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RESEARCH ARTICLE

Identification of low-light-tolerant rice (*Oryza sativa* L.) genotypes based on agro-morphological traits, combined stress tolerance and stability index

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Abstract

Low light is a major abiotic stress during the wet season, leading to an approximate 35% reduction in rice yield compared to the dry season. Developing rice varieties with improved yields and tolerance to low light conditions is therefore critical. This study aimed to identify low-light-tolerant rice genotypes using a Combined Stress Tolerance and Stability Index (CSTSI). A panel of 192 genotypes was evaluated for 12 agro-morphological traits during the Kharif (wet) seasons of 2021 and 2022. Results showed that low light significantly reduced key traits such as tiller number, grain number, spikelet number, spikelet fertility, panicle number, grain weight, biomass, and grain yield. Two-way ANOVA indicated significant genotypic variation under low light stress, with grain yield and biomass reductions of 41.96 and 28.49%, respectively. Yield Stability Index (YSI) and Relative Yield (RY) were calculated to assess genotype performance. The CSTSI was developed to evaluate overall stress tolerance among the 192 genotypes. Regression analysis revealed strong correlations of CSTSI with RY (0.897) and YSI (0.791), confirming its effectiveness in identifying low-light-tolerant genotypes. Based on the CSTSI, nine genotypes were identified as highly tolerant, outperforming the tolerant check variety, Swarnaprabha. Cluster analysis grouped the 192 genotypes into five clusters. Clusters IV and V included tolerant genotypes such as Purnandu, Ambika, Laxmichura, Chamarmani, Bhasamanik, TRB-468, VL Dhan209, Swarnaprabha, and TRB-451, which exhibited superior performance in YSI, RY, and CSTSI. In contrast, cluster I contained low-performing genotypes like Kunti, Sanwal Basumati, IR8, IR64, Pusa-834, Srabani, Sahabhagi Dhan and Khandagiri. Identifying low-light-tolerant genotypes provides valuable insights for identifying QTLs, genes, and superior haplotypes associated with low-light tolerance. These findings are critical for molecular breeding programs aiming to develop resilient rice varieties for low-light environments. Additionally, the study establishes CSTSI as a reliable parameter for screening genotypes for low-light tolerance.

Keywords: Agro-morphological traits, vcorrelation, CSTSI, low-light, PAR, PCA, RY, YSI

Introduction

Low-light stress is one of the major constraints, causing significant yield reduction during the wet (*Kharif*) season in the northeastern and eastern regions of India and other Southeast Asian countries. It is due to the low incidence of solar radiation coupled with fluctuating light and frequent, prolonged cloudy weather during the dry (*Rabi*) season, which severely impacts rice production. Low-light is defined as photosynthetically active radiation (PAR) below 500 μmol/m²/s (Ganguly et al. 2020). The reproductive stage is particularly sensitive due to impaired photosynthesis and reduced grain yield (Ganguly et al. 2020). Low light hampers key physiological and metabolic processes, such as photosynthesis and carbohydrate translocation, which decreases tiller number, panicle number, grain number, spikelet number, grain filling, grain weight, and biomass. These effects result in yield losses ranging from 20-55% (Nayak and Murty 1978; Voleti and Singh 1996; Dingkuhn

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et al. 1999; Sridevi and Chellamuthu 2015; Peng et al. 2023). Despite this, some low-light-tolerant genotypes maintain relatively stable photosynthetic rates and reallocate carbohydrates effectively, supporting grain filling and preserving traits such as grain number, spikelet number, panicle number, thousand-grain weight, and grain yield under low-light conditions (Sharma et al. 2019). These genotypes offer significant potential for breeding programs to enhance rice resilience in low-light-prone regions.

As climate change intensifies, low-light stress is becoming more frequent and severe due to declining solar radiation and environmental pollution, exacerbating its impact on rice yields (Kumar et al. 2021). The effects of low-light stress on grain yield are compounded by its interactions with other stressors, including nutrient deficiencies, fluctuating temperatures, and water scarcity, making it increasingly crucial to identify and develop low-light-tolerant genotypes. Several studies have identified promising genotypes with tolerance to low-light stress. Nayak and Murty (1980) reported significant yield reductions in the sensitive variety IR8 compared to the shade-tolerant variety Vijaya. Similarly, Swarnaprabha demonstrated better grain filling, higher grain number, and improved yield under low light compared to the susceptible variety Ratna (Voleti and Singh 1996). Dutta et al. (2018) identified eight low-light-tolerant genotypes, including IRCTN 91-84, IRCTN 91-94, PS-4, Phyllo Red, Kunti, Danteswari, Mahisugandh and Megha Rice 1, which performed well for 14 agro-morphological and physiological traits under reduced light conditions. Ganguly et al. (2020) further highlighted tolerant genotypes such as Purnendu, Sashi, and Pantdhan19, emphasizing their ability to maintain yield under low-light stress. These genotypes demonstrate resilience by optimizing light utilization, preserving physiological processes, and ensuring stable productivity in adverse lighting conditions.

