

# Integrated stability analysis of compact cotton genotypes for yield and plant architecture under rainfed conditions using AMMI, GGE biplot, WAAS, BLUP, and MTSI

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## Research Article

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1 **Integrated stability analysis of compact cotton genotypes for yield and plant**  
2 **architecture under rainfed conditions using AMMI, GGE biplot, WAAS,**  
3 **BLUP, and MTSI**

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13 **Abstract**

14 **Background** The development of high-yielding stable cotton genotypes with compact plant  
15 architecture is critical for improving productivity and sustainability in rainfed ecosystems of  
16 India. This study evaluated 22 compact to semi-compact genotypes, including two check  
17 varieties (ARBC1651, CSH3075), across three distinct environments in Tamil Nadu during  
18 Kharif 2024.

19 **Results** Genotypic performance was analyzed using a suite of stability assessment tools  
20 including AMMI, GGE biplot, WAAS, BLUP, and MTSI. Joint ANOVA revealed highly  
21 significant ( $p \leq 0.001$ ) genotype, environment, and GEI effects for most traits, with genetic

22 variance contributing up to 72% of phenotypic variation in seed cotton yield (SCY). The first  
23 two IPCs of AMMI and GGE biplots explained >75% of GEI variation and consistently  
24 identified Suraksha, Subiksha, and Suraj as stable, high-yielding genotypes. Whereas RS2818,  
25 CO17, and Nano represented compact types with plant height <90 cm, reduced internode length  
26 (~5.7 cm), and sympodial branching (~18.8 cm), aligning with ideotypes suitable for high-  
27 density planting and mechanized harvesting. BLUP analysis showed high heritability for SCY  
28 ( $h^2_{mg} = 0.91$ ), with strong genotypic variance (71.99%) and high selection accuracy (0.95). It  
29 confirmed AMMI and GGE biplots results, identifying Suraksha, Subiksha, and Suraj as superior  
30 yielders, while CO17, Nano, and TVH002 promising compact types with high predictive  
31 accuracy. WAAS/WAASBY indices confirmed Suraksha and Subiksha as the most stable and  
32 productive genotypes, whereas MTSI ranked Suraj (MTSI = 2.16), Subiksha, F2383, and  
33 RS2818 as top multi-trait stable performers. Compact plant traits were found to be negatively  
34 correlated with excessive vegetative growth but positively associated with yield stability under  
35 rainfed conditions. Among the test environments, Veppanthattai (E3) effectively discriminated  
36 genotypes, while Coimbatore (E1) and Srivilliputhur (E2) were representative for selecting  
37 compact and stable high-yielding types.

38 **Conclusion** This integrated stability models enabled precise identification of compact, high-  
39 yielding genotypes, supporting breeding of rainfed-adapted and machine-harvestable genotypes.

40 **Keywords:** Compact plant architecture, AMMI, GGE biplot, WAAS, BLUP, MTSI, yield  
41 stability, rainfed cotton

## 42 **Introduction**

43 Cotton is one of the most important fiber crops in India, and the country is among the largest  
44 producers and users of cotton in the world. Nearly 82% of the cotton area in the country is

45 cultivated under rainfed conditions, primarily in central and southern states (Madhu et al., 2023),  
46 where farmers face challenges of erratic rainfall, fluctuating yields, and high production costs.  
47 Harvesting is usually done by hand, but this practice is becoming less sustainable because of  
48 rising labor costs, shortage of workers during the picking season, and inefficiencies in  
49 completing harvests on time (Venugopalan et al., 2011). Manual picking increases production  
50 expenses, delays harvesting, and often reduces both yield and lint quality. Given that over 95%  
51 of Indian cotton is composed of long-duration Bt hybrids, which are typically tall and possess  
52 monopodial branching with extended boll-opening duration, which requires multiple hand  
53 pickings (Sivakumar et al., 2024). These traits require several rounds of hand-picking and make  
54 the crop unsuitable for machine harvesting; it suggests that urgent need for architectural and  
55 agronomic improvements.

56 In contrast, compact cotton plants with shorter height, reduced internodes, absence of  
57 monopodia, shorter fruiting branches, and uniform boll maturity are more suitable for modern  
58 farming. Such plants allow high-density planting, better use of light, improved boll retention,  
59 easier crop management, and mechanical harvesting (Venugopalan et al., 2011; Yan et al., 2019;  
60 Gunasekaran et al., 2020). For machine harvesting, ideal plant height is less than 120 cm for  
61 spindle pickers and less than 80 cm for stripper pickers (Williford et al., 1994; Van der Sluijs  
62 2015; Madhu et al., 2023). Plant types with the first fruiting branch appearing higher on the stem  
63 and a uniform canopy also improve harvest efficiency (Van der Sluijs, 2015). However, while  
64 plant architecture is important, high seed cotton yield is the main target in breeding. Both yield  
65 and plant architecture are strongly affected by the interaction between genotype and environment  
66 (GEI), which makes it necessary to test genotypes in multi-environment trials (METs) to assess

67 their performance, adaptability, and stability (Sheeba et al., 2025; Shahzad et al., 2019;  
68 Sivakumar et al., 2024).

69 Past studies have shown that the environment plays a major role in yield variation and  
70 contributes more than 80% of the total variance (Meredith et al., 2012). Still, GEI can also affect  
71 specific traits. For example, a study with 82 germplasm lines showed that GEI explained 46% of  
72 the variation in boll weight (Campbell et al., 2012). Evidence suggests that for traits like branch  
73 height and number, the effects of genotype and GEI are stronger than the environment (Madhu et  
74 al., 2023, Sivakumar et al., 2024). Since yield and architecture are complex traits controlled by  
75 many genes and affected by environmental conditions. GEI reduces the relationship between the  
76 genetic and observed values of traits (Yan and Tinker, 2006), making stability analysis essential  
77 to find genotypes that perform well across locations and years (Vaezi et al., 2019).

78 Several statistical models are used to study GEI and stability. The Additive Main Effects  
79 and Multiplicative Interaction (AMMI) model is widely applied in many crops (Gauch, 1988). It  
80 combines variance analysis with principal component analysis (PCA) to explain GEI and create  
81 biplots to show genotype performance. Another improvement is the WAAS index, which  
82 considers all significant components and gives a more detailed picture of genotype stability  
83 (Olivoto et al., 2019a). Along with AMMI, the genotype plus genotype-by-environment  
84 interaction (GGE) biplot is also popular. It helps compare test locations, identify mega-  
85 environments, and select winning genotypes (Yan, 2001; Yan et al., 2007; Yan, 2024). Apart  
86 from AMMI, the Best Linear Unbiased Prediction (BLUP) method is also used in stability  
87 analysis, as it provides accurate estimates of genetic values (Smith et al., 2005). Unlike AMMI,  
88 which treat genotypes as random effect, BLUP uses linear mixed models to separate effects  
89 (Piepho 1994, Gauch 2013). To combine the strengths of both methods, weighted average of

90 absolute scores (WAAS) and WAAS from BLUP and yield (WAASBY) indices were developed,  
91 which link stability and mean yield in genotype evaluation (Olivoto et al., 2019a; Smith et al.,  
92 2005). Selecting superior genotypes for cotton cannot be based on yield alone, as yield depends  
93 on several growth and physiological traits. Improving compact plant architecture together with  
94 yield is important for developing varieties suitable for modern farming. However, selection of  
95 multiple traits at time is difficult because of negative correlations among them (Elsamman et al.,  
96 2024). To tackle this, the Multi-Trait Stability Index (MTSI) was introduced (Olivoto et al.,  
97 2019b). MTSI uses factor analysis to measure the distance of each genotype from an “ideal”  
98 genotype and allows simultaneous selection of multiple traits based on performance and stability.

99 In this background, the present study aims to evaluate cotton genotypes that combine  
100 compact architecture with high yield using different stability assessment tools such as AMMI,  
101 GGE, WAAS, BLUP and MTSI, tested across three environments. This integrated approach can  
102 help identify promising cotton lines with desirable plant type and stable yield, improving the  
103 profitability and sustainability of cotton cultivation in rainfed areas of India.

## 104 **Materials and Methods**

### 105 **Plant material selection**

106 A total of twenty-two elite compact to semi-compact cotton genotypes were sourced from ICAR-  
107 CICR Regional Station and the Department of Cotton, TNAU, Coimbatore. Two widely  
108 cultivated check varieties, ARBC1651 and CSH3075, known for their high yield and zero  
109 monopodial compact plant architecture suitable for rainfed regions, were included for  
110 comparison is given in Table 1.

### 111 **Experimental sites and setup**

112 Field trials were conducted during the Kharif season of 2024 across three distinct agro-climatic  
113 zones in Tamil Nadu, India. The first site (E1) was at Coimbatore characterized by red clay and  
114 laterite soils under semi-arid climate. The second site (E2) at Veppanthattai featured very deep,  
115 calcareous clay soils with moderate drainage and low hydraulic conductivity. The third site (E3)  
116 was Srivilliputhur, comprised of vertisols with clay loam texture over canker nodules. These  
117 locations represent the Western, Cauvery Delta, and Southern agro-climatic zones of Tamil  
118 Nadu, respectively. Fig. 1 shows the geographical locations of experimental sites and their  
119 agroclimatic characteristics. A randomized complete block design (RCBD) with three  
120 replications was used for the experiments. Each plot measured 4 meters in length, consisting of  
121 six rows per genotype, with row and plant spacing set at 90 cm and 30 cm, respectively.

### 122 **Crop management practices**

123 During August 2024, three fuzzy cotton seeds were sown per hill at a depth of 3-5 cm. Three  
124 weeks of post-sowing thinning was performed to retain a single healthy plant per hill. Fertilizer  
125 was applied at a recommended rate of 16:16:8 kg/ha (NPK) as a basal dose during sowing,  
126 followed by a top dressing of 16:0:8 kg/ha at 40-45 days after sowing. Pendimethalin 30% EC  
127 (3.3 l/ha) was applied as a pre-emergence herbicide three days after sowing, and manual weeding  
128 was carried out twice during the crop growth period. Pest and disease management followed  
129 standard agronomic practices. Irrigation was supplied artificially at critical stages to avoid  
130 drought stress, ensuring uniform growth and reliable data.

### 131 **Data collection and trait measurement**

132 At harvest, five plants were randomly selected from the inner rows of each plot in every  
133 replication. The following traits were recorded: plant height (PH, cm), first sympodial branch  
134 height from ground (FSB, cm), main stem internode length (MIL, cm), and sympodial branch

135 length (SBL, cm). Plant height was measured from the cotyledonary node to shoot apex using a  
136 tape. The methods described by (Madhu et al., 2023) were followed for MIL and SBL  
137 measurements. The number of monopodial (NMB) and sympodial branches (NSB) were counted  
138 per plant. Boll count per plant (BP) was recorded, and five randomly selected bolls per plant  
139 were weighed to determine average boll weight (BW, g). Seed cotton yield (SCY, g per plant)  
140 was calculated by hand-picking bolls during the first fortnight of December.

### 141 **Statistical analysis approach**

142 All analysis were conducted using R Studio v.4.0 (R-Studio Team, 2020) and the “metan”  
143 package (Olivoto and Lúcio, 2020). Bartlett’s test (Bartlett, 1937) used to verify homogeneity of  
144 error variances across locations before performing joint ANOVA. The joint RCBD ANOVA and  
145 AMMI analysis (Bradu and Gabriel, 1978) were used to to evaluate the additive mean effects of  
146 genotypes and locations. PCA was then used to identify non-additive interaction effects within  
147 the experimental setup (Zobel et al., 1988). AMMI biplots were constructed to illustrate the  
148 relationship between genotype means and the first two principal components (PC1 and PC2),  
149 following Gauch (1988). GGE biplots (Yan, 2024) were employed to visualize genotype  
150 performance and stability. The environment-centered data and symmetrical singular value  
151 partitioning (SVP) with row metric preservation method enabled consistent comparison across  
152 environments (Yan, 2002; Yan, 2024). The WAAS method involved singular value  
153 decomposition (SVD) of the GEI matrix from AMMI ANOVA, providing stability measures  
154 based on the first IPC (Olivoto et al., 2019a). BLUP analysis was applied using a linear mixed  
155 model with genotypes as random effects to predict genotypic performance across environments  
156 (Olivoto et al., 2019a). Variance components were estimated through restricted maximum  
157 likelihood, with the likelihood ratio test used for random effects significance. WAAS values

158 derived from BLUP (WAASB) were calculated by applying SVD to the BLUP-based GEI  
159 matrix. The WAASBY index (Olivoto et al., 2019a) integrated yield and stability for  
160 comprehensive genotype selection. The MTSI was calculated from the Euclidean distance  
161 between each genotype and an ideotype, based on on scores obtained through factor analysis  
162 with varimax rotation (Olivoto et al., 2019b). MTSI was estimated to use all yield and plant  
163 architecture traits, whereas boll count per plant was excluded as it showed no significant  
164 correlation with yield components.

