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BASIC AREA - Article

Statistical methods to study adaptability and stability of wheat genotypes

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ABSTRACT: The sensitivity of wheat crop to environmental variations frequently results in significant genotype (G) x environment (E) interaction (GEI). We compared statistical methods to analyze adaptability and stability of wheat genotypes in value for cultivation and use (VCU) trials. We used yield performance data of 22 wheat genotypes evaluated in three locations (Guarapuava, Cascavel, and Abelardo Luz) in 2012 and 2013. Each trial consisted of a complete randomized block design with three replications. The GEI was evaluated using methodologies based on mixed models, analysis of variance, linear regression, multivariate, and nonparametric analysis. The Spearman's rank correlation coefficient was used to verify similarities in the genotype selection process by different methodologies. The Annicchiarico, Lin and Binns modified methodologies, as well as the Harmonic Mean of the Genetic Values (HMGV) allowed to identify simultaneously highly stable and productive genotypes. The grain yield is not associated with Wricke, Eberhart and Russell stability parameters, scores of the first principal component of the AMMI1 method, and GGE biplot stability, indicating that stable genotypes are not always more productive. The data analyzed in this study showed that the AMMI1 and GGE biplot methods are equivalent to rank genotypes for stability and adaptability.

Key words: *Triticum aestivum* L., univariate and multivariate methods, rank correlation, grain yield, multi-environment trials.

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INTRODUCTION

Wheat (*Triticum aestivum* L.) can be grown in a vast region of Brazil, being an important crop, especially in the South as well as low latitude and high altitude regions. These producing regions display wide environmental variability. Breeding programs aim at producing highly-productive genotypes with desirable traits, which results from the selection process in different environments (years and locations). The same genotype grown in different environments often shows significant variation regarding productive performance (Condé et al. 2010; De Vita et al. 2010). This fluctuation is the result of the environmental component and refers to the genotype (G) × environment (E) interaction (GEI).

This interaction brings difficulties to the selection of wheat cultivars, especially because it changes the genotypic performance across environments (Mohamed 2013) and minimizes the magnitude of the association between the phenotypic and genotypic values (Alwala et al. 2010), reducing the genetic progress due to selection. Therefore, breeding programs need an extensive testing network. In this case, breeders test genotypes in multi-environment trials, alternating favorable and unfavorable conditions (Alwala et al. 2010). Moreover, GEI allows identifying genotypes adapted to specific environments, which may constitute good opportunities.

There are 2 ways to minimize the GEI effects. The first is to subdivide heterogeneous regions into smaller and more homogeneous sub-regions so that the breeding programs can develop specific cultivars for each sub-region (Mohammadi et al. 2007; Munaro et al. 2014). The second strategy is to select genotypes with high stability across different environments (Eberhart and Russell 1966). In the literature, the different levels of association between methodologies to evaluate adaptability and stability indicate that more than one method should be used for reliable prediction of genotypic performance (Silva and Duarte 2006; Roostaei et al. 2014). However, the most appropriate methods to evaluate GEI can change depending on the data set.

Numerous methods have been proposed for estimating adaptability and stability parameters in multi-environment trials. These methods use different concepts of parametric models, such as univariate (Eberhart and Russell 1966; Wricke 1965), multivariate (Zobel et al. 1988; Yan 2001), mixed (Resende 2006) and non-parametric (Lin and Binns 1988). The ability to explain the sum of squares of GEI is, primarily, the factor promoting the differences between the existing methods.

Studies comparing the methods to assess wheat adaptability and stability parameters are scarce, and there is no consensus on the most appropriate procedures to be used (Mohammadi et al. 2010; Tadege et al. 2014). There is a need to perform studies that compare traditional methods and recent statistical models, indicating the methodologies that can increase the accuracy of the selection process of wheat genotypes, which results in greater genetic gain.

To this end, due to the diversity of models for studying the GEI and the importance of this phenomenon for wheat cultivation, this study aimed at comparing different methods to estimate wheat adaptability and stability.