However, despite significant progress, several gaps remain in understanding low-light stress and developing resilient rice varieties. Most studies focus on a limited range of genotypes, potentially overlooking varieties with unique adaptive traits that could enhance resilience. Furthermore, low-light stress is often studied in isolation, neglecting the complexity of real-world conditions where multiple stressors, such as fluctuating temperatures, nutrient deficiencies, or biotic pressures, occur simultaneously. Controlled-environment studies, though insightful, do not accurately replicate field conditions, including soil variability, day-night cycles, and fluctuating light intensity, limiting the applicability of findings (Teng et al. 2023).

Traditional stress indices, such as the Stress Tolerance Index (STI) and Stress Susceptibility Index (SSI), are inadequate for capturing the specific physiological and morphological responses of rice to low-light stress, highlighting the necessity for specialized evaluation methods. To address this limitation, the Combined Stress Tolerance and Stability Index (CSTSI) has been introduced as a comprehensive approach for assessing rice genotypes under low-light conditions. This index provides a more precise tool for selecting low-light-tolerant genotypes, thereby supporting breeding programs aimed at developing resilient rice varieties. The genotypes identified as tolerant in this study can contribute to the creation of rice varieties that maintain high productivity under low-light and challenging environmental conditions, helping to secure yields in regions affected by climate change. Additionally, CSTSI needsto be evaluated under various stress conditions in rice to enhance its utility as a robust selection parameter.

Materials and methods

In this study, a panel of 192 rice genotypes was evaluated at the Experimentation Field of the Crop Improvement Division, ICAR-National Rice Research Institute, Cuttack, Odisha, during the *Kharif* seasons of 2021 and 2022, following an alpha-lattice design with two replications. The panel includes landraces, high-yielding varieties, elite IRRI breeding genotypes, donors, and popular rice varieties. Sixty breeding genotypes were selected from 72 top-performing lines of an elite core panel (ECP) representing the genetic diversity of 15,286 IRRI breeding lines (including released varieties) based on breeding values for grain yield with the highest heritable yield values (Juma et al. 2021). Juma et al. (2021) conducted 102 historical yield trials in the Philippines during the period 2012–2016 representing 15,286 breeding lines (including released varieties). A mixed model approach based on the pedigree relationship matrix was used to estimate breeding values for grain yield, which ranged from 2.12 to 6.27 $t \cdot ha^{-1}$. The rate of genetic gain for grain yield was estimated at 8.75 $kg \cdot ha^{-1}$ $year^{-1}$ (0.23%) for crosses made in the period from 1964 to 2014. They constituted an elite core panel (ECP) of 72 lines representing the genetic diversity of these 15,286 breeding lines with the highest heritable yield. Swarnaprabha and IR8 were included as tolerant and susceptible low-light genotypes, respectively.

Crop establishment and data recording

25-day-old rice seedlings were transplanted into the main field with two experimental setups during the *Kharif* seasons of 2021 and 2022. We grew one set of genotypes under Agro-Shade nets mounted on wooden frames to simulate 75% light intensity during the tillering stage. The other set was grown under controlled conditions with 100% natural light. Plant spacing was maintained at 20 cm between rows and 15 cm between plants. Recommended doses of NPK fertilizers were applied following standard schedules. Standard agronomic and pest management practices were employed. Photosynthetically active radiation (PAR) at the canopy level was measured with a radiometer (LI-1500 LICOR, USA) three times daily (9:00 a.m., 12:00 p.m., and

3:00 p.m., IST). Measurements were repeated ten times for accuracy. Data on 12 agronomic traits, including days to 50% flowering, plant height, tiller and panicle number, biomass, grain yield, etc. were collected from five randomly chosen plants per replication, with mean values calculated for each trait.

Combined Stress Tolerance and Stability Index (CSTSI)

The yield under control (Yc) and low-light stress (Ys) conditions was recorded for each genotype. The low-light stress conditions were simulated by providing reduced light intensity (25%) compared to the control (open) conditions using Agro-Shade Net.

Calculation of indices

Two indices, Yield Stability Index (YSI) and Relative Yield (RY), were calculated for each genotype to assess their performance. YSI was computed using the formula:

YSI=Yield under Control (Yc)/Yield under Stress (Ys)

This index measures the genotype's ability to maintain yield under low light stress conditions compared to its yield under normal control (no shade) conditions.

