TZEI 10	Resistant	Early	IITA

Table 2. Genotype code, hybrid and origin of 20 maize genotypes.

Genotype code	Hybrid	Origin	Genotype code	Hybrid	Origin
G1	TZEEI 9 x TZEEI 108	Akure	G11	TZEI 27 x TZEI 16	Akure
G2	TZEEI 82 x TZEEI 108	Akure	G12	TZEI 9 x TZEI 14	Akure
G2	TZEEI 14 x TZEEI 108	Akure	G13	TZEI 16 x TZEI 10	Akure
G4	TZEEI 82 x TZEEI 14	Akure	G14	TZEI 9 x TZEI 10	Akure
G5	TZEEI 108 x TZEEI 108	Akure	G15	TZEEI 14 x TZEI 14	Akure
G6	TZEEI 14 x TZEI 27	Akure	G16	TZEI 134 x TZEI 16	Akure
G7	TZEEI 14 x TZEI 16	Akure	G17	TZEI 14 x TZEI 10	Akure
G8	TZEEI 14 x TZEI 9	Akure	G18	TZEEI 14 x TZEI 14	Akure
G9	TZEEI 14 x TZEI 134	Akure	G19	TZEEI 14 x TZEI 10	Akure
G10	TZEI 9 x TZEI 16	Akure	G20	TZEI 134 x TZEI 10	Akure

2.2. Experimental Design and Field Evaluation

A Randomized Complete Block Design (RCBD) with three replications was adopted in each test environment. A single row plot of 5m long with 75cm × 25cm intra-row and inter-row planting distance were used. Two seeds were planted per hill and thinned to one plant per stand at 21 days after planting (DAP) to achieve a plant population density of 53,333 plants per hectare in each test environment. Three border rows of local cultivars were planted on each side of the block. At one week after planting (1WAP), 7-day old *E. turcicum* conidia, with a spore concentration of 10⁶ CFU/ml, were used to infest the test plants, and each test plant was covered with a plastic bag for proper spore infectivity. NPK 15-15-15 was applied at 60 kg N, 60 kg P, and 60 kg K ha⁻¹ at 21 DAP, followed by top dressing with 60 kg N ha⁻¹ 2 weeks later. Gramazone and atrazine were sprayed for weed control at low pressure, using a 20L knapsack sprayer. Manual weeding was done as necessary. Seed yield data were collected from the middle rows of each plot for each genotype, across research locations, in each planting year. Grain yield was adjusted to 15% seed moisture content based on 80% shelling percentage.

2.3. Statistical Analysis

Analysis of variance (ANOVA) for Genotype × Environment interaction (GEI) was determined using three nonparametric statistical methods viz: [28-30], as described in the equation below. The parametric combined ANOVAF-test was carried out using Statistical Analysis System version 9.4 [31] following the procedure of SAS macro program developed by [32] for computing statistical tests for a two-way table and stability indices of a nonparametric method from GEI. The analysis of parametric and nonparametric statistical parameters was performed using GEA-R 4.1 [33] statistical tools and STABILITYSOFT software [34].

$$\frac{12}{\ln(N+1)} \sum_{i=1}^l \sum_{j=1}^m (\overline{R_{ij}^{**}} - \overline{R_{i..}^{**}} - \overline{R_{.j.}^{**}} + \overline{R_{...}^{**}})^2 \text{ (source: [28])}$$

$$\frac{12}{\ln(N+1)} \sum_{i=1}^l \sum_{j=1}^m (\overline{R_{ij}} - \overline{R_{i..}} - \overline{R_{.j.}} + \overline{R_{...}})^2 \text{ (source: [29])}$$

$$\frac{12}{n^2 l(nl+1)} \left(\sum_{i=1}^l \sum_{j=1}^m R_{ij}^2 - \frac{l}{m} \sum_{i=1}^l R_{i..}^2 \right) \text{ (source: [30])}$$

Where, 1 = 1,2,, 1 genotypes; j = 1, 1,....., m

environments; k = 1, 2, ..., n replications; R_{ij} = rank of original data X_{ijk} ; R_{ij}^{**} = rank of transformed data $X^{*}ijk (= X_{ijk} - X_{i...}X_{.j.} + 2X_{...})$ and R = mean of ranks. The test statistics of non-parametric methods are approximately χ^2 - distributed with (n-1) (m-1) degrees of freedom, where n = number of genotypes and m = number of environments.

2.3.1. Parametric Stability Statistics

Superiority index (P_i)

Superiority index (P_i) was estimated following the procedure of [7], as shown in the equation below.

$$P_i = \sum_{j=1}^n (x_{ij} - M_j)^2 / 2E$$

Where X_{ij} is the grain yield of genotype i in environment j, M_j is the yield of the genotype with a maximum yield at environment j, and E is the number of environments.

Coefficient of variation (CV_i)

Coefficient of variation (CV_i) was estimated following the method of [9] as shown in the equation below.

$$CV_i = \sqrt{(S_i^2 / \bar{x}_i)} \times 100$$

i. Wricke's Ecovalence (W_i^2)

Wricke's ecovalence was estimated for genotype i as shown by the equation below.

$$W_i^2 = \sum_{i=1}^n (x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..})^2$$

$\bar{x}_{i.}$ = mean yield of genotype

$\bar{x}_{.j}$ = mean yield of genotype

$\bar{x}_{..}$ = grand mean

ii. Stability Variance (σ_i^2)

The stability variance (σ_i^2) was calculated as described by [11] as follow:

$$\sigma_i^2 = [p/(p-2)(q-1)]W_i^2 - [SS(GE)/(p-1)(p-2)(q-1)]$$

Where, p = number of genotypes, q = number of environments.

iii. Regression Approach

Evaluation of genotype response to environmental changes with both linear regression coefficient (b_i) and regression deviation variance (S_{di}^2) [13] was adopted for the regression technique as follows.

$$b_i = 1 + \sum_i (x_{ij} - \bar{x}_{i.} - \bar{x}_{.j} + \bar{x}_{..})(\bar{x}_{.j} + \bar{x}_{..}) / \sum_i (\bar{x}_{.j} + \bar{x}_{..})^2$$

$$S_{di}^2 = \frac{1}{E-2} \left[\sum_i (x_{ij} - \bar{x}_i - \bar{x}_j + \bar{x}_{..}) - (b_i - 1)^2 \sum_i ((\bar{x}_j + \bar{x}_{..})^2) \right]$$

Where X_{ij} = grain yield of genotype i in environment j , \bar{x}_i = mean yield of genotype i , \bar{x}_j = mean yield of the environment j , $\bar{x}_{..}$ = grand mean and, E = the number of environments.

iv. Coefficient of Determination (R_i^2)

The coefficient of determination (R_i^2) was propounded by [8] as a stability measure to replace the variance of regression deviations (S_{di}^2). The most stable genotype displays a minimum coefficient of determination (R_i^2).

