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Analysis of yield stability and genotype–environment interaction for open-pollinated tomato varieties in the Kashmir Himalaya using the AMMI model

Ummyiah H. Masoodi[1], Immad A. Shah[1], Walid Emam[2], Yusra Tashkandy[2], Pradeep Mishra[3]✉, Neha Mishra[4] & Adelajda Matuka[5]

This study investigates the yield stability and adaptability of sixteen open-pollinated tomato (Solanum lycopersicum Mill.) genotypes across multiple environments in the Kashmir Valley, employing Additive Main Effect and Multiplicative Interaction (AMMI) analysis to examine genotype-environment interactions (GEI). A Randomized Complete Block Design (RCBD) with three replications was implemented at six locations over two years, representing the region's diverse environmental conditions. Analysis of variance indicated that the effects of environment (E), genotype (G), and GEI were all highly significant ($p<0.001$) in influencing yield per hectare, with the environment contributing 47.5% of the total variation, underscoring the impact of local conditions on performance. Key stability indicators, including Weighted Average of Absolute Scores (WAAS) and Multi-Trait Stability Index (MTSI), assessed genotype stability and yield, with Arka Meghali and NDF-9 emerging as top-performing varieties across locations. Arka Meghali achieved the highest yield, while NDF-9 showed remarkable adaptability. The consistent rankings provided by stability indices reinforced the reliability of WAAS and MTSI as selection tools in multi-environment trials. Based on multi-environment stability analysis, Arka Meghali and NDF-9 were identified as superior open-pollinated tomato genotypes combining high yield and stability across diverse environments. These varieties are recommended for cultivation in the Kashmir Valley to enhance tomato productivity under variable agro-climatic conditions.These findings underscore the utility of GEI analysis in identifying tomato genotypes with robust yield and stability, providing valuable insights for breeding programs and crop management in ecologically sensitive regions like the Northern Himalayas. This research establishes a foundation for future studies on environmental adaptability in crop improvement, highlighting the potential of selected genotypes for sustainable cultivation in Kashmir.

Keywords Tomato, AMMI analysis, Stability indices, IPCA, Biplot graph, Genotype–environment interaction

Tomato (*Solanum lycopersicum*Mill.) is one of the most widely grown crops, thriving in diverse climatic zones[1]. Originating in Peru and Ecuador[2], tomatoes are cultivated during the kharif season in Kashmir, where fresh tomatoes are available only briefly, coinciding with specific climatic conditions at the end of summer. Tomatois a major vegetable crop globally, valued for its nutritional and economic importance. Across diverse agro-ecological regions, including temperate zones like Kashmir, achieving stable and high-yielding tomato production is critical for ensuring food security and enhancing farmers livelihoods. Genotype × environment interaction (GEI) significantly influences tomato performance, making it essential to identify varieties with broad adaptability and stability. Although the current study focuses on the Kashmir Valley, the findings contribute to a broader

[1]Sher-e-Kashmir University of Agricultural Sciences and Technology of Kashmir, Shalimar, Srinagar, J&K 190025, India. [2]Department of Statistics and Operations Research, College of Science, King Saud University, P.O. Box 2455, Riyadh 11451, Saudi Arabia. [3]College of Agriculture, JNKVV, Rewa, MP, India. [4]Department of Mathematics and Statistics School of Physical Sciences, Amity University, Mohali, Punjab, India. [5]Department of Economics, Faculty of Economics, University of Bologna, Bologna, Italy. ✉email: pradeepjnkvv@gmail.com

understanding of crop improvement strategies in regions with short growing seasons, fluctuating climates, and resource constraints, offering insights relevant to plant breeders, farmers, and policymakers aiming to optimize production systems under environmental variability.The lack of high-yielding tomato varieties limits productivity in this region[3]. To address the growing demand for tomatoes, it is essential to develop varieties that offer both high yield and quality[4]. However, genotype-environment interactions (GEI) create challenges in breeding and selecting tomato varieties adaptable to the region[5–8]. It becomes difficult to identify the most promising genotypes due to their relative ranking over several locations or environments[9]. Genotype by environment interaction (GEI) reflects the different responsesof the genotypes to environment conditions[10]. Many varieties have been recommended for cultivation in Kashmir, but the information on the stability is missing[11]. There is a need to identify genotypes with consistent performance over years so that they are selected based on the stability parameter, for yield and maturity attributes[12]. The interaction between genotypes and environmental conditions compels breeders to make a choice, either develop cultivars that are broadly adaptable or focus on creating varieties tailored to specific environmental niches[13].The study is supported by previous research by[11,14].

In plant breeding, understanding GEI is crucial as it directly impacts genotype selection and cultivar development[15]. GEI occurs when genotypes exhibit different responses to environmental variations, which can complicate the selection process across multiple locations[11]. As elucidated in[11], genotype-environment interaction (GEI) manifests when various genotypes exhibit disparate reactions to distinct environmental factors. Plant breeders acknowledge the necessity of encompassing the entire spectrum of genetic diversity, rather than solely focusing on GEI[13]. To effectively delineate the GEI component from the broader genetic variation, modified models offer advantages[16]. The AMMI model and the GGE biplot serve as illustrations of such models employed for delineating, analyzing, comprehending, and forecasting GEI[16]. GEI poses a substantial challenge in crop breeding and assumes a pivotal role in understanding the genetic mechanisms underpinning environmental adaptation[12].

Several statistical methods for analyzing the interaction of genotypes and environments (GEI) have been developed[17]. Additive main effects and multiplicative Interaction (AMMI) is an effective way to show adaptive responses[18]. AMMI analysis has shown that it significantly improves selection[19] and in many crops, is used to analyzeGxE interactions more accurately[18,20]. This model combines the usual analysis ofvariance for main effects of genotype and environment with PCA to break the interaction into several Interaction Principal Component Axes (IPCA).AMMI analysis considers the main and interaction effects as fixed[21]. The major source of variation for any crossover (qualitative) interaction is that the PCA scores exhibit a disproportionate genotype response[22]. This disproportionate genotype response is referred to as crossover GEI and same sign or near zero scores represent a non-crossover (quantitative) GEI or a proportionate genotype response[23]. Genotypes and environments are displayed in the same scatter plot using the AMMI analysis biplot tool[26–30]. Moreover, various stability indices can be brought to use for evaluating the genotypes[31–33]. This study employs AMMI analysis and stability indices to evaluate the yield stability of 16 open-pollinated tomato varieties across six locations over two years in Kashmir. By analyzing yield stability and adaptability, we aim to identify tomato genotypes with optimal performance for both yield and environmental adaptability.Stability analysis in tomato has been extensively explored to understand yield fluctuations across environments. Previous studies have emphasized the importance of selecting genotypes with consistent performance across multiple locations and seasons[20,22]. Focusing on tomato-specific GEI research ensures that recommendations align closely with the crop's physiological responses and market demands, avoiding generalizations based on unrelated crops.A similar study aimed at enhancing tomato cultivation in Assam demonstrated the importance of evaluating genotypic performance across diverse environments to achieve consistent yields.

