

Genotype by environment interaction for grain yield in foxtail millet (*Setaria italica*) using AMMI model and GGE Biplot

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Abstract

Genotype by environment interaction (GEI) is a major limiting factor in the regional planting and breeding of cultivars. The objective of this study was to assess GEI for grain yield in foxtail millet cultivars grown in northwest China and identify promising genotypes and representative seed production environments. The study used 12 genotypes in eight environments, representative of early-maturing growing areas. Additive main effects and multiplicative interaction (AMMI) and genotype and genotype by environment (GGE) biplot analysis were used to analyze the data. AMMI analysis of variance (ANOVA) indicated that genotype (G), environment (E), and GEI had significant effects ($p < 0.01$). The E contributed the highest percentage of the total sum of squares (SS) (43.4%), followed by G×E (28.6%) and G (19.5%). Six stability parameters based on AMMI were used to analyze yielding stability. YG35, FH9, DT29, and ZZG21 were more stable. The correlation coefficients between the six parameters were > 0.8 . The genomic selection index (GSI) was then used to identify the stable and high-yield genotypes (YG35, ZZG21, and DT29). GGE biplot analysis revealed the same cultivars as the best performers for being closest to the ideal cultivar. The test sites were classified into two mega-environments using GGE biplot analysis for genotype assessment and seed production. CF and XJ were identified as the closest to the ideal test site, with relatively strong discriminatory ability and representativeness. Therefore, the findings of this study provide insights for the regional planting and breeding of foxtail millet in the future.

1 Introduction

Foxtail millet (*Setaria italica*) is one of the oldest food crops in China. It has nurtured the splendid civilization of China for several years (Yang et al. 2012). Foxtail millet has emerged as an environment-friendly crop for dry sloping land, mainly due to its drought resistance, barren soil tolerance, and short growth cycle compared with other water-consuming staple crops (Li et al. 2021a; Wang et al. 2021a, b). Foxtail millet is also important in dryland ecological agriculture, food production diversity, and national food security. Dehusked foxtail millet offers rich and balanced nutrients (Na et al. 2017; Trivedi et al. 2018), including high-quality proteins, dietary fibers, unsaturated fatty acids, vitamins, and mineral elements. Therefore, it is essential for adjusting dietary structure and maintaining human health (Li et al. 2021b; Zhang et al. 2021). China has complex geomorphology and diverse ecotypes across different ecotopes, indicating that a cultivar suitable for one ecotope may not adapt to another. Therefore, it is necessary to evaluate the ecological adaptability of new cultivars and assess their yielding ability and stability to improve the yield and market competitiveness of foxtail millet.

Multi-environment trials (METs), an important and generally activity, can accurately identify cultivars suitable for different ecotopes and representative growth environments (Cooper et al. 1994; Abakemal et al. 2016). However, extreme climates, e.g., drought and rainstorms, and environmental differences between experiment sites often lead to excessive data disparities among the studies exploring ecological adaptability based on multi-year METs. As a result, genotype (G)×environment (E) interaction (GEI) and breeding programs significantly affect the performance of genotypes (Simmonds, 1991). Therefore, a suitable and effective data analysis tool is essential for analyzing the structural patterns of such complicated data. Among them, the most famous analysis tool is the Finlay and Wilkinson joint regression model (1963), which describes G×E by linear regression and can explain the degree to which a genotype is affected by environments. However, it only uses one regression coefficient to characterize the G×E. Although this model has given rise to multiple statistical methods, the methods have not achieved satisfactory results when used to assess genotype/phenotype stability. In 1966, Eberhart and Russel proposed a modified Finlay and Wilkinson model by introducing a new stability parameter, a deviation from the conventional linear response to environments. Currently, additive main effect and multiplicative interaction (AMMI) model and genotype main effects and G×E interaction (GGE) biplots (Gauch 2006) are the common and more efficient analysis methods.

The AMMI model combines ANOVA for main effects of genotype and environment with principal component analysis (PCA) for multiplicative interactions (Zobel et al. 1988). Meanwhile, several stability parameters based on AMMI, such as ASI (Jambhulkar et al. 2017), ASV (Purchase et al. 2000), AVAMGE (Zali et al. 2012), MASI (Ajay et al. 2019), MASV (Ajay et al. 2018), and WAAS (Olivoto et al. 2019) can be used to rank the tested germplasms. This model has been extensively used to analyze crop yields and agronomic traits (Alam et al. 2017; Gupta et al. 2021; Peric et al. 2021; Tadesse et al. 2021). Some studies have focused on quality analysis (Bocianowski et al. 2020a; Gurmu et al. 2020; Thungo et al. 2020), with only a few assessing the advanced analysis of stress resistance (Bocianowski et al. 2020b; Joshi et al. 2021; Arif et al. 2021).