RY (Relative yield) was calculated as:

RY=Mean Yield under Stress (Ys)/yield of i^{th}-genotype under Stress (Ysi)

RY allowed for the comparison of each genotype's performance relative to the population mean under stress conditions.

To develop a comprehensive measure of performance, the YSI and RY were combined into a single matrix, CSTSI, by summing the values of YSI and RY for each genotype:

$$CSTSI = YSI + RY$$

This combined index was used to assess the genotypes' overall performance, considering their yield stability and relative yield under low-light stress conditions.

A regression analysis was conducted to evaluate the relationship between CSTSI (independent variable), RY, and YSI (dependent variables). The analysis was performed using the Ordinary Least Squares (OLS) method, and the statistical significance of the results was determined based on the p-values and the R-squared value of the regression model.

Statistical analysis

Mean values of each trait for *the kharif* seasons of 2021and 2022were used for three way analysis of variance (ANOVA) considering genotypes, seasons, and light conditions to assess the significance of each trait and each factor following the methodology proposed by Panse and Sukhatme (1967) to assess the significance of each trait and each factor. After ensuring there is no significant difference between the two *kharif* seasons, the rest of the statistical analysis were conducted using pooled data. The descriptive statistical analysis was conducted for standard measures such as mean, range, standard deviation (SD), standard error (SE), coefficient of variation (CV), skewness, and kurtosis for each of the 12 agro-morphological traits in the panel using XL-STAT version 23.0 (Addinsoft). Analysis of variance was done using software SPSS version 23.0. Phenotypic correlation and PCA were done using PAST 4.03 software (Hammer et al. 2001). Cluster analysis was done using the web-based tool SR-Plot (Tang et al. 2023). The regression analysis was done using Python 3 version 12.4.

Results and discussion

Photosynthetically Active Radiation (PAR)

During the *Kharif* seasons of 2021 and 2022, measurements of photosynthetically active radiation (PAR) under both control and low-light stress conditions revealed significant variations across 12 traits critical for assessing the effects of shading on crop performance (Fig. 2). Under control conditions, peak PAR values ranged from approximately 900 µmol/m²/s at noon (12.0) in July to around 600 µmol/m²/s at 3.0 PM in October, with an average PAR of 637 µmol/m²/s over four months and two time periods (12 noon and 3.0 PM). In contrast, under low-light stress conditions, the highest PAR values ranged from about 670 µmol/m²/s at noon in July to around 470 µmol/m²/s at 3.0 PM in October, with an average PAR of 477 µmol/m²/s during the same period (12 noon and 3.0 PM). This represents an approximate 25% reduction in PAR under agro-shade net conditions compared to control (open) conditions. The differences in PAR between control and low-light stress conditions were statistically significant, with several time points showing significance at $p< 0.05$. The observed reduction in PAR reflects the typical decrease in light intensity due to cloud cover during the monsoon season. Cloud cover during this period significantly reduces solar radiation reaching the crop canopy, impacting photosynthetic efficiency and overall crop growth. Prior studies have demonstrated that reduced light intensity during critical growth stages can lower photosynthetic activity, potentially reducing yields (Dutta et al. 2018; Yang et al. 2019; Panda et al. 2022).

The progressive decline in PAR values from July to October aligns with the seasonal progression of the monsoon. These findings are consistent with earlier research that reported similar reductions in solar radiation during the monsoon period, which in turn affects light availability for crops (Gautam et al. 2018).

Descriptive statistics

The mean performance of all 192 genotypes revealed significant variation across 12 agro-morphological traits under control and low light-stress conditions. The range and coefficient of variation (CV) values across these genotypes during the *Kharif* seasons of 2021 and 2022 indicated considerable diversity, reflecting the inherent variability among the genotypes. Grain yield and biomass exhibited

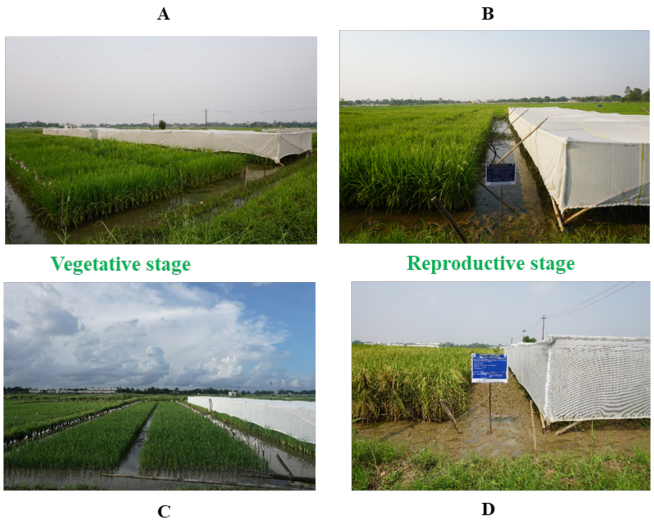

Fig. 1. Field photo of 192 genotypes grown under control (open) and low light stress conditions during *Kharif* seasons of 2021 (A, C) and 2022 (B,D)