## 165 **Results and discussion**

### 166 **Additive main effects and multiplicative interaction (AMMI)**

167 Considering the homogeneity of error variance across locations, a joint ANOVA based on RCBD  
168 and AMMI's additive model was performed for plant architecture, yield, and yield-related traits  
169 are given in Table 2. The environment (E) had a highly significant effect on all traits, indicating  
170 substantial variation between test locations. The genotype (G) effect was also highly significant  
171 ( $p \leq 0.001$ ) for all traits, except for BP, reflecting strong genetic differences among the tested  
172 genotypes due to their diverse backgrounds and performance under contrasting environments  
173 (Ali et al., 2018; Madhu et al., 2023). In addition, the GEI was highly significant ( $p \leq 0.001$ ) for  
174 all traits, causing differential genotype ranking across environments and revealing the complex  
175 nature of genotype adaptability (Sheeba, et al., 2025). These findings agree with earlier cotton  
176 multi-location studies (Orawu et al., 2017; Shahzad et al., 2019; Sivakumar et al., 2024).

177 The evaluation of genotypes across three environments (E1, E2, and E3) for nine traits  
178 showed notable differences in trait distribution and variability, as illustrated the violin plots in  
179 Fig. 2 and mean values are presented in Supplementary Table 1. Plant height (PH) ranged from  
180 87.99 cm (E2) to 92.29 cm (E3), with E2 showing a narrower distribution and lower median,

181 indicating conditions favoring shorter plant growth. The number of monopodial branches (NMB)  
182 was lowest in E2 (0.61) and highest in E3 (0.79), while the first sympodial branch height (FSB)  
183 varied from 21.37 cm (E2) to 22.04 cm (E3). Sympodial branch number (NSB) ranged from  
184 20.13 (E2) to 21.11 (E3), and sympodial branch length (SBL) ranged from 18.27 cm (E2) to  
185 19.67 cm (E3). Mainstem internode length (MIL) was lowest in E2 (5.51 cm) and highest in E3  
186 (5.90 cm). The number of bolls per plant (BP) remained stable across environments (21.47 to  
187 21.89), while boll weight (BW) was lowest in E2 (4.88 g) and highest in E1 (5.03 g). Seed cotton  
188 yield (SCY) was highest in E3 (116.30 g) and lowest in E1 (114.90 g). The violin plots revealed  
189 that E3 consistently exhibited broader trait distributions and higher medians, indicating a more  
190 favorable environment for trait expression and higher yield, whereas E1 and E2 provided  
191 favorable conditions for developing a compact plant type with narrower distributions and lower  
192 trait values. These results align with previous multi-environment cotton studies reporting the  
193 significant influence of environment on yield and architectural traits (Gul et al., 2016; Ali et al.,  
194 2018; Sivakumar et al., 2024).

195 The partitioning of phenotypic variance among the studied traits revealed differential  
196 contributions from genotype, environment, and GEI is depicted in Fig. 3. Genetic variance  
197 contributed the highest proportion for most traits, ranging from 42.22% (SBL) to 78.98% (SCY),  
198 with SCY showing the strongest genetic control, followed by PH, and FSB. This indicates that  
199 these traits are largely heritable and can be efficiently improved through selection. In contrast,  
200 NSB was predominantly influenced by the environment, accounting for 83.73% of the total  
201 variance, making it the most environmentally driven trait. BP showed the strongest GEI effect  
202 (53.07%), while other traits also exhibited substantial GEI influence, indicating their sensitivity  
203 to environmental changes. Except for NSB, the genetic-to-environmental variance ratio was

204 higher across traits, suggesting more reliable genotype selection under diverse conditions (Ali et  
205 al., 2018). Overall, most traits were mainly controlled by genetics, with moderate to high GEI  
206 effects, aiding the selection of suitable genotypes for specific environments (Madhu et al.,  
207 2023). Whereas, NSB was almost entirely shaped by environmental variation, and BP was largely  
208 driven by GEI, both contributing to yield variation across environments (Sivakumar et al., 2024).  
209 These findings differ from earlier studies (Shahzad et al., 2019; Ali et al., 2018; Gul et al., 2016;  
210 Farias et al., 2016), which reported environmental dominance in controlling SCY, BW, and BP,  
211 while (Ali et al., 2017) found genotype as the major source of yield variation, reflecting  
212 significant genetic diversity.

213         Investigating GEI is essential for identifying stable and high-yielding compact cotton  
214 genotypes across specific or diverse environments using AMMI analysis. The first two principal  
215 components (PC1 and PC2) significantly explained the GEI for all traits, with the AMMI model  
216 using two significant IPCs identified as the most reliable for stability analysis (Zobel et al.,  
217 1988). PC1 explained the majority of GEI variation, ranging from 76.2% (SCY) to 96.2%  
218 (NSB), while PC2 contributed between 3.8% and 23.8%, offering additional clarification.  
219 Specifically, traits such as NSB (96.2%), SBL (92.2%), BP (92.3%), NMB (90.8%), and FSB  
220 (86.4%) were predominantly explained by PC1. PH (76.8%) and SCY (76.2%) showed a  
221 relatively higher contribution of PC2 (23.2% and 23.8%, respectively), indicating its moderate  
222 influence. MIL (83.4%) and BW (86.2%) also displayed a strong PC1 effect with some  
223 contribution from PC2 (16.6% and 13.8%). These results suggest that PC1 is the most  
224 informative axis for assessing genotype adaptability and stability across environments, while  
225 PC2 provides useful but minor additional insight into GEI. Our findings align with previous

226 studies (Sheeba et al., 2025; Sivakumar et al., 2024; Shahzad et al., 2019; Ali et al., 2018), which  
227 similarly reported that PC1 explains a greater portion of GEI variation than PC2.

## 228 **Genotype plus genotype-by-environment interaction (GGE) biplot**

### 229 **Mean vs. stability biplot**

230 A two-dimensional biplot was constructed based on the first two PCs using the row metric  
231 preservation method to assess genotype mean performance and stability (Yan, 2002; Yan, 2024;  
232 Memon et al., 2023). From the average environment coordination (AEC) perspective, the AEC  
233 line, represented by a single arrow passing through the origin, indicated the direction of  
234 increasing mean performance, whereas short perpendicular projections (dotted lines) from the  
235 AEC axis identified genotypes with greater stability. Fig. 4 shows the GGE biplots for plant  
236 height (Fig. 4A), sympodial branch length (Fig. 4B), mainstem internode length (Fig. 4C), and  
237 seed cotton yield (Fig. 4D) were explained by PC1 and PC2, accounting for 91.80%, 96.59%,  
238 93.43%, and 96.42% of the total GGE variation, respectively (PH: PC1 = 69.34%, PC2 =  
239 22.46%; SBL: PC1 = 74.38%, PC2 = 22.21%; MIL: PC1 = 64.47%, PC2 = 28.96%; SCY: PC1 =  
240 84.46%, PC2 = 11.96%). It indicating that PC1 predominantly captured the mean trait  
241 performance across genotypes, while PC2 reflected the GEI and stability.

242 Genotypes showed significant variation in mean performance and stability for studied  
243 traits. Anjali, ARBC19, ARBC1651, and PKV-081 Bt exhibited higher mean plant height, but  
244 their stability differed, with Anjali showing greater stability due to shorter projections from the  
245 AEC axis. In contrast, Nano, Rajat-Bt, and CO17 were shorter but less stable, while Suraj,  
246 Subiksha, Roja, F2383, RS2818, and Bt/C-62 showed stable performance with average or below-  
247 average PH. For SBL, PKV-081Bt and Bt/C-63 recorded longer branches with high stability,  
248 whereas Nano and HC-54 had shorter branches and less stability. Genotypes CO17, Suraj,

249 Subiksha, F2383, and Anjali were positioned closer to the origin, indicating greater stability with  
250 average to below-average SBL. MIL varied widely, with Anjali showing the longest and RS2818  
251 the shortest internode length. Nano, Rajat Bt, and H C-54 had shorter internodes but lower  
252 stability, while CO15, Suraj, Bt/C-62, CO17, and F2383 showed short and stable internodes.  
253 Roja, Subiksha, Bt/C-61, and F2381 exhibited moderate internode length with stable  
254 performance. Suraksha, Suraj, and Subiksha demonstrated the highest mean SCY and stability,  
255 indicating wide adaptability under rainfed conditions, whereas CO17 showed strong GEI,  
256 indicating specific adaptation. ARBC1601, PKV-081Bt, and Bt/C-63 had lower mean yield and  
257 stability. Among environments, Veppanthattai (E3) was most discriminative for trait expression,  
258 while Coimbatore (E1) and Srivilliputtur (E2) were more representative, making them suitable  
259 for selecting high-yielding, compact, and stable genotypes. Similar studies by Ali et al. (2018),  
260 Verma et al. (2022), and McPherson (2022) used GGE biplot to identify high-yielding stable  
261 genotypes, and Sivakumar et al. (2023) applied it for selecting compact, high-yield cotton  
262 genotypes under multi-environment trials.

### 263 **Which-won-where biplot**

264 The which-won-where GGE biplot helps identify the best genotype for each environment (Aditi  
265 Rani et al., 2023; Yan, 2024). It forms a polygon by connecting the top-performing genotypes,  
266 with dotted lines (rays) originating from the biplot center and extend perpendicularly to the sides  
267 of the polygon, dividing the plot into sectors called mega-environments (Yan, 2024). The  
268 genotype at a vertex performs best in the environments within its sector, showing specific  
269 adaptation. Genotypes near the origin are more stable across environments, while those at the  
270 vertices are highly interactive (Yan and Tinker, 2006).

271 Fig. 5A shows the plant height (PH) biplot revealed three distinct mega-environments.  
272 Anjali and ARBC19 exhibited the tallest PH at E1 and E2, while PKV-081Bt performed best at  
273 E3. Vertex genotypes such as Nano, Rajat-Bt, RS2818, and HC54, which did not fall into any  
274 environment sector, were associated with shorter PH across the sites. Genotypes located near the  
275 origin (e.g., Subiksha, Roja, Bt/C-61, F2383, Suraj) showed more stable and below average PH.  
276 Fig. 5B shows the biplot for sympodial branch length, two mega-environments were identified:  
277 E1 and E2 formed one, while E3 was distinct. ARBC1651, Bt/C-63, and HC54 were high  
278 performers in E1 and E2, whereas PKV-081Bt and Suraksha excelled in E3. Other vertex  
279 genotypes (Nano, Suraksha, Subiksha, RS2818) showed shorter branch length responses in  
280 specific environments. Genotypes near the origin, including Roja, Bt/C-61, CSH3075, F2381,  
281 and CO15, were stable across locations but lacked superior performance in any single  
282 environment. Fig. 5C shows the biplot for mainstem internodal length (MIL) biplot, three  
283 separate mega-environments were formed by E1, E2, and E3. Anjali and ARBC19 were top  
284 performers in E1; PKV-081Bt excelled in E2; no genotype showed superiority in E3. Vertex  
285 genotypes such as Nano, Rajat-Bt, RS2818, and CO17 were linked to shorter MIL under certain  
286 conditions. Genotypes near the origin (ARBC1051, Subiksha, DSC1651) demonstrated stable  
287 and below average MIL across environments. Fig. 5D shows the biplot for seed cotton yield, the  
288 three environments constituted a single common mega-environment, with Suraksha as the high-  
289 yielding vertex genotype. Other vertex genotypes without associated environments in their sector  
290 indicated lower yields across sites. Genotypes located near the origin (Suraj, Subiksha, F2383,  
291 RS2818, Nano) were stable and showed no significant interaction with the environments.  
292 However, these genotypes were not positioned at the vertices and exhibited very poor yield  
293 performance across the tested environments (Ali et al., 2017). Our findings agree with previous

294 studies showing that the environment divides cotton-growing sites into distinct mega-  
295 environments (Abro et al., 2022; Verma et al., 2022).