GGE is a multivariate analytical approach that integrates the main genotypic effect with the GEI effect (Yan and Kang 2003). This approach decomposes the eigenvalue based on different goals (focus on cultivars and focus on environments) after eliminating environmental effects from two-dimensional data on G×E. Eigenvalue decomposition produces several principal components, and then, the top two principal components explaining variations are extracted for plotting (Yan 2001). GGE biplots have been valuable to plant breeders and agronomists in demonstrating: (1) “which-won-where” pattern, (2) environment evaluation based on the discriminatory ability and representativeness, (3) genotype ranking based on yield and stability, and (4) comparison of genotypes/environments to identify ideal genotypes/environments (Cooper et al. 1997; Gauch and Zoble 1997; Yan et al. 2007). This model has been widely used to study multiple crops, including rice (Zewdu et al. 2020), sorghum (Enyew et al. 2021; Kumar et al. 2021), maize (Pramitha et al. 2020; Singamsetti et al. 2021), barley (Vaezi et al. 2017), and rapeseed (Nowosad et al. 2016). However, AMMI is more suitable for G×E interaction analysis, while GGE biplot is more adaptable to environmental evaluation (Gauch et al. 2008).

To date, no study has combined AMMI and GGE biplot to analyze the GEI of foxtail millet cultivars in regional trials. In this study, AMMI and GGE biplot were combined for data analysis. The data were collected from regional adaptability trials on foxtail millet cultivars conducted in early-maturing growing areas of northwest China in 2019 ~ 2020. This study aimed to comprehensively evaluate the effect of G×E interaction on foxtail millet yield. As a result, environments with strong discriminatory ability and representativeness were selected. Moreover, superior cultivars suitable for different ecotopes were identified. Therefore, this study may provide insights for improving the productivity of crops, promoting the applications of new cultivars, and meeting the demands of consumers. Moreover, this study can guide the formulation of breeding strategies and the development of commercially competitive germplasms.

2 Materials And Methods

2.1 Germplasm sources and test sites

This study was conducted in early-maturing growing areas of northwest China in the growing seasons of foxtail millet (from May 2019 to October 2020). Eight sites were selected, containing Datong (DT), Lanzhou (LZ), Zhangjiakou (ZJK), Yulin (YL), Huhehaote (HEHT), Chifeng (CF), Guyuan (GY), and Wulumuqi (XJ). Twelve foxtail millet cultivars, namely DT45, DT48, ZZG21, Y14-31, 022-4, FGZ19, FYG4, FH9, CG26, YG35, YG38, and DT29, were investigated.

2.2 Experimental design

All the experiment were conducted in a randomized complete block design with three replicates (6 ~ 8 rows, 16 m²). At the mature time, the harvested area, excluding side rows and row ends, was 13.34 m². DT29 was used as the control for all test sites. All trials were put under unified conventional field management. Weeds were hand-removed without using any herbicide. Mature foxtail millet was harvested and weighed in kg ha⁻¹).

2.3 Data analysis

The data collected were used to analyze the significance level of genotype, environment, and G×E interaction effects. GenStat 21st statistical software (Payne et al. 2007) was used for AMMI and GGE biplot analyses.

The AMMI model can be expressed as follows:

$$y_{jk} = m + \alpha_j + \beta_k + \sum \lambda_n \gamma_{jn} \delta_{kn} + \varepsilon_{jk}$$

(1)

where y_{jk} is the yield of the j^{th} genotype in the k^{th} environment; m is the average total yield; α_j refers to deviation between the mean of genotype j and m ; β_k is the deviation between the mean of environment k and m ; λ_n is the eigenvalue of the n^{th} PCA; γ_{jn} is the principal component score for the j^{th} genotype of the n^{th} PCA; δ_{kn} is the principal component score for the k^{th} environment of the n^{th} PCA; ε_{jk} is the residual error.

The GGE biplot model can be expressed as follows:

$$y_{ij} = \mu + g_i + e_j + (g \times e)_{ij} + \varepsilon_{ij}$$

(2)

where μ is the average total yield; g_i is the deviation between the mean of genotype i and μ ; e_j is the deviation between the mean of environment j and μ ; $(g \times e)_{ij}$ is the corresponding G×E interaction; ε_{ij} is the residual error.

The six stability parameters based on AMMI were calculated as follows:

$$ASI = \sqrt{[IPCA1^2 \times \theta_1^2] + [IPCA2^2 \times \theta_2^2]}$$

(3)

where θ_1 and θ_2 represent the percentage sums of squares explained by IPCA1 and IPCA2, respectively.

$$ASV = \sqrt{\left(\frac{SS_{IPCA1}}{SS_{IPCA2}} IPCA1 \text{ Score} \right)^2 + (IPCA2 \text{ Score})^2}$$

(4)

where SS is the sum of squares, IPCA1 and IPCA2 are the first and second interaction principal component axes (IPCA), respectively.

$$AVAMGE = \sum_{j=1}^E \sum_{n=1}^N |\lambda_n \gamma_{jn} \delta_{jn}|$$

(5)

where E is the number of environments; N is the number of significant IPCAs retained in the AMMI model via F tests; λ_n is the singular value of the n^{th} IPCA; γ_{jn}^2 is the eigen value; γ_{jn} is the eigenvector value for the i^{th} genotype; δ_{jn} is the eigenvector value for the j^{th} environment.

$$MASI = \sqrt{\sum_{n=1}^N IPCA_n^2 \times \theta_n^2}$$

(6)

$$MASV = \sqrt{\sum_{n=1}^{N-1} \left(\frac{SSIPCA_n}{SSIPCA_{n+1}} \times IPCA_n \right)^2 + (IPCA_N)^2}$$

(7)

where SSIPCA1, SSIPCA2, ..., SSIPCAN is the sum of squares of the 1st, 2nd, ..., nth IPCA.

$$WAAS_i = \sum_{k=1}^M |IPCA_{ik} \times \theta_k| / \sum_{k=1}^M \theta_k$$

(8)

where $WAAS_i$ is the weighted average of the absolute scores of the ith genotype; p is the number of singular values.