Materials and methods

This study evaluated sixteen open-pollinated tomato (Solanum lycopersicum Mill.) varieties sourced from the Division of Vegetable Science at Sher-e-Kashmir University of Agricultural Sciences & Technology of Kashmir, as well as from private seed dealers. The varieties were chosen for their prevalence in local cultivation and potential yield stability. Trials were conducted over two consecutive growing seasons across six distinct locations in the Kashmir Valley, encompassing varied environmental conditions (Table 1). These sites were strategically selected to capture the diverse agro-climatic conditions of the region, including variations in altitude, soil type, rainfall, and temperature, which are critical factors influencing crop performance. The selection of these sites enabled a comprehensive evaluation of genotype performance under a realistic range of environmental conditions encountered in the valley, enhancing the relevance and applicability of the findings for local agriculture.

Location	Latitude	Longitude	Climate of district	Soil type	Altitide (above mean sea level)	Average annual rainfall	Tmax	Tmin
KVK Malnagpora (1,2)	33.891774	74.992062	Sub humid temperate	Lower Plain Soils Karewas, Group of Locustine origin, High altitude soils	1652 m	505.3 mm	31.4 °C	-3.3 °C
Shalimar (1,2)	34.14554	74.87842	Temperate humid subtropical climate	Clay to clay loam, sandy loam	1585 m	721.8 mm	32.4 °C	-4.2 °C
Wadura (1,2)	34.34777	74.40092	Temperate climate	Clayey, loamy rich and light, peaty	1593 m	1270 mm	31.8 °C	-7.4 °C

Table 1. Environmental description of the experimental sites.

The experimental design was a Randomized Complete Block Design (RCBD) with three replications per location. The randomization process involved assigning the sixteen tomato genotypes randomly to plots within each block, with each block containing all genotypes once. This setup minimized potential systematic errors and ensured that each genotype was equally represented across different environmental conditions, allowing for an accurate assessment of yield stability and GEI.Each plot consisted of four rows of three plants each, with a spacing of 60 × 45 cm between plants to ensure optimal growth and avoid competition. Standard agronomic practices, including irrigation, fertilization, and pest management, were applied uniformly across all plots in each environment.The average of the absolute score was calculated as follows.

$$\frac{WAAS = \sum_{k=1}^{p} |IPCA_{ik} \times EP_k|}{\sum_{k=1}^{p} EP_k}$$

is the weighted average of absolute scores of the ith genotype (or environment); $IPCA_{ik}$ is the score of the ith genotype (or environment) in the kth IPCA, and EP_k is the amount of the variance explained by the kth IPCA[34]. Genotypes and environments with higher IPCA scores indicated greater interaction effects, while lower scores suggested consistency across environments[35,36].The stability index weight was set to 50:50 for yield and stability to capture genotypes with balanced traits[37].

Environmental descriptions

The six experimental sites were chosen to represent a range of altitudes, soil types, and climatic conditions commonly encountered in the Kashmir Valley. Locations included SKUAST-Kashmir research fields, Krishi Vigyan Kendra (KVK) Malangpora, and Regional Research Station & Faculty of Agriculture (RRS & FOA) Wadura. These sites provide diverse environmental variables, allowing for a comprehensive analysis of genotype-environment interaction (GEI). Detailed descriptions of latitude, altitude, climate, and soil characteristics are presented in Table 1.

Data collection and trait measurement

Yield-related traits, including plant yield per hectare, plant height, number of fruits per plant, and average fruit weight, were recorded for each genotype across all environments. Days to first fruit picking (FFP), fruit length, and fruit diameter were also measured to capture aspects of fruit maturity and quality. Data were collected according to standard protocols, and mean values for each trait were calculated for each genotype in each environment.

Statistical analysis

The Additive Main Effects and Multiplicative Interaction (AMMI) model was used to analyze the GEI and assess genotype stability. AMMI analysis combines analysis of variance (ANOVA) for genotype and environment main effects with principal component analysis (PCA) to partition the GEI into Interaction Principal Component Axes (IPCA). The AMMI model provides detailed insights into how genotypes respond to different environmental conditions, identifying genotypes with consistent performance across environments.

Stability indices, including the Weighted Average of Absolute Scores (WAAS) and Multi-Trait Stability Index (MTSI), were calculated to rank genotypes based on yield stability and adaptability. WAAS measures stability by calculating the average absolute scores of each genotype across IPCA values, with lower scores indicating higher stability. The MTSI, a multi-trait stability index, was used to rank genotypes considering multiple yield-related traits, with a 50:50 weighting between yield and stability parameters.

All statistical analyses were conducted using the ***{metan}*** package in R software (version 3.4.4)[38]. Stability indices were computed to compare genotype performance across different environments, and the combined stability measures provided a basis for genotype selection.

Results and discussion

Analysis of variance and descriptive statistics

Shapiro-Wilk test was conducted to assess normality, and Normal Probability plots were visualized for ANOVA residuals obtained from both test environments and confirmed data. Results indicated that the data followed a normal distribution. Analysis of variance using Generalized Linear Mixed Model (GLMM) was performed to examine the characteristics of experimental environments and various parameters, such as yield. In this analysis, genotypes were treated as fixed factors, while environment, replication, and blocks within replication were considered random factors.