### 296 **Weighted average of absolute scores (WAAS)**

297 The WAAS biplot, which assesses the mean performance (Y) against WAAS and provides a  
298 comprehensive stability evaluation by incorporating all scores of IPCs, unlike the AMMI model  
299 that considers only the first IPC. This approach captures the total variance of GEI when  
300 identifying stable genotypes (Olivoto et al., 2019a). In the WAAS biplot, the vertical axis  
301 represents the average mean of traits such as PH (Fig. 6A), SBL (Fig. 6B), MIL (Fig. 6C) and  
302 SCY (Fig. 6D) across environments, with genotypes or environments placed to the right of this  
303 line performing above average, and those on the left performing below average. The horizontal  
304 axis indicates mean WAAS values, and its intersection with the vertical axis divides the plot into  
305 four quadrants, each representing groups of genotypes with distinct adaptability and stability  
306 patterns for studied environments. Genotypes positioned in the first quadrant of the biplot,  
307 including Nano and Rajat-Bt for PH in environments E1-Coimbatore and E2-Srivilliputtur,  
308 Nano, ARBC19, TVH002, and Rajat-Bt for SBL in E1 and E2, Nano, Rajat-Bt, and HC-54 for  
309 MIL in E2, and ARBC1601, Bt/C-62, CO15, RS2818, and ARBC19 for SCY in E1 and E2,  
310 recorded high WAAS values but below-mean performance. This reflects their instability and  
311 inconsistent response across environments and making them generally unsuitable for cultivation.  
312 However, genotypes expressing lower PH, SBL, and MIL values are desirable for developing  
313 compact plant types and thus recommended for cultivation where reduced plant height, internode  
314 and branch length are advantageous. Genotypes such as TCHB213, ARBC19, HC-54, and PKV-  
315 081Bt were placed in the second quadrant of the PH biplot under environment E3-Veppanthattai.  
316 Similarly, HC-54, ARBC1651, Suraksha, and F2381 for SBL in E3, while Suraksha, TCHB213,

317 ARBC19, CSH3075, and PKV-081Bt for MIL under E1 and E3. For SCY, CO17, Roja, Bt/C-61,  
318 and TCHB213 occupied the second quadrant in E3. These genotypes showed high WAAS values  
319 combined with performance above the average mean, indicating strong adaptability to favorable  
320 environments. Environment E3 for PH, SBL, and SCY, while both E1 and E3 for MIL served as  
321 effective discriminators for genotypes. Under favorable environmental conditions, these  
322 genotypes are likely to achieve high yield potential and can be recommended for cultivation in  
323 regions suited to cotton growth and development.

324 Genotypes CO17, RS2818, Suraksha, Suraj, F2383, Bt/C-62, CO15, and DSC1651 were  
325 clustered in the third quadrant of the PH biplot, whereas Suraksha, RS2818, Suraj, CO17, Bt/C-  
326 62, and CO15 for SBL. Similarly genotypes RS2818, CO17, Suraj, TVH002, F2383, Bt/C-62,  
327 CO15 and DSC1651 for MIL and CSH3075, PKV-081Bt, Bt/C-63, F2381, ARBC1651, Anjali,  
328 Rajat-Bt and DSC1651 SCY. These genotypes exhibited lower WAAS values, indicating greater  
329 stability and minimal environmental influence. However, they also showed lower mean  
330 performance for the evaluated traits. The genotypes associated with PH, SBL, and MIL traits  
331 represent the most desirable compact types, characterized by shorter plant height, reduced  
332 internode length, and shorter sympodial branches, making them well-suited for cultivation in  
333 rainfed ecosystems than for yield maximization. Genotypes Anjali, ARBC1651, Subiksha, Roja,  
334 Bt/C-63, Bt/C-61, ARBC1601, F2381, and CSH3075 were positioned in the fourth quadrant of  
335 the PH biplot; PKV-081Bt, Roja, Bt/C-63, Anjali, ARBC1601, Bt/C-61, F2383, TCHB213,  
336 CSH3075, and DSC1651 in the SBL biplot; Anjali, Bt/C-63, Roja, ARBC1601, Suraksha, Bt/C-  
337 61, F2381, and ARBC1651 in the MIL biplot; and Suraksha, Suraj, Subiksha, Nano, F2383,  
338 TVH002, and HC-54 in the SCY biplot. These genotypes exhibited low WAAS values and  
339 above-average performance, indicating they are stable with minimal environmental sensitivity

340 while maintaining optimal trait expression. Such genotypes are ideal for cultivation due to their  
341 consistent performance across varying conditions. In general, genotypes with WAAS values  
342 close to zero are considered the most stable. Accordingly, Anjali, Subiksha, F2383, Suraj, and  
343 ARBC1651 for PH; PKV-081Bt, Anjali, Roja, CO17, and ARBC1601 for SBL; Anjali, Roja,  
344 Bt/C-62, Suraj, and CO15 for MIL; and Suraksha, CSH3075, Subiksha, Suraj, Nano, and PKV-  
345 081Bt for SCY exhibited low GEI and high stability. However, ideal genotypes not only have  
346 low WAAS values but also performance above the average mean. Therefore, Anjali, Subiksha,  
347 and ARBC1651 (PH), PKV-081Bt, Anjali, and Roja (SBL), Anjali, Roja, Subiksha, and Bt/C-63  
348 (MIL), and Suraksha, Subiksha, Suraj, Nano, and F2383 (SCY) were identified as stable  
349 genotypes with superior performance. The genotypes with high mean SCY performance are most  
350 desirable for yield, whereas low values in PH, SBL, and MIL contribute to a more compact plant  
351 type, advantageous for agronomic adaptability. Despite various yield stability methods, WAAS  
352 biplot from AMMI analysis provides valuable insight for accurate stability assessment (Vineeth  
353 et al., 2022; Taleghani et al., 2023; Mostafavi and Saremirad 2021; Sharifi et al 2017).

#### 354 **Weighted average of absolute scores from BLUP and yield (WAASBY)**

355 The simultaneous ranking and selection of genotypes based on trait performance and stability  
356 were performed using the WAASBY index, which combines the WAASB stability measure with  
357 the trait mean (Olivoto et al., 2019a). Blue circles represent genotypes with WAASBY values  
358 above the mean, while red circles indicate those below the mean. For plant height (PH), among  
359 12 high-performing genotypes (blue circle), Anjali showed a WAASBY index above the mean,  
360 while ARBC1651 and Subiksha also exhibited relatively high stability and lengthier plant height  
361 compared to others (Fig. 7A). In the case of SBL, PKV-081Bt, Bt/C-63, and Roja had the highest  
362 WAASBY indices among 11 genotypes exceeding the mean branch length (Fig. 7B). For trait

363 MIL, Anjali again displayed the highest WAASBY index among 15 above mean internodal  
364 length genotypes, making it the top-performing and most stable genotype (Fig. 7C). For SCY  
365 (Fig. 7D), eight genotypes showed high WAASBY values, with Suraksha surpassing the mean  
366 WAASBY index, and it identified as most stable and highest-yielding genotype, followed by  
367 Subiksha and Suraj. These results confirm that the WAASBY index efficiently identifies  
368 genotypes combining high trait performance and stability (Olivoto et al., 2019a), which is  
369 essential for breeding programs targeting consistent performance across varied rainfed  
370 ecosystems.

371         Considering the advantage of WAASB approach, it is possible to customize the  
372 magnitude of this stability index in relation to trait performance for identifying desirable  
373 genotypes (Olivoto et al., 2019a). Therefore, WAASB values were plotted against the  
374 responsible variable (WAASBY) across several weights of WAASB for each trait (Fig. 8A).  
375 Accordingly, variation in genotype rankings was recorded based on the weighted contribution of  
376 traits PH (Fig. 4A), SBL (Fig. 8B), MIL (Fig. 8C), SCY (Fig. 8D), and their stability index  
377 (WAASB). The WAASB/GY heatmap was partitioned into two columns, first on left side of  
378 heatmap and second on right side on 50/50 WAASB weights. In the first column, where  
379 genotypes rankings were determined exclusively by the WAASB index (0/100). It revealed,  
380 Subiksha < ARBC1651 < Anjali was identified as stable genotypes with lengthier PH; Roja <  
381 Anjali < PKV-081Bt as stable genotypes with longer SBL; Bt/C-63 < Roja < Anjali as stable  
382 genotypes with longer MIL; and Suraj < Subiksha < CSH3075 < Suraksha as stable genotypes  
383 with higher SCY. In the second column, when ranking was based only on WAASB index  
384 (100/0), genotypes Anjali > ARBC19 > ARBC1651 were identified superior for PH, PKV-081Bt  
385 > Bt/C-63 > ARBC1601 for SBL, Anjali > PKV-081Bt > ARBC1601 for MIL, and Suraksha >

386 Suraj > Subiksha for SCY, and it highlighting that these genotypes are most superior and stable  
387 with desirable trait expression. The ranking of genotypes based on equal weights (50/50) is  
388 assigned to stability and the respective trait. Under this criterion, Anjali > ARBC1651 >  
389 Subiksha was identified as the most promising genotypes for PH, PKV-081Bt > Bt/C-63 > Roja  
390 for SBL, Anjali > Bt/C-63 > ARBC1601 for MIL, and Suraksha > Subiksha > Suraj for SCY.  
391 The WAASBY method effectively integrates trait performance and stability with WAASB  
392 analysis (Olivoto et al., 2019a), enabling the selection of cotton genotypes with consistent yield  
393 across variable environments. This approach helps breeders develop high-yielding, stable, and  
394 adaptable cultivars for diverse climates and farming practices. While most cotton yield stability  
395 studies have applied GGE biplot (Sivakumar et al., 2024), non-parametric methods (Baraki et al.,  
396 2024), and AMMI (Shahzad et al., 2019), the WAASB method-derived from AMMI and BLUP  
397 techniques-offers a powerful tool for identifying compact plant types in cotton genotypes  
398 adapted to rainfed conditions.

### 399 **Best linear unbiased prediction (BLUP)**

400 AMMI ANOVA applies a fixed-effects model treating genotype and environment as fixed  
401 factors, while LMM treat genotypic effects as random, providing a more realistic estimation of  
402 GEI (Piepho, 1994; Olivoto et al., 2019). In this study, LMM with genotype as a random effect  
403 was used, and BLUPs enabled accurate prediction of genotypic performance, especially with  
404 incomplete data (Smith et al., 2005). Variance component analysis confirmed significant effects  
405 of genotype and GEI for all traits except boll per plant (BP), which showed non-significant  
406 genotypic variance and was excluded from MTSI analysis. SCY had the highest genotypic  
407 variance proportion (71.99%), followed by BW and PH, indicating strong genetic control (Table  
408 3). In contrast, NSB exhibited low genotypic variance (22.74%) and high environmental

409 influence. GEI variance was highest for NSB (52.20%) and SBL (50.70%), while SCY showed  
410 the lowest (19.26%), reflecting greater yield stability. Heritability ( $h^2$ ) ranged from 0.23 (NSB)  
411 to 0.72 (SCY), with moderate estimates for PH, NMB, FSB, and MIL. Genotypic mean  
412 heritability ( $h^2_{mg}$ ) was high for SCY (0.91), BW (0.77), and PH, NMB, FSB (0.71 each),  
413 confirming reliable selection based on multi-environment performance. Selection accuracy ( $A_s$ )  
414 was highest for SCY (0.95), followed by BW (0.88) and PH, NMB, FSB (0.84 each),  
415 demonstrating model robustness. The GEI coefficient of determination ( $GEI_r^2$ ) ranged from 0.19  
416 (SCY) to 0.52 (NSB), indicating stronger GEI influence on branch-related traits, while SCY  
417 showed greater stability. The low  $GEI_r^2$  for SCY and moderate values for PH, NMB, and FSB  
418 suggested higher residual variation in the interaction component compared with AMMI ANOVA  
419 which explained most of the GEI through the first two IPCAs (Koundinya et al., 2021).

