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RESPONSE OF HEAT-STRESS TOLERANT AND SUSCEPTIBLE WHEAT LINES IN DIVERSE PLANTING ENVIRONMENTS BY USING PARAMETRIC STABILITY MODELS

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SUMMARY

In Pakistan, wheat planting is delayed because of dawn sowing, which reduces yield due to terminal heat stress. This effect can be alleviated by changing sowing times. Therefore, parametric stability analysis was carried out with eight different sowing dates (environments), namely, early, normal, late, and very late, with 10-day intervals in 2019–2020 and 2020–2021 at the Wheat Research Institute, Faisalabad, Pakistan. Significant heat stress responses were observed at the latter two sowing dates. The genetic and phenotypic relationship among the traits revealed that the normalized vegetation index (NI) had a positive correlation with grain yield (kg ha^{-1}) (Yi) and 1000-grain weight (g) (GrWt). However, canopy temperature (CaTe) had a negative correlation with Yi, GrWt, and NI. For Yi and GrWt, the linear environmental response (ɑ) and deviation from linear response (λ) were observed as transformed forms of regression coefficient (bi) and deviation from regression (S^2d). Planting dates, i.e., E1, E6, and E7, had slight effects on Yi, and E6, E7, E2, and E8 had slight effects on GrWt. Meanwhile, E3, E4, E5, E1, E3, and E4 exerted a strong effect on the genotype by environment interactions for Yi and GrWt. For Yi, lines G23, G20, and G21 were adapted to E8; G9 and G19 were adapted to E1; and G15, G17, and G22 were adapted to E5. For GrWt, G13, G20, G3, G11, G21, and G15 were adapted to E8 and E4; G10, G7, G8, and G5 were adapted to E5; G4, G22, and G17 were adapted to E6 and E4; and G24 and G2 were adapted to E2 and E3. The candidate wheat lines with enhanced GrWt and Yi were found in E5 and E6 (late sowing) and E7 and E8 (very late) and presented tolerance to terminal heat stress.

Keywords: Probing, heat stress, candidate lines, sowing date, parametric stability models, bread wheat

Key findings: In this study, candidate lines with significant GrWt and Yi enhancements under late and very late sowing and to terminal heat stress were identified. These candidate lines must be registered and recommended to ensure national food security.

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INTRODUCTION

Pakistan is no stranger to the influences of temperature variation. Over the last few years, the countries like Haiti, the Philippines, and Pakistan, which are recurrently affected by calamities, continuously rank among the most affected countries both in the long-term index and in the index for each respective year (Eckstein *et al.,* 2021). Temperature increases over 1980–2008 have decreased the average global wheat harvest by 5.5%, and the average global temperature is expected to increase by 2 °C–4 °C by the end of 2050 (Asseng *et al*., 2015). The effects of extreme heat on wheat crop must be considered because wheat is an indispensable component of the human diet. Approximately 31%, 59%, and 12.5% of the cultivators plant wheat till mid-November, at the end of December, and after December, respectively, in the irrigated zones of Punjab, Pakistan (Mudasser *et al.,* 2001). In Pakistan, summers are lengthening and winters are shortening, thus decreasing the extent of wheat cultivation.

Late wheat planting is performed due to the late harvesting of rice, cotton, and sugarcane crops. Grain yield (Yi) and 1000-grain weight (GrWt) are complex quantitative traits, and their performances are greatly influenced by shifting sowing dates. Despite substantial breeding improvements, Yi and one of its determinants, GrWt, have experienced many changes likely due to plant biomass, architecture, biotic and abiotic constraints, the interaction between genotype (G) and the environment (E), or by other unidentified mechanisms The genetic improvement of desired wheat genotypes in production environments is needed because late sowing results in lower grain weight and yield than timely harvesting. Reductions of approximately 1.3% in yield ensues with each delay of one day; subsequently, sowing is done in the early days of December due to terminal heat stress (Hossain *et al.,* 2011; Shaukat *et al*., 2021). Various wheat experiments have indicated that terminal heat stress results in substantial yield reductions, which can be lessened by shifting sowing times (Dwivedi *et al*., 2018; Raj *et al.,* 2018).

Heat stress usually peaks at postanthesis and throughout the grain filling period; the morphological, physiological, anatomical, biochemical, phenological, and physiochemical changes due to heat stress during the postanthesis stage reduce yield (Gazal *et al*., 2016; Zulkiffal *et al.,* 2021). Therefore, the sowing period must be changed and heat-resilient genotypes must be developed to lessen the adverse effects of temperature at the postanthesis phase and maintain high grain weight and yield. Plant breeders frequently perform trials to obtain stable genotypes that are capable of withstanding postanthesis stresses. However, the performances of most of the highly stable genotypes are poorly predictable across shifted sowing dates due to heat stress at this stage. Hence, candidate lines with enhanced gain weight and yield parameters must be evaluated for their stability in withstanding erratic temperature situations at different locations and diverse sowing dates. For this objective, plant breeders often perform parametric stability analysis given that highly stable candidate lines are less predictable in late sowing periods. Macas *et al*. (2000) appraised the response of some wheat and durum genotypes under increasing temperature stress during and after anthesis by planting them on different sowing dates. Similarly, Modhej *et al*. (2008) conducted field experiments on delayed and optimum sowing dates and studied the effects of postanthesis heat stress on the Yi and GrWt of wheat and durum genotypes. Therefore, in this work, we identified high-yielding and highly stable wheat candidate lines over different sowing dates (environments) that can withstand the contradicting effects of postanthesis heat stress, particularly heat stress at late sowing dates, by using parametric stability models. These advanced lines with greater variations could be used for the development of heat-tolerant wheat cultivars which is an enormous wish for food security.