The combined ANOVA of all test sites revealed that all measured traits had significant variations. Mean sum of squares for all the charactersexhibited significant variation among environments, genotypes and GEI (Table 2). The percentage variation contributed to the overall variation (G + E + GEI) of the environment is maximum for Days to FFP (78.52%), followed by No. of fruits/Plant (53.74%), Yield (Kg/Plant) (47.05%), Yield (Q/ha) (46.66%), Average fruit Weight (g) (38.24%) whereas genotypescontributed about 88.64% for fruit length (cm) followed by Plant Height (cm) (78.68%), Fruit Diameter (cm) (76.21%) and Avg. fruit weight (g) (55.26%). Since the genotypic main effect (G) contributed the most to the total sum of squares for yield, the most important source of variation was the inherent genetic component (Fiseha et al., 2014). Contribution of GEI of about 8.22% was higher for Yield (Kg/Plant) and Avg. fruit weight (6.24%) respectively. Yield (Kg/Plant) showed 470.05% variation contributed by the location, and 43.30% and 8.22% contributed by the Genotypes and GEI towards total variability respectively. Mean values of the characters studied are given in the summary asTable3 given below along with the corresponding boxplots in Fig. 1:

	Environments		Varieties		GEI		Residual
Degrees offreedom	5		15		75		190
Traits	Mean squares	% (G + E + GEI)	Mean squares	% (G + E + GEI)	Mean squares	% (G + E + GEI)	Mean squares
Plant height	832***	20.63%	3174***	78.68%	22***	0.55%	2
Days to FFP	211.73***	78.52%	45.82***	16.99%	10.93***	4.05%	0.19
Fruit length	0.989***	8.65%	10.130***	88.64%	0.281***	2.46%	0.015
Fruit diameter	2.250***	19.62%	8.739***	76.21%	0.441***	3.85%	0.021
No. of fruit/plant	827.1***	53.74%	625.6***	40.65%	77.3***	5.02%	0.7
Avg. fruit weight	1481.1***	38.24%	2140.3***	55.26%	241.6***	6.24%	0.8
Yield (Q/ha)	226,132***	46.66%	209,846***	42.89%	39,858***	8.12%	473
Yield (Kg /Plant)	1.6690***	47.05%	1.5214***	43.30%	0.2880***	8.22%	0.0035

Table 2. ANOVA and mean performances of tomato varieties. *** Significant at 1%. * Significant at 5%.All percentage contributions of genotype, environment, and genotype-environment interactions (GEI) reported are derived from their respective sums of squares (SS) from the analysis of variance.

Variable	Mean	SE Mean	StDev	Minimum	Maximum
Plant height (cm)	86.571	0.808	13.707	50.140	120.960
Days to first fruit picking	70.556	0.177	3.012	62.800	77.000
Fruit length (cm)	4.2931	0.0468	0.7935	2.4800	6.9900
Fruit diameter (cm)	4.7687	0.0466	0.7906	2.9900	6.3200
Fruit no/plant	27.494	0.485	8.236	12.400	51.200
Avg fruit weight (g)	49.847	0.836	14.190	14.000	95.120
Yield (Kg/Plant)	1.3199	0.0255	0.4320	0.4800	2.4900
Yield (Q/Ha)	490.06	9.45	160.29	185.16	922.09

Table 3. Descriptive statistics for the traits.

GEI analysis

The AMMI ANOVA for Yield (Kg/Plant) of the 16 genotypes tested in six environments is presented in Table 4. The environment (E), genotype (G), and GEI (GEI) were highly significant in influencing plant yield per hectare ($p < 0.001$). The environments contribute about 47.05% of the total sum of squares due to treatments (G + E + GI) while 43.30% ofthe total sum of squares is contributed by genotypic effects, and GEI explained a significant portion of 8.22% of the treatment variation. The genotype-environment interaction (GEI), accounting for 8.2%, is critically important from a plant breeding perspective. GEI, despite its relatively lower numerical contribution, significantly affects the consistency and predictability of genotype performance across environments. A high GEI indicates that genotype rankings can change across environments, complicating cultivar recommendations. Thus, understanding and managing GEI is fundamental to breeding strategies aimed at stable production. The presence of a significant GEI highlights the necessity for breeding programs in the Kashmir Himalayas to either identify genotypes with broad adaptability or strategically develop genotypes adapted to specific micro-environments within the region. The partitioning of GEI indicates that the first four main axes of AMMI interactions (IPCAs) are significant using approximate F statistics[39]. The utilization of AMMI analysis in this study effectively partitioned GEI into interpretable components (IPCA1 and IPCA2 explaining 84.4% of GEI), facilitating targeted genotype selection and allowing breeders to better predict genotype performance across varying environments.It can be seen that the first and second IPCAs explained approximately 48.6 per cent and 35.9 per cent of the total GEI of the sum of squares respectively, which makes it 84.4% in totality.

AMMI

Genetic yield potential, stability level and the association of environments under study were visually represented using AMMI biplots. In biplot displays, the average yield of genotypes and environments appearing in or near vertical lines is similar, and the ones falling on almost horizontal lines have similar interaction[40]. The environments Shalimar, Malangpora and Shalimar 2 as shown in Fig. 2 are longer vectors far from their origins and represent a strong interaction force, while Malangpora2, Wadura and Wadura2 environments have shorter vectors and are very close to the origin showed weak interaction forces.

Varieties ArkaMeghali followed by Roma, CO-3, Arka Alok showed higher plant yield than overall mean yield. S1, Ajanta, DVRT 2, Arka Abha, VR-35, PunjabChuhara, Heemsona, VTG-93 are closer to the origin; they are generally acceptable or insensitive to environments with an average yield capacity close to the mean yield.