MATERIAL AND METHODS

The data used in the study referred to wheat grain yield from experiments conducted in 3 locations: Abelardo Luz (SC), Cascavel (PR) and Guarapuava (PR) for 2 consecutive crop seasons (2012 and 2013). Figure 1 shows

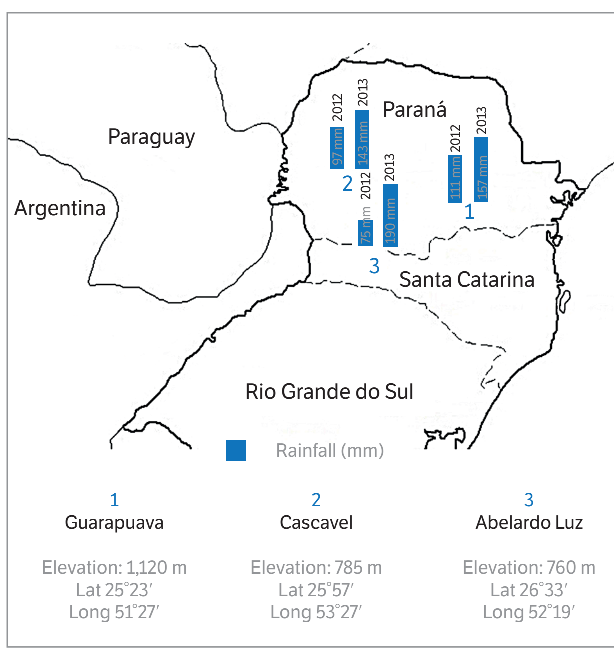

Figure 1. Map of southern Brazil showing the testing environments of wheat genotypes, including geographical position and average monthly rainfall during crop growth in the 2-year trial (2012 and 2013).

the environmental data. For purposes of analysis and interpretation, each location in each year was considered an environment, totaling 6 test environments, named as follows: Guarapuava — 2012 (E1) and 2013 (E2); Cascavel — 2012 (E3) and 2013 (E4); Abelardo Luz — 2012 (E5) and 2013 (E6).

Twenty-two genotypes, including wheat lines and commercial cultivars (coded G1 to G22), were evaluated in Value for Cultivation and Use (VCU) trials, as follows: BRS Guamirim (G1); CD 0940 (G2); CD 105 (G3); CD 114 (G4); CD 117 (G5); CD 119 (G6); CD 120 (G7); CD 121 (G8); CD 122 (G9); CD 123 (G10); CD 124 (G11); CD 12860 (G12); CD 12862 (G13); CD 12864 (G14); CD 12880 (G15); CD 12882 (G16); CD 12884 (G17); CD 1440 (G18); CD 1550 (G19); Fundacep Raízes (G20); Mirante (G21); and Quartzo (G22). The experimental design was a randomized complete block design with 3 replications. Each experimental unit consisted of six 5-m long rows, spaced 0.20 m (1.2 m × 5 m). Sowing density was 360 seeds·m^{-2} and the employed cultivation techniques followed the technical requirements of a wheat crop, published annually. Grain yield (GY) estimates, in kg·ha^{-1}, were obtained by converting the grain mass harvested per experimental unit to 1 ha, with moisture correction to 13%.

For the environments tested, individual and joint analyses of variance were performed. The significance of G, E and GEI effects was determined by F-test. ANOVA assumptions were tested using the Genes software (Cruz 2013). The homogeneity of residual variance (MSE) was verified according to Cruz et al. (2004), in which the ratio between the highest and lowest residual mean square was less than 7. In addition, the Lilliefors test was used to confirm the normal distribution of ANOVA model residuals. Selective accuracy was calculated as described in Resende and Duarte (2007).

The stability and adaptability of the 22 wheat genotypes were tested by the following methods: Wricke (1965) (WR), Eberhart and Russell (1966) (E-R), and additive main effects and multiplicative interaction — AMMI (Zobel et al. 1988). In the AMMI method, the scores of the first principal component (IPCA1) of each genotype were used as a measure of stability. The magnitude of these scores reflects the contribution to the interaction (GEI). The lower the score, in absolute IPCA1 values, the more stable the genotype. Also, the other methods used were: Annicchiarico (1992) (ANN); Lin and Binns (1988) modified by Carneiro (1998)[3] (L-A/C) (method described in Cruz et al. 2004); mixed models — REML/BLUP, model 54 (Resende 2006), in which the measurement of simultaneous adaptability and stability for each genotype was obtained by the Harmonic Mean of Relative Performance of Genotypic Values (HMRPGV) and stability of genotypes by Harmonic Mean of Genotypic Values through environments (HMGV). In this case, the environment effect was considered as fixed and the genotype effect was considered as random. The GGE biplot analysis (Yan et al. 2000) was based on the plot of the scores associated with the environments and genotypes. The larger the vector projection, perpendicular to the straight line of the averages, the lower the genotype stability. Genes (Cruz 2013), Selegen (Resende 2006) and GGE biplot (Yan 2001) software were used.