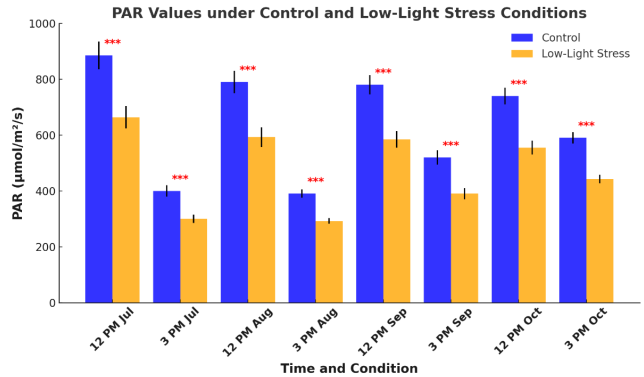

Fig. 2. Photosynthetically active radiation (PAR) levels under control (open) and low light stress conditions

the most substantial reductions under LL conditions, with decreases of -41.96% and -28.49%, respectively (P = 0.0001). Other traits, like TN, PN, GN, SN, SFP, PW, TGW, and PL, showed significant reductions (P = 0.0001) with -16.25%, -20.41%, -17.49%, -15.28%, -8.42%, -7.03%, -3.69%, and -3.26%, respectively. This suggests that GY, BIOM, PN, GN, TN, SN, and SFP are particularly vulnerable to low light stress (Table 1). The normality test indicated near-symmetrical distributions for all 12 traits (Fig. 3). Our findings are consistent with earlier studies (Singh 2005; Liu et al. 2014; Sridevi and Chellamuthu 2015; Dutta et al. 2017; Ganguly et al. 2020; Panda et al. 2022).

Analysis of variance

A three-way ANOVA was conducted to analyze the effects of light conditions, genotypes, and seasons on 12 agronomic traits of rice (Table 2). While significant variations were observed for light conditions and genotypes across all traits ($P \leq 0.05$), seasonal effects were not significant (P = 1.0), due to the similarity of environmental conditions between the two *Kharif* seasons. Light conditions had a profound impact on all traits, with grain yield (GY) showing a highly significant reduction under low light ($F = 55.26$, $p<0.0001$), emphasizing its sensitivity to changes in light availability. This substantial reduction in GY aligns with findings by Deng et al. (2023), who highlighted that low irradiance, particularly during the reproductive phase, diminishes grain yield in rice due to impaired photosynthesis and reduced energy availability for grain filling. Similarly, GN and SN were significantly affected by light stress (GN: $F = 114.85$, $p<0.0001$; SN: $F = 171.16$, $p<0.0001$). These results are consistent with Liu et al. (2014), who reported severe reductions in the number of grains per panicle under low light conditions during the panicle initiation stage, likely caused by limited energy for spikelet and grain development. Thousand-grain weight (TGW), a critical determinant of yield, was significantly influenced by light conditions ($F = 36.93$, $p<0.0001$), reflecting a reduction in grain-filling capacity. This finding is supported by Teng et al. (2023), who observed lower grain weight under reduced light intensity. Biomass, a key indicator of overall plant growth and productivity, was also significantly impacted by light conditions ($F = 20.68$, $p<0.0001$), with reductions likely attributed to decreased photosynthetic efficiency. These observations align with Naveed et al. (2024), who noted reduced biomass accumulation under low-light conditions due to lower energy capture and stunted growth. The significant interaction between light and genotype for all traits indicates that the response to low-light stress is genotype-dependent, with some genotypes showing greater resilience than others. This interaction, combined with the lack of seasonal significance, highlights the potential for identifying and breeding rice varieties that maintain stable productivity under suboptimal light conditions. These findings emphasize the importance of selecting genotypes with consistent performance across varying light environments to develop robust rice varieties capable of sustaining yields in diverse agro-climatic settings.