GGE biplot, between the first two components, explained 58.0% of the GEI, and IPCA1 and IPCA2 represented 48.6% and 35.9%, respectively, of total variation.The GGE biplot focuses on genotype (G) and genotype × environment interaction (GE), whereas the AMMI biplot includes the environment (E) main effects separately. This is consistent with the results of[41]. Polygon view as shown in Fig. 3 formed from the dots of the genotypes

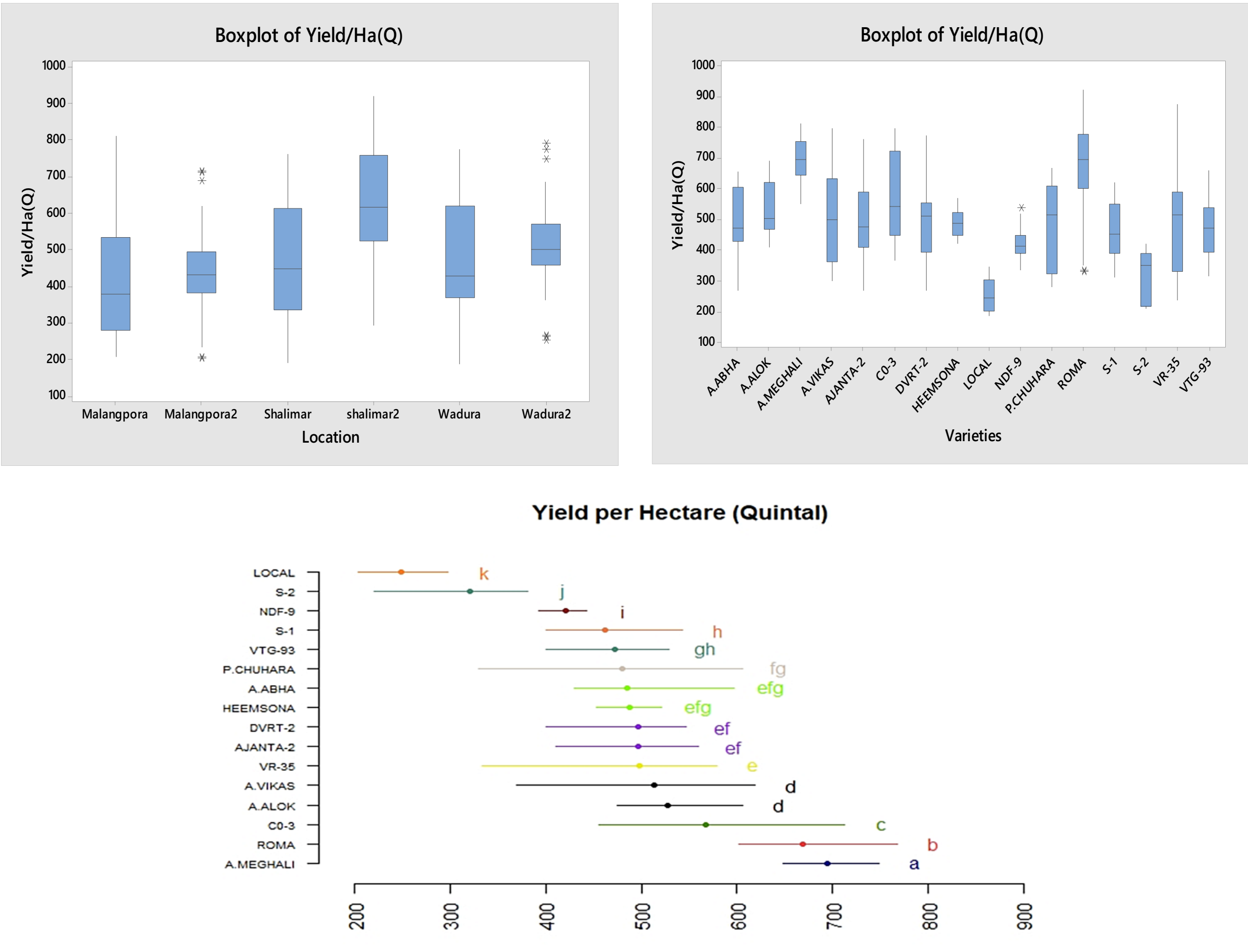

Fig. 1. Boxplots for yield (Q/ha) of the locations and genotypes along with the plot of DMRT for the genotypes.

Source	df	SS	MSS	F value	Pr(> F)	Proportion	Accumulated
ENV	5	1,130,658	226131.6***	92.15829	3.79E-09	NA	NA
REP(ENV)	12	29444.77	2453.731***	5.729086	2.46E-08	NA	NA
GEN	15	3,147,695	209846.3***	489.959	3.50E-137	NA	NA
GEN: ENV	75	2,989,361	39858.15***	93.06267	3.44E-113	NA	NA
PC1	19	1,451,542	76396.93*	178.38	0.00E+00	**48.6**	**48.6**
PC2	17	1,071,941	63055.35*	147.22	0.00E+00	**35.9**	**84.4**
PC3	15	376214.5	25080.97*	58.56	0.00E+00	**12.6**	**97.0**
PC4	13	81393.76	6261.059*	14.62	0.00E+00	2.7	**99.7**
PC5	11	8270.211	751.8374	1.76	6.40E-02	0.3	**100**
Residuals	180	77092.85	428.2936	NA	NA	NA	NA

Table 4. AMMI analysis of variance for fruit yield (Q/Ha) among 16 tomato varieties across six test environments. *df* Degrees of freedom, *SS* Sum of squares, *MSS* Mean sum of squares, *GEI* genotype × environment interaction. *** Significant at 1%. * Significant at 5%.

linked to the vertex, the grain yield was shown to be maximum or minimum, and specific environmental adaptations.The vertical projection of genotypes to environmental vectors showed the relationship between these environments.The Figure shows that S-2, Local, Hemsona, VTG-93, S1 are the genotypes with higher or lower yields and poor stability in all environments.In the GGE biplot (Fig. 2), differences in vector lengths among environments were observed. Environments such as Shalimar and Malangpora exhibited relatively longer vectors from the origin, suggesting a greater contribution to genotype–environment interaction patterns. In contrast, environments like Wadura and its associated trials had comparatively shorter vectors, indicating