$$R_i^2 = b_i^2 \frac{\sum_j (\bar{x}_j + \bar{x}_{..})^2}{(\bar{x}_j + \bar{x}_{..})^2}$$

v. AMMI Stability Value (ASV)

This stability parameter (ASV) was proposed by [37] for each cultivar and each environment based on the relative contribution of IPCA1 to IPCA2 to the interaction SS following the equation below.

$$ASV = \sqrt{\left[\frac{IPCA1_{sum\ of\ square}}{IPCA2_{sum\ of\ square}} (IPAC1_{score}) \right]^2 + (IPAC1_{score})^2}$$

vi. Mean-variance Component (θ_i)

The variance component of the GEI approach was suggested by [38]. This stability procedure for parametric test studies the average of the evaluation for all combinations with a common genotype as a stability estimate. Hence, genotypes with lower θ_i values are reported to be more stable.

vii. Genotype x Environment Variance Component ($\theta_{(i)}$)

In this parametric stability technique, the i th genotype is deleted from the complete data set, and the variance of genotype \times environment interaction from this subset stands for the stability index for the i th genotype. So, genotypes with higher values for the (i) are said to be more stable.

2.3.2. Nonparametric Stability Approaches

Huehn [39, 22] suggested four nonparametric stability statistics derived as revealed by the equation below.

$$S_i^{(1)} = 2 \sum_j^{m-1} \sum_{j'=j+1}^m |r_{ij} - r_{ij'}| / [m(m-1)]$$

$$S_i^{(2)} = \sum_j^{m-1} (r_{ij} - \bar{r}_i)^2 / (m-1)$$

$$S_i^{(3)} = \sum_j^{m-1} (r_{ij} - \bar{r}_i)^2 / \bar{r}_i$$

$$S_i^{(6)} = \sum_j^m |r_{ij} - \bar{r}_i| / \bar{r}_i$$

i. Kang's Rank-sum (KR)

Kang's rank-sum [40] combines yield and stability variance of [11] as a selection measure. The KR gives a weight of 1 to yield and stability variance to identify stable and high-yielding cultivars. A cultivar with the highest yield and lower stability variance is allocated a rank of 1. So, yield and stability variance ranks are added for each cultivar, and the cultivars with the lowest rank-sum are the

most desirable.

ii. Thennarasu's non-parametric Statistics

Four sets of nonparametric stability statistics were suggested by [26]. The parameters are based on the ranks of adjusted means of the genotypes in each environment. The low values of these statistics reflect high stability.

$$NP_i^{(1)} = \frac{1}{m} \sum_j^m [r_{ij}^* - M_{di}^*]$$

$$NP_i^{(2)} = \frac{1}{m} (\sum_j^m [r_{ij}^* - M_{di}^*] / M_{di})$$

$$NP_i^{(3)} = \frac{\sqrt{\sum_j (r_{ij}^* - M_{di}^*)^2 / m}}{\bar{r}_i}$$

$$NP_i^{(4)} = \frac{2}{m(m-1)} \left(\sum_{j=1}^{m-1} \sum_{j'=j+1}^m |r_{ij}^* - r_{ij'}^*| / \bar{r}_i \right)$$

In the above formulas, r_{ij}^* is the rank of r_{ij} , $r_{ij'}$ and M_{di} are the mean and median ranks for adjusted values, where r_{ij} and M_{di} are the same parameters computed from the original (unadjusted) data. Standard deviation of rank (SDR) and rank mean (R) [41] were measured as

$$S_i^{(3)} = \sum_j^m [(R_{ij} - \bar{R}_i)^2] / (l-1)$$

Where R_{ij} is the rank of X_{ij} within the j th environment, \bar{R}_i is the mean rank across all environments for the i th genotype and SDR = $(S_{di}^2 / 0.5)$. Genotypes with minimum R and SDR are the most stable.

Spearman's coefficient of rank correlation (r_s) was employed [42] as

$$r_s = 1 - \frac{6 \sum d_i^2}{(n-1)n(n+1)}$$

3. Results

Table 3 showed the results of the combined analysis of variance (ANOVA) for genotype \times environment interaction (GEI) on the yield of 20 maize genotypes across five environments. The GEI effects were highly significant (with the lowest χ^2) for both parametric and nonparametric statistical measurements used except the De Kroon and Van der Laan (1981) nonparametric measurement.

Table 3. Parametric (ANOVA) and nonparametric tests statistics for GEI across test environments.

Statistics	χ^2 - statistics
ANOVA (F)	7372.12**
Bredenkamp (1974)	1689.15**
Hildebrand (1980)	296.04**
Kubinger (1986)	269.27**
De Kroon and Van der Laan (1981)	80.83ns

3.1. Parametric Statistical Results

The mean seed yield of the genotypes evaluated across research environments ranged from 8.01 tons/hectare to 5.68 tons/ha with a total grand means of 6.88 tons/ha (Table 4). The

highest mean seed yield was recorded for G10 (8.01 tons/ha) and G5 (7.93 tons/ ha), with the least mean seed yield revealed by G17 (5.68 tons/ha). The stability index (P_i) parameter revealed that genotype G10 is the least stable genotype followed by G5, G3, and G15 (Table 4), while the most stable genotypes were genotypes G13, G19, G8, G7, and G2 (Table 4).

Genotype G5 had the highest environmental coefficient of variance CV_i and G10 (Table 4). In contrast, the lowest CV_i

value was recorded for genotype G13 and G14 across the test environments. From the ecovalence (W_i^2) values in Table 4, G20 is the most stable genotype among the genotypes evaluated because it has the least value (0.07), followed by G6 (0.11), G16 (0.27) and G17 (0.33). The least stable genotypes among the tested genotypes based on W_i^2 stability measure are G5 (8.18), G18 (8.01), G10 (6.42), and G15 (4.42) (Table 4).

Table 4. Parametric stability statistics and seed yield of 20 maize genotypes evaluated across 5 environments.