420         The correlation of genotypic values across environments ( $r_{ge}$ ) was highest for PH (0.76)  
421 and lowest for BW (0.47), with most traits showing  $r_{ge} > 0.66$ , aiding stable genotype selection  
422 (Table 3). Genotypic coefficient of variation ( $CV_g$ ) was highest for NMB (26.26%) and  
423 moderate for SCY (6.42%), while residual variation ( $CV_r$ ) ranged from 2.24% (SCY) to 19.39%  
424 (NMB). The CV ratio exceeded unity for most traits, especially SCY (2.87), indicating strong  
425 selection potential, whereas NSB and SBL showed greater environmental masking. BLUP-  
426 predicted mean values (Fig. 9) showed 13 genotypes above average for PH, with Anjali and  
427 ARBC 19 as tallest, and RS 2818, CO 17, Rajat Bt, Suraksha, and Nano as most compact (Fig.  
428 9A). For SBL, 14 genotypes performed above average, led by PKV-081 Bt and Bt C-63, whereas  
429 Subiksha, RS 2818, and Nano had the shortest SBL (Fig. 9B). Similarly, 13 genotypes showed  
430 above-average predicted mean for MIL, with Anjali and PKV-081 Bt recording the longest  
431 internodes, and RS 2818, CO 17, and Rajat Bt having the shortest (Fig. 9C). For SCY, 11

432 genotypes exceeded the average, with Suraksha, Suraj, and Subiksha showing the highest  
433 predicted means (Fig. 9D). Additionally, 14 genotypes exhibited above-average predicted means  
434 for NSB, 13 for FSB, 11 for NMB, and 13 for boll weight (BW) (Supplementary Fig. 1). Overall,  
435 Suraksha, Suraj, and Subiksha emerged as superior yield performers, while RS 2818, CO 17,  
436 Rajat Bt, and Nano represented compact types with lower PH, SBL, and MIL. These results  
437 highlight substantial genetic variability, supporting selection for both vigorous and compact  
438 types depending on breeding goals. The BLUP method proved effective for multi-environment  
439 prediction, consistent with previous studies in crops such as cowpea (Sousa, et al., 2019), cotton  
440 under saline conditions (Vineeth et al., 2022), cassava (Koundinya et al., 2021), and olive (Li et  
441 al., 2025).

#### 442 **Multi-trait stability index (MTSI)**

443 MTSI is an advanced tool designed to overcome the limitations of traditional stability models  
444 that assess single traits independently (Memon et al., 2023). Traditional stability models focus on  
445 mean performance, regression, and deviations but fail to fully capture genotype stability or key  
446 trait strengths and weaknesses (Bhering et al., 2012; Yue et al., 2022). MTSI overcomes these  
447 limitations by analyzing multiple traits simultaneously, helping breeders identify superior and  
448 stable genotypes more effectively (Olivoto et al., 2019). In this study, MTSI was applied to  
449 evaluate the performance and stability of cotton genotypes for multiple yield and plant  
450 architecture traits across environments. Factor analysis (PCA with Varimax rotation) grouped  
451 eight traits into three factors explaining 70.78% of the total variation (Table 4, Table 5). FA1  
452 (eigenvalue 2.84, 35.50% variance) was associated with PH, SBL, and MIL; FA2 (eigenvalue  
453 1.48, 18.45%) related to BW and SCY; and FA3 (eigenvalue 1.35, 16.83%) involved NMB,  
454 FSB, and NSB. Mean communality of 0.72 indicated a good representation of trait variation.

455 The MTSI ranked genotypes from lowest (most desirable) to highest values (Fig. 10a),  
456 with Suraj (MTSI = 2.16), Subiksha (2.53), F2383 (2.54), and RS2818 (3.08) identified as the  
457 most promising under a 15% selection intensity (Supplementary Table 2). The red dot in (Fig.  
458 10A) marks the cut-off MTSI value (3.08), highlighting genotypes for future evaluation. Selected  
459 genotypes showed favorable selection differentials (SDp), ranging from -8.48% (SBL) to  
460 +5.50% (BW), and high heritability for SCY (0.91) and BW (0.77). However, negative selection  
461 gains were observed for PH, SBL, MIL, NMB, FSB, and NSB. The radar plot (Fig. 10B)  
462 illustrated the strengths and weaknesses of selected genotypes, with RS2818 driven mainly by  
463 FA1, F2383 by FA3, Subiksha by FA2, and Suraj showing balanced contributions from FA2 and  
464 FA3. These results suggest that Suraj and F2383 are stable and widely adaptable compact  
465 genotypes, while Subiksha offers intermediate stability, and RS2818 is suited for targeted trait  
466 improvement. Similar successful applications of MTSI have been reported in Cotton (DS Raj et  
467 al., 2024; Elsamman et al., 2024), cassava (Koundinya et al., 2021), rice (Sharifi et al., 2021),  
468 and pearl millet (Yadav et al., 2022), confirming its efficiency in identifying superior and stable  
469 genotypes, consistent with the findings of this study.

#### 470 **Trait correlation patterns**

471 The scatterplot matrix (Fig. 11) revealed clear patterns of association among plant architecture  
472 and yield-related traits in cotton. PH showed a moderate positive correlations with NMB, SBL,  
473 and NSB, indicating that taller plants tended to have more and longer branches (Madhu et al.,  
474 2023). PH was also strongly correlated with MIL, confirming that longer internodes contribute to  
475 greater plant height. However, excessive vegetative growth can hinder crop management  
476 (Venugopalan et al., 2011; Kerby et al., 2010). In contrast, shorter MIL and SBL were associated  
477 with compact plant architecture, which improves resource allocation to reproductive growth,

478 enhances boll retention, and suits high-density planting (Gunasekaran et al., 2020; Yan et al.,  
479 2019; Sivakumar et al., 2024). NMB and FSB showed weak correlations with yield traits,  
480 suggesting limited impact on yield improvement (Van der Sluijs, 2015). SCY was primarily  
481 driven by BP and BW, while PH, SBL, MIL, and NSB showed negative correlations with SCY.  
482 These findings suggest that excessive vegetative growth does not enhance yield, contradicting  
483 several earlier studies that reported positive associations (Meredith et al., 2012; Ali et al., 2017;  
484 Ul-Allah et al., 2017; Ali et al., 2018) but aligning with studies that found negative correlations  
485 (Pujer et al., 2014; Yan et al., 2019; Sivakumar et al., 2024; Madhu et al., 2023). The results  
486 highlight the importance of selecting compact plant types that improve reproductive efficiency,  
487 supporting the goals of ideotype breeding in cotton.

## 488 **Conclusion**

489 This METs identified cotton genotypes combining compact plant architecture with stable high  
490 yield, suitable for rainfed systems in Tamil Nadu. Yield variation was largely governed by  
491 genetic factors with moderate GEI, whereas branch number and boll count were predominantly  
492 influenced by environmental conditions. Suraksha emerged as the most stable and highest-  
493 yielding genotype, while Suraj, Subiksha, and F2383 exhibited a favorable balance of compact  
494 growth and adaptability across environments. Genotypes RS2818, Nano, and CO17,  
495 characterized by reduced plant height and internode length, represent valuable donors for  
496 compact plant traits. The integration of AMMI, GGE, WAAS, BLUP, WAASBY, and MTSI  
497 analyses provided complementary insights into genotype evaluation, underscoring the  
498 importance of multi-trait and multi-location testing in cotton ideotype breeding. For practical  
499 applications, these selected genotypes offer potential as parental lines for developing compact,  
500 high-density, and machine-harvestable cotton hybrids. These findings form a strong basis for

501 breeding programs targeting compact architecture and sustainable yield under rainfed conditions  
502 in India.

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### 507 **Author's contribution**

508 All the authors contributed to the study conception and design. Banoth M executed the  
509 experiment, analysed the data, results interpreted and written original draft. All authors critically  
510 revised the manuscript for important intellectual contents and approved the final manuscript.

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### 513 **Data availability**

514 Data will be made available on request.

### 515 **Declarations**

### 516 **Ethics approval and consent to participate**

517 Not applicable.

### 518 **Consent for publication**

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### 520 **Competing interests**

521 Authors declare that they don't have competing interests.

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685 **Table 1** List of twenty-two elite cotton genotypes used in the study

Genotypes	Released Institute	Year	Source	Genotypes	Released Institute	Year	Source
CO15	TNAU, Coimbatore	2018	Dept. of Cotton, TNAU, Coimbatore	Bt/C-61	ICAR-CICR, Coimbatore	2022	ICAR-CICR, Coimbatore
CO17	TNAU, Coimbatore	2020	-do-	Bt/C-62	-do-	2022	-do-
TCHB213	TNAU, Srivilliputhur	2020	-do-	Bt/C-63	-do-	2022	-do-
TVH002	TNAU, Veppanthattai	2023	-do-	Subiksha	-do-	2018	-do-
F2381	PAU, Faridkot	2016	-do-	PKV-081Bt	-do-	2017	-do-
F2383	PAU, Faridkot	2016	-do-	Nano	-do-	2023	-do-
ARBC1601	UAS, Dharwad	2020	-do-	Anjali	-do-	1992	-do-
ARBC1651*	UAS, Dharwad	2020	-do-	Rajat-Bt	-do-	2017	-do-
ARBC19	UAS, Dharwad	2016	-do-	Suraj	-do-	2008	-do-
DSC1651	UAS, Dharwad	2020	-do-	Suraksha	-do-	2018	-do-
RS2818	SKRAU, Sriganaganagar	2020	-do-	HC-54	-do-	2002	-do-
CSH3075*	ICAR-CICR, Sirsa	2017	ICAR-CICR, Coimbatore	Roja	-do-	2011	-do-

686 \*Checks included

687

688 **Table 2** Combined analysis of variance, principal components and their contributions as per AMMI model for GEI of yield and plant  
689 architecture traits in cotton

Traits	Joint RCBD + AMMI ANOVA mean squares					PC1 (df: 24)		PC2 (df: 22)		CV (%)	Bartlett's K-squared (df: 2)	Mean over Environments
	Environment (E) (df: 2)	Genotype (G) (df:23)	Replication within (E) (df: 6)	GEI (df: 46)	Residual (df: 138)	Mean Square	Contribution (%)	Mean Square	Contribution (%)			
PH	361.76***	326.44***	1.95	93.61***	8.89	137.88***	76.8	45.32**	23.2	10.78	1.34	89.77
NMB	0.70***	0.46***	0.01	0.23***	0.01	0.23***	90.8	0.03*	9.2	14.62	0.33	0.72
FSB	7.97***	13.22***	0.59	3.80***	0.49	6.30***	86.4	1.08**	13.6	8.99	0.33	21.70
NSB	18.10***	9.51***	0.57	4.48***	0.62	8.25***	96.2	0.36*	3.8	10.35	1.80	20.56
SBL	40.67***	20.42***	1.15	8.65***	1.13	15.30***	92.2	1.40*	7.8	13.63	1.80	18.81
MIL	2.68***	1.20***	0.01	0.42***	0.04	0.68***	83.4	0.15***	16.6	11.40	4.41	5.71
BP	3.71*	7.47***	1.70	7.74***	0.91	13.70***	92.3	1.24*	7.7	12.80	1.51	21.73
BW	0.49***	0.68***	0.02	0.16***	0.04	0.28***	86.2	0.04*	13.8	7.93	0.72	4.98
SCY	35.80**	546.88***	2.04	50.93***	6.69	74.42***	76.2	25.30***	23.8	6.18	1.68	115.57