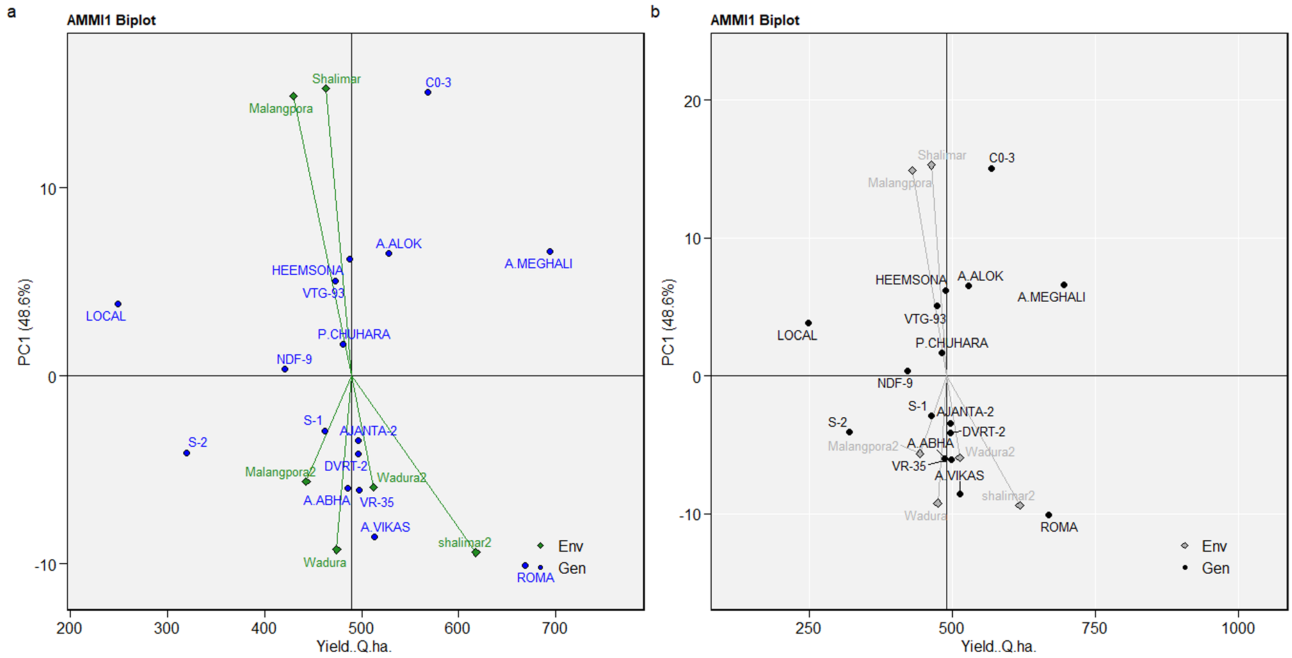

Fig. 2. AMMI 1 Biplot (Mean Plant yield vs. IPC1) for Plant yield (Q/ha) of 16 tomato genotypes and six environments.

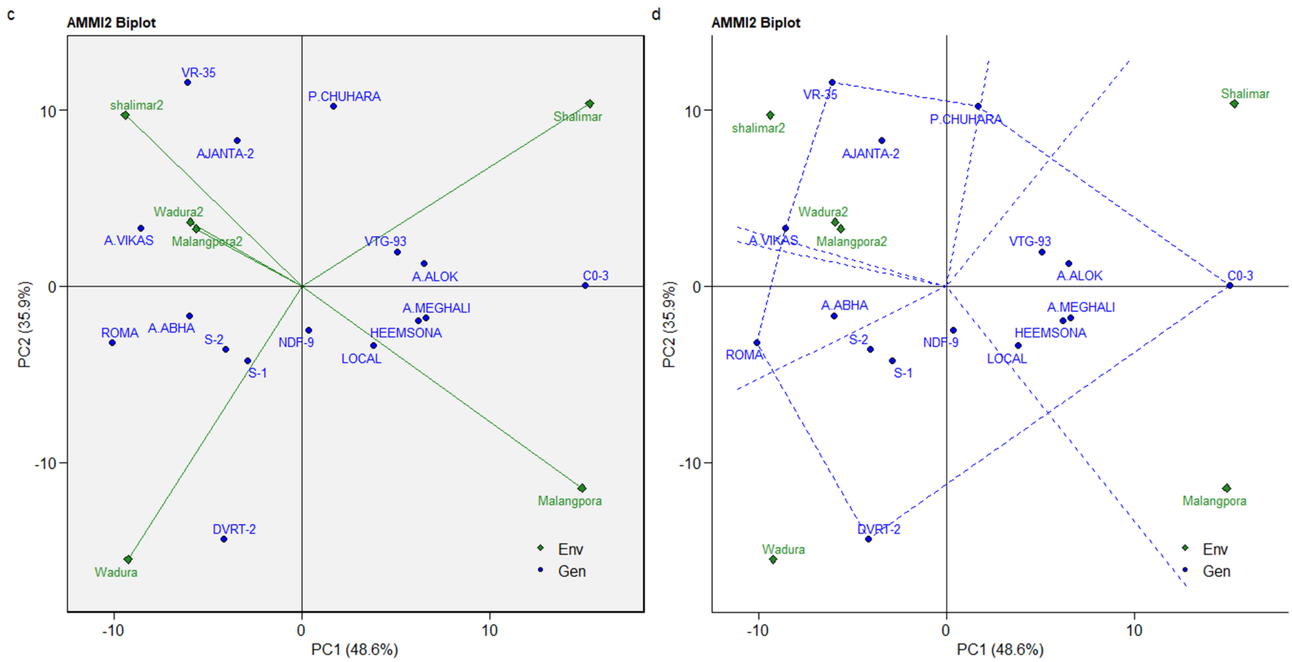

Fig. 3. Polygon view of the GGE-biplot for 16 tomato varieties evaluated across six environments.

lower relative interaction effects[43,44]. As formal IPCA scores for environments were not separately extracted in the current analysis, these interpretations are based on visual observations from the biplot. Future studies could incorporate environment-specific IPCA score extraction to provide a more quantitative assessment of interaction strength and further refine environmental classifications.