Genotype	P_i	CV_i	W_i^2	σ_i^2	s^2d_i	b_i	R_i^2	PCA1	PCA2	ASV	$\theta_{(i)}$	θ_i	Yield
G1	2.81	4.79	1.18	0.30	0.04	-0.40	0.18	-0.53	-0.89	6.43	0.59	0.46	6.43
G2	4.55	14.23	1.52	0.39	0.18	1.81	0.88	-1.53	0.49	5.75	0.58	0.50	7.39
G3	0.91	9.05	0.56	0.12	0.03	1.88	0.34	0.62	0.64	7.39	0.59	0.37	5.83
G4	2.86	4.38	0.81	0.19	0.04	-0.06	0.00	-0.58	-0.78	6.40	0.59	0.41	6.40
G5	3.77	28.05	8.18	2.24	0.34	4.60	0.30	-1.07	2.18	6.17	0.48	1.38	7.93
G6	1.99	5.13	0.11	0.00	0.01	0.92	0.81	-0.19	-0.06	6.73	0.60	0.32	6.17
G7	0.57	5.38	1.67	0.43	0.09	-0.54	0.06	1.47	-0.73	8.01	0.58	0.52	6.69
G8	0.88	14.34	2.41	0.64	0.10	2.97	0.78	0.71	1.37	7.49	0.57	0.62	6.73
G9	2.18	7.42	1.09	0.27	0.13	0.38	0.85	-0.18	-0.55	6.69	0.59	0.44	7.49
G10	5.26	25.63	6.42	1.75	0.71	2.81	0.16	-1.71	1.05	5.68	0.51	1.15	8.01
G11	0.83	12.61	2.20	0.58	0.22	2.19	0.45	0.88	0.84	7.63	0.57	0.59	7.59
G12	3.03	6.79	0.77	0.18	0.09	0.45	0.54	-0.70	-0.50	6.29	0.59	0.40	5.75
G13	0.52	2.49	0.59	0.13	0.02	0.00	0.46	1.29	-0.49	7.85	0.59	0.38	7.20
G14	3.62	3.69	0.98	0.24	0.02	-0.37	0.88	-0.97	-0.90	6.10	0.59	0.43	7.32
G15	4.76	14.18	4.46	1.21	0.26	-1.45	0.58	-1.24	-1.79	5.83	0.54	0.89	7.63
G16	1.25	4.18	0.27	0.04	0.03	0.61	0.29	0.42	-0.25	7.20	0.60	0.34	6.10
G17	1.31	4.12	0.33	0.06	0.03	0.52	0.42	0.37	-0.29	7.14	0.60	0.34	5.68
G18	1.18	21.34	8.01	2.19	0.81	3.30	0.12	0.94	1.49	7.59	0.49	1.36	6.29
G19	0.65	5.30	1.77	0.46	0.07	-0.70	0.00	1.40	-0.88	7.93	0.58	0.53	7.85
G20	1.00	5.15	0.07	-0.01	0.01	1.06	0.34	0.58	0.04	7.32	0.60	0.31	7.14
Mean	2.20	9.91	2.17	0.57	0.16	1.00	0.42			6.88	0.57	0.59	6.88

P_i - superiority index; S^2d_i - deviation from regression; CV_i - environmental coefficient of variance; W_i^2 - Wricke's ecovalence stability index; σ_i^2 - Shukla's stability variance; b_i - regression coefficient; R_i^2 - coefficient of determination; IPCA1 and IPCA2- interaction principal components axes 1 and 2, respectively; ASV-AMMI stability value; $\theta_{(i)}$ - GE variance component; θ_i - Mean variance component.

The regression coefficients (b_i) for genotypes G1, G4, G7, G14, G15, G19, G13, and G9 were significantly less than 1.00, expressing specific adaptability to poor environments. All the evaluated genotypes across the test environments except genotypes G10 and G18 revealed deviation from linear regression (s^2d_i), that is not significantly different from zero (Table 4). The results of the mean-variance component (θ_i) showed that G20 had the lowest value for θ_i followed by G16 and G17 (Table 4). The highest values for θ_i were recorded for G5 and G18. The results of GE variance component $\theta_{(i)}$, showed that genotypes G6, G16, G17, and G20 had the highest values for $\theta_{(i)}$ across the test environments. In contrast, the lowest value for $\theta_{(i)}$ was revealed by genotype G5 (Table 4). Genotypes G2 and G14 had the highest values for the coefficient of determination (R_i^2), while G4 and G19 displayed the lowest value for R_i^2 (Table 4). Based on the results of AMMI stability value (ASV), G7 and G10 had the highest and lowest ASV, respectively.

3.2. Nonparametric Measures of Stability

The results of nonparametric stability statistics for grain yield of 20 maize genotypes evaluated across five test environments are presented in Table 5. The $S_i^{(1)}$ and $S_i^{(2)}$ of the evaluated genotypes showed that genotypes G2 and G20 had

the lowest value, while genotype G5 was the highest. For $S_i^{(3)}$ nonparametric statistics, genotype G20 had the lowest value, followed by genotype G6, while the highest value for $S_i^{(3)}$ was by genotype G5 followed by genotype G15. The values for $S_i^{(6)}$, a nonparametric stability procedure, suggested by [22], were highest for G15 and G5 but lowest for G20 and G13 (Table 5). For each genotype, $Z_i^{(1)}$ and $Z_i^{(2)}$ values were estimated according to the rank of the corrected data and summed over genotypes to generate Z values. $Z_i^{(1)}$ had 30. 29 summations across genotypes, and 23.95 was recorded for $Z_i^{(2)}$ (Table 5); both $Z_i^{(1)}$ and $Z_i^{(2)}$ values were lower than the critical value of the chi-square, χ^2 (31.41).

Based on stability parameter, genotype G6 had the lowest value for $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(4)}$, while genotype G20 was lowest for $NP_i^{(3)}$. G15 showed the highest value for the same parameter recorded followed by genotype G10. The highest value for $NP_i^{(1)}$ and $NP_i^{(4)}$ parameters was for genotype G5, while the highest value for $NP_i^{(3)}$ parameter was for genotype G15 (Table 5). From the result of Kang's rank-sum, genotypes G13 and G20 had the lowest rank-sum, while the highest rank-sum was revealed by genotype G10 followed by G5 (Table 5). Based on the result of the stability index (Y_{si}) parameter, genotype G10 had the lowest index value, whereas, G7 had the highest value among the genotypes evaluated across the test

environments (Table 5). As shown in table 5, genotype G6 had the highest standard deviation rank (SDR) value followed by

genotype G11, while the lowest SDR value was recorded by genotype G19 followed by genotype G16.

Table 5. Nonparametric stability statistics for grain yield for the 20 evaluated maize genotypes across test environments.