The genotypes were ranked in regard to adaptability and stability according to the concept and number of parameters of each statistical method. The Spearman correlation coefficients (r_s) (Steel and Torrie 1960) were estimated between the ranks of all pairs of adaptability and stability statistics and the GY. The Spearman correlations were estimated using the average of the ranks of the parameters involved with the GY average to determine the relationship between the methods. To this end, in the WR methodology, the genotypes were initially ranked by the GY, in which the genotype with the highest value was ranked first, up to the g^{th} genotype. Subsequently, the genotypes were ranked according to stability. Finally, the average of ranks per genotype was calculated to determine the new rank, in which the genotype with the lowest value was ranked first, up to the g^{th} genotype. In the ANN method, the ranks of the 3 parameters (I_i, $I_{i(f)}$ and $I_{i(d)}$) were averaged. Subsequently, a new rank was determined; the genotype with the lowest value was ranked first, up to g^{th} genotype. Similarly, the genotypes were ranked using the L-B/C method. In the E-R method, the genotypes were ranked increasingly using the parameters $\hat{\beta}_{1i}$ and $\hat{\sigma}^2_{di}$; the average ranking was calculated and summed to the ranking by GY to obtain a new rank, similarly to the other methods. These procedures followed the methodology →

[3] Carneiro, P. C. S. (1998). Novas metodologias de análise da adaptabilidade e estabilidade de comportamento (PhD thesis). Viçosa: Universidade Federal de Viçosa.

proposed by Roostaei et al. (2014) and Domingues et al. (2013). The ranking from the HMRPGV parameter was used for simultaneous expression of adaptability and stability by the methodology of mixed models (Resende 2006). The ranking of genotypes by the AMMI1 and GGE methods was performed from the output file of the GGE biplot software, which contains the projection values of genotypes on the ordinate and abscissa axes, thus ranking the genotypes according to stability and productive performance. Subsequently, the ranks were averaged, and a new rank was generated, similarly to that described by Alwala et al. (2010).

Each pair of correlated variables was plotted in a scatter plot. The combination of all graphs resulted in correlation figures, where significant associations ($p < 0.05$) were highlighted. The Sigmaplot v.11 software was used for this procedure.

RESULTS AND DISCUSSION

The rainfall was different in the 3 sites, in the 2 years (Figure 1). Guarapuava, Cascavel, and Abelardo Luz had average monthly rainfall of 111 and 157 mm; 97 and 143 mm; 75 and 190 mm; in 2012 and 2013, respectively. De Vita et al. (2010) found a correlation of 0.82 ($p < 0.01$) between wheat grain yield (GY) and rainfall, indicating that this trait is highly dependent on environmental variations. The average monthly rainfall was 42% lower in 2012 compared to 2013. In addition, altitude is significantly different (760 – 1,120 m) among locations, implying sharp temperature differences. These factors contributed to environmental variation and, consequently, significant ($p \leq 0.05$) occurrence of genotype × environment interaction (GEI) (Table 1). Therefore, it becomes difficult to select superior genotypes across environments (Hagos and Abay 2013), requiring other specific statistical procedures to assist in the genotype selection.

The environmental effect was responsible for most of the total sum of squares (SS) of GY (79.3%) after subtraction of SS due to blocks and error, corroborating other studies (De Vita et al. 2010; Hagos and Abay 2013; Roostaei et al. 2014). The effects of genotypes (8.8%) and GEI (13.0%) represented a minor portion of the SS (G + E + GEI). De Vita et al. (2010) reported that

Table 1. Statistical tests for the effects of genotypes, environment and their interaction by parametric analysis (ANOVA) for 22 wheat genotypes in 6 environments.

Analysis per environment							
Environment	MS			CV (%)	Mean (kg·ha⁻¹)	F-test	$\hat{r}_{\hat{g}g}$
	Block	Genotype	Error				
E1	663,647.9	687,795.3	109,884.6	9.4	3,494.8	6.2**	0.91
E2	209,214.6	647,501.0	221,047.8	9.3	5,125.4	2.9**	0.81
E3	58,146.7	472,827.0	32,628.6	4.6	3,901.7	14.5**	0.96
E4	18,369.9	419,903.6	63,509.4	9.7	2,594.9	6.6**	0.92
E5	621,443.5	390,486.5	218,596.2	12.5	3,744.8	1.8*	0.67
E6	80,566.1	264,646.1	165,997.1	10.3	3,936.9	1.6^{ns}	0.61
DF	2	21	42				
> MS / < MS ratio = 6.77							