Phenotypic correlation

Phenotypic correlation analysis is crucial for understanding the mutual relationships among plant characteristics, allowing for the identification of key traits for genetic improvement in yield. Grain yield per plant (GY) was significantly and positively correlated ($P \leq 0.05$) with all the traits (DFF, PH, TN, PN, PL, GN, SN, SFP, PW, TGW, and BIOM) under LL stress. Similarly, under the control condition, GY has a significant correlation with PH, TN, PN, PL, GN, SN, SFP, PW, TGW, and BIOM ($P \leq 0.05$), except for DFF and TGW (Fig. 4). Similar observations were obtained in previous findings (Tiwari *et al.* 2019). Grain yield, being the primary target trait for selecting shading-tolerant rice, necessitates evaluating genotypes from the vegetative to reproductive

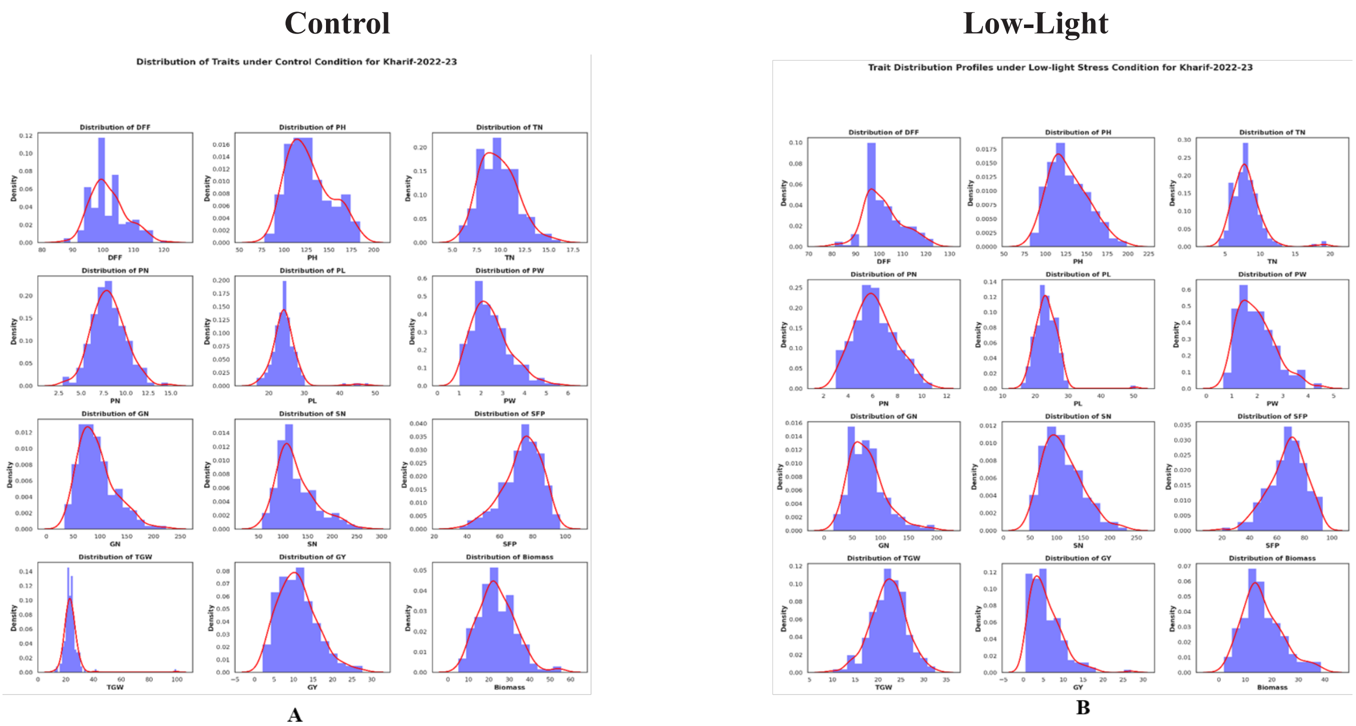

Fig. 3. Distribution of 12 agro-morphological traits in 192 rice genotypes under control (open) (A), and low light stress (B) conditions

stages under shading.

Principal component analysis (PCA)

In LL conditions, the first two principal components explained 76.25% of the total variability, with PC1 accounting for 55.92% and PC2 for 20.33%, while under control conditions, these components explained 71.53% of the variability, with PC1 contributing 50.33% and PC2 21.19%. Under LL stress, yield traits clustered closer to the origin, indicating reduced influence on genotype performance.PN and TN, positioned in Quadrant IV, contributed positively to PC2 but negatively to PC1, indicating that under stress, plants may prioritize vegetative growth over yield traits like grain weight and biomass (Sarma et al. 2023). These findings suggest a resource reallocation under LL stress and emphasize the importance of selecting genotypes that maintain yield stability while adapting through vegetative traits, a crucial aspect for breeding programs focused on resilience under varying environmental conditions (Yang et al. 2019) (Fig. 5). Dutta et al. (2018), also found that the first three principal components explained 58.209% and 63.952% of the variance among 38 hill rice genotypes under control and low light conditions, respectively. This study also supports the role of translocation efficiency in low light tolerance.