MATERIALS AND METHODS

The 23 wheat genotypes were sown with on eight different sowing dates with 10 days intervals i.e., 20th October (E1), 1st November (E2), 10th November (E3), 20th November (E4), 30th November (E5), 10th December (E6), 20th December (E7), and 30th December (E8) in 2019–2020 and 2020–2021 at the Wheat Research Institute, Faisalabad, Pakistan (31°25'N, 73°04'E and 610 feet above sea level). In Pakistan, E1 and E2 are considered as early, E3 and E4 as normal, E5 and E6 as late, and E7 and E8 as very late sowings dates. In the present trial, late and very late sowings were performed to expose the candidate lines to heat stress. Fertilizer was applied at the rate of 120:90:60 NPK kg ha^{-1} with three irrigations. Four typical checks (G1, G3, G6, and G11) were used with two replications in a RCB design. Sowing was done in plots with dimensions of 1.62 m × 6 m with a six-row tractor-driven Wintersteiger planter. Harvesting was carried out on six rows with a self-driven Wintersteiger harvester. Data on GrWt in grams, Yi in kg ha^{-1}, heat stress indicators normalized differential vegetation index (NI), and canopy temperature (CaTe) in °C were documented at the postanthesis phases. NI and CaTe were taken with a green seeker (handheld-505) and infrared thermometer (LT.300) in sunshiny times with the slightest wind speed at mid-day spell when the precipitation had evaporated from the plant canopy.

Data analysis

For statistical analysis, data for 2 years were combined for the average binary reading and further subjected to analysis with parametric stability models. These models included a regression model (Eberhart, 1966; Russel and Tai, 1972), variance measures (Wricke, 1962; Lin and Binns, 1988), multivariate analysis (Gauch, 1988), and genotype + genotype × environment (GGE) biplot (Yan, 2001) with the help of statistical software package STATISTICA-5.0, SPSS-12 (Sneath and Sokal, 2014), and multienvironment trial analysis (Alvarado *et al.,* 2015).

RESULTS AND DISCUSSION

The mean squares from analysis of variance specified in Table 1 indicated that genotypic differences were highly significant ($P \leq 0.01$), excluding NI (G × E) and GrWt (PC2), which were proven to be significant ($P \leq 0.05$) These results validated the presence of adequate variability among environments and candidate lines. Environments made the major contributions to the variability of Yi (92%), GrWt (85%), NI (63%), and CaTe (57%), followed by G × E, particularly for CaTe (19%) and GrWt (13%). The candidate lines showed considerable variation for CaTe (24%) and NI (23%) (Aberkane *et al.,* 2021). The significance of the environment and G × E interaction indicated the presence of differences in the responses of the considered traits of the advanced lines to various environments. PC1 significantly contributed exclusively to the variation in GrWt (52%), CaTe (48%), and Yi (47%), and PC2 contributed considerably to CaTe (28%) and NI (25%) traits. The highly significant G × E interaction revealed that Yi and GrWt changed over sowing dates due to the existence of environment interaction. The changes in the traits indicated the usefulness of of different parametric stability methods for defining the behavior of advanced lines in eight environments. Such statistical interaction among the candidate lines stemmed from the modification in the degrees of change between candidate lines from one environment to another.

Genetic and phenotypic correlation matrixes

In wheat breeding, multiple traits are conventionally partitioned in multiple environments due to the phenotypic linkages among inspected traits because they are affected by environmental factors. Genetic correlation is essential because it reveals the heritable affiliation between traits. However, neither strong nor weak connection was observed between the phenotypic and genetic correlations. For an effective breeding program, there must be both genetic and phenotypic variations in the populations, and the same found in these wheat advanced lines provide sufficient selection opportunities. The study of relationships between traits revealed that NI has a positive association with Yi and GrWt at the genetic and phenotypic levels (Table 2). The significant positive correlation of Yi with NI and GrWt showed that candidate lines with high chlorophyll content had advanced harvest and can be discarded as an energetic parameter for screening candidate lines in eight environments due to their stay-green presence. The stay-green trait in development-specific reflectance directories and their consequent factors are based on the cumulative rates of photosynthesis and photoassimilates in the greeneries. Therefore, Yi and GrWt can be improved if the selection is based on NI. GrWt has positive links with Yi. Khan *et al.* (2012) also concluded in their trial that among yield components, only GrWt showed phenotypic and genotypic relationships with Yi likely because Yi is extremely dependent on traits that are expressed during the grain filling stage. After all, final GrWt is attributed to changes in grain-filling frequency from anthesis to maturity. These results were consistent with previously reported findings (Shiferaw *et al.,* 2016; Zulkiffal *et al.,* 2018). Yi, GrWt, and NI had negative correlations with CaTe. A negative CaTe indicates that during the sun-drying period of wheat, the plant canopy was warmer than the air, which is

Table 1. Mean squares and interface proportion of the traits of interest of wheat accessions in eight environments.