ASV and the mean grain yield of every genotype across environments were used to derive the genomic selection parameter (GSI), a parameter of stability and yield-based rank of genotypes in the various environments (Farshadfar 2008).

$$GSI = R_{ASV} + R_Y$$

(9)

where R_{ASV} and R_Y represent the rank of ASV and the mean grain yield rank of the genotype, respectively. The genotype with the lowest ASV value and the highest mean yield was ranked first. Genotype with the lowest stability parameter was deemed stable, and that with a lower GSI value had higher mean yield and stability.

3 Results And Analysis

3.1 AMMI ANOVA

The ANOVA on the yields of the 12 foxtail millet cultivars in eight environments is shown in Table 1. G, E, and G×E interaction reached significant levels based on AMMI ANOVA ($p < 0.01$). Specifically, G, E, and G×E interaction contributed 19.5%, 43.4%, and 28.6% of the total sum of squares, respectively. This finding suggests that GEI affects the yield performance of cultivars across environments. Therefore, performing GEI analysis on cultivars based on AMMI is necessary. The G×E interaction was further decomposed into IPCA1-IPCA4 and residual effects. The decomposition results showed that the first three principal components were highly significant. PCA1, PCA2, and PCA3 accounted for 63.0%, 14.9%, and 9.9% of the sum of squares of G×E interaction, respectively. However, the residual only accounted for 5.9%. These results show that AMMI can effectively evaluate the stability of cultivars since the first three principal components explained 87.9%.

Table 1
AMMI ANOVA for grain yield (kg ha⁻¹) of foxtail millet tested across eight environments

Source	df	SS	MS	%SS	%GE	F	p-value
Total	191	526844829	2758350				
Treatments	95	482201301	5075803	91.5	-	122.95	< 0.001
Genotypes	11	102561810	9323801	19.5	-	225.85	< 0.001
Environments	7	228767771	32681110	43.4	-	6.38	< 0.001
Block	8	41010568	5126321	7.8	-	124.17	< 0.001
Interactions	77	150871720	1959373	28.6	-	47.46	< 0.001
IPCA1	17	95116387	5595082	-	63.0	135.53	< 0.001
IPCA2	15	22525315	1501688	-	14.9	36.37	< 0.001
IPCA3	13	14891571	1145505	-	9.9	27.75	< 0.001
IPCA4	11	9493387	863035	-	6.3	20.90	
Residuals	21	8845060	421193		5.9	10.20	
Error	88	3632959	41284				
NB: The block source of variation refers to blocks within environments. df, degree of freedom; SS, sum of squares; MS, mean sum of squares.							

According to AMMI 1, high-yield cultivars or environments were distributed in quadrants I and IV, while low-yield ones were distributed in quadrants II and III (Fig. 1). Therefore, ZJK and HEHT are high-potential environments, while CF and LZ are low-potential environments. Similarly, cultivars ZZG21, CG26, and YG35 are specifically adapted to high-potential environments to some extent. In contrast, cultivars FGZ19 and Y14-31 are specifically adapted to low-potential

environments. IPCA1 scores reflect stability in some degree, an IPCA1 score of approximate 0 indicates that the cultivar has a relatively weak interaction relationship with environments (stable). Thus, cultivars YG35, FH9, DT29, and DT48 might be the most stable genotypes among the range of environments based on IPCA1. However, IPCA2 also significantly affects G×E. Therefore, the IPCA1 scores were plotted against IPCA2 further to analyze the stability of cultivars. It was found that YG35 and DT29 were outliers, suggesting that they significantly respond to the second principal component (Fig. 2). Classifying YG35 and DT29 as stable cultivars was correct based on IPCA1 alone, but it was incorrect based on IPCA1 and IPCA2. Therefore, FH9, ZZG21, and DT48 were stable and high-yield cultivars for all environments.

In AMMI II, each environment was linked with the origin by a line. The length of the environmental vector denotes the discriminatory ability of each environment. In Fig. 2, XJ and LZ were farthest from the origin, suggesting that the two environments had the best discriminatory ability but were not representative (unstable). In contrast, YL, CF, and GY were nearest to the origin, suggesting they were the most representative (stable) but with a relatively weak discriminatory ability. Other environments had a general discriminatory ability for cultivars.

The ranking orders of the yielding stability of cultivars were evaluated according to the AMMI-based stability parameters (Table 2). In this study, six stability parameters were selected. The corresponding cultivar was more stable when any of these stability parameters had a value closer to 0. Therefore, for ASV, the cultivars were ranked in the following descending order of stability: YG35, FH9, DT29, ZZG21, DT48, 022 – 4, FYG-4, YG38, DT45, CG26, Y14-31, and FGZ19. For ASI, YG35, FH9, DT29 were relatively stable cultivars, while CG26, Y14-31, and FGZ19 had the lowest stability. YG35, with the lowest AVAMGE value of 3,357.7, was the most stable cultivar. However, FGZ19, with the highest value of 7,768.4, was the least stable. YG35, FH9, and DT29, with the lowest MASI values of 6.7, 7.5, and 10.6, respectively, were relatively stable cultivars. Similarly, for MASV/WAAS, YG35, DT29, and ZZG21/YG35, FH9, and DT29 were relatively stable. FGZ19, with the highest MASI, MASV, and WAAS values (6.7, 59.0, and 10.0, respectively), was the most unstable cultivar. However, YG35, ZZG21, and DT29, with GSI values of 4, 5, and 7, respectively, were the stable and high-yield cultivars according to yield and stability parameter GSI.