690 \*, \*\*, \*\*\* represents significant at p-value  $\leq 0.001$ ,  $\leq 0.01$ , and  $\leq 0.05$ , respectively. PH Plant-height, NMB Number of monopodial branches, FSB Height of  
691 first sympodial branch origin from ground, NSB Number of sympodial branches, SBL Sympodial branches length, MIL Mainstem internodes length, BP Bolls  
692 per plant, BW Boll weight, SCY Seed cotton yield

693 **Table 3** Estimation of variance components from LMM for nine studied traits in cotton

Variance components	PH	NMB	FSB	NSB	SBL	MIL	BP	BW	SCY
GEN	25.87**	0.04***	1.05***	0.56*	1.31*	0.09**	0.00	0.06***	55.11***
GEN:ENV	28.24***	0.04***	1.11***	1.29***	2.51***	0.13***	2.25***	0.04***	14.75***
Residual	8.89	0.02	0.49	0.62	1.13	0.04	0.91	0.04	6.69
% GV in PV	41.06	38.30	39.65	22.74	26.43	33.51	0	42.12	71.99
%IV in PV	44.83	40.81	41.89	52.20	50.70	49.03	71.23	27.27	19.26
%EV in PV	14.11	20.89	18.46	25.06	22.87	17.46	28.77	30.60	8.74
Phenotypic variance (PV)	63.00	0.09	2.64	2.46	4.95	0.26	3.15	0.14	76.55
Heritability	0.41	0.38	0.40	0.23	0.26	0.34	0.00	0.42	0.72
GEI <sup>2</sup>	0.45	0.41	0.42	0.52	0.51	0.49	0.71	0.27	0.19
h <sup>2</sup> <sub>mg</sub>	0.71	0.71	0.71	0.53	0.58	0.65	0.00	0.77	0.91
Accuracy of selection (A <sub>s</sub> )	0.84	0.84	0.84	0.73	0.76	0.80	0.00	0.88	0.95
r <sub>ge</sub>	0.76	0.66	0.69	0.68	0.69	0.74	0.71	0.47	0.69
CV <sub>g</sub>	5.67	26.26	4.71	3.64	6.08	5.14	0.00	4.85	6.42
CV <sub>r</sub>	3.32	19.39	3.22	3.82	5.65	3.71	4.38	4.14	2.24
CV ratio	1.71	1.35	1.47	0.95	1.08	1.39	0.00	1.17	2.87

694 GV Genotypic variation, IV Interaction variance, EV Environment variation, h<sup>2</sup><sub>mg</sub> heritability of genotypic mean,  
 695 GEI<sup>2</sup> GEI coefficient of determination, r<sub>ge</sub> correlation between genotypic value across environments, CV<sub>g</sub> genotypic  
 696 coefficient of variation (%), CV<sub>r</sub> residual coefficient of variation (%), CV ratio between the coefficients of genotypic  
 697 and residual variations (%)

699 **Table 4** Factor loadings derived through varimax rotation and communalities obtained from  
 700 factor analysis

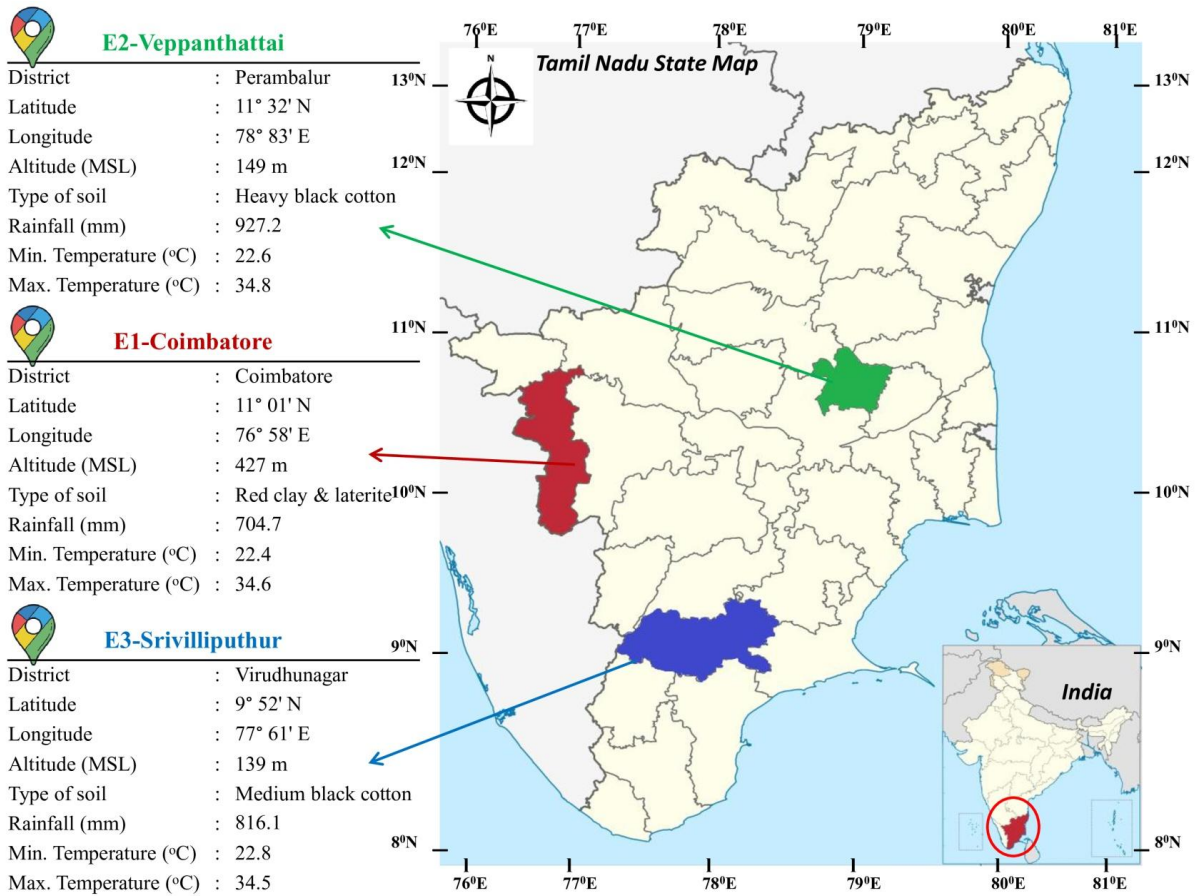
Factor components	FA1	FA2	FA3	Communality	Uniquenesses
Eigenvalues	2.84	1.48	1.35		
Variance (%)	35.50	18.45	16.83		
Cum. variance (%)	35.50	53.95	70.78		
PH	-0.85	0.28	0.00	0.80	0.20
NMB	-0.30	0.40	0.63	0.65	0.35
FSB	0.22	0.26	-0.85	0.84	0.16
NSB	-0.19	-0.21	-0.52	0.35	0.65
SBL	-0.77	0.04	0.19	0.63	0.37
MIL	-0.93	0.00	-0.03	0.86	0.14
BW	-0.28	0.87	-0.11	0.85	0.15
SCY	0.03	0.79	0.25	0.68	0.32
Mean				0.71	0.29

701 **Table 5** Assessment of traits and selection differential in cotton genotypes using the WAASBY  
 702 index derived from MTSI

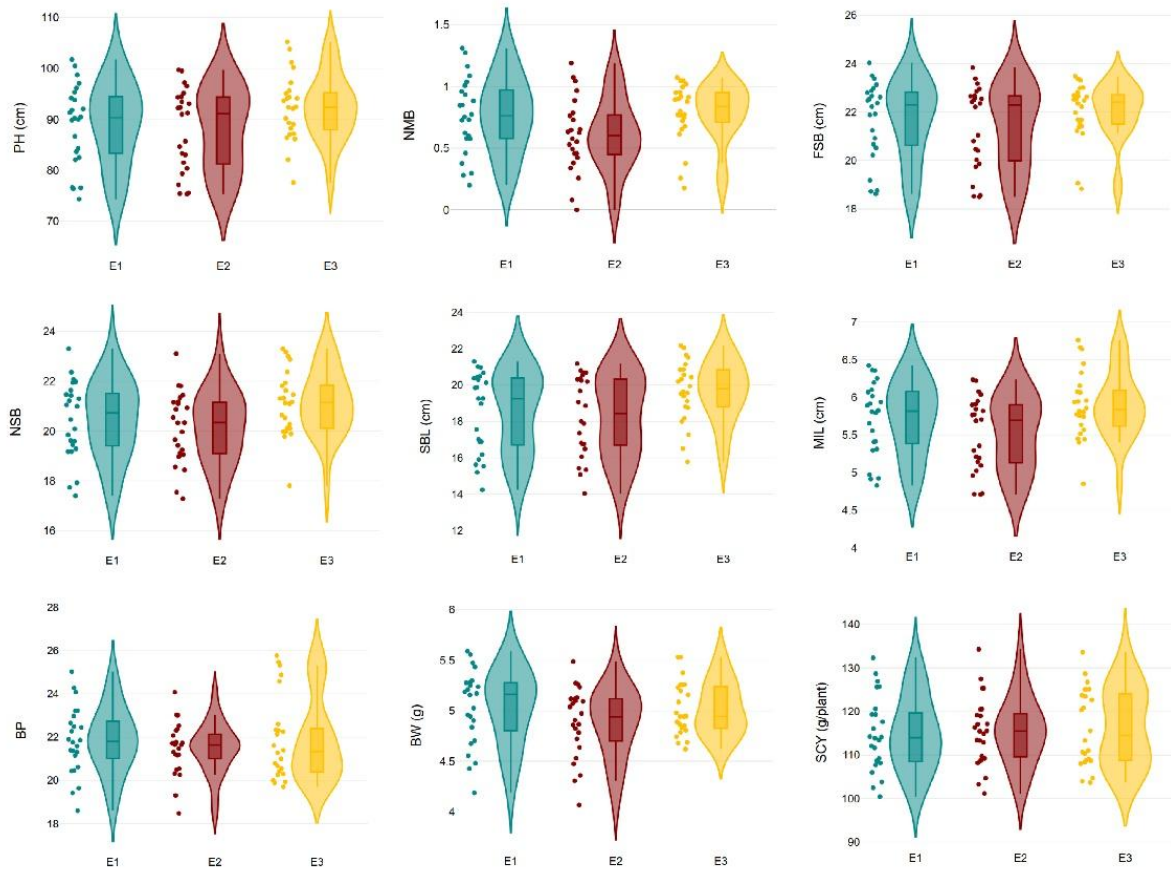
Traits	Factor	X <sub>o</sub>	X <sub>s</sub>	SD	SD <sub>P</sub> (%)	h <sup>2</sup>	SG	SG <sub>P</sub> (%)	Sense
PH	FA 1	89.77	85.54	-4.23	-4.71	0.71	-3.02	-3.36	Decrease
SBL	FA 1	18.81	17.22	-1.60	-8.48	0.58	-0.92	-4.89	Decrease
MIL	FA 1	5.71	5.44	-0.27	-4.76	0.65	-0.18	-3.08	Decrease
BW	FA 2	4.98	5.25	0.27	5.50	0.77	0.21	4.24	Increase
SCY	FA 2	115.57	121.59	6.02	5.21	0.91	5.46	4.73	Increase
NMB	FA 3	0.72	0.69	-0.03	-3.54	0.71	-0.02	-2.50	Decrease
FSB	FA 3	21.70	21.09	-0.61	-2.81	0.71	-0.43	-2.00	Increase
NSB	FA 3	20.56	20.54	-0.03	-0.13	0.53	-0.01	-0.07	Increase

704 X<sub>o</sub> Original genotypes mean, X<sub>s</sub> Selected genotypes mean, SD Selection differential, SD<sub>P</sub> selection differential  
 705 percent, h<sup>2</sup> heritability; SG Selection gain, SG<sub>P</sub> selection gain percent.