Stability indices

Stability statistics of AMMI and their classification are demonstrated in Table 5. According to AVAMGE stability statistics, the highest stability was identified with the less amount of this statistic for genotypes NDF-9, Local, S-1, Arka Abha, S-2 and Heemsona. Genotypes viz.C0-3, DVRT-2 and Roma had the highest vales for the AVAMGE

Genotypes	Y	IPCA1	EV	ASV	ASTAB	SIPC	WAAS	ZA	MASV	AVAMGE	MASI	DA
A.ABHA	485.7	−5.97	0.060	8.25	104	15.9	4.53	0.189	38.5	351	3.13	223
A.ALOK	527.5	6.49	0.045	8.89	75	15.5	4.3	0.176	24.1	406	3.25	199
A.MEGHALI	694.4	6.6	0.018	9.11	47.5	9.59	3.94	0.153	10.6	404	3.27	180
A.VIKAS	513.7	−8.58	0.047	12.1	96.7	16.7	5.67	0.225	17.4	517	4.34	246
AJANTA-2	496.4	−3.43	0.037	9.47	84.7	14.7	4.91	0.199	25.5	476	3.41	224
C0-3	568.0	15.1	0.097	20.4	248	20.5	7.93	0.310	29.1	906	7.34	406
DVRT-2	496.4	−4.15	0.110	15.4	237	23.4	7.49	0.305	42.1	750	5.54	372
HEEMSONA	488.0	6.2	0.055	8.62	68.4	13.4	3.87	0.155	11.3	363	3.10	182
LOCAL	248.7	3.82	0.039	6.18	57.4	14.9	3.75	0.158	24.6	295	2.30	162
NDF-9	420.5	0.368	0.016	2.53	21.2	8.09	1.55	0.069	17.2	172	1.00	91
P.CHUHARA	480.6	1.67	0.077	10.5	137	19.5	5.07	0.214	34.3	556	3.79	268
ROMA	668.4	−10.1	0.126	14.0	232	24.2	7.44	0.306	53.3	616	5.22	345
S-1	462.3	−2.91	0.048	5.76	79.4	14.7	3.86	0.165	36	331	2.26	188
S-2	320.1	−4.07	0.059	6.59	63.7	15.2	3.69	0.153	16	362	2.38	160
VR-35	497.5	−6.08	0.077	14.2	182	21.3	7.55	0.305	37.2	707	5.12	331
VTG-93	472.6	5.05	0.087	7.12	80	14.7	3.43	0.141	11.6	397	2.56	169

Table 5. Stability indices. Y: Yield/ha (Q), IPCA1: Interaction PCA1, EV: Averages of the squared Eigen Vector values, ASV: AMMI Stability Value, ASTAB: AMMI based Stability Parameter, SIPC: Sums od absolute values of the IPC Scores, WAAS: Weighted Average of Absolute Scores, ZA: Absolute value of the relative contribution of IPCs to the interaction, MASV: Modified AMMI stability Value, AVAMGE: Sum Across Environments of Absolute Value of GEI Modelled by AMMI, MASI: Modified AMMI stability Index, DA: Annicchiarico's D parameter.

indicating that they are the un-stable genotypes. According to statistics ASV, MASI and MASV the genotypes NDF-9, S-1, ArkaMeghali had the least values for these statistics and hence higher stabilities.DA: NDF-9, S-2, Arka Meghali; SIPC: NDF-9, Arka Meghali; ZA: NDF-9, Arka Meghali, S-2; EV: NDF-9, Arka Meghali, Ajanta-2; ASTAB: NDF-9, Local.

Identification of highly productive and widely adaptable genotypes using WAAS

The quantitative stability measurement (WAAS) used in the study is an important tool for identifying highly productive and widely adaptable genotypes.WAAS is a mixed effect model version of the stability index based on AMMI and has some advantages.: (i) Similar to ASV, WAAS is a function of GEI model components for cultivar and environment, However, the mixed effect model, which is shown in this paper, enables us to overcome the predictive accuracy of fixed effect models or random models based on the mixed effect model.; (ii) WAAS is based on absolute deviations rather than square deviations such as ASV, so some stability is obtained because the sensitivity to deviations is lower; (iii) WAAS takes into account all IPCA estimates to quantify the stability of complex GEI structures, so WAAS is more realistic. (iv) Unlike SIPC, WAAS takes into account the total of the absolute values of IPCA scores, and takes into account the average weighted value of IPCA scores.; as a result, higher scores on the last axis should contribute less to estimating, so more reliable results should be obtained.; (v) In the WAASB × GY biplot (Fig. 5), all IPCAs in the model can be used to jointly explain stability and productivity. Figure 4 represents the genotypes identified by the simultaneous selection criteria based on the average yield of plants (PY Q/ha) and the WAAS stability index. The weight considered is 50:50 (i.e., equal to the importance of yield and stability of the plant)Arka Meghali, NDF-9, VTG-93 had high WAAS values and were the stable genotypes.

Multi-Trait stability index (MTSI) and genotype selection

The radar plot based on the MTSI (Fig. 5) displays the rankings of the genotypes based on the multi-trait stability index[42] and indicates Arka Meghali and NDF-9 as the selected genotypes. The red circle shows the cut point. This plot of the MTSI index shows the genotype rank in ascending order based on the index. The results from the other stability parameters are in line with the MTSI parameters.

In addition to yield performance, the Multi-Trait Stability Index (MTSI) incorporated other agronomic and quality traits, including plant height, number of fruits per plant, average fruit weight, and days to first fruit picking (FFP). Although yield was a primary selection criterion, traits such as fruit size and earliness were also factored into the overall ranking of genotypes. Notably, genotypes like Arka Meghali and NDF-9 showed not only high yield and stability but also favourable performance for traits like fruit weight and early maturity, making them suitable for both productivity and market-oriented breeding objectives. This multi-trait approach allows breeders to identify genotypes that can fulfil diverse goals, including maximizing yield, improving fruit quality, and promoting early harvesting, thereby offering a broader utility for various cultivation strategies.