Joint analysis							
	DF	MS	F-test	% SS	CV (%)	Mean (kg·ha⁻¹)	$\hat{r}_{\hat{g}g}$
Blocks/environment	12	275,231.4					
G	21	1,165,200.4	3.4**	8.8[1]			
E	5	44,013,812.1	159.9**	79.3	**9.67**	**3,799.8**	**0.84**
GEI	105	343,591.8	2.5**	13.0			
Erro	**252**	**135,277.3**					

[1]Total sum of squares (SS), in percentage, remaining after removal of the sum of squares due to blocks and error; **,*Significant at 1 and 5% by F-test; nsNon-significant. MS = Mean square; CV (%) = Coefficient of variation; $\hat{r}_{\hat{g}g}$ = Genotype selective accuracy; E1 = Guarapuava — 2012; E2 = Guarapuava — 2013; E3 = Cascavel — 2012; E4 = Cascavel — 2013; E5 = Abelardo Luz — 2012; E6 = Abelardo Luz — 2013; DF = Degrees of freedom; G = Genotype; E = Environment; GEI = Genotype × environment interaction.

selection for more productive genotypes over the years contributed to the improvement of phenotypic stability in modern genotypes of *Triticum durum* L. This fact results in decreasing GEI and, consequently, a trend towards constant performance among environments and crop seasons. However, no matter how small, the GEI cannot be disregarded (Condé et al. 2010). The GEI observed in the present study justifies the need to conduct trials in all 3 crop sites. Also, we obtained a good experimental precision, confirmed by the low coefficient of variation (9.67%) and high selective accuracy of genotype ($\hat{r}_{\hat{g}g} = 0.84$). The magnitude of selective accuracy also shows that, in these environments, the experiments were able to discriminate the genotypes, contributing to the largest SS of this effect.

The productive performances of the tested genotypes, as well as the ranking assigned by the methods used to evaluate the phenotypic stability, are shown in Table 2. From the data presented in this table, we calculated the Spearman correlation coefficients between all statistic pairs. The study of statistic correlations is of great importance to define what statistical methods should be used to identify the promising genotypes (Scapim et al. 2010; Domingues et al. 2013). Significant and high magnitude correlation coefficients indicate similarity in the ranking of genotypes. It is observed that, of the 66 presented associations, significance occurred in 55% of the time (Figure 2). The use of statistics with a high degree of association generates redundant information

Table 2. Ranking of 22 wheat genotypes evaluated in 6 environments, consisted of 3 locations (Guarapuava, Cascavel, and Abelardo Luz), during 2 years of tests (2012 and 2013), regarding grain yield, adaptability, and stability given by each statistical method.

G	GY ($kg \cdot ha^{-1}$)	Rank	ω_i	I_i	$I_{i(f)}$	$I_{i(d)}$	$\hat{\sigma}^2_{di}$	P_i	$P_{i(f)}$	$P_{i(d)}$	HMGV	IPCA1	GGE
G1	3,559 b[1]	20	14	20	18	20	12	18	13	20	21	6	8
G2	4,245 a	1	21	15	9	3	17	1	9	1	1	21	21
G3	3,767 b	12	15	13	11	13	14	13	19	7	12	18	18
G4	3,606 b	18	17	19	21	18	18	19	22	14	17	16	17
G5	3,599 b	19	16	18	22	15	16	15	18	13	18	15	13
G6	3,721 b	13	13	16	20	11	15	12	11	10	13	8	1
G7	3,453 b	21	1	14	17	12	8	21	21	19	20	11	11
G8	3,627 b	16	8	12	10	17	3	14	15	15	15	10	10
G9	3,921 a	10	6	5	8	7	2	9	10	9	9	1	3
G10	3,200 c	22	19	22	15	22	21	22	16	22	22	22	22
G11	3,857 a	11	18	17	5	19	20	10	5	17	11	17	15
G12	3,636 b	14	9	11	16	9	6	16	20	12	14	4	7
G13	4,015 a	6	4	4	1	8	9	6	6	6	6	2	4
G14	4,088 a	2	22	10	19	5	19	2	1	5	5	12	16
G15	3,981 a	8	10	7	3	16	13	7	2	11	10	13	12
G16	3,630 b	15	20	21	14	21	22	20	12	21	19	20	20
G17	3,939 a	9	11	6	13	1	4	11	14	4	7	14	14
G18	4,036 a	4	7	3	2	6	1	5	4	8	4	9	9
G19	3,985 a	7	12	8	4	14	11	8	3	16	8	19	19
G20	3,617 b	17	5	9	12	10	5	17	17	18	16	5	5
G21	3,559 b	5	2	2	7	4	10	3	7	3	3	3	2
G22	4,245 a	3	3	1	6	2	7	4	8	2	2	7	6