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 709 **Fig. 1** Geographical locations of experimental sites in Tamil Nadu, India with their agro-climatic  
 710 characteristics, where the study was conducted under rainfed conditions during Kharif 2024 in  
 711 cotton



712

713 **Fig. 2** Violin plots depicting the mean performance of nine traits evaluated in 24 cotton

714 genotypes across three environments under rainfed conditions during Kharif 2024. PH Plant-

715 height, NMB Number of monopodial branches, FSB Height of first sympodial branch origin

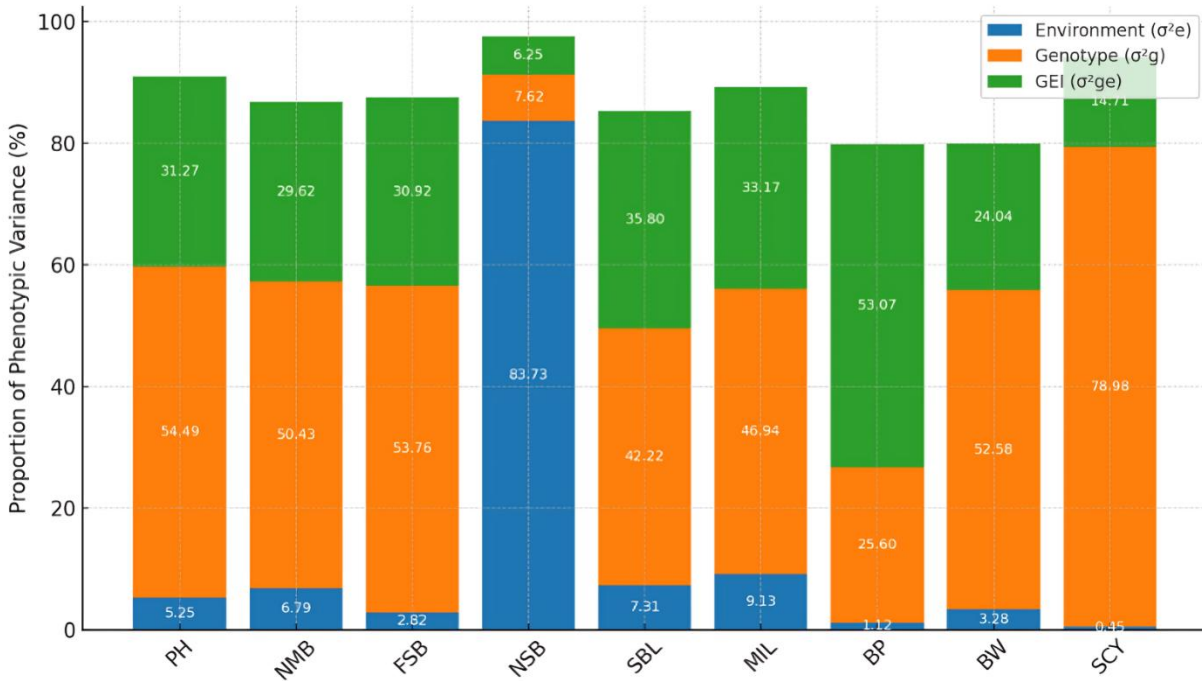
716 from ground, NSB Number of sympodial branches, SBL Sympodial branches length, MIL

717 Mainstem internodes length, BP Bolls per plant, BW Boll weight, SCY Seed cotton yield

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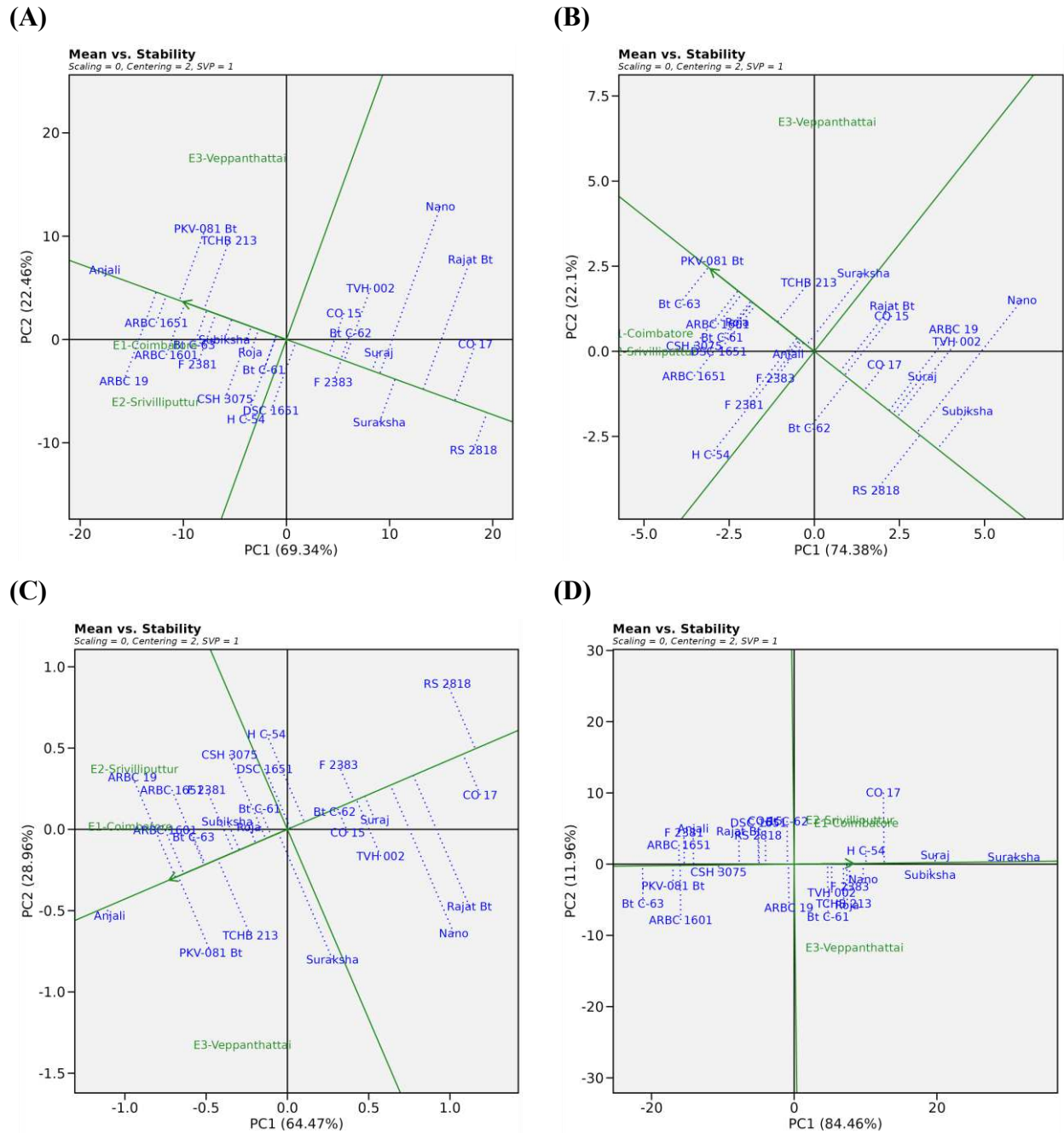
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 722 **Fig. 3** Proportion of phenotypic variance for nine traits in 24 cotton genotypes evaluated under  
 723 rainfed conditions during Kharif 2024. PH Plant-height, NMB Number of monopodial branches,  
 724 FSB Height of first sympodial branch origin from ground, NSB Number of sympodial branches,  
 725 SBL Sympodial branches length, MIL Mainstem internodes length, BP Bolls per plant, BW Boll  
 726 weight, SCY Seed cotton yield

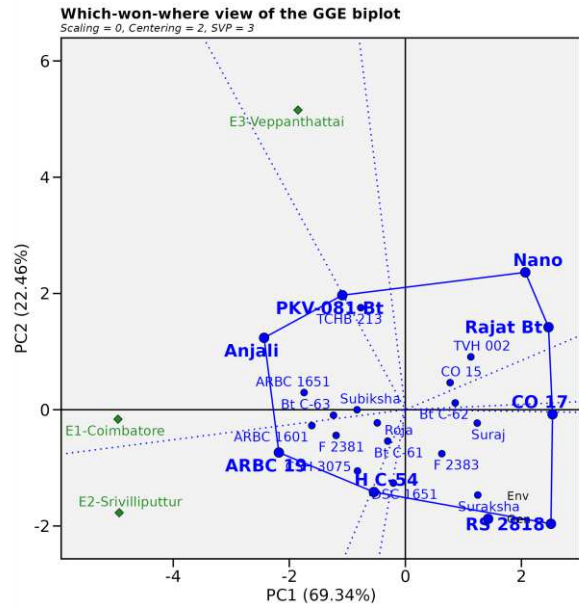
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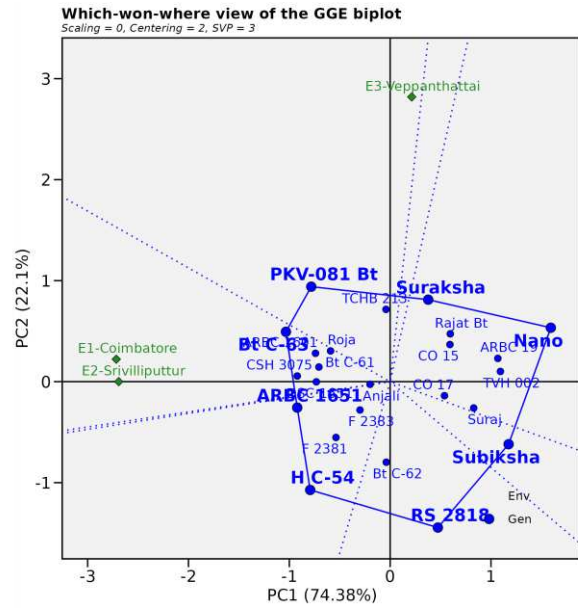
738 **Fig. 4** The mean vs. stability GGE biplot of **(A)** plant height, **(B)** sympodial branch length, **(C)**  
 739 mainstem internode length, and **(D)** seed cotton yield across three environments

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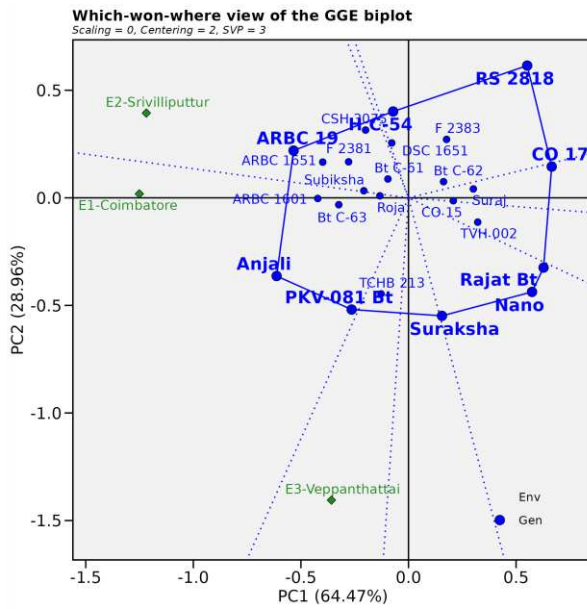
(A)



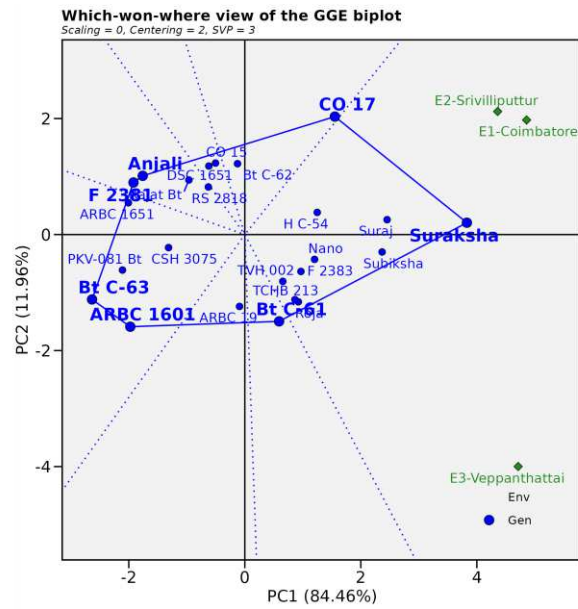
(B)