Genotype	S _i ⁽¹⁾	Z _i ⁽¹⁾	S _i ⁽²⁾	Z _i ⁽²⁾	S _i ⁽³⁾	S _i ⁽⁶⁾	NP _i ⁽¹⁾	NP _i ⁽²⁾	NP _i ⁽³⁾	NP _i ⁽⁴⁾	K R	R	SDR	Y _{si}
G1	3.40	0.04	8.30	0.01	4.37	1.26	2.80	0.33	0.60	0.45	24.00	11.0	0.31	6.43
G2	0.80	0.16	0.80	0.04	0.70	0.70	3.80	2.28	1.11	0.17	31.00	10.2	0.67	5.75
G3	4.40	2.46	17.80	2.93	4.94	1.03	4.00	0.14	0.26	0.31	12.00	11.8	0.83	7.39
G4	3.80	5.34	9.80	9.47*	5.16	1.63	4.00	0.60	0.60	0.50	22.00	9.6	0.28	6.41
G5	9.80	1.30	74.30	1.76	39.11	4.95	10.40	0.71	1.13	1.29	36.00	9.2	0.42	6.13
G6	1.20	2.46	1.20	3.35	0.52	0.52	2.20	0.08	0.32	0.13	13.00	10.2	1.70	6.73
G7	4.40	1.30	13.20	0.89	3.14	0.90	7.00	0.16	0.41	0.26	14.00	10.2	0.49	8.00
G8	6.80	0.02	33.20	0.03	9.62	1.51	8.00	0.26	0.47	0.49	22.00	11.8	0.35	7.49
G9	3.60	1.30	9.70	0.92	4.41	1.23	4.60	0.38	0.66	0.41	22.00	10.0	1.07	6.69
G10	4.20	5.59	14.30	3.14	12.43	2.78	5.60	3.85	1.53	0.91	38.00	12.4	0.43	5.68
G11	6.00	0.20	37.20	0.39	10.05	1.46	3.80	0.19	0.38	0.41	19.00	9.8	1.62	7.63
G12	3.60	0.86	8.70	1.48	6.00	1.93	4.40	0.89	0.81	0.62	22.00	12.4	0.82	6.29
G13	2.00	1.56	2.80	1.55	0.67	0.39	2.40	0.33	0.18	0.12	9.00	9.6	0.30	7.85
G14	3.20	0.68	7.20	0.63	6.00	2.33	3.80	1.53	0.96	0.67	26.00	9.8	0.38	6.10
G15	6.20	0.51	42.30	0.23	38.45	5.27	4.80	3.10	1.54	1.41	35.00	9.6	0.96	5.83
G16	3.60	0.44	8.80	0.59	2.84	1.00	3.00	0.17	0.23	0.29	12.00	10.8	0.22	7.19
G17	3.00	2.13	7.30	2.32	2.35	0.74	3.20	0.13	0.24	0.24	14.00	10.0	1.45	7.14
G18	8.60	1.98	49.30	1.84	14.50	2.09	9.60	0.31	0.61	0.63	24.00	10.4	0.43	7.59
G19	4.00	1.19	12.20	0.85	2.90	0.90	6.20	0.16	0.42	0.24	16.00	10.8	0.19	7.93
G20	1.00	0.77	0.80	1.00	0.24	0.27	2.80	0.10	0.21	0.07	9.00	10.4	0.29	7.33
Mean	4.18	30.29	17.96	23.95	8.42	1.64	4.82	0.79	0.63	0.48	21.00	10.5	0.66	6.88
Test Statistics														
E(S _i ⁽¹⁾) = 6.65							E(S _i ⁽²⁾) = 33.25							
V(S _i ⁽¹⁾) = 3.54							V(S _i ⁽²⁾) = 286.12							
χ ² Sum = 31.41							χ ² Z ₁ Z ₂ = 9.14							
Yield Mean: 6.88 tons/ha														

$S_i^{(1)}$ - mean of absolute rank difference of a genotype over environments; $S_i^{(2)}$ - sum of square deviations of the rank; Z-statistics- measures of stability; Z1, Z2- chi- square for $Z_i^{(1)}$ and $Z_i^{(2)}$; χ - sum chi-square for sum of $Z_i^{(1)}$ and $Z_i^{(2)}$; $S_i^{(3)}$ - variance among the ranks over environments; $S_i^{(6)}$ - sum of absolute deviation; $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ - Thennarasu's nonparametric stability statistics; KR- Kang's rank-sum; Y_{si} - simultaneous selection for yield and stability; SDR- standard deviation of rank, R = mean of rank.

Correlation between mean yield and stability parameters

Spearman's rank correlation coefficient results for mean yield, and the parametric and nonparametric stability parameters are shown in Table 6. A significant positive association exists between mean seed yield and some parametric and non-parameter statistical parameters across test environments. Parameters such as $\theta_{(i)}$, θ_i , CV_i , W_i^2 , σ_i^2 , and s^2d_i showed no significant correlation with P_i , R_i^2 , b_i , and ASV. However, no significant correlation was recorded between mean seed yield and $S_i^{(1)}$, $S_i^{(2)}$, $S_i^{(3)}$, $S_i^{(6)}$, $NP_i^{(1)}$, and $NP_i^{(4)}$. A significant positive correlation exists for mean seed yield and $NP_i^{(2)}$, $NP_i^{(3)}$, and Y_{si} (Table 6). A similar relationship existed between Kang's rank-sum (KR) and mean seed yield; mean seed yield had no significant correlation with SDR (Table 6). A highly significant positive correlation was recorded between $S_i^{(1)}$ and $S_i^{(2)}$, $S_i^{(3)}$, $S_i^{(6)}$, and $NP_i^{(1)}$ and $NP_i^{(4)}$, but the relationship was not significant with $NP_i^{(2)}$, $NP_i^{(3)}$, KR, SDR, and Y_{si} . However, a highly significant positive correlation was recorded between $S_i^{(1)}$ and θ_i , CV_i , W_i^2 , σ_i^2 , and s^2d_i , but not with $\theta_{(i)}$. The relationship was not significant with P_i , R_i^2 , b_i , and ASV (Table 6). A highly significant positive correlation

was recorded between $S_i^{(2)}$ and $S_i^{(3)}$, $S_i^{(6)}$, $NP_i^{(1)}$, $NP_i^{(4)}$, θ_i , CV_i , W_i^2 , σ_i^2 , and s^2d_i , but not with $\theta_{(i)}$ and other stability measure parameters evaluated in this study (Table 6). $S_i^{(3)}$ and $S_i^{(6)}$ parameters had a significant positive correlation with $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$, $NP_i^{(4)}$, KR, θ_i , CV_i , W_i^2 , σ_i^2 , and s^2d_i . KR was positively correlated with the parametric stability parameters evaluated except with ASV and $\theta_{(i)}$. Spearman's rank correlation between Kang's rank-sum measure with $S_i^{(3)}$, $S_i^{(6)}$, $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$, and $NP_i^{(4)}$ was positive and significant (Table 6). However, the Standard deviation of rank (SDR) and Kang's rank-sum parameter are not correlated (Table 6), neither was the simultaneous selection for yield and stability (Y_{si}) with all parametric stability parameters measured.

To better understand the relationships among the parametric and nonparametric measures, a principal component analysis (PCA) based on the rank correlation matrix (Table 6) was carried out. The rank loadings of the first two principal components (PC) of ranks of different parametric and nonparametric stability measures are shown in Table 7. The first two PC explained 96.27% (85.42 and 10.85% by PC1 and PC2) of the variance of the original

variables. Based on the genotype ranking results (Table 8), G2 is the most stable genotype following the nonparametric statistics procedure of Nassar and Huhn's ($S_i^{(1)}$ and $S_i^{(2)}$) and Huhn's statistics ($S_i^{(3)}$ and $S_i^{(6)}$); and genotype G5 appeared most unstable. However, G20 appeared the most stable genotype under $S_i^{(3)}$ and $S_i^{(6)}$ measure (Table 8). Genotype G20 had the highest mean yield ranking, with G7 recording the lowest mean yield ranking (Table 8). As shown in Table 8, G20 was the most stable genotype according to the Wricke

ecovalence (W_i^2) parametric measure, and G5 appeared the least stable.