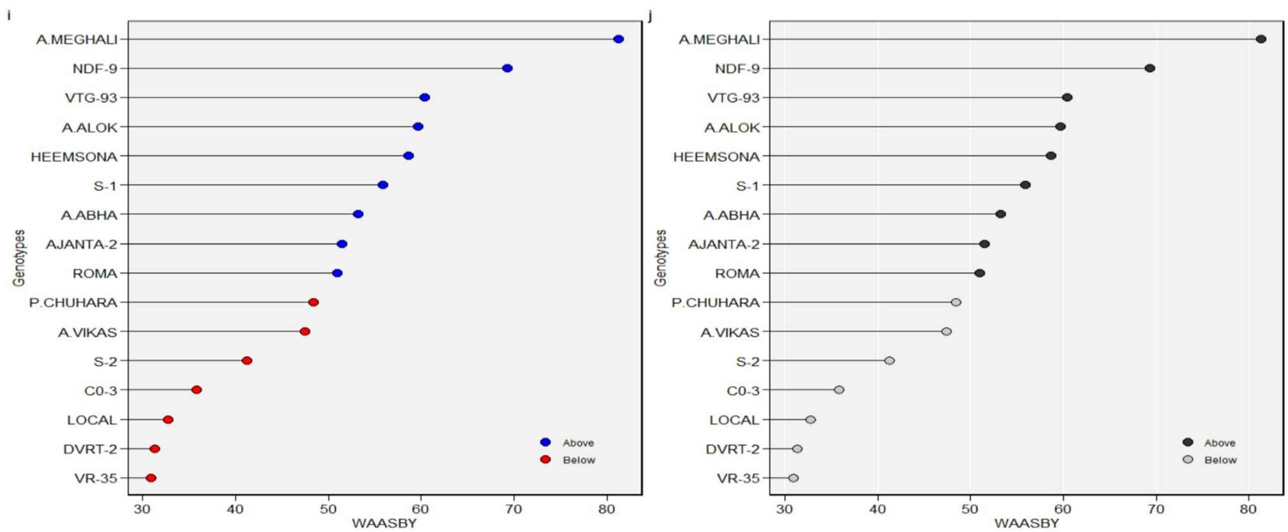

Fig. 4. Estimated values of WAAS and mean performance (Y) for 16 tomato varietiesby taking the weights of 50 (Plant Yield) and 50 for (Stability).

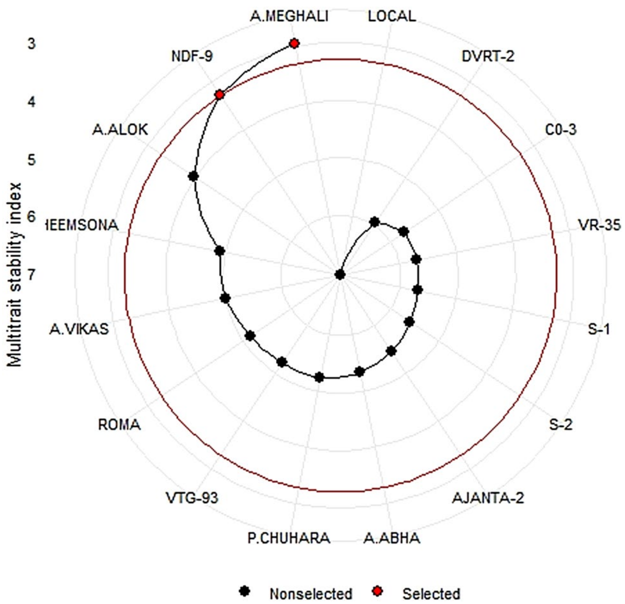

Fig. 5. Ranks of the genotype and the selection of the genotype (The selected genotypes are shown in the redcolour).

Conclusion

This study underscores the critical role of genotype-environment interactions (GEI) in determining the yield and stability of tomato varieties, highlighting the adaptability requirements for successful crop production in Kashmir's variable agro-ecological settings. The use of the Additive Main Effects and Multiplicative Interaction (AMMI) model, coupled with stability indices like Weighted Average of Absolute Scores (WAAS) and the Multi-Trait Stability Index (MTSI), provided robust insights into the yield performance and stability of 16 open-pollinated tomato genotypes evaluated over multiple environments.

Our findings indicate that genotypes Arka Meghali and NDF-9 demonstrated optimal stability and yield performance across diverse environmental conditions. Arka Meghali consistently achieved higher yield outputs, making it an advantageous selection for maximizing productivity, while NDF-9 exhibited exceptional stability across environments. These characteristics make Arka Meghali and NDF-9 ideal candidates for addressing the region's agricultural needs, as they offer both productivity and resiliencekey attributes for sustained production in the face of environmental variability.In addition to Arka Meghali and NDF-9, genotypes such as Roma and CO-3 also exhibited yields higher than the overall mean across environments. However, their performance was characterized by greater instability, as reflected in their higher ASV, SIPC, and WAAS values. Despite their lower stability scores, these genotypes could be of considerable interest in specific environments where conditions favor their performance, or where maximizing yield potential is prioritized over broader adaptability. For instance, Roma, known for its fruit size and quality, could be particularly suitable for targeted market-driven cultivation under favorable environmental conditions. Similarly, CO-3, although less stable, demonstrated high yield potential that could be exploited through environment-specific recommendations or intensive management practices. Thus, recognizing these yield–stability trade-offs is crucial for breeders aiming to match genotypes to varied cultivation niches and farmer preferences.

The AMMI analysis identified significant contributions of both genotypic and environmental factors to yield variability, with a notable portion of the treatment sum of squares attributed to the environment (47.5%), genotype (43.3%), and GEI (8.2%). The partitioning of GEI into interaction principal component axes (IPCA1 and IPCA2) allowed for precise stability assessments, with the first two IPCAs explaining approximately 84.4% of the total GEI, affirming the AMMI model's utility in multi-environment trials.

The integration of stability metrics such as WAAS, which emphasizes absolute deviations, and MTSI, a multi-trait index, facilitated a comprehensive evaluation of genotypic adaptability. The identification of genotypes with balanced yield and stability suggests that WAAS and MTSI can serve as practical tools for breeders focused on developing broadly adaptable tomato cultivars that maintain high yield potential under fluctuating environmental conditions.

Beyond yield stability, several genotypes exhibited moderate stability but valuable quality traits that may appeal to breeders or farmers targeting specific markets. For instance, genotypes like Roma and CO-3, although less stable across environments, demonstrated superior fruit size and weight, making them attractive for fresh market or processing industries where fruit quality parameters are prioritized over stability alone. Similarly, genotypes with earlier maturity (shorter days to first fruit picking) could be advantageous in regions with short growing seasons. Such quality-oriented traits were integrated into the Multi-Trait Stability Index (MTSI) calculations to enable a broader selection perspective beyond yield alone. Furthermore, a comparative assessment of stability indices revealed that while traditional indices like ASV (AMMI Stability Value) and SIPC (Sum of IPC Scores) offer valuable insights based primarily on GEI decomposition, WAAS and MTSI provide a more comprehensive evaluation by integrating absolute deviations across multiple IPCAs and incorporating multiple traits, respectively. This integrative approach enhances their practical utility for genotype selection in multi-environment and multi-trait breeding programs. A summary of the comparative strengths of these indices has been provided in the supplementary material for reference.