[1]Means followed by the same letter do not differ by the Scott-Knott test ($p = 0.05$). G = Genotype; GY = Grain yield; Parameters to evaluate adaptability and stability: ω_i = Ecovalence (Wricke 1965); I_i, $I_{i(f)}$ and $I_{i(d)}$ = Annicchiarico (1992) at $\alpha = 0.05$; $\hat{\sigma}^2_{di}$ = Eberhart and Russell (1966); P_i, $P_{i(f)}$ and $P_{i(d)}$ = Lin and Binns (1988) modified by Carneiro (1998); HMGV = Stability by mixed models (REML/BLUP); IPCA1 = First principal component of the AMMI1 analysis; GGE = Stability by GGE biplot analysis; *i*, (*f*), and (*d*) = performance in general, favorable, and unfavorable environments, respectively.

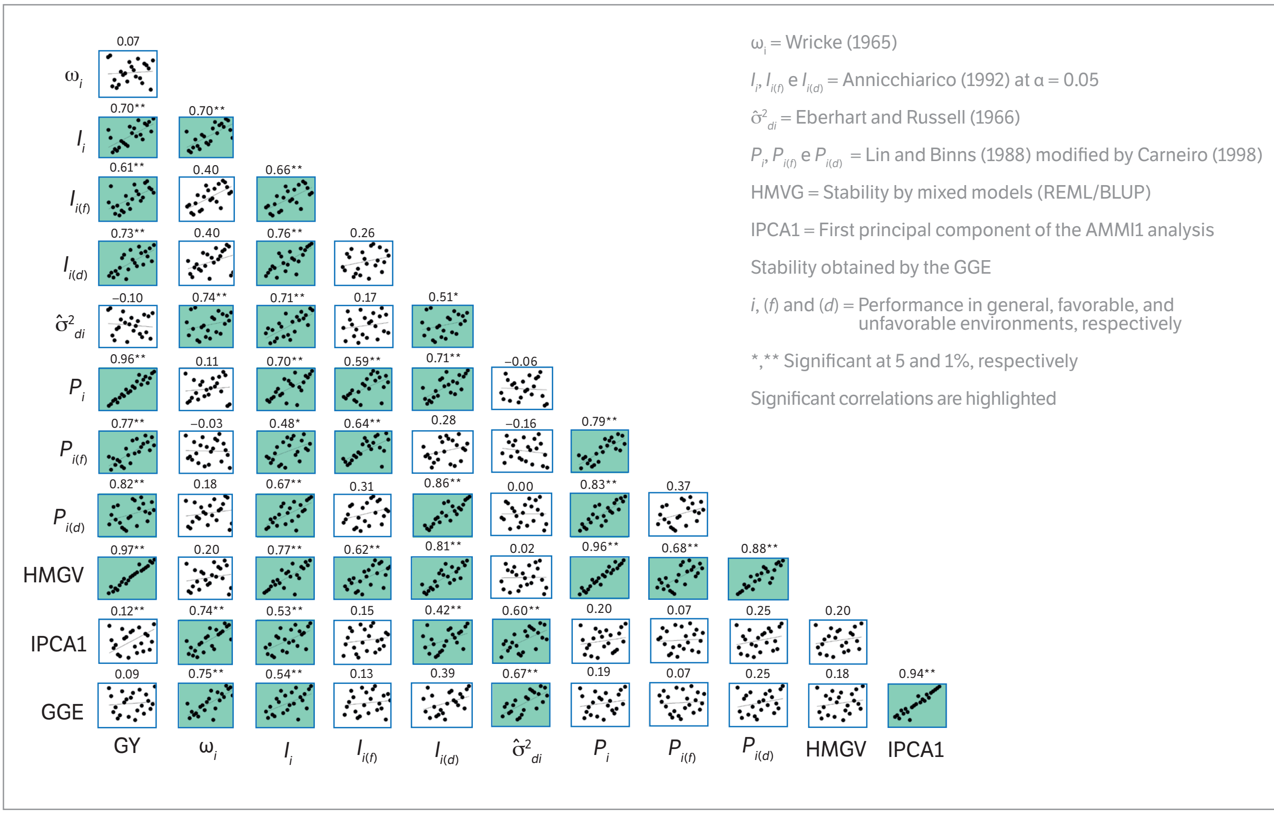

Figure 2. Spearman correlation coefficients between the ranks of 22 wheat genotypes obtained for grain yield (GY) and the stability statistics.