SOV	DF	NI	CaTe	GrWt	Yi
E	07	0.03**	58.96**	2264.04**	89640155**
		63.39	56.87	84.82	91.82
G	23	0.00**	7.58**	20.55**	803210**
		22.89	24.02	2.53	2.70
G × E	161	0.00**	0.86**	14.68**	232527**
		3.72	19.11	12.65	5.48
PC1	29	0.00**	2.27**	42.52**	600897**
		26.85	47.53	52.17	46.55
PC2	27	0.00**	1.42	15.85*	293629**
		25.61	27.69	18.10	21.18
Residual	192	0.00	0.47	1.54	10707
		0	0	0	0

* = $P \leq 0.05$, **= $P \leq 0.01$. The upper values specify the sum of squares and the lower values designate explained disparity (%). NI, CaTe (^{0}C), GrWt (g), Yi (Kgha^{-1}), E, and G indicate normalized vegetation index (postanthesis), canopy temperature (postanthesis), 1000-grain weight, yield, environments, and candidate lines, respectively.

Table 2. Genetic and phenotypic correlation matrixes for the various studied traits of 24 candidate lines.

Traits	Correlations	NI1/	CaTe	GrWt	Yi
NI	Genetic	1			
	Phenotypic				
CaTe	Genetic	−0.9999**	1		
	Phenotypic	−0.9418			
GrWt	Genetic	0.357733**	−0.16196**	1	
	Phenotypic	0.195636	−0.11324		
Yi	Genetic	0.655808**	−0.66432**	0.3247**	1
	Phenotypic	0.513555	−0.55687	0.356216	

**= $P \leq 0.05$, 1/ as indicated in Table 1.

indicative of terminal heat stress that causes inferior GrWt and accordingly decreases Yi. A low CaTe is related to increased yield mainly in a postanthesis heat stress environment. Thus, CaTe is a prospective tool for the indirect assessment of the suitability of a genotype to stress environments and can be used as a special element for developing heat stress-tolerant genotypes (Fischer *et al.,* 1998).

Parametric stability methods

Regression methods

The regression approach included two stability methods that were described by Eberhart and Russell (1966) and Tai (1971).

Comparison bi and S^2d values

The regression model suggested by Eberhart and Russell is based on regression coefficient (bi) and deviation from regression (S^2d). The candidate lines with bi values higher than 1 had superior yield and low S^2d value and likely had high levels of stability. For example, candidate lines 23, 21, 2, 24, 17, 11, and 18 exhibited bi >1 with small S^2d, which indicated high yield performance with adaptability to the favorable environment (Figure 1). By contrast, candidate lines 4, 13, 5, 22, and 6 with bi < 1 and excessively high S^2d indicated low yield and were least affected by environmental phenomena. Candidate lines 10, 15, 7, 20, and 9 with bi near unity had average yield and moderate response (S^2d) to environmental effects. The remaining genotypes no significant results in all environments. Similarly, for GrWt, candidate lines 21, 9, 24, 20, 23, and 10 had bi >1 with small S^2 d, indicating high GrWt performance with adaptability to the favorable environment, whereas the candidate lines 5, 4, 13, 12, and 8 with bi < 1 and excessively high S^2d had low GrWt and were least affected by

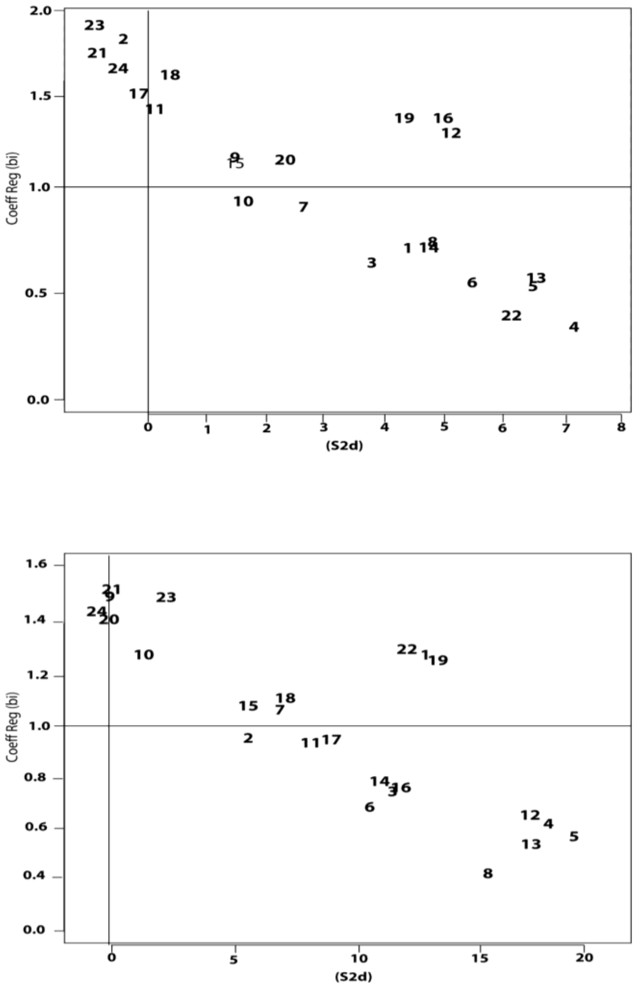

Figure 1. Regression coefficient and deviation from regression for Yi and GrWt traits correspondingly. G1: Faisalabad08, G2: 17086, G3: Anaj17, G4: 17175, G5: 17157, G6: Ujala16, G7: 20355, G8: HYT70-40, G9: 17157, G10: 19308, G11: Akbar19, G12: 19332, G13: 17005, G14: 19352, G15: 19347, G16: 17179, G17: 19325, G18: HYT70-16, G19: 16024, G20: 18352, G21: 18381, G22: HYT100-74, G23: 17189, G24: 19317.