Table 2
Mean yield (kg ha⁻¹), ranking, and AMMI-based stability indices parameters and rankings

GEN	Yield (kg ha ⁻¹)	Y_R	ASI	ASLR	ASV	ASV_R	AVAMGE	AVAMGE_R	MASI	MASLR	MASV	MASV_R	WAAS	WAAS_R	G
ZZG21	7674.5	1	10.6	4	71.1	4	4,461.9	3	10.7	4	94.8	3	14.5	4	5
CG26	6620.5	2	17.8	10	119.3	10	6,946.3	10	18.2	11	139.9	10	23.7	11	11
YG35	6353.8	3	6.7	1	45.1	1	3,357.8	1	6.7	1	59.0	1	10.0	1	4
DT29	6197.6	4	10.6	3	70.7	3	5,458.5	8	10.6	3	80.5	2	14.5	3	7
022 – 4	5957.5	5	15.5	6	103.6	6	5,024.6	6	15.5	6	117.4	6	18.4	6	11
FH9	5867.4	6	7.4	2	49.5	2	4,347.6	2	7.5	2	101.7	5	11.4	2	8
FYG4	5529.5	7	16.2	7	108.3	7	7,157.4	11	16.4	7	124.5	8	22.9	10	14
DT48	5517.8	8	11.4	5	76.5	5	4,886.1	5	11.5	5	96.6	4	14.5	5	11
DT45	5477.4	9	17.0	9	114.1	9	6,667.6	9	17.0	9	144.3	11	20.9	8	11
YG38	5371.3	10	16.4	8	110.1	8	4,581.6	4	16.5	8	117.9	7	19.9	7	11
Y14-31	5141.7	11	18.0	11	120.8	11	5,059.9	7	18.1	10	130.2	9	22.3	9	21
FGZ19	4835.8	12	25.6	12	171.8	12	7,768.4	12	25.6	12	186.1	12	29.4	12	21

The correlation between stability parameters was then determined (Table 3), and significant correlations were found in pairwise comparisons, which indicating that the six stability parameters had similar stability. The first four cultivars suitable for each environment were then analyzed, and ZZG21 was the first-choice cultivar suitable for five environments and the second-choice cultivar suitable for the other three environments (Table 4), showing the superiority of hybrid foxtail millet.

Table 3
Correlation of six stability parameters based on AMMI

Stability indexes	ASI	ASV	AVAMGE	MASI	MASV	WAAS
ASI	1.00**					
ASV	1.00**	1.00**				
AVAMGE	0.80**	0.80**	1.00**			
MASI	1.00**	1.00**	0.80**	1.00**		
MASV	0.94**	0.94**	0.83**	0.94**	1.00**	
WAAS	0.98**	0.98**	0.86**	0.98**	0.93**	1.00**
NB: **: significant at $p < 0.01$.						

Table 4
The first four AMMI selections of foxtail millet per environment

Number	Environment	Mean	Score	1	2	3	4
1	CF	4216	21.17	CG26	ZZG21	YG35	FH9
2	DT	6742	-0.37	YG35	ZZG21	022 - 4	DT48
3	GY	6203	13.04	ZZG21	YG35	CG26	DT48
4	HEHT	7381	-17.22	ZZG21	YG35	DT45	022 - 4
5	LZ	4710	-66.7	ZZG21	DT29	022 - 4	FGZ19
6	XJ	5198	21.96	CG26	ZZG21	DT29	FYG4
7	YL	5427	-4.03	ZZG21	DT29	FYG4	YG35
8	ZJK	7153	32.15	ZZG21	CG26	YG35	FYG4

3.2 Adaptability of tested cultivars

The biplot (Fig. 3) shows the “which-won-where” pattern of test data in multiple environments, and the x-axis PC1 and y-axis PC2 explained 44.20% and 37.29% of the total variation (81.49%). The cultivars farthest from the origin in various directions formed a polygon, encompassing all the other cultivars. The polygon was divided into four sectors when a vertical line was drawn from the origin to each side of the polygon, dividing each test site into two sectors. The eight environments were divided into two groups (ZJK as one group and the other seven environments as the second group), and suitable cultivars were then identified for each group.

The cultivar at the vertex angle of a sector was the cultivar with the highest yield in various test sites. Conversely, for cultivars inside the polygon, the one closer to the origin had a yield closer to the mean yield and lower sensitivity to environmental changes. The tested cultivars at vertex angles included ZZG21, CG26, Y14-31, and FGZ-19. ZZG21 belonged to sectors DT, LZ, YL, HEHT, CF, GY, and XJ, suggesting that ZZG21 has the strongest yielding ability. In contrast, CG26 belonged to only one sector, suggesting that CG26 performs best only in ZJK. The performance of other cultivars was not ideal in any test site.