(C)

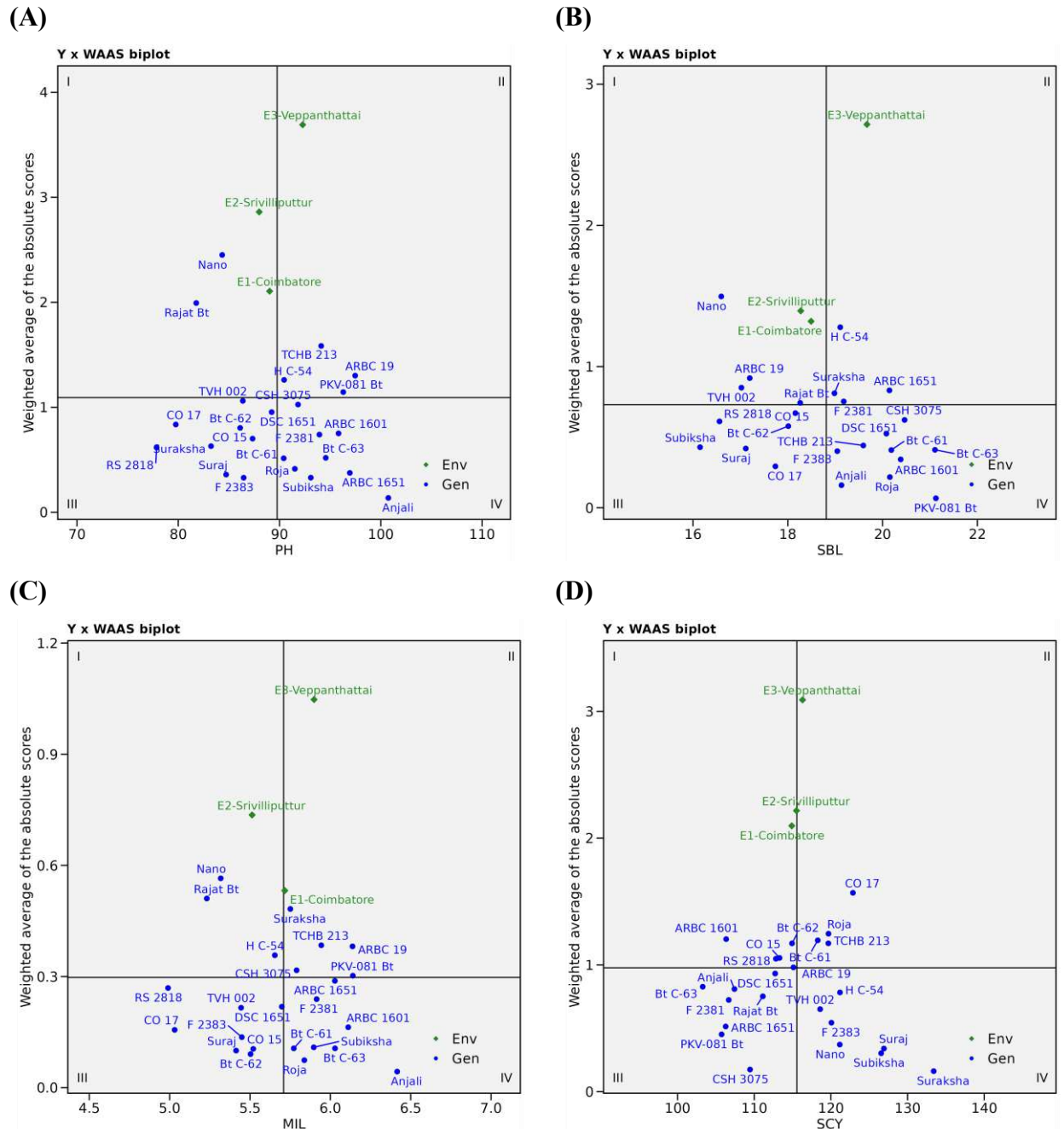


(D)



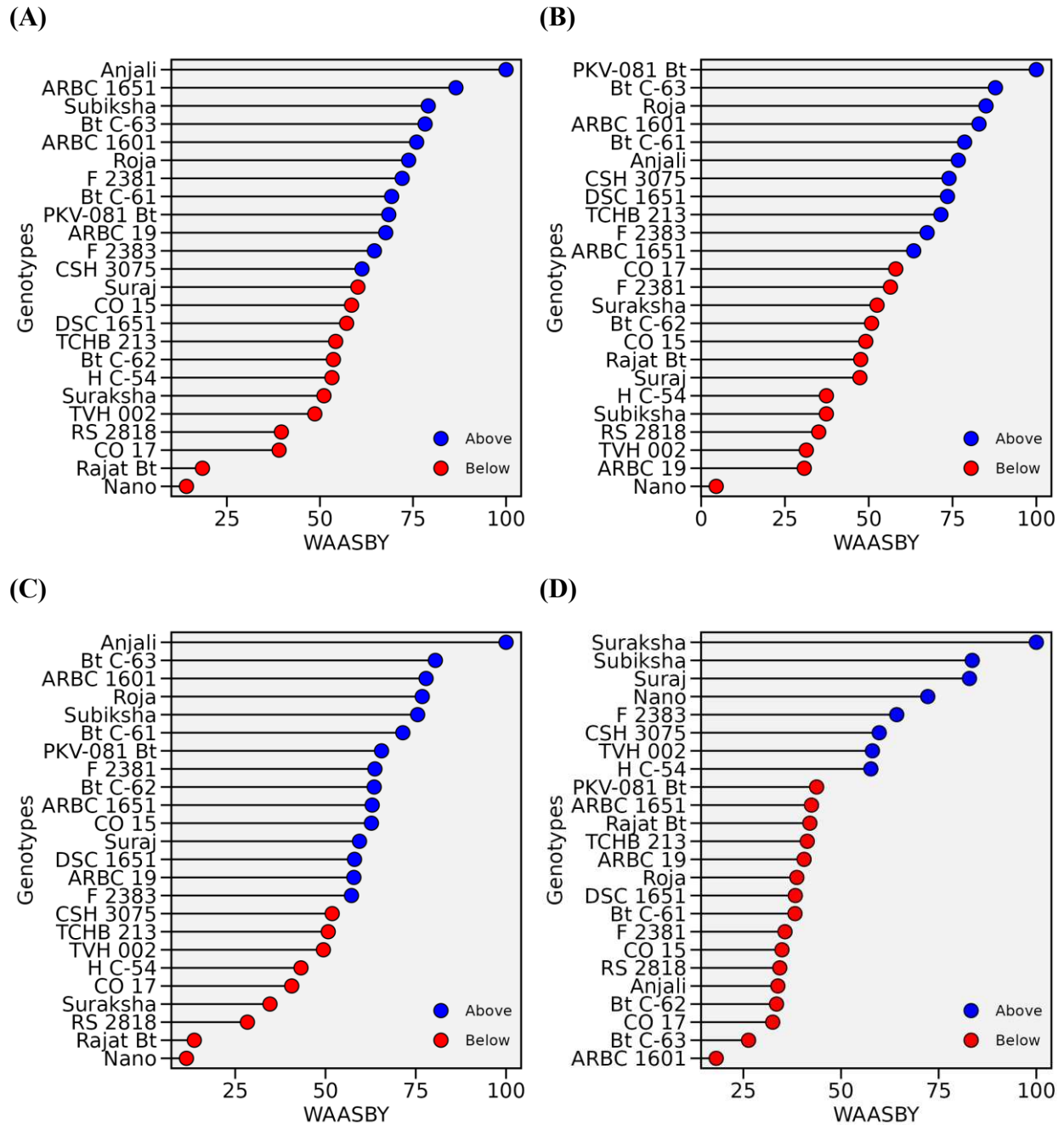
744 **Fig. 5** The Which-Won-Where GGE biplot of (A) plant height, (B) sympodial branch length, (C)  
 745 mainstem internode length, and (D) seed cotton yield across three environments

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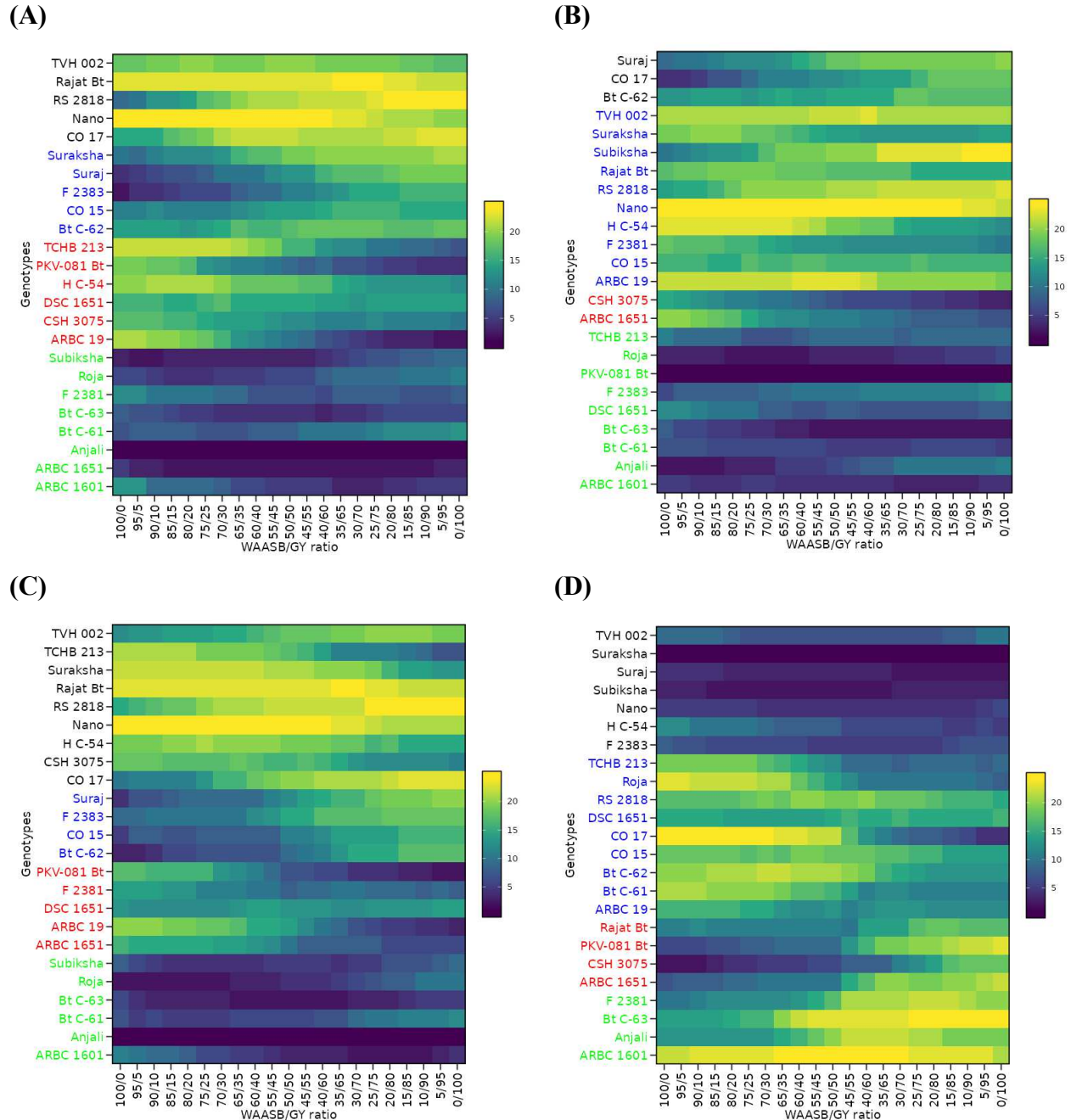
750 **Fig. 6** Mean performance vs. WAAS biplot derived from the AMMI model for (A) plant height,  
 751 (B) sympodial branch length, (C) mainstem internode length, and (D) seed cotton yield across  
 752 three environments. The x-axis represents the arithmetic mean of each trait across environments,  
 753 while the y-axis indicates the WAAS index