the environment. Candidate lines 7, 2, 11, 17, 15, and 18 with bi near unity exhibited average GrWt and moderate response (S^2d) to environmental effects, whereas all other genotypes showed no significant responses to all environments. Anwar *et al.* (2007) and Amin *et al.* (2005) evaluated wheat GrWt and Yi stability and identified stable and unstable wheat genotypes on the basis of their regression coefficients in varying environments. Their results indicated that the linear response of genotypes to environmental changes had considerable variation. On the basis of GrWt and Yi parameters, the overall results from this type of stability analysis showed that high mean yield and stability were not jointly elite and candidate lines with high yields could differ in stability. Therefore, different candidate lines with high yield and stability over a range of different environments should be considered for selection. Abdallah *et al.* (2011) reported a comparable conclusion when they predicted the stability parameters of various crops by utilizing this model (Figure 1).

Comparing α and λ values

The second regression model involved the alterations in bi and S^2d and was recommended by Tai (1971). It is similarly based on binary dimensions, linear environmental response (α), and deviation from linear response (λ). For Yi, candidate lines 9, 10, 5, 20, and 7 with α = 0 and λ = 1 showed mediocre stability; candidate lines 11, 18, 24, 21, 17, 23, and 2 with α < 0 and λ = 1

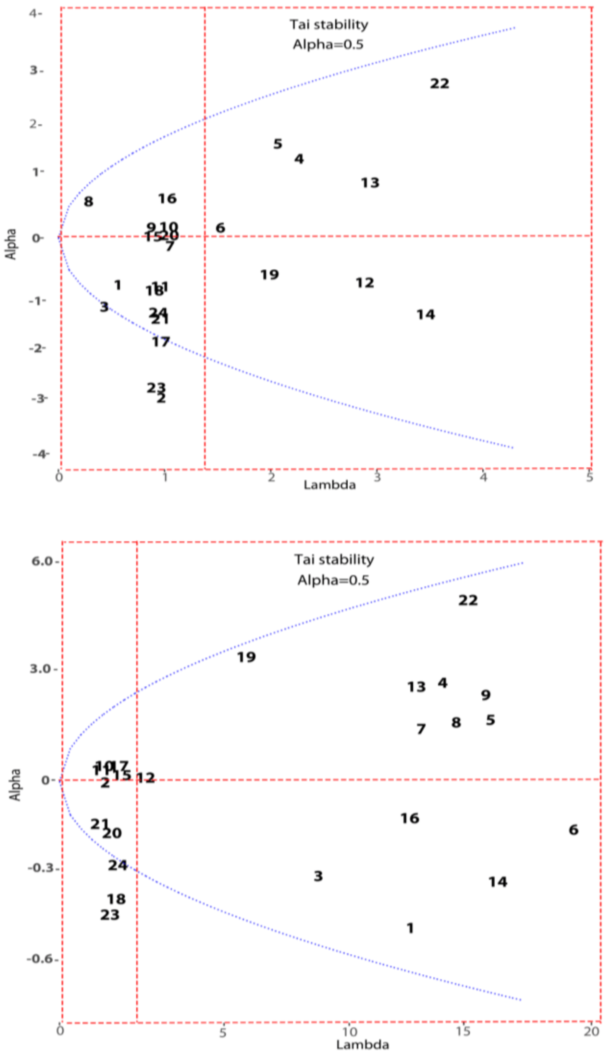

Figure 2. Tai model grounded outlook for Yi and GrWt traits respectively.

presented above-average stability; and candidate lines 6, 5, 4, 13, and 22 with ɑ > 0 and λ > 1 exhibited below-average stability. For GrWt, candidate lines 12, 11, 17, 15, 2, and 10 displayed average stability, whereas candidate lines, 21, 24, 20, 23, and 18 had above-average stability. However, candidates 4, 9, 8, 5, 13, and 7 showed below-average stability (Figure 2). The almost linger candidate lines were unhinged as they outdo the significant point. These results clearly showed that ɑ and λ could be regarded as altered forms of b and S^2d. Such results have been validated by a previous work (Morsy *et al.,* 2015).

Variance measurement concept-based method

Wricke's ecovalence (1962) and Lin and Binns (1988) are the most frequently used variance methods for measuring yield stability.

Wi^2 value

Wricke (1962) suggested using ecovalence (Wi^2) as a stability parameter. Candidate lines with the smallest ecovalence values are considered stable and vice versa. Candidate line 6, followed by candidate lines 12, 5, and 18, had the lowest Wi^2 values for Yi and candidate line 6 followed by candidate lines 4, 19, and 12 had the lowest Wi^2 values for GrWt; these lines were found to be the most stable (Table 3).

Table 3. Ecovalence and superiority standards for the Yi and GrWt of candidate lines.