3.3 Representativeness and discriminatory ability of test sites

The similarity between environments in cultivar evaluation was analyzed by drawing a line segment from the center to each environment (Fig. 4), and the cosine of the angle between two line segments reflected the correlation between two environments. An angle $< 90^\circ$ and $> 90^\circ$ indicated positive and negative correlations, respectively, while 90° indicated no correlation. In this experiment, a high correlation was observed between ZJK, XJ, CF, and GY, between DT and YL, and between HEHT and LZ.

In Fig. 5, the arrow line passing through the origin represents an average environment axis (AEA). The direction of the AEA arrow is a comprehensive evaluation of the representativeness and discriminatory ability of the test site. The length of the line segment from the origin to the test site denotes the discriminatory ability of the test site for cultivars. The longer the line segment, the stronger the discriminatory ability of the test site. The angle between the environmental vector and AEA denotes the representativeness of the test site. The smaller the angle, the stronger the representativeness of the test site. LZ, XJ, and CF had a relatively strong discriminatory ability, followed by ZJK, HEHT, GY, and YL, while DT had a relatively weak discriminatory ability. DT and YL had the strongest representativeness, followed by GY, HEHT, CF, and XJ, with moderate representativeness. ZJK and LZ had the least representativeness. A test site with strong discriminatory ability and weak representativeness can eliminate unstable cultivars, but not for selecting superior cultivars. An ideal test site should have a strong discriminatory ability for cultivars and strong representativeness for ecotopes. Herein, CF and XJ were the ideal test sites.

3.4 Yielding ability and stability of tested cultivars

The top-ranking and stable cultivars were identified using GGE biplot through average environment coordinate (AEC). The yielding ability and stability of cultivars were assessed by drawing a vertical line from each tested cultivar to AEA. The arrow of AEA pointed to the trend under which a cultivar approaches the mean yield in all environments. The vertical line drawn from a cultivar to AEA denoted the stability of G×E interaction. The longer the vertical line, the more unstable the cultivar. It can be seen that ZZG21 had the highest yielding ability, followed by CG26, DT29, YG35, FH9, 022 - 4, FYG4, DT48, DT45, YG38, and

Y14-31, while FGZ19 had the lowest yielding ability. Moreover, YG35, FH9, DT29, and ZZG21 had the highest yielding stability, while FGZ19 and CG26 had the lowest yielding stability, and other cultivars had general stability. Thus, ZZG21, DT29, YG35, and FH9 were the stable and high-yield cultivars (Fig. 6).

3.5 Comparisons of tested environments/cultivars with the ideal environment/cultivar

An ideal cultivar has the highest and most stable yield across all environments, and an ideal environment is a representative environment with the strongest discriminatory ability. The average environment point is usually taken as the center to draw concentric circles outwards, and the distances from the center are then used to judge the merits of genotypes and environments. An environment closer to the center circle has a stronger discriminatory ability and representativeness. All test sites were ranked in descending order as follows: XJ > CF > YL > GY > HEHT > DT > ZJK > LZ (Fig. 7a), and XJ, CF, YL, and GY were relatively ideal test sites, consistent with the test result in Fig. 5. Similarly, a cultivar closer to the center has a higher and more stable yielding ability, as shown in Fig. 7b. ZZG21, CG26, DT29, YG35, and FH9 had relatively high yielding ability and stability, consistent with the test result in Fig. 6.

4 Discussions

G, E, and G×E interaction greatly affect the growth of crops. GEI is a ubiquitous phenomenon in the biological world, which is also the basis of affecting the stability of cultivars. The more significant the G×E interaction effect, the lower the stability of cultivars. Therefore, an objective and accurate evaluation of test data are necessary to promote the practical applications and layout of tested cultivars.

In this study, AMMI and GGE biplot were combined to perform MET analysis on data obtained from the regional trials on foxtail millet in 2019 ~ 2020 and measure the performance of tested genotypes in different environments. AMMI analysis indicated that G, E, and G×E interaction had extremely significant effects (Table 1). Among them, E explained most variations (43.4%), followed by G×E interaction (28.6%) and G (19.5%). The significant effect of E implies that top-ranking and stable genotypes with sound ecological adaptability should be selected. The significant effect of G×E interaction suggests that foxtail millet cultivars of different genotypes respond differently to environmental changes (soil type, temperature, illumination, and precipitation). Therefore, it is necessary to select genotypes adapted to certain environments. Additionally, cultivars selected for different environments based on AMMI had some differences (Table 4), indicating the effect of G×E interaction on yield. Similar studies were also reported in other crops on AMMI analysis of the pattern of G×E interaction (Nzuve et al. 2013; Bashir et al. 2014; Vaezi et al. 2017).

Several parameters have been used to establish the stability of genotypes in multi-location trials. In this study, six parameters were used to evaluate the stability of cultivars, and it was found that YG35, FH9, DT29, and ZZG21 were more stable than others. The correlation coefficients between the six parameters were > 0.80, suggesting that any of them can be used to describe the stability of tested cultivars. However, the stability value is not the only criterion for selection since the yield performance of stable cultivars may not be desirable in actual production. GSI based on AMMI stability value can be calculated to select top ranking genotypes both in yield performance and stability. Therefore, YG35, ZZG21, and DT29 were identified as superior cultivars. This method has been successfully used in other crops (Nduwumuremyi et al. 2017; Donkor et al. 2020). AMMI can be used to select stable cultivars with high and low yields, but some high yield cultivars with poor stability were ignored (Yan et al. 2007; Gauch et al. 2008).