Based on the GE variance component ($\theta_{(i)}$) and the mean-variance component (θ), genotype G5, being the highest-ranking genotype, was to be the most stable, while genotype G20 was the least stable (Table 8). According to Kang's rank-sum nonparametric measure, genotype G20 appeared the most desirable, while genotype G15 appeared most undesirable among the evaluated genotypes (Table 8).

Table 6. Spearman rank correlation between mean yield, parametric, and nonparametric stability measures of 20 hybrid genotypes evaluated across five test environments.

Parameter	$S_i^{(1)}$	$S_i^{(2)}$	$S_i^{(3)}$	$S_i^{(6)}$	$NP_i^{(1)}$	$NP_i^{(2)}$	$NP_i^{(3)}$	$NP_i^{(4)}$	KR	SDR	Y_{si}
$S_i^{(2)}$	0.99**										
$S_i^{(3)}$	0.84**	0.85**									
$S_i^{(6)}$	0.69**	0.70**	0.95**								
$NP_i^{(1)}$	0.82**	0.80**	0.72**	0.62**							
$NP_i^{(2)}$	0.16 ^{ns}	0.18 ^{ns}	0.57**	0.68**	0.32 ^{ns}						
$NP_i^{(3)}$	0.35 ^{ns}	0.36 ^{ns}	0.69**	0.78**	0.57**	0.85**					
$NP_i^{(4)}$	0.67**	0.67**	0.94**	1.00**	0.61**	0.69**	0.78**				
KR	0.37 ^{ns}	0.39 ^{ns}	0.72**	0.79**	0.53*	0.82**	0.96**	0.79**			
SDR	0.04 ^{ns}	0.10 ^{ns}	0.14 ^{ns}	0.06 ^{ns}	-0.03 ^{ns}	-0.04 ^{ns}	0.16 ^{ns}	0.06 ^{ns}	0.11 ^{ns}		
Y_{si}	0.17 ^{ns}	0.13 ^{ns}	-0.29 ^{ns}	-0.49**	0.01 ^{ns}	-0.73**	-0.73**	-0.51*	-0.71**	-0.16 ^{ns}	
$\theta_{(i)}$	-0.77**	-0.77**	-0.78**	-0.65**	-0.80**	-0.52*	-0.65**	-0.62**	-0.69**	-0.05 ^{ns}	0.09 ^{ns}
θ_i	0.76**	0.76**	0.79**	0.68**	0.80**	0.54*	0.69**	0.67**	0.76**	0.01 ^{ns}	-0.13 ^{ns}
Pi	-0.06 ^{ns}	-0.02 ^{ns}	0.38 ^{ns}	0.57**	0.09 ^{ns}	0.73**	0.80**	0.59**	0.78**	0.18 ^{ns}	-0.98**
CVi	0.65**	0.67**	0.65**	0.50*	0.72**	0.34 ^{ns}	0.59**	0.48*	0.58**	0.28 ^{ns}	-0.21 ^{ns}
W_i^2	0.75**	0.76**	0.79**	0.68**	0.80**	0.54*	0.69**	0.66**	0.76**	0.02 ^{ns}	-0.13 ^{ns}
σ_i^2	0.75**	0.76**	0.79**	0.68**	0.80**	0.54*	0.69**	0.66**	0.76**	0.02 ^{ns}	-0.13 ^{ns}
s^2d_i	0.69**	0.73**	0.76**	0.65**	0.76**	0.56**	0.70**	0.63**	0.73**	0.22 ^{ns}	-0.23 ^{ns}
b_i	0.28 ^{ns}	0.29 ^{ns}	0.27 ^{ns}	0.13 ^{ns}	0.22 ^{ns}	-0.06 ^{ns}	0.02 ^{ns}	0.11 ^{ns}	0.12 ^{ns}	0.18 ^{ns}	-0.04 ^{ns}
R_i^2	-0.37 ^{ns}	-0.37 ^{ns}	-0.11 ^{ns}	-0.07 ^{ns}	-0.30 ^{ns}	0.21 ^{ns}	0.16 ^{ns}	-0.07 ^{ns}	0.09 ^{ns}	0.49 ^{ns}	-0.35 ^{ns}
ASV	0.17 ^{ns}	0.13 ^{ns}	-0.29 ^{ns}	-0.49*	0.01 ^{ns}	-0.73**	-0.73**	-0.51*	-0.71**	-0.16 ^{ns}	1.00**
Yield	0.25 ^{ns}	0.29 ^{ns}	0.35 ^{ns}	0.31 ^{ns}	0.36 ^{ns}	0.49**	0.50*	0.28 ^{ns}	0.51*	-0.11 ^{ns}	-0.22 ^{ns}

Table 6. Continued.

Parameter	$\Theta_{(i)}$	θ_i	Pi	CVi	W_i^2	σ_i^2	s^2d_i	b_i	R_i^2	ASV
$S_i^{(2)}$										
$S_i^{(3)}$										
$S_i^{(6)}$										
$NP_i^{(1)}$										
$NP_i^{(2)}$										
$NP_i^{(3)}$										
$NP_i^{(4)}$										
KR										
SDR										
Y_{si}										
$\theta_{(i)}$										
θ_i	-0.97**									
Pi	-0.18 ^{ns}	0.22 ^{ns}								
CVi	-0.81**	0.76**	0.28 ^{ns}							
W_i^2	-0.97**	1.00**	0.23 ^{ns}	0.75**						
σ_i^2	-0.97**	1.00**	0.23 ^{ns}	0.75**	1.00**					
s^2d_i	-0.89**	0.90**	0.34 ^{ns}	0.85**	0.90**	0.90**				
b_i	-0.31 ^{ns}	0.22 ^{ns}	0.05 ^{ns}	0.60**	0.22 ^{ns}	0.22 ^{ns}	0.34 ^{ns}			
R_i^2	0.18 ^{ns}	-0.20 ^{ns}	0.26 ^{ns}	-0.02 ^{ns}	-0.19 ^{ns}	-0.19 ^{ns}	-0.14 ^{ns}	0.07 ^{ns}		
ASV	0.09 ^{ns}	-0.13 ^{ns}	-0.98**	-0.21 ^{ns}	-0.13 ^{ns}	-0.13 ^{ns}	-0.23 ^{ns}	-0.04 ^{ns}	-0.35 ^{ns}	
Yield	-0.63**	0.64**	0.23 ^{ns}	0.44*	0.64**	0.64**	0.49*	0.01 ^{ns}	0.04 ^{ns}	-0.22 ^{ns}

ns – non significant, * - significant at 0.05 probability level, ** - significant at 0.01 probability level.

Table 7. First two principal components loadings of ranks obtained from both parametric and nonparametric measurements used for estimating GEI of 20 maize genotype yields.