Genotypes	Yi		GrWt	
	Wi*	Pi*	Wi	Pi
1	1425394	534652	22.8	19.1
2	518838	448840	52.0	9.2
3	629101	234427	42.8	10.6
4	593328	251182	11.1	7.9
5	415751	506958	17.5	16.4
6	196874	453235	7.7	19.2
7	635675	641979	35.0	28.4
8	827802	326685	139.1	28.3
9	3009772	277011	93.9	25.5
10	1426499	410920	119.3	28.9
11	457216	468757	28.7	27.9
12	251326	156667	19.2	7.6
13	913481	558883	140.3	17.5
14	483062	496412	21.9	14.6
15	619678	160169	106.3	19.3
16	517596	153917	36.7	12.5
17	705095	184255	52.7	17.2
18	429097	255144	34.2	22.2
19	801517	172213	12.3	14.5
20	689626	267012	61.2	18.3
21	1139566	383724	51.1	22.8
22	817144	99900	23.1	5.7
23	679593	154532	31.5	17.3
24	535037	348889	21.4	17.3

*Wi = Ecovalence value**, ***Pi = Superiority index

Pi value

Lin and Binns (1988) introduced the superiority index Pi to indicate the general superiority of a genotype. The genotypes of greatest interest for stability would have the lowest Pi values. For example, candidate line 22, followed by candidate lines 16, 23, and 12, had the lowest Pi values for Yi, and candidate line 22, followed by 12, 4, and 2, had the lowest Pi values for GrWt. For low values of Wi and Pi (more stable), the candidate line 12 was common in two stability cases for two traits while 6 for Yi, and line 22 for GrWt were common for the low value of Wi and Pi, respectively. Candidate line 4 was common in Wi and Pi stability parameters for GrWt only which showed that this line computed for yield trait and not for stability. Laghari et al. (2021) selected stable high-yielding wheat genotypes by considering the Pi value (Table 3).

Multivariate analysis

Two parametric stability models were used in the third approach.

Additive main effects and multiplicative interactions

Only the additive main effects and multiplicative interaction (AMMI) biplots of PC1 vs PC2 were used to examine the multiplicative effects of G × E. The biplots illuminated 46.5% (PC1) and 21.2% (PC2) of discrepancy for Yi and 52.2% (PC1) and 18.1% (PC2) for GrWt (Figure 3). These proportions were the major components of the GEI arrangement. In these biplots, environments notches were related to the origin by vectors in such a way that environments with short lines exerted weak interactive forces and vice versa. For example, E1, E6, and E7 for Yi and E6, E7, E2, and E8 for GrWt were located adjacent to the origin, reflecting the revealed minor influence of G × E interactions on these traits. The environments with a solid interface (vector endpoints distant from their source) were E3, E4, and E5 for Yi and E1, E3, and E4 for GrWt. The environments E1 and E8 for Yi and E2 and E8 for GrWt were very alike. The high deviation due to the environment indicated that the study environments were unlike with the large differences between environmental means producing most of the variation in genotypic

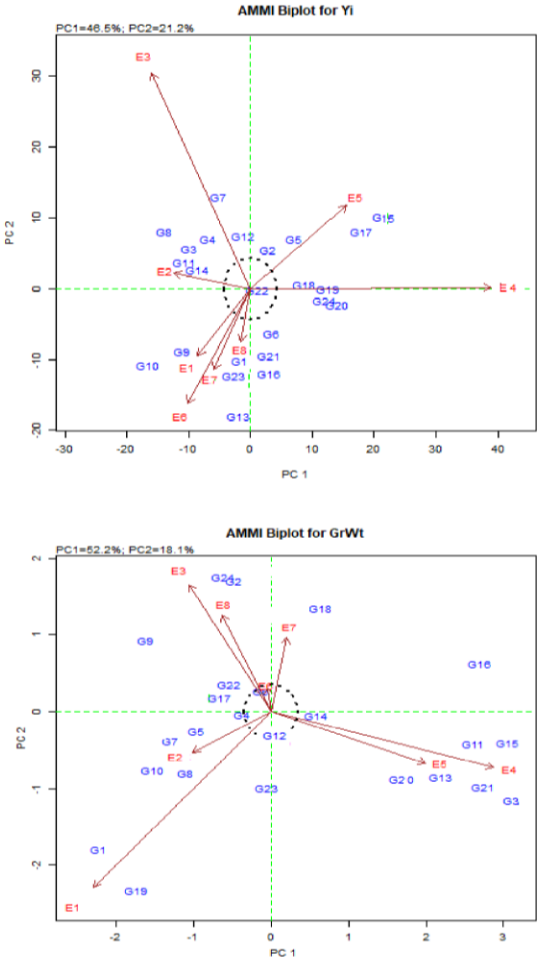

Figure 3. Biplot appearance in 1st against 2nd component for Yi and GrWt traits, respectively in deliberated genotypes and environments.

responses from early (E1 and E2) to late sowing (E7 and E8). The AMMI analysis by Kamara *et al.* (2021) also identify vastly adopted genotypes under heat stress in dawn sowing dates. The precise adaptation specified a high mean efficiency of candidate lines in a selected environment. For example, for Yi, candidate lines G9 and G10 were adapted to E1; G11 and G14 were adapted to E2; G18 and G15 were adapted to E4; G15 and G17 were adapted to E5; and G1, G23, G13, G6, G21, and G16 were adapted to E8. For GrWt, candidate lines G10, G7, G8, and G5 were adapted to E2; G11, G15, G3, G21, G13, and G20 were adapted to E4 and E5; G18 was adapted to E7; and G2 and G24 were adapted to E8 (Figure 3). These placements were not only direct the status of a piece constituent of the interaction to attaining high GrWt and Yi, but also the candidate line's potential to exploit such relations to maximize grain yield. Substantial connections between the environment and wheat candidate lines concerning Yi and GrWt were also observed in a previous work (Popovic *et al.,* 2020).