GGE biplot can explain more information about genotypes and environments, which can further evaluate cultivars objectively and comprehensively (Yan 2002; Yan and Tinker 2006). Visualized biplots can help identify which genotypes perform best for specific environments, and also which genotypes are more broadly adapted. For instance, in this study, CG26 had a larger projection on AEC (higher yield) with a longer vector on AEA (lower stability), but it was best suitable for ZJK (Fig. 3). Moreover, GGE biplot identified ZZG21, DT29, YG35, and FH9 as stable and high-yield cultivars, similar to the result obtained by AMMI. The discriminatory ability and representativeness of environments have also attracted much interest in breeding since multi-year METs require a lot of field recording and yield monitoring, thus consuming a lot of time, manpower, and materials. Therefore, test sites with strong discriminatory ability and representativeness should be selected to increase breeding efficiency (Ferfua et al. 2021). In this study, LZ, XJ, and CF had relatively strong discriminatory abilities, while DT and YL had the strongest representativeness. The angle between XJ and CF was extremely small, indicating that the two test sites were very close. However, trade-offs are needed based on long-term production experience.

High and stable yields are important goals for foxtail millet breeders. However, it is difficult to obtain high and stable yields in practical agricultural production and breeding. Although AMMI can identify some stable cultivars based on MET data, these cultivars are often unsuitable for extensive plantation due to low yield. Therefore, applying both AMMI and GGE biplot to create complementary advantages and comparative analysis can not only identify some high-yield cultivars with moderate stability specifically adapted to certain environments but also make scientific and accurate judgments regarding genotypes and environments, thus offering some references for selecting superior cultivars suitable for regional planting in multi-environment layouts.

Conclusions

The G×E interaction, promising genotypes, and representativeness and discriminatory ability of environments for grain yield of foxtail millet in northwest China were investigated in this study. AMMI and GGE biplot can effectively analyze the G×E interaction of data from METs. On the other hand, GGE biplot can powerfully visualize the performance of genotypes and environments. In this study, YG35, ZZG21, and DT29 were identified as relatively stable and high-yield genotypes and ideal foxtail millet cultivars suitable for regional planting and breeding based on the two models and six stability parameters. Moreover, GGE biplot analysis identified CF and XJ as the closest to the ideal test site in terms of discriminatory ability and representativeness.

Abbreviations

GEI, Genotype by environment interaction; AMMI, Additive main effects and multiplicative interaction; GGE, genotype and genotype by environment; MET, Multi-environment trial.

Declarations

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships.

AUTHOR CONTRIBUTIONS

HZ contributed statistical analysis and drafted the manuscript; QW, JW, XY and FQ performed the experiments and collected the data; HZ and XY prepared figures and tables; QW and XY revised the language of this manuscript; HZ, CS and ZF conceived and designed the research.

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Figures

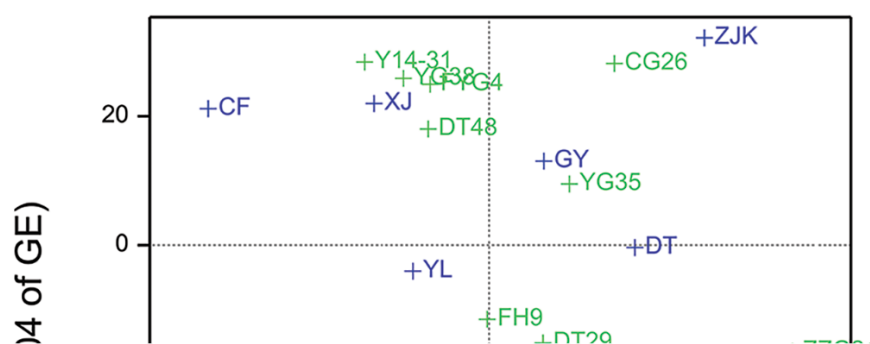


Figure 1

AMMI 1 biplot for the primary component of interaction (IPCA 1) and average grain yield (kg ha^{-1}) of 12 cultivars in eight environments.