Combined Stress Tolerance and Stability Index

The utilization of the Yield Stability Index (YSI), Relative Yield (RY), and the innovative combined metric CSTSI has facilitated the identification of genotypes' performance under low light stress. YSI serves as an indicator of a genotype's capability to maintain consistent yield across diverse environments, while RY compares the yield of a genotype under stress to the average yield of all genotypes under similar conditions, thus highlighting those with

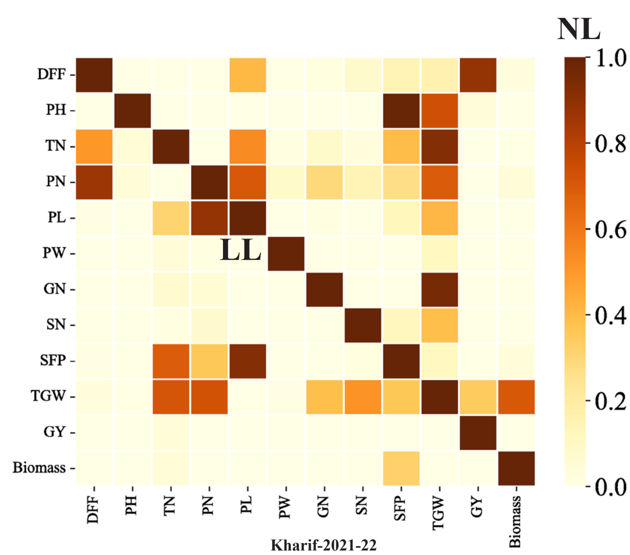

Fig. 4. Corr-plot showing correlation coefficients (P-value) among 12 agro-morphological traits under control (open) and low light stress conditions

Table 1. Descriptive statistics of 192 genotypes for 12 agro-morphological traits under control (open) and low-light stress conditions

Traits	Light	Range	Mean	Std. Deviation	Std. Error of Mean	Coefficient of variation (%)	% change(NL-LL)	P-value (Significant reduction
	NL	89-121	102.300	6.185	0.421	6.049	-1.93	0.0184
DFF	LL	81-125	101.900	8.188	0.557	8.037		
	NL	78.2-199.3	128.900	25.070	1.706	19.45	1.10	0.0416
PH	LL	79.8-198.2	129.600	25.350	1.725	19.55		
	NL	5.67-16.2	9.706	1.951	0.133	20.10	-16.25	0.0001
TN	LL	4.4-19.43	8.037	2.080	0.142	25.88		
	NL	2.9-14.7	7.981	1.870	0.127	23.43	-20.41	0.0001
PN	LL	3-10.8	6.195	1.647	0.112	26.58		
	NL	16.54-48.09	24.420	3.881	0.264	15.90	-3.26	0.0001
PL	LL	15.6-50.57	23.400	3.454	0.235	14.76		
	NL	33.05-223.8	94.800	35.310	2.402	37.24	-17.49	0.0001
GN	LL	16.3-196	77.060	31.680	2.155	41.11		
	NL	52.5-261.8	126.900	40.670	2.767	32.06	-15.28	0.0001
SN	LL	41-232.1	112.000	36.370	2.475	32.48		
	NL	42.28-96.79	74.130	11.100	0.755	14.97	-8.42	0.0001
SFP	LL	20.21-91.42	67.830	13.060	0.889	19.25		
	NL	0.83-15.25	2.563	1.402	0.095	54.69	-7.03	0.0001
PW	LL	0.66-5.6	2.142	0.971	0.066	45.31		
	NL	11.85-99.4	23.460	6.334	0.431	27.00	-3.69	0.0001
TGW	LL	10.05-32.65	22.220	3.708	0.252	16.69		
	NL	0.7-27.71	10.790	5.030	0.342	46.61	-41.96	0.0001
GY	LL	0.45-26.95	5.825	4.076	0.277	69.98		
	NL	3.73-55.31	24.040	8.938	0.608	37.18	-28.49	0.0001
Biom	LL	1.92-45.28	16.850	7.735	0.526	45.90		

Table 2. Two-way ANOVA of 192 genotypes for 12 agro-morphological traits under control (open) and low-light stress conditions