Nominal yield and environment

As a role of the tally on the environment, PC1 adaptation maps were drawn to forecast nominal Yi and GrWt for wheat candidate lines in tested environments (Figure 4). Regarding Yi, the slope of the lines indicated the adaptation patterns of the candidate lines transversely to the environmental IPCA1 scores. The results indicated that these interactions led to different rankings of the candidate lines across environments in such a way that the candidate lines exhibited high nominal yields in environments with large

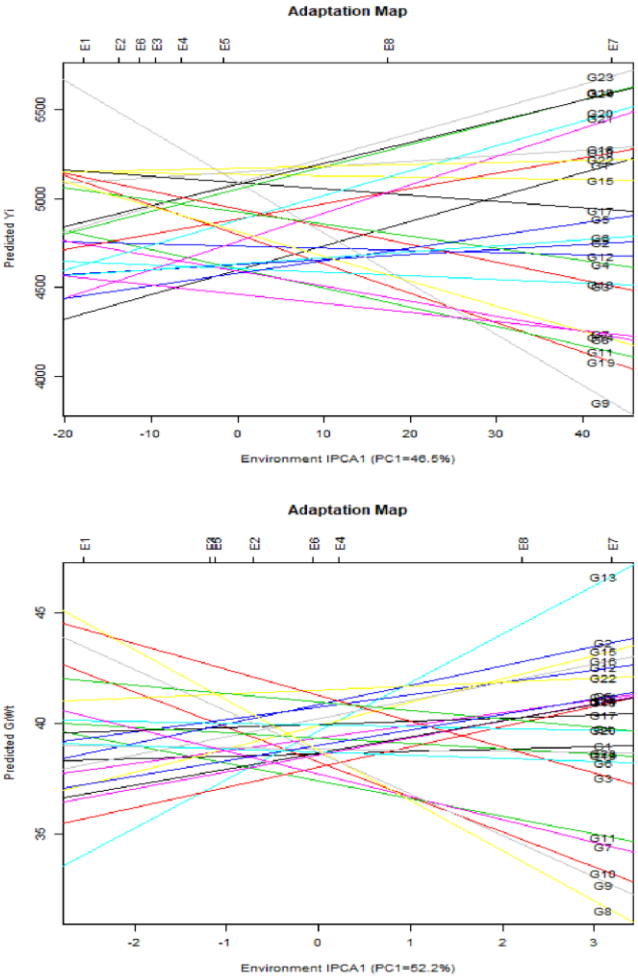

Figure 4. Nominal plans for Yi and GrWt traits, respectively.

IPCA1 values and low nominal yields in environments with small IPCA1 values. The candidate lines G23, G24, and G13 showed a sharp slope (highest instability); the lowest yield output in E1 and E2 (low IPCA1 values); the highest mean yield in E8; and average yield in E7 (high and average IPCA1 values). By contrast, G9 and G19 showed the peak yield in E1, E2, and E6 but exhibited the lowest IPCA1 values in these environments. For GrWt, the candidate line G13 showed a sharp slope (highest instability); the lowest GrWt productivity in E1 (low IPCA1 values); the highest mean GrWt in E7; and average GrWt in E4 and E5. G8, G9, and G10 exhibited the highest GrWt productivity in E1 but exhibited the lowest IPCA1 values in these environments.

GGE biplot

The GGE biplot revealed one more G + GE interaction in AMMI due to the presence of "which-won-where" inherited feature of candidate lines and environments. In this graph, a polygon was initially sketched on candidate lines that were farthest from the biplot basis to all other candidate lines that were limited inside the polygon. Formerly perpendicular lines (equality lines) to each side of the polygon were drawn beginning from the biplot origin on the basis of which visual comparison between candidate lines was made (Yan, 2006). For example, the parity lines divided the biplot into segments, and the winning candidate lines for each segment were the ones positioned on the particular apex.

G23, G20, G21, and G1 were superior in E8, whereas G9 was superior in E1. The equality line between (G22 and G19) showed that G22 was superior in E5, whereas G19 was superior in the other environments. The equality line between G22 and G23 indicated that G22 was better than G23 in all environments. Similarly, G16, G24, and G19 were set on the line that attached G22 and G23. This result indicated that the rank G22 > G16 > G24 > G19 > G23 was true in all environments. For GrWt, G13 > G18 > G11, G3, and G15 was superior in E8 and E4, whereas G8, G10, and G7 were superior in E5. In the present study, the candidate lines with significant GrWt and Yi improvements in E5 and E6 (late sowing) and E7 and E8 (very late) showed tolerance to terminal heat stress. These results indicated that different candidate lines can be selected and arranged likewise (Figure 5). These recognized lines are recommended for precise adaptation because environment-specific adapted genotypes have the benefit to counter environmental alterations in contrast to broadly adapted genotypes (Laurie and Booyse, 2015).