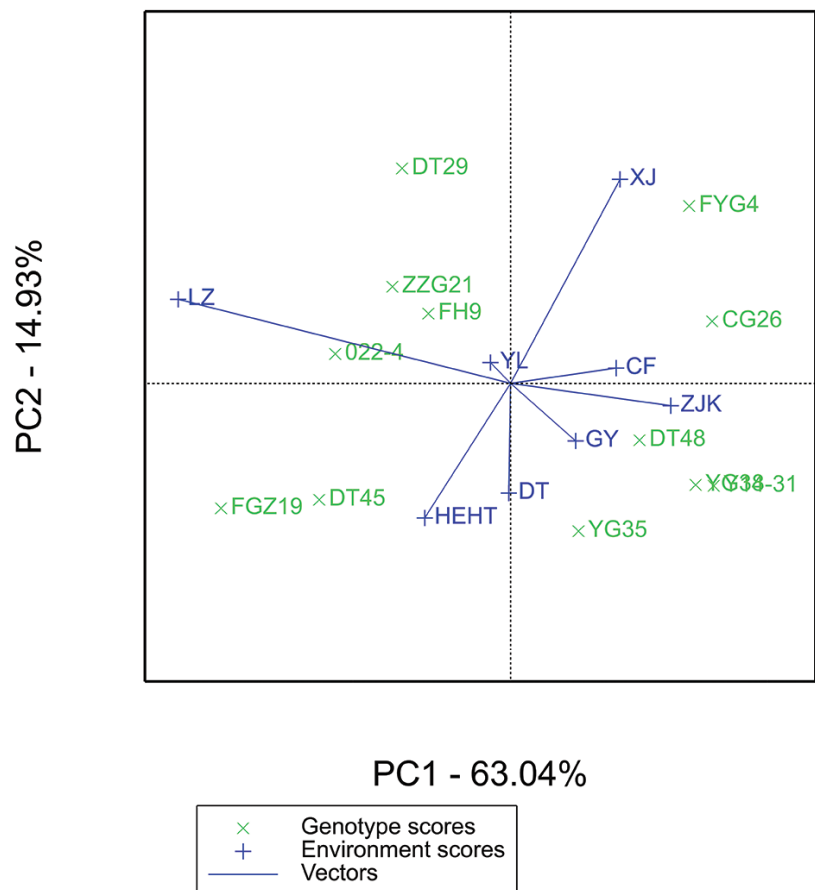


Fig. 2 AMMI II biplot of IPCA 1 and IPCA 2 for grain yield display

Figure 2

AMMI II biplot of IPCA 1 and IPCA 2 for grain yield display.

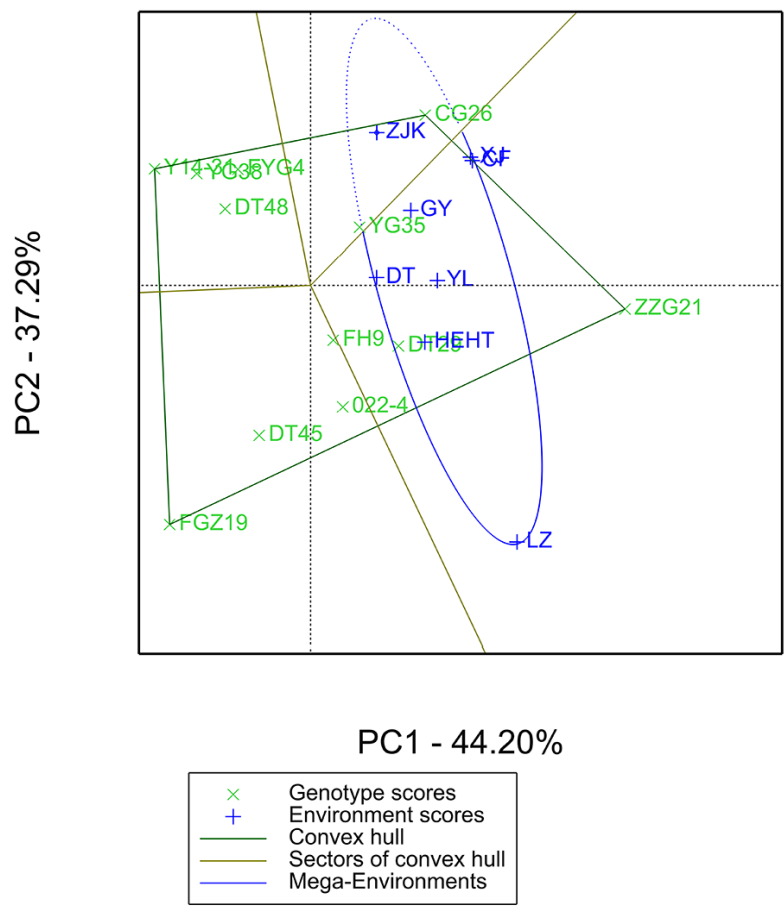


Fig. 3 GGE biplot analysis on the adaptability of tested cultivars

Figure 3

GGE biplot analysis on the adaptability of tested cultivars.