and does not help in the selection process. On the other hand, using statistics that complement each other can increase the confidence in the ranking and selection of cultivars. A significant association was observed between the GY and the statistics from the methodology ANN, L-B/C and stability for mixed models (HMGV). This result indicated that these methods allow identifying more stable and high yield genotypes. In contrast, GY was not associated with ω_i; $\hat{\sigma}^2_{di}$; IPCA1 and with stability analysis by GGE biplot, indicating that stable genotypes are not necessarily more productive, a fact also reported by Franceschi et al. (2010). Flores et al. (1998) reported that methodologies which measure genotype performance, by integrating GY and stability, are strongly associated with GY.

The static concept of stability refers to the constancy of genotype performance across environments, unresponsive to environmental enhancement, whereas the dynamic concept refers to the GY response of the genotype parallel to the average genotypes tested in each environment (Annicchiarico 2002). Figure 2 shows that it is possible to establish 2 statistics groups for the stability evaluation. Group 1 has the ANN, L-B/C and HMGV statistics and, because these statistics are associated with GY, they are related to the dynamic concept of stability. On the other hand, group 2 has the ω_i;$\hat{\sigma}^2_{di}$, IPCA1 and GGE biplot statistics, which, in turn, are related to the concept of static stability. However, contrary to the report of Mohammadi et al. (2010), some parameters were associated between the 2 groups. It is important to highlight the association of statistics of the ANN method with all other statistics, ranged from $r_s = 0.48^{*}$ to $r_s = 0.77^{**}$.

An association was found between the statistics ω_i of the WR method with the IPCA1 ($r_s = 0.74^{**}$) and the E-R regression deviation ($r_s = 0.74^{**}$). Tadege et al. (2014) reported an association of 0.98^{**} between the WR method and E-R regression deviation. Mohammadi et al. (2010) reported the association between these 3 methods, with high repeatability between trial groups. This scenario occurred because these parameters indicate stability regardless of the average yield. Genotypes that demonstrate this kind of stability do not necessarily respond to environment improvement, which is not preferable from the agricultural viewpoint. Also, the AMMI1 analysis and the E-R method provided similar results when identifying stable genotypes ($r_s = 0.60^{**}$), corroborating Mendes de Paula et al. (2014).

The mixed model method (HMGV) showed association with GY and with the 3 parameters of ANN and L-B/C. This methodology is advantageous because the results are on the same measurement scale of the evaluated trait (Rodovalho et al. 2015) and can be efficiently used to estimate the stability and adaptability of unbalanced data, characteristic of wheat trials in multi-environment. In addition, the 3 methods were associated with each other ($r_s \geq 0.62^{**}$), generating redundant information, which corroborates Condé et al. (2010). Mendes de Paula et al. (2014) investigated sugarcane and observed agreement between the ANN, L-B and mixed model methodologies, reporting a preference for the latter. Likewise, Smith and Duarte (2006) suggested the possible use of these methods in combination with E-R to add information. In fact, the possibility of working with unbalanced data is important, particularly for VCU trials. In these tests, not all genotypes are sown everywhere where assessment is taking place, resulting in an unbalanced condition.

The statistics of P_i L-B/C, and HMGV were highly associated with GY, as reported in other studies (Pourdad 2011). Mohammadi et al. (2010) also reported that the P_i index was one of the best methods for ranking genotypes in GEI trials since it is associated with GY and the dynamic concept of stability. Sabaghnia et al. (2006) also reinforced the preference for non-parametric methods, arguing about the ease of use and interpretation.

The presence of a significant and high magnitude association between stability statistics indicates similar ranking of genotypes. Consequently, only one statistic may be sufficient to select stable genotypes for breeding programs (Sabaghnia et al. 2006). However, while high magnitude association can occur, it is essential to observe the best genotypes in each method, as these might not be the same. For example, although there is association ($r_s = 0.96^{**}$) between P_i and HMGV (Figure 2), these statistics do not share the second rank of the most stable genotype (Table 2). The existence of an association between methods does not guarantee the general agreement regarding the best genotypes (Silva and Duarte 2006). This confirms the need to use more than one tool when evaluating adaptability and stability.