Stability Parameters	PC 1	PC 2
$S_i^{(1)}$	0.095	-0.062
$S_i^{(2)}$	0.838	-0.410
$S_i^{(3)}$	0.454	0.299
$S_i^{(6)}$	0.051	0.068
$NP_i^{(1)}$	0.079	-0.038
$NP_i^{(2)}$	0.011	0.116
$NP_i^{(3)}$	0.009	0.044
$NP_i^{(4)}$	0.013	0.020
KR	0.247	0.816
SDR	0.000	-0.005
Y_{si}	-0.007	-0.085
$\theta_{(i)}$	-0.001	-0.001
θ_i	0.013	0.007
Pi	0.020	0.176
W_i^2	0.095	0.052
σ_i^2	0.027	0.014
s^2d_i	0.006	0.006
b_i	0.037	-0.034
R_i^2	-0.002	0.009
ASV	-0.006	-0.085
Yield	0.012	0.036
Eigenvalue	518.101	65.826
% variance	85.416	10.852

Table 8. Ranks of 20 maize genotypes across five environments using some of the parametric and nonparametric statistical procedures.

Genotype	Yield	$S^{(1)}$	$S^{(2)}$	$S^{(3)}$	$S^{(6)}$	$NP^{(1)}$	$NP^{(2)}$	$NP^{(3)}$	$NP^{(4)}$	W_i^2	σ_i^2	s^2d_i	CVi	KR	$\theta_{(i)}$	θ_i
G1	13	7	7	9	11	3	11	11	12	11	11	8	6	14	11	10
G2	19	1	1	4	4	7	18	17	4	12	12	15	16	17	12	9
G3	7	14	15	11	9	10	4	5	9	5	5	6	13	3	5	16
G4	14	11	11	12	14	10	14	11	14	8	8	9	5	10	8	13
G5	16	20	20	20	19	20	15	18	19	20	20	18	20	19	20	1
G6	11	3	3	2	3	1	1	6	3	2	2	2	7	5	2	19
G7	1	14	13	8	6	17	6	8	7	13	13	11	10	6	13	8
G8	6	18	16	15	13	18	9	10	13	16	16	13	17	10	16	5
G9	12	8	10	10	10	13	13	14	11	10	10	14	12	10	10	11
G10	20	13	14	17	18	15	20	19	18	18	18	19	19	20	18	3
G11	4	16	17	16	12	7	8	7	10	15	15	16	14	9	15	6
G12	15	8	8	13	15	12	16	15	15	7	7	12	11	10	7	14
G13	3	4	4	3	2	2	12	1	2	6	6	4	1	1	6	15
G14	17	6	5	13	17	7	17	16	17	9	9	3	2	16	9	12
G15	18	17	18	19	20	14	19	20	20	17	17	17	15	18	17	4
G16	9	8	9	6	8	5	7	3	8	3	3	5	4	3	3	18
G17	10	5	6	5	5	6	3	4	6	4	4	7	3	6	4	17
G18	5	19	19	18	16	19	10	13	16	19	19	20	18	14	19	2
G19	2	12	12	7	6	16	5	9	5	14	14	10	9	8	14	7
G20	8	2	2	1	1	3	2	2	1	1	1	1	8	1	1	20

4. Discussion

Stability statistical procedures are employed by plant breeders to identify genotypes with expected potential and ability to respond positively to improvements in diverse environments. Crop breeders utilize different methods to estimate stability and adaptability of crop yield for the identification of superior genotypes in the presence of significant GEI [43]. Although breeders often encounter challenges in selecting appropriate stability procedures for use in diverse situations, the choice of the best procedure relies on many factors, including the number of genotypes and experimental location and variation, mathematical model

fit to the data set, stability concept adopted, and the capability to apply and interpret the results.

GE interactions are important sources of variation in any crop, and breeders use the term stability to occasionally describe a genotype that exhibits comparatively persistent yield, independent of environmental fluctuations. Therefore, genotypes that exhibit minimum variance for yield through diverse environments are said to be stable. This knowledge of stability could be a biological or static [44]. Plant breeders and agronomists prefer an agronomic or dynamic concept of stability because they are more interested in genotypes with high mean yields and with potential to respond to better environmental conditions [45-47]. GEI becomes more relevant when there are changes in the ranking of genotypes

across diverse environments. The changes in the ranking have been defined as crossover genotype \times environment interaction [48].

As established in the results of parametric and nonparametric measurements adopted in this study (Table 3), the presence of significant differences for the parametric and nonparametric, except [30], indicated the absence of additive Genotype \times Environment interaction among the evaluated maize genotypes. A non-significant GEI displayed by [30] nonparametric measurements suggested a non-crossover GEI. The results conform to the conventional ANOVA but gave more precise information about the additive or crossover nature of the GE interactions (GEI) [47].

From the results of the parametric parameters, the highest value for superiority index (P_i) displayed by G10 (TZEI 9 \times TZEI 16) indicated that the genotype appeared least stable genotype among the evaluated maize genotypes, while G13 (TZEI 16 \times TZEI 10) appeared most stable genotype. For the environmental coefficient of variance (CV_i) method, genotype G13 (TZEI 16 \times TZEI 10) appeared the most desirable genotype because of its ability to display low CV_i and high mean seed yield among the genotypes evaluated. The Wricke ecovalence [15] parametric stability parameter defines the influence of individually evaluated genotype on GEI by partitioning it into variance components allocated to each genotype. Wricke proposed that genotype with least ecovalence (W_i^2) value was reported most stable. Therefore, G20 (TZEI 134 \times TZEI 10), with the least W_i^2 value, appeared the most stable among the evaluated genotypes. As shown in table 4, mean-variance component ($\theta_{(i)}$) and GE variance component (θ_i) indicated G20 to be more stable across test environments.

Generally, breeders prefer to apply nonparametric tests to stability studies because i. they reduce biases introduced by outliers; ii. they do not require assumptions in distributing observed values; iii. they are easy to apply and interpret; and iv. additions or deletions of one or a few genotypes rarely cause variations in results [48-50]. The most debated stability parameters have a relationship with either of two divergent stability concepts: static/biological concept or dynamic concept [42, 50]. In dynamic stability concepts, equality of the responses of genotypes to environmental conditions is unnecessary [10]. Estimation of dynamic stability relies on the specific set of evaluated genotypes, unlike static stability measurement [6].

The nonparametric stability measurements of [22] similarly classified the genotypes. Our results conform to those of [51, 47, 52]. [37] reported that $S_i^{(1)}$ and $S_i^{(2)}$ are functions of stability measurements only, while numerical values of $S_i^{(3)}$ and $S_i^{(6)}$ is the combination of yield and stability according to genotypes yield ranks per environment. Also, the positive significant ($P < 0.05$) correlation among these parameters in our study aligns with the results of [22], who reported a significant positive relationship between $S_i^{(1)}$ and $S_i^{(2)}$, and [54], and a highly positive significant correlation amongst $S_i^{(1)}$, $S_i^{(2)}$ and $S_i^{(3)}$. Our result indicates that any of the four methods of [22] nonparametric statistical

parameter could be adopted in assessing genotype stability. [22] noted that $S_i^{(1)}$ and $S_i^{(2)}$ have a close relationship with the static biological concept of stability, as they describe stability in homeostatic sense. Also, [49] reported that $S_i^{(1)}$ and $S_i^{(2)}$ represent the static concept of stability. Therefore, $S_i^{(1)}$ and $S_i^{(2)}$ can be employed as a concession method that select genotypes with moderate yield and yield stability.