Source	Traits	df	Mean Square	F	Sig.	Source	Traits	df	Mean Square	F	Sig.
Light	DFF	1	14.8148	0.5617	< 0.0001	Error	DFF	191	26.373		
	PH	1	166.8553	8.342	0.0043		PH	191	20.0019		
	TN	1	2663.7368	228.893	< 0.0001		TN	191	11.6375		
	PN	1	5584.7427	227.447	< 0.0001		PN	191	24.554		
	PL	1	62.1707	0.6586	0.0417		PL	191	94.3939		
	GN	1	300.8061	114.849	< 0.0001		GN	191	2.6191	##	
	SN	1	344.5706	171.162	< 0.0001		SN	191	2.0131		
	SFP	1	111.3174	13.0724	0.0004		SFP	191	8.5155		
	PW	1	33983.424	80.2541	< 0.0001		PW	191	423.448		
	TGW	1	23853.198	36.9343	< 0.0001		TGW	191	645.828		
	GY	1	4282.6194	55.2633	< 0.0001		GY	191	77.4949		
	BIOM	1	19.1688	20.6794	< 0.0001		BIOM	191	0.927		
Genotype	DFF	191	78.9264	2.9927	0.4544	Total	DFF	767			
	PH	191	33.8712	1.6934	< 0.0001		PH	767			
	TN	191	30.2825	2.6021	< 0.0001		TN	767			
	PN	191	115.1593	4.69	< 0.0001		PN	767			
	PL	191	1176.6342	12.4652	< 0.0001		PL	767			
	GN	191	5.5141	2.1053	< 0.0001		GN	767	###		
	SN	191	4.1962	2.0844	< 0.0001		SN	767			
	SFP	191	18.4802	2.1702	< 0.0001		SFP	767			
	PW	191	1826.7458	4.314	< 0.0001		PW	767			
	TGW	191	2331.2032	3.6096	< 0.0001		TGW	767			
	GY	191	216.1945	2.7898	< 0.0001		GY	767			
	BIOM	191	1.9786	2.1345	< 0.0001		BIOM	767			
Season	DFF	1	0.0168403	0.01722	1.000						
	PH	1	0.043502	0.04572	1.000						
	TN	1	0.0548442	0.05833	1.000						
	PN	1	0.0495623	0.05242	1.000						
	PL	1	0.0203131	0.02084	1.000						
	GN	1	0.5089196	1.04174	0.344						
	SN	1	0.1168237	0.13297	1.000						
	SFP	1	0.1408219	0.16476	1.000						
	PW	1	0.486416	0.95205	0.685						
	TGW	1	0.0383108	0.04005	1.000						
	GY	1	0.1738183	0.21149	1.000						
	BIOM	1	0.146209	0.17214	1.000						

##: The 'Error' source represents the residual or unexplained variability within the dataset, serving as the denominator in the F-value calculations for each factor, but it does not have its own F-value or significance level because it is the baseline variability used for comparison, not an effect being tested.
###: The 'Total' source reflects all variability in the data, both explained by the factors and unexplained. While it provides a comprehensive measure of all variance, it does not contribute to hypothesis testing and thus lacks Mean Square, F-value, and significance, serving mainly as a descriptive statistic and a foundation for calculating overall model fit indicators.

superior performance (Lin et al. 1988; Fernandez 1992). The integration of YSI and RY into the CSTSI metric provides a holistic view of a genotype's robustness under stress (Montgomery 2013). A regression analysis further validated

Table 3. List of lowlighttolerant and susceptible genotypes along with YSI (Yield stability index), RY (Relative yield) and derived CSTSI (Combined Tolerance and Stability index)