The stability and adaptability analysis with graphic appeal have recently become popular in plant breeding (Figure 3). The analysis which-won-where (Figure 3a) is a unique feature of the GGE biplot, in which the partitioning of the genotype in the sectors indicates the presence of significant GEI (Alwala

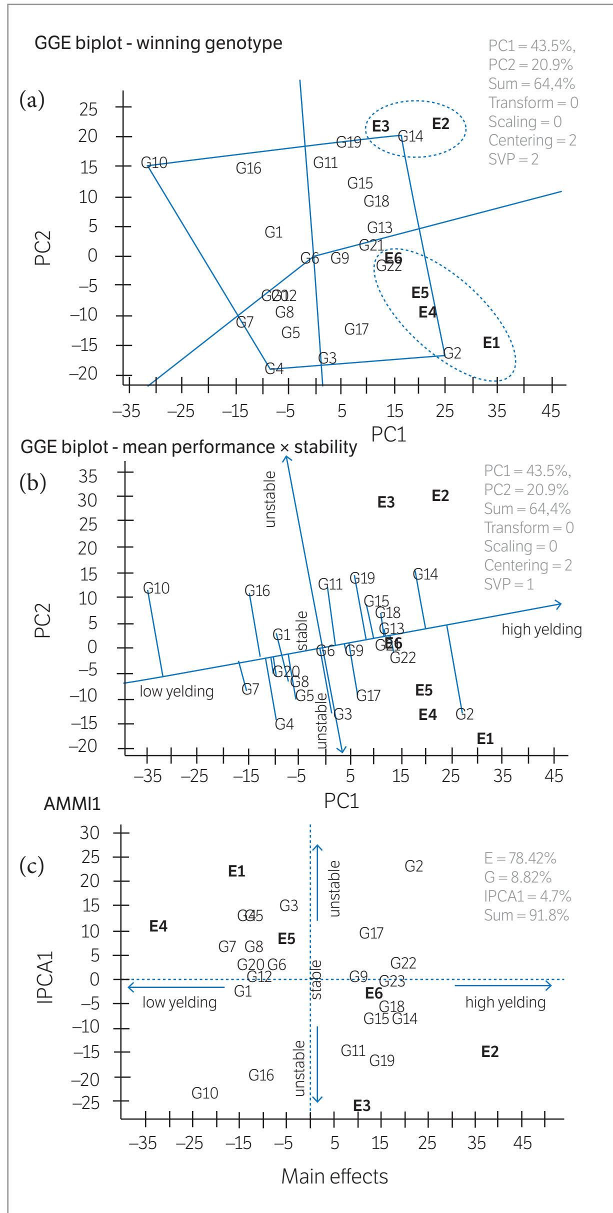

Figure 3. GGE biplot graphs showing the scores of genotypes and environments, regarding best genotypes (a), as well as adaptability and stability (b). AMMI1 Biplot shows the scores of the first principal component (IPCA1) and average performing genotypes and environments (c). G1 to G22 refer to the genotypes, and E1 to E6 refer to environments. PC1 and PC2 = First and second principal components, respectively.

et al. 2010). The graphical analysis mean *versus* stability using the GGE biplot (Figure 3b) allows identifying the magnitude of the stability of each genotype by the projection vector length (Yan and Tinker 2006), where a longer projection, regardless of the direction, represents a greater tendency of GEI. The smaller this vector, the more stable the genotype. In the AMMI1 analysis, the abscissa represents the average effect of genotype and environment while the ordinate infers the stability (IPCA1 scores) (Figure 3c). The results show that the axis of the first principal component of the interaction (IPCA1) explained more than 90% of the data variability, justifying the choice for the AMMI1 model.

When the statistical methods used are not associated with GY, the selection of genotypes must come from the joint evaluation of the stability parameters and productive performance of each genotype. Therefore, Figure 4 shows the Spearman correlation coefficients between the 7 methodologies to study GEI; however, in this case, only 1 ranking was obtained between each method by integrating the GY effect. All methods were associated with each other, and the correlation magnitudes ranged from $r_s = 0.50^*$ to $r_s = 0.96^{**}$. A strong association was observed between the AMMI and GGE biplot ($r_s = 0.94^{**}$), which indicates relative redundancy of information regarding the ranking of the genotypes by stability and GY, corroborating Roostaei et al. 2014. The use of GGE biplot analysis only has been questioned, and the use of mixed models is indicated (Yang et al. 2009).