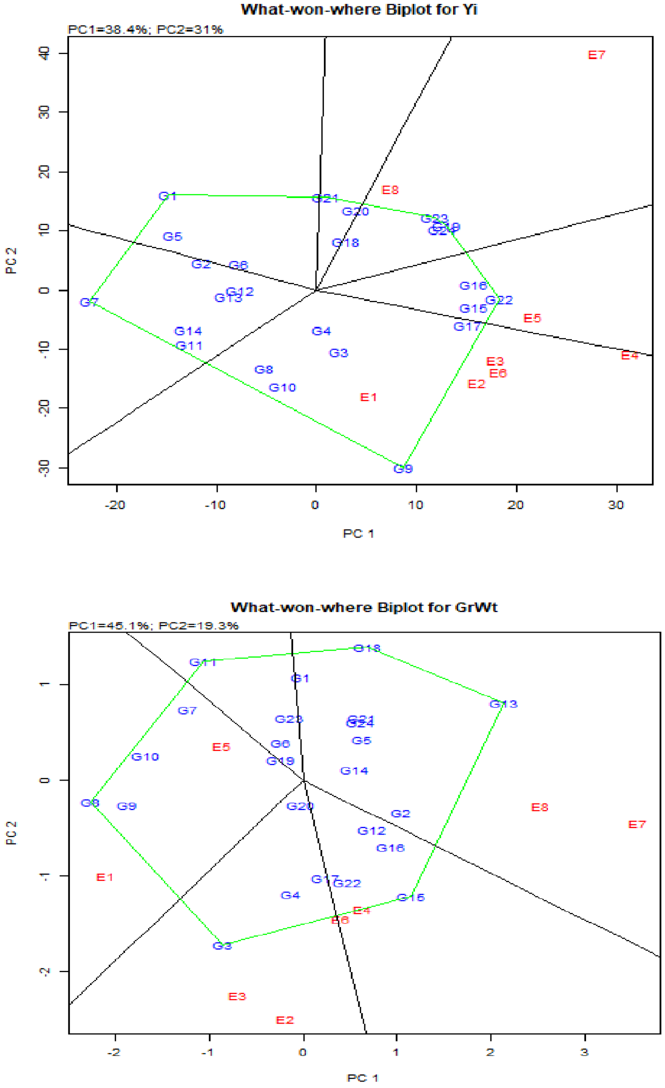

Figure 5. What won where GGE biplots for Yi and GrWt traits, congruently.

Environment evaluation based on GGE biplots

The biplots described the aggregate PCI and PCII score as 69.4% for Yi and 64.4% for GrWt, respectively, of the entire disparity of the environment-centered G × E sectors and the cosine of the angle between the vectors of two environments estimates the relationship between them (Yan *et al.,* 2006). For example, E8 and E7 were positively interrelated (an acute angle) for Yi and GrWt, indicating that these candidate lines had similar responses and were comparable all environments. E8 and E1 for Yi and E8 and E3 for GrWt were negatively correlated (an obtuse angle). An obtuse angle means that the two candidate lines had opposite responses, i.e., the first candidate lines performed well, whereas the other candidate lines performed poorly. E7 and E5 for Yi and E8 and E2 for GrWt were not correlated (slight right angle). A right angle indicates that the two candidate lines had different responses to the environments. In the two primary cases, the dissimilarity between the candidate lines had a greater contribution to G than to GE. In the third case, the difference was contributed to G × E. The incidence of wide obtuse angles (i.e., strong negative correlations) between test environments is a sign of strong G × E effect. Here, the largest angle was slightly larger than 90° (between E8 and E1), indicating that G × E was high for Yi. This interaction was very small for Yi in E5 and E4 for Yi and for GrWt in E7 and E8. The distance between two environments quantifies their ability to discriminate among candidate lines. Thus, the eight environments fell into two distinct groups, i.e., E7 and E5 formed one group, and the remaining environments formed another. The existence of adjacent associations between test environments suggested that similar information about the candidate lines could be obtained from few test environments, indicating that if two test environments showed steady correlations across years, one could be discarded to decrease costs (Figure 6).

Discriminating ability of test environments

The concentric rings on the biplot helped predict the span of the environment vectors and were the measure of the discriminating ability of the environments. Therefore, among the eight tested environments, E7 and E4 were most discriminating (informative) and E1 and E8 were the least discriminating for Yi, whereas E7 was the most discriminating (informative) and E5 the least discriminating for GrWt. Test environments that were reliably nondiscriminating (noninformative) delivered little information on the candidate lines and thus could not be used as test environments. Discriminating but nonrepresentative test environments are valuable for discarding unbalanced candidate lines, and nondiscriminating test environments are less beneficial because they provided little discriminating information about the candidate lines for Yi and GrWt (Figure 6).

Candidate line assessment based on GGE biplots

The vectors of the candidate lines were drawn to illustrate the explicit interactions between lines in each environment. The performance of a candidate line in an environment was better than average if the angle between its vector and the environment's vector was <90°; inferior to average if the angle was >90°, and near average if the angle was approximately 90°. For example, G1 and G5 were below average in all environments (>90° obtuse angles) for Yi and G7 and G11 for GrWt, whereas G3 and G4 were above average in all environments (<90°, acute angles), except E8 and E7 for Yi and G2 and G12 for GrWt. G16 for yield and G14 for GrWt were near average if their angles were approximately 90°.

Comparison among the candidate lines

The Euclidean distance between two candidate lines is a measure of the overall difference between the two genotypes. For example, G9 and G1 for Yi and G17 and G7 for GrWt were very different, whereas G19 and G24 for Yi and G21 and G24 Gr Wt were quite similar. Therefore, the length of the candidate line vector, which is the distance between candidate lines and the biplot origin, measures the difference of the candidate lines from the average candidate lines, i.e., the impact on either G or GE or both. The candidate lines located close to the biplot origin had little contribution to G and GE, and candidate lines with long vectors had large contributions to either G or GE or both (Zerihun, 2011). Therefore, candidate lines with the longest vectors were either the best (G9) or the poorest (G7) or the most unstable (G1) for Yi. Similarly, candidate lines with the longest vectors were either the best (G15), the poorest (G3), or most unstable (G8) for GrWt (Figure 7).