In conclusion, the selection of Arka Meghali and NDF-9, based on multi-environment data, signifies a step forward in identifying stable, high-yielding tomato cultivars suitable for the Kashmir valley. These insights contribute to the broader objectives of breeding programs aimed at enhancing food security through the development of crop varieties capable of delivering consistent performance under a range of environmental challenges. The methodological approach and findings of this study advocate for the application of AMMI and stability indices in crop improvement programs across diverse agricultural settings, fostering the selection of varieties that meet both productivity and adaptability criteria essential for sustainable agriculture.For breeders, incorporating stability indices like WAAS and MTSI in multi-environment trials can accelerate the selection of resilient varieties. Farmers are recommended to adopt these varieties to ensure reliable yields despite climatic fluctuations.

Future prospects

This study confirmed the substantial impact of genotype × environment interactions on tomato yield performance under Kashmir's agro-ecological conditions. Through AMMI, GGE biplot, WAAS, and MTSI analyses, Arka Meghali and NDF-9 emerged as the most promising genotypes combining high yield potential and stability. Their selection offers immediate options for breeders and farmers aiming to achieve reliable tomato production. Future breeding efforts should further emphasize early maturity and fruit quality traits to expand cropping system opportunities in the region.While this study provides valuable insights into the performance of open-pollinated tomato varieties, further research is warranted to expand on these findings. Future studies could examine the same varieties under controlled abiotic stress conditions, such as drought, salinity, or temperature extremes, to determine resilience to specific environmental challenges. Incorporating molecular or genomic approaches to assess genetic markers associated with stability and stress tolerance could also support breeding programs aimed at developing more resilient tomato varieties. Additionally, long-term studies across a broader geographic range could enhance the generalizability of these results and inform adaptive breeding strategies for diverse agro-ecological zones. By addressing these areas, future research could advance sustainable crop production, contributing to food security in regions with fluctuating climates.

Limitations

While this study provides valuable data on genotype performance in real-world conditions, it has limitations. First, the absence of controlled abiotic stress conditionssuch as drought or salinitylimits the ability to determine the resilience of these varieties under specific environmental stressors. Additionally, the study's geographic scope is limited to the Kashmir Valley, which, while diverse, may not encompass the full range of environmental conditions encountered in other regions. Furthermore, the study focused on open-pollinated varieties, which may have different yield and stability responses compared to hybrids commonly used in commercial agriculture.

Data availability
The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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Author contributions
1. Ummyiah H. Masoodi (UHM): Conceptualization: Developed the core idea and objectives of the research. Methodology: Designed the experimental layout and the overall methodological approach.Data Generation: Oversaw and conducted the data collection process.Formal Analysis: Analyzed the data generated from the experiments.Editing: Reviewed and edited the full manuscript, with a focus on ensuring the accuracy of the data and findings reported.Sections Worked On: IntroductionMaterial and MethodsResults and Discussion (Data analysis sections)Conclusion. 2. Immad A. Shah (IAS): Writing - Original Draft: Created the initial draft of the manuscript.Data Management and Cleaning: Ensured that the data was accurate and suitable for analysis.Statistical Analysis and Data Visualization: Performed statistical tests and created visual representations of the data. Formal Analysis and Editing: Engaged in critical revision of the data interpretation and presentation in the manuscript.Review and Editing: Reviewed the entire manuscript to refine the content for clarity and coherence.Sections Worked On: AbstractIntroductionResults and Discussion (Especially sections involving statistical data and interpretations)Conclusion. 3.Walid EmamWriting - Original Draft: Created the initial draft of the manuscript. Data Management and Cleaning: Ensured that the data was accurate and suitable for analysis.Statistical Analysis and Data Visualization: Performed statistical tests and created visual representations of the data.Formal Analysis and Editing: Engaged in critical revision of the data interpretation and presentation in the manuscript.Review and Editing: Reviewed the entire manuscript to refine the content for clarity and coherence. Sections Worked On: AbstractIntroductionResults and Discussion (Especially sections involving statistical data and interpretations). 4.Yusra TashkandyWriting - Original Draft: Created the initial draft of the manuscript.Data Management and Cleaning: Ensured that the data was accurate and suitable for analysis. Statistical Analysis and Data Visualization: Performed statistical tests and created visual representations of the data.Formal Analysis and Editing: Engaged in critical revision of the data interpretation and presentation in the manuscript.Review and Editing: Reviewed the entire manuscript to refine the content for clarity and coherence.Sections Worked On: AbstractIntroductionResults and Discussion (Especially sections involving statistical data and interpretations)Conclusion. 5.Pradeep MishraWriting - Original Draft: Created the initial draft of the manuscript. Data Management and Cleaning: Ensured that the data was accurate and suitable for analysis.Statistical Analysis and Data Visualization: Performed statistical tests and created visual representations of the data.Formal Analysis and Editing: Engaged in critical revision of the data interpretation and presentation in the manuscript.Review and Editing: Reviewed the entire manuscript to refine the content for clarity and coherence.Sections Worked On: AbstractIntroductionResults and Discussion (Especially sections involving statistical data and interpretations)Conclusion. 6.Neha MishraWriting - Original Draft: Created the initial draft of the manuscript.Data Management and Cleaning: Ensured that the data was accurate and suitable for analysis.Statistical Analysis and Data Visualization: Performed statistical tests and created visual representations of the data.Formal Analysis and Editing: Engaged in critical revision of the data interpretation and presentation in the manuscript.Review and Editing: Reviewed the entire manuscript to refine the content for clarity and coherence.Sections Worked On: AbstractIntroductionResults and Discussion (Especially sections involving statistical data and interpretations)Conclusion. 7. Adelajda MatukaData Management and Cleaning: Ensured that the data was accurate and suitable for analysis.Statistical Analysis and Data Visualization: Performed statistical tests and created visual representations of the data.Formal Analysis and Editing: Engaged in critical revision of the data interpretation and presentation in the manuscript.

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Declarations

Competing interests
The authors declare no competing interests.

Additional information

Correspondence and requests for materials should be addressed to P.M.

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