The correlation coefficient of $r_s = 0.96^{**}$ was obtained from the HMRPGV and L-B/C association. Mendes de Paula et al. (2014) reported high association between these methods, as well as between HMRPGV and ANN, noting that HMRPGV is suitable for selection aiming at sowing in environments with different GEI patterns. Likewise, Rodovalho et al. (2015) reported a strong association between these methodologies and underlined the advantage of the HMRPGV method because it presents the results in the measurement units of the trait. Thus, the indication based on mixed model method is justified because it is based on statistical models that allow greater accuracy in predicting the genotypic values.

Agronomists and breeders usually prefer genotypes with high productive potential that respond to favorable environments and improvement of the environment by using inputs. In this sense, the identification of genotypes that meet this concept is important. Of the tested methodologies, E-R was able to estimate the response of the genotypes to environmental improvement using regression coefficients and may be used as a complement to other methods. However, because it is not associated with GY (Alwala et al. 2010), the simultaneous use of another method is highly recommended. Silva and Duarte (2006) indicated the combined use of E-R and AMMI, aiming at complementary information. Alwala et al. (2010) reported the superiority of GGE biplot analysis over E-R. Moreover, easy interpretation methods such as the GGE biplot simplify the selection process when a large number of genotypes is examined.

Often the occurrence of complex type GEI leads to uncertainty in the selection of a genotype; in this case, graphical inference techniques about adaptability and stability can provide accurate and easy-to-understand information. The identification of stable and highly productive genotypes between different

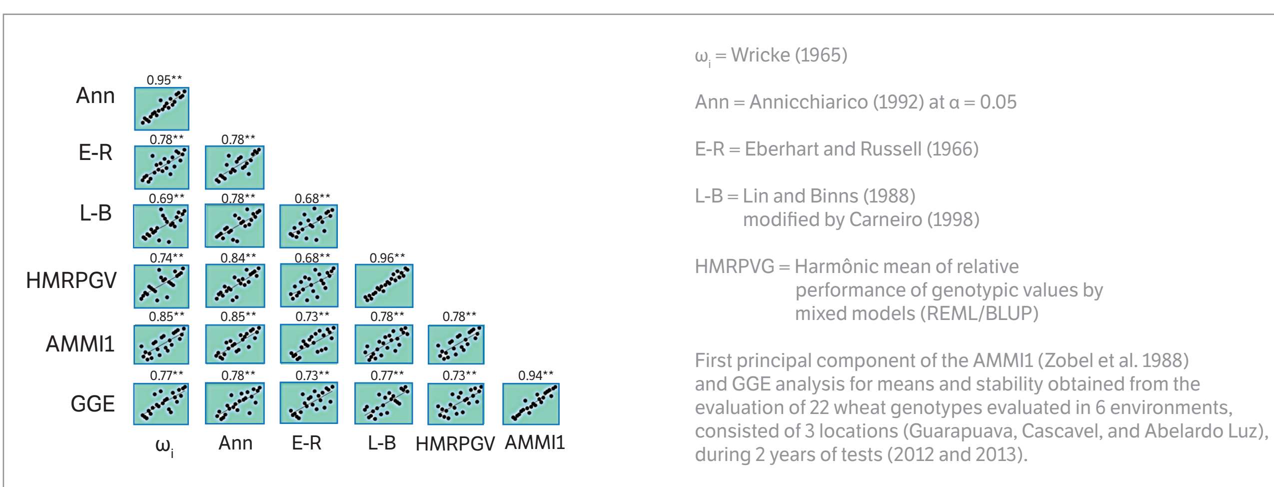

Figure 4. Spearman correlation coefficients between the average ranks of methodologies to interpret the interactions genotype × environment, focusing on yield and stability.

environments remains a constant challenge for breeders of various crop species around the world. In addition, studies about GEI and their bases focusing on the stable parental selection are essential, as well as on determining environments where it is possible to intensify the selection pressure.

CONCLUSION

The selection of wheat genotypes regarding grain yield depends on the method employed to analyze adaptability and stability and on the dataset (sample of genotypes and environments).

The methodologies of Annicchiarico (1992), Lin and Binns (1988) modified by Carneiro (1998) and stability estimated by the harmonic mean of genotypic values using mixed models allow to identify the more stable and productive genotypes, at the same time.

The ranking of genotypes regarding stability and adaptability using the AMMI and GGE biplot showed a trend towards redundancy between the methods ($r_s = 0.94^{**}$).

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