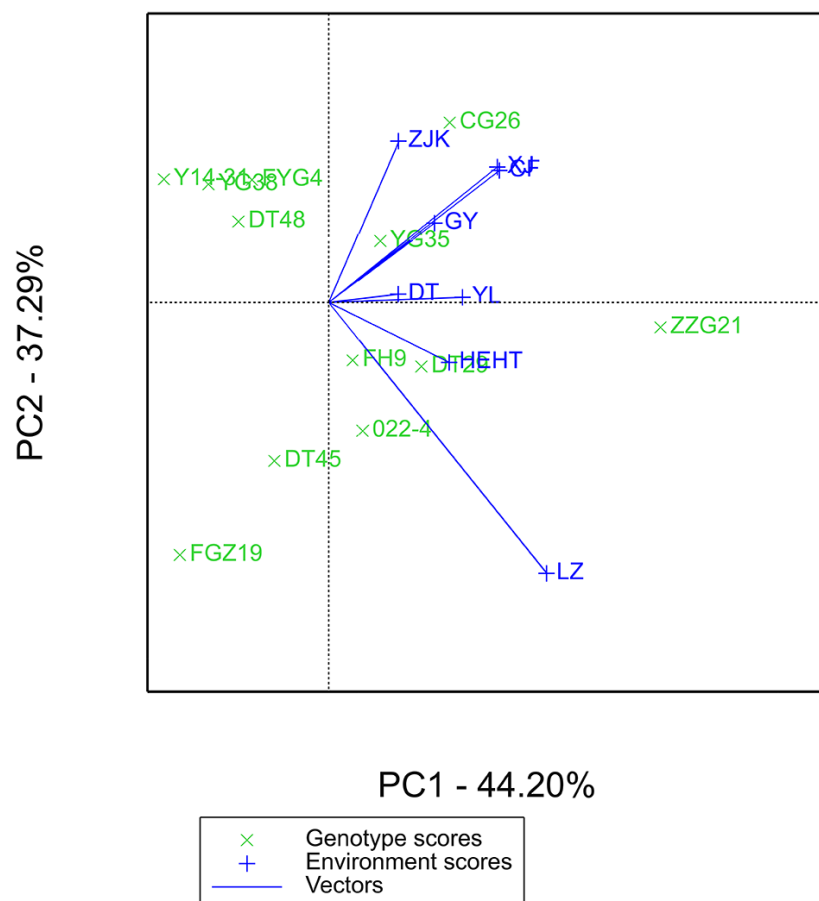


Fig. 4 Vector view of the GGE biplot based on environment-focused singular-value partitioning

Figure 4

Vector view of the GGE biplot based on environment-focused singular-value partitioning.

7.29%

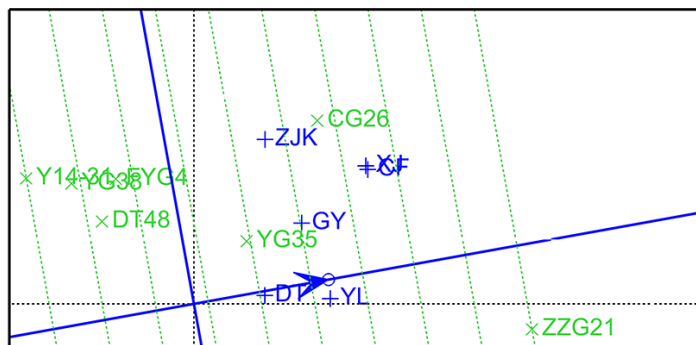


Figure 5

Analysis of discriminatory ability and representativeness between environments based on GGE biplot.

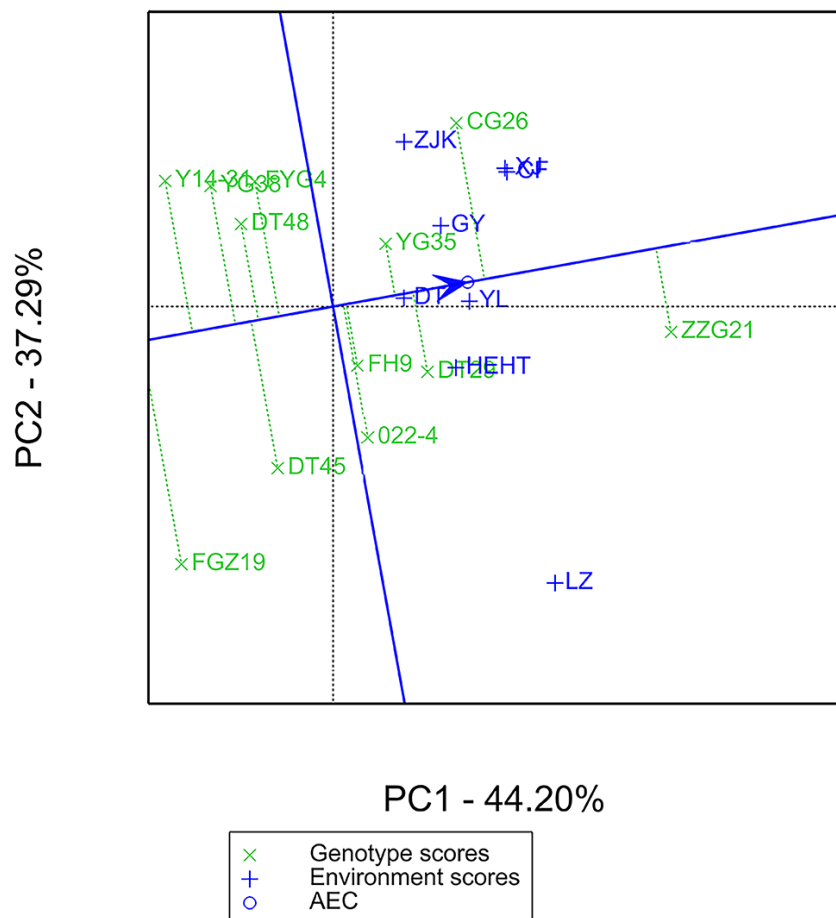


Fig. 6 Genotype focus scaling of GGE biplot showing stability and mean ranking of the 12 genotypes for grain yield

Figure 6

Genotype focus scaling of GGE biplot showing stability and mean ranking of the 12 genotypes for grain yield.

Figure 7

Comparisons of tested environments (a)/cultivars (b) with the ideal environment/cultivar.