The highly significant positive relationship between $S_i^{(3)}$ and $S_i^{(6)}$ and nonparametric measurements of Thennarasu in our study is supported by [49] and [50], who reported a significant, positive correlation between $S_i^{(3)}$ and $NP_i^{(1)}$, $S_i^{(6)}$ and $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$. According to Thennarasu's nonparametric stability methods, stable genotypes are the genotypes whose adjusted ranks are not altered regarding the others across test environments. Since $NP_i^{(3)}$ and $NP_i^{(4)}$ define stability in units of mean ranks, this method shares a similarity with $S_i^{(3)}$ and $S_i^{(6)}$. Therefore, the highly significant positive relationship between $S_i^{(6)}$, $NP_i^{(1)}$, $NP_i^{(2)}$, $NP_i^{(3)}$ and $NP_i^{(4)}$ indicates that stability procedure of Thennarasu's contributes little information to the statistics obtained by [22]. Therefore, using the [39] stability parameters could be better since there is a statistical procedure to determine the significance of $S_i^{(1)}$ and $S_i^{(2)}$. Nevertheless, the nonparametric procedure of [26] stability estimates will be a better option for parametric models. The nonparametric procedures adopted for this study did not appear to represent each genotype's reaction to the environment. Some genotypes expressed stability according to some parameters but unstable for other parameters, making it challenging to reconcile the statistical parameters into a unified inference. [6] identified this limitation in a Genotype \times Environment Interaction study. The challenge was because parametric techniques transform the responses of genotypes to environments from its multivariate to a univariate state. To overcome this challenge, genotypes are partitioned into qualitatively homogeneous stability subsets using principal component analysis. Given the unanimity of most of the stability estimates, the genotype G13 was the most stable with the highest yield.

5. Conclusions

The major challenge with stability statistics is that they hardly give a precise picture of the whole response pattern because of the multivariate response of genotypes to diverse environments. This study demonstrated that ASV has the advantage of a small increase of repeatability in comparison with other measures such as multivariate response and dynamic/agronomic concept of stability; hence it is recommended as the most suitable stability procedure. Most of the stability methods indicated that genotype G13 (TZEI 16 \times TZEI 10) and G20 (TZEI 134 \times TZEI 10) appeared most phenotypically stable with a high mean yield. Most of the stability procedures employed in this study measured genotypes stability based on yield, stability, or both. Hence, both yield and stability have to be simultaneously considered for more effective use of GEI, and to enhance genotypes

selection. Arguably, the procedures producing highly correlated ranks with yield do not necessarily produce the same ranks for stability or simultaneously for stability and yield. Therefore, the mean yield was also incorporated as a comparison. The results of the correlation matrix and the PCA from parametric and nonparametric measures revealed that these parameters could evaluate the responses of maize genotypes to fluctuating environments. Therefore, either of them is useful for genotype assessment. Based on this, the repeatability, similarity, and power of parametric and nonparametric procedures for selecting the best genotypes in different crops have to be further studied.

Conflict of Interest

The authors declare that they have no conflict of interest.

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References

- [1] FAO (Food and Agriculture Organization) (2019). Maize. Retrieved July 20, 2020, from <http://www.fao.org/ag/AGS/agse/activity>.
- [2] Ohunakin, AO., Odiyi, AC. & Akinyele, BO. Genetic variance components and GGE interaction of tropical maize genotypes under Northern leaf blight disease infection. *CEREAL RESEARCH COMMUNICATIONS* (2020). <https://doi.org/10.1007/s42976-020-00100-6>.
- [3] Yue, GL, Roozeboom KL, Schapaugh WT, and Liang GH (1997) Evaluation of soybean cultivars using parametric and nonparametric stability estimates. *Plant Breeding* 116: 271-275.
- [4] Ebadi Segherloo A, Sabaghpour SH, Dehghani H, and Kamrani M (2008) Nonparametric measures of phenotypic stability in chickpea genotypes (*Cicer arietinum* L.). *Euphytica* 162: 221-229.
- [5] Zali H, Farshadfar E, and Sabaghpour SH (2011) Nonparametric analysis of phenotypic Stability in chickpea (*Cicer arietinum* L.) genotypes in Iran. *Crop Breed* 1: 89-100.
- [6] Lin CS, Binns MR, Lefkovitch LP (1986) Stability analysis: Where do we stand? *Crop Sci* 26: 894- 900.
- [7] Lin CS and Binns MR (1988a) A superiority measure of cultivar performance for cultivar x location data. *CJPS* 68: 193-198.
- [8] Pinthus MJ (1973) Estimate of genotypic value: A proposed method. *Euphytica* 22, 121-123.
- [9] Francis TR and Kannenberg LW (1978) Yield stability studies in short-season maize. 1. A descriptive method for grouping genotypes. *CJPS* 58: 1029-1034.
- [10] Becker HC and Léon J (1988) Stability analysis in plant breeding. *Plant Breed* 101: 1-23.
- [11] Shukla GK (1972) Some statistical aspects of partitioning genotype-environmental components of variability. *Heredity* 29: 237-245.
- [12] Finlay K. W. and Wilkinson G. N. (1963). The analysis of adaptation in a plant-breeding programs. *AJARs* 14: 742-754.
- [13] Eberhart S. A. and Russel W. A. (1966) Stability parameters for comparing varieties. *Crop Sci* 6: 36-40.
- [14] Perkins J. M. and Jinks J. L. (1968). Environmental and genotype-environmental components of variability: III. Multiple lines and crosses. *Heredity* 23: 339-356.
- [15] Wricke G (1962) Über eine Methode zur Erfassung der Ökologischen Streubreite in Feldresuchen. *Z. Pflanzenzuchtg* 47: 92-96.
- [16] Lin CS and Binns MR (1988b) A method of analyzing cultivar × location × year experiments: A new stability parameter. *TAG* 76: 425- 430.
- [17] Holts T (1995) Analysis of genotype environment interactions. *SAJS* 91: 121-124.
- [18] Gauch HG (1988) Model selection and validation for yield trials with interaction. *Biometrics* 44: 705-715.
- [19] Crossa J. (1990) Statistical analysis of multi-location trials. *Adv in Agron.* 44: 55-85.
- [20] Zobel RW, Wright MJ, and Gauch HG (1988) Statistical analysis of a yield trial. *Agron J* 80: 388-393.
- [21] Gauch HG, Zobel RW (1996) AMMI analysis of yield trials. In: Kang MS, Gauch HG (eds) *Genotype by environment interaction*. CRCP Boca Raton, FL.
- [22] Nassar R., Huehn M. (1987). Studies on estimation of phenotypic stability: Tests of significance for nonparametric measures of phenotypic stability. *Biometrics* 43: 45-53.
- [23] Fox PN, Skovmand B, Thompson BK, Braun HJ, and Cormier R (1990) Yield and adaptation of hexaploid spring triticale *Euphytica* 47: 57- 64.
- [24] Kang MS and Pham HN (1991) Simultaneous selection for high yielding and stable crop genotypes. *Agron J* 83: 161-165.
- [25] Kang MS (1993) Simultaneous selection for yield and stability in crop performance trials: Consequences for growers. *Agron J* 85: 754-757.
- [26] Thennarasu K (1995). On certain nonparametric procedures for studying genotype-environment interactions and yield stability. Ph.D. Thesis. P. J. School, IARI, New Delhi.
- [27] Ohunakin A. O., Odiyi A. C. and Akinyele B. O. (2019) Comparison of rank sum and Area under Disease Progress Curve (AUDPC) as determinant for relative resistance status of maize populations to Northern leaf blight disease of maize. *Adv Plants Agric Res.* 2019; 9 (3): 395–400. DOI: 10.15406/apar.2019.09.00455.