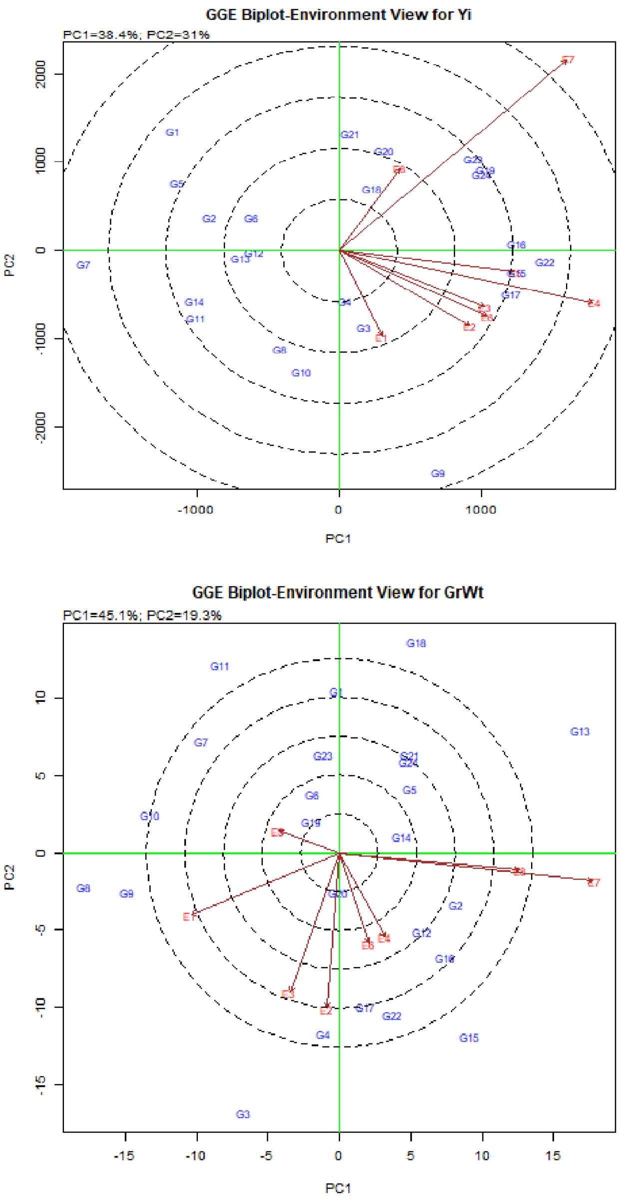

Figure 6. Environment view GGE biplots for Yi and GrWt traits, congruently.

CONCLUSIONS

Mitigating heat stresses by obtaining stable candidate lines on the basis of sowing dates is vital for the high wheat yield against the background of climate change, especially when heat waves occur at the postanthesis phase. The model used in this work was very valuable for the detection of performance and stability and will further aid the precise assessment, recommendation, and release of stable high-yielding candidate lines. In the present study, candidate lines with high GrWt and Yi enhancements were observed under late and very late sowing and displayed tolerance to terminal heat stress.

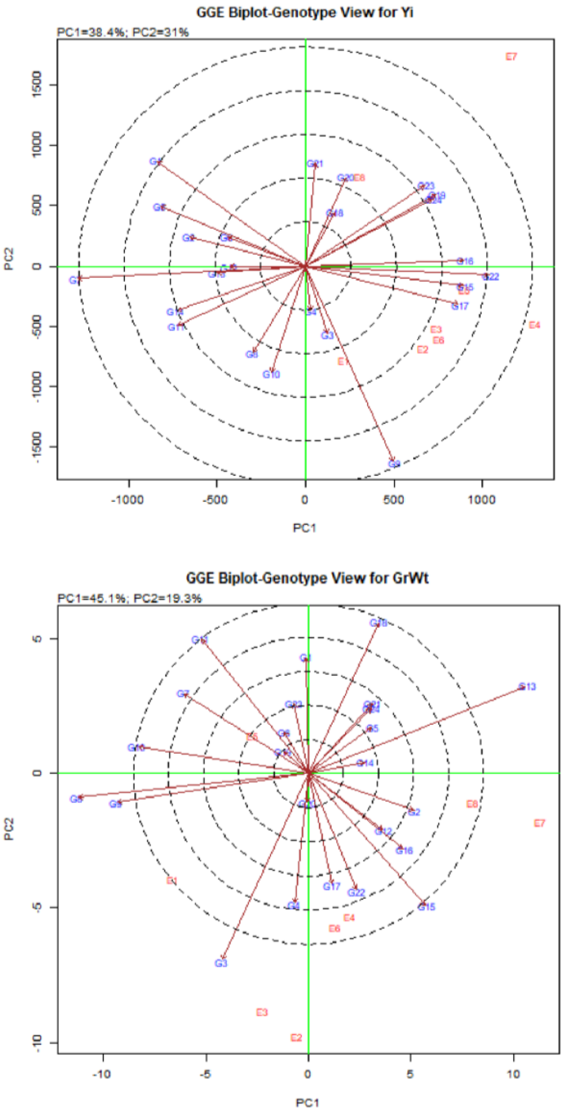

Figure 7. Genotypes view GGE biplots for Yi and GrWt traits, congruently.

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