754

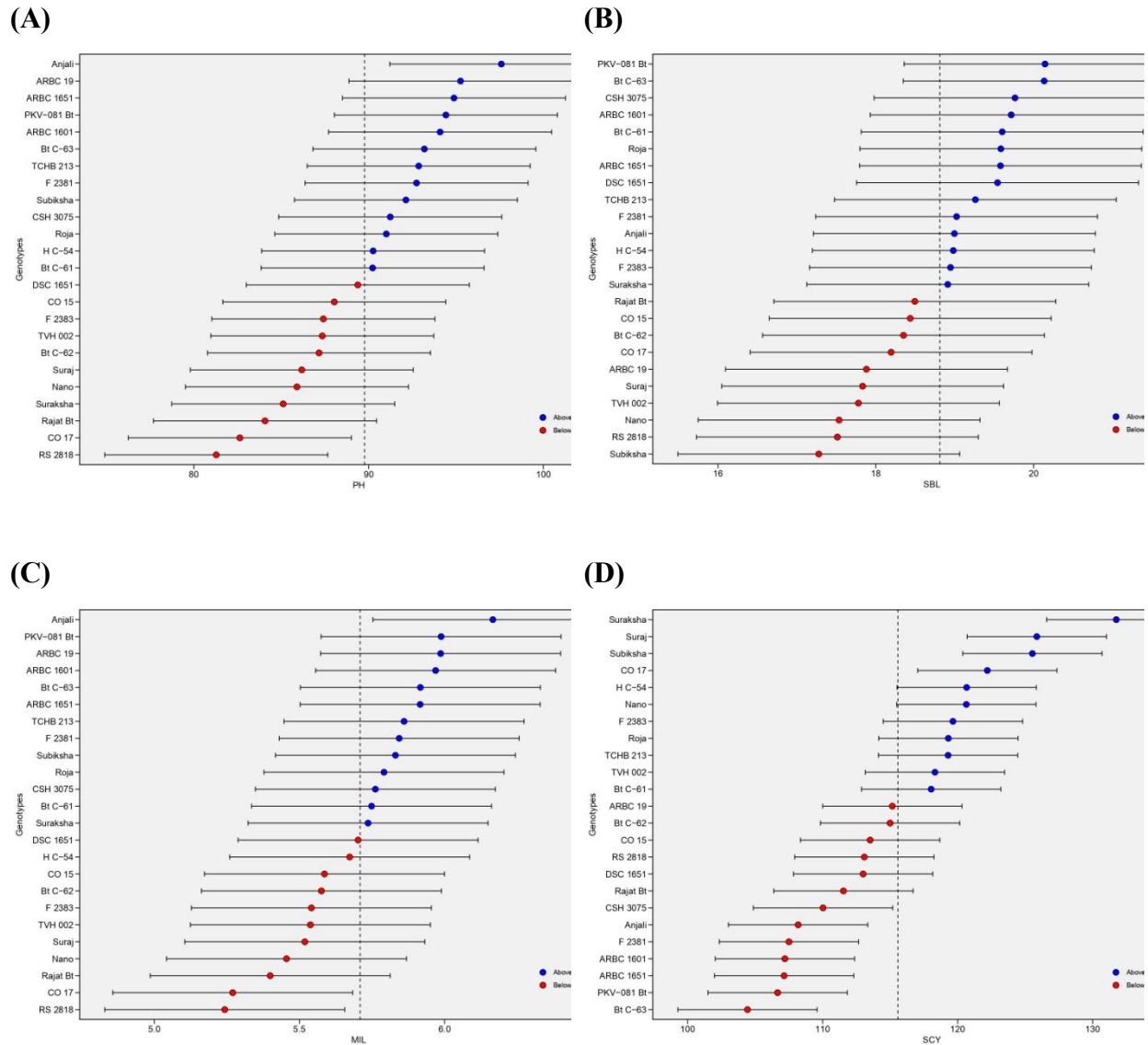


755 **Fig. 7** Estimated WAASBY index values for **(A)** plant height, **(B)** sympodial branch length, **(C)**  
 756 mainstem internode length, and **(D)** seed cotton yield in cotton genotypes, calculated by  
 757 assigning equal weights (50:50) to mean performance and stability

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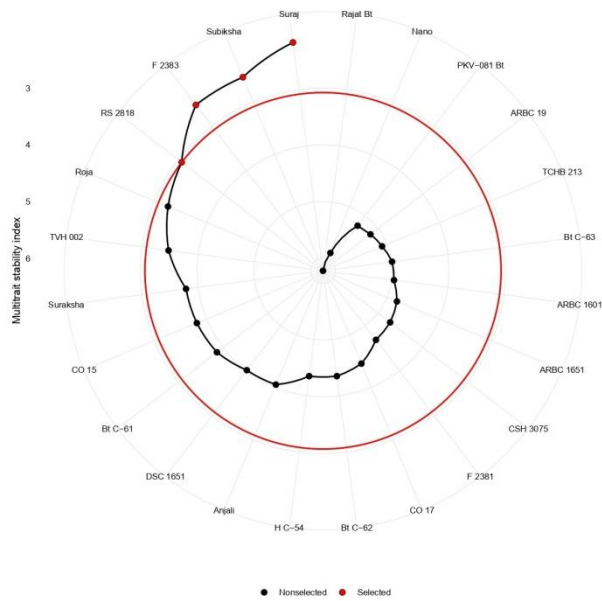


761 **Fig. 8** WAASB/GY heatmap showing the ranking of 24 cotton genotypes based on different  
 762 weight combinations of trait mean performance and WAASB stability index. Relative genotype  
 763 rankings are represented by color intensity, where darker shades indicate higher ranks and lighter  
 764 shades indicate lower ranks. Results are presented for **(A)** plant height, **(B)** sympodial branch  
 765 length, **(C)** mainstem internode length, and **(D)** seed cotton yield

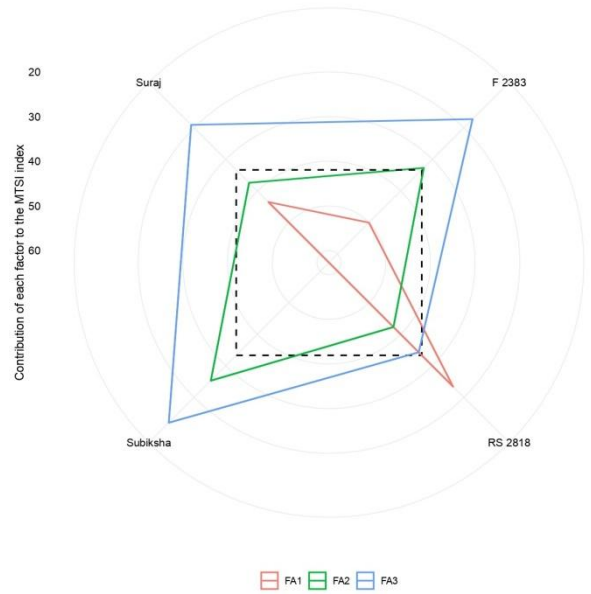


766 **Fig. 9** BLUP mean values for (A) plant height, (B) sympodial branch length, (C) mainstem  
 767 internode length, and (D) seed cotton yield in 24 cotton genotypes evaluated across three  
 768 environments

(A)

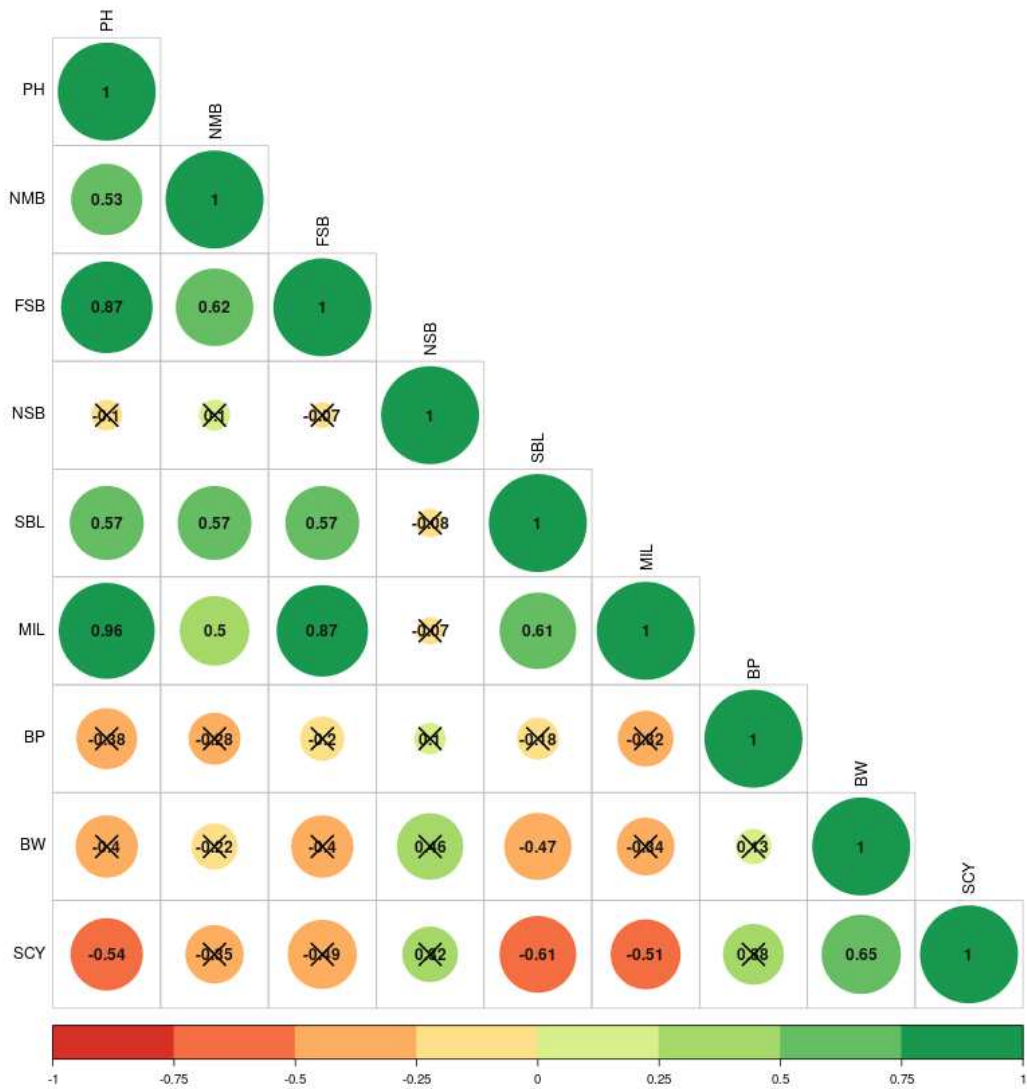


(B)



769 **Fig. 10 (A)** Ranking of cotton genotypes in ascending order based on MTSI score, with selected  
770 genotypes are highlighted in red. The radar plot scale represents the MTSI score. **(B)** The  
771 strengths and weaknesses of selected genotypes are presented as the proportional contribution of  
772 each factor to the computed MTSI score

773



774

775 **Fig. 11** Correlogram of plant architecture and yield traits across three environments. Every  
 776 correlation coefficient (r) which matches two traits was calculated with Pearson method.  
 777 Numbers ranges from -1 to 1 are Pearson rank of traits on horizontal and vertical axes. Color  
 778 depth and size of the circle diagrams indicates the correlation strength

779

## Supplementary Files

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