Tolerant genotypes					Susceptible genotypes				
S. No.	LINES	YSI	RY	CSTSI	Sl. No	LINES	YSI	RY	CSTSI
1	Purnandu	0.86	1.63	2.49	1	IR8 (Susceptible check)	0.24	0.19	0.43
2	TRB-466	0.79	1.56	2.35	2	Vandana	0.20	0.23	0.43
3	Chamarmani	0.86	1.33	2.19	3	Local Black	0.33	0.11	0.43
4	Bhasamanik	0.83	1.30	2.14	4	TRB-422	0.20	0.23	0.42
5	Ambika	0.81	1.27	2.08	5	JR-503	0.20	0.22	0.42
6	Laxmichura	0.87	1.18	2.06	6	CO-49	0.21	0.19	0.40
7	TRB-467	0.70	1.32	2.03	7	IR64	0.29	0.10	0.39
8	TRB-468	0.76	1.26	2.02	8	TRB-439	0.19	0.18	0.38
9	TRB-451	0.78	1.17	1.96	9	Sinsatsu	0.19	0.18	0.37
10	Swarnaprabpha (Tolerant check)	0.74	1.17	1.91	10	Bhalum-3	0.27	0.10	0.37
11	Jaladhi-II	0.91	0.97	1.89	11	Khira	0.27	0.10	0.36
12	RR-8585	0.82	1.04	1.86	12	Samyakhala	0.26	0.10	0.36
13	VL Dhan-209	0.87	0.98	1.85	13	Srabani	0.18	0.17	0.35
14	Neta Dhan	0.85	1.00	1.84	14	Sahabhagi Dhan	0.18	0.15	0.33
15	Lal Dhan	0.81	1.04	1.84	15	Radhunipagal	0.19	0.12	0.32
16	Saroj-52	0.87	0.97	1.83	16	GAR-2	0.25	0.07	0.32
17	Dullo	0.90	0.93	1.83	17	Danteswari	0.15	0.16	0.31
18	Santhi	0.75	1.08	1.83	18	CO-48	0.16	0.14	0.30
19	Kalabhutia	0.94	0.84	1.78	19	Rajendra Dhan102	0.21	0.08	0.29
20	Chota Gora	0.78	0.96	1.74	20	BVS-1	0.11	0.15	0.26
21	Vaisak	0.83	0.91	1.74	21	IRCTN91-85	0.12	0.13	0.25
22	Sabita Patnai	0.70	1.04	1.74	22	Pantdhan-19	0.11	0.13	0.24
23	TRB-433	0.88	0.85	1.73	23	CSR-35	0.14	0.09	0.23
24	Deshi Khaidhan	0.89	0.82	1.71	24	TRB-448	0.11	0.12	0.22
25	TRB-423	0.56	1.15	1.71	25	Ratnagiri-4	0.10	0.10	0.20
26	TRB-405	0.82	0.88	1.70	26	Pusa-834	0.11	0.07	0.18
27	TRB-412	0.73	0.93	1.66	27	Golaka	0.08	0.08	0.16
28	Lallakra	0.68	0.93	1.61	28	Khandagiri	0.08	0.07	0.16
29	Sashi	0.93	0.68	1.61	29	Sanwal Basumati	0.10	0.05	0.15
					30	Kunti	0.06	0.08	0.15

Table 4. Phenotypic clustering of 192 rice genotypes using Euclidean distance based on 12 agro-morphological traits under low light stress condition

Clusters	List of Genotypes	No. of Genotypes	Centroid	Distance
I	Kunti, Sanwal Basumati, Khandagiri, Golaka, Pusa-834, CSR-35,TRB448, Ratnagiri-4, Pantdhan 19, IRCTN91-85, BVS-1, Co-48	35	0.33	0.31
	Rajendra Dhan-102, Danteswari, Gar-2, Radhunipagal, Sahabhagi Dhan, Srabani, Khira, Samyakhala, Bhalum-3,			
	Sinsatsu, TRB-439, IR-64, Co-49, JR-503,TRB422, Vandana, IR8, Local Black, VLD-221, Sarasa, Dandi, Borkot, Maliksali			
II	TRB 418,TRB 415, TRB 424, TRB 435, Dullo-A,TRB 416, TRB 420, CR 310, Dhamandhania, TRB 434, TRB 465, Mawalong, Ladu,	86	0.85	0.67
	TRB 431, TRB 446, TRB 450, Red Tribeni, TRB-445,TRB-437, Pyari, Thebaru, TRB 454, TRB 438, TRB 457, TRB 404, CR 2711-76, TRB 447, Manasarabar,			
	TRB 427, Jyati,TRB 444, Satabdi, Pant Sugandhadhan-21, Bahivardhan, TRB 403, Tara, Swarna, TRB 436, Kalinga-3, TRB 409, Pusa Sugandh-2, TRB 440,			
	TRB 453, CR 801,SRA 142-1, TRB 419, TRB 455, JohaDhan, TRB 449 ,Carlrose, Nilanjana, Dahamagra, Udaygiri, Indrabans, GR-4, Bardhan, TRB 462			
	HPR 2143, PS-4, Mahisungadh, TRB 429, TRB 441,TRB 458, Bhoi, Abor Red 4, Suwon, Bhagabati, TRB 452, Govinda, TRB 475			
III	Kranti, Binni, TRB 421, TRB 417, NDR-97, Nagarisail, Kumargore, Luna Sankhi, Latisali, TRB 469, Niroja, Megha Rice-2, Varsa, IRCTN 91-89, Miyang-46, TRB 414,	44	1.34	0.41
	TRB 401, TRB 402,VLD-16,Gitanajli Patnai, TRB 408, TRB 428, CR 602,Tulsibhog,TRB 411, TRB 410, TRB 443,Ratnagiri-711,TRB 442, Rasadhan,			
	DRR Dhan-39, Murgibalaram, TRB 470, TRB 413, TRB 459,Mahananda, Sarathi, Sukhardhan-1,TRB 460, Kataribhog, Sashi, Lalkara			
IV	TRB 412,TRB 405, TRB 423, Deshi Khaidan, TRB 433, SabitaPatnai, Vaisak, Chota Gora, Dullo, Saroj-52,Lal Dhan, Neta Dhan	19	1.8	0.27
	VL Dhan 209, RR