- [28] Kubinger KD (1986) A note on nonparametric tests for the interaction on two-way layouts. *Biometric J* 28: 67-72.
- [29] Hildebrand H (1980) Asymptotisch verteilungsfreie rangtests in linearen modellen. *Med, Inform. Stak* 17: 344-349.
- [30] De Kroon J, and Van der Laan P (1981) Distribution-free test procedures in two-way layouts: A Concept of rank-interaction. *Stat. Neeri* 35: 189-213.
- [31] SAS Institute Inc. (2016). Statistical Analysis Software (SAS) user's guide. SAS Institute, Inc., Cary, NC, USA.
- [32] Akbarpour, Omid, Dehghani, Hamid, Sorkhi-Lalelo, Beza and Kang Manjit. (2016). A SAS macro for computing statistical tests for two-way table and stability indices of nonparametric method from genotype-by-environment interaction. *Acta Scientiarum. Agronomy*. 38. 35. 10.4025.
- [33] GEA-R 4.1: Pacheco, Ángela; Vargas, Mateo; Alvarado, Gregorio; Rodríguez, Francisco; Crossa, José; Burgueño, Juan, 2015, "GEA-R (Genotype x Environment Analysis with R for Windows) Version 4.1", <https://hdl.handle.net/11529/10203>, CIMMYT Research Data & Software Repository Network, V16.
- [34] STABILITYSOFT (2019). Pour-Aboughadareh, A, Yousefian M, Moradkhani M, Pocza P, and Siddique KHM. (2019): A new online program to calculate parametric and nonparametric stability statistics for crop traits. Applications in Plant Sciences 7 (1): e1211. doi: 10.1002/aps3.1211.
- [35] Purchase, J. L., Hatting, H., & Van Deventer, C. S. (2000). Genotype× environment interaction of winter wheat (*Triticum aestivum* L.) in South Africa: II. Stability analysis of yield performance. *South African Journal of Plant and Soil*, 17 (3), 101-107.
- [36] Plaisted, R. L., & Peterson, L. C. (1959). A technique for evaluating the ability of selections to yield consistently in different locations or seasons. *American Potato Journal*, 36 (11), 381-385.
- [37] Huehn M (1990) Non-parametric measures of phenotypic stability. Part I: Theory. *Euphytica* 47: 189-194.
- [38] Kang, M. S. (1988). A rank-sum method for selecting high yielding, stable corn genotypes. *Cereal Research Communications*, 16, 113-115.
- [39] Ketata, H. (1988). Genotype× environment interaction. Proceedings of Biometrical Techniques for Cereal Breeders. ICARDA, Aleppo, Syria, 16-32.
- [40] Steel, R. G., & Torrie, J. H. (1980). Principles and Procedures of Statistics McGraw-Hill Book Co. Inc., New York, 481.
- [41] Badu-Apraku, B., Fakorede, B., Akinwale, R., Annor, B., Adewale, S., Toyinbo, J., & Akintibu, S. (2020). Application of the GGE Biplot as a Statistical Tool in the Breeding and Testing of Early and Extra-Early Maturing Maize in Sub-Saharan Africa. *Crop Breeding, Genetics and Genomics*, 2 (3).
- [42] Mohammadi, R, and Amri, A. (2008) Comparison of parametric and nonparametric methods for selecting stable and adapted durum wheat genotypes in variable environments. *Euphytica*, 159 (3), 419-432.
- [43] Alwala, S, Kwolek, T, McPherson, M, Pellow, J, and Meyer, D. (2010). A comprehensive comparison between Eberhart and Russell joint regression and GGE biplot analyses to identify stable and high yielding maize hybrids. *Field crops research*, 119 (2-3), 225-230.
- [44] Piepho, H. P. (2000). A mixed-model approach to mapping quantitative trait loci in barley on the basis of multiple environment data. *Genetics*, 156 (4), 2043-2050.
- [45] Robert N (2002) Comparison of stability statistics for yield and quality traits in bread wheat. *Euphytica* 128: 333-341.
- [46] Baker, RJ (1988). Tests for crossover genotype-environmental interactions. *Canadian Journal of Plant Science* 68: 405-410.
- [47] Sabaghnia N, Dehghani H, Sabaghpour SH (2006) Nonparametric methods for interpreting genotype × environment interaction of Lentil genotypes. *Crop Sci* 46: 1100-1106.
- [48] Solomon KF, Smith HA, Malan E, and DuToit WJ (2007). Comparison study using rank based nonparametric stability statistics of durum wheat. *WJAS* 3: 444-450.
- [49] Mevlüt Akçura and Yuksel Kaya (2008). Nonparametric stability methods for interpreting genotype by environment interaction of bread wheat genotypes (*Triticum aestivum* L.). *Genetics and Molecular Biology*. 31. 10.1590/S1415-47572008000500018.
- [50] Mohammadi, R, Armion, M, Kahrizi, D, and Amri A (2012) Efficiency of screening techniques for evaluating durum wheat genotypes under mild drought conditions. *International Journal of Plant Production*, 4 (1), 11-24.
- [51] Scapim CA, Oliveira VR, Braccini AL, Cruz CD, Andrade CAB, and Gonçalves-Vidigal MC (2000) Yield stability in maize (*Zea mays* L.) and correlations among the parameters of the Eberhart & Russel, Lin & Binns and Huehn models. *Genet Mol Biol* 23: 387-393.
- [52] Yaksel K, Seyfi T, and Sait C (2003) Nonparametric stability analysis of yield performances in Oat (*Avena sativa* L.) genotypes across environments. *AJPS* 2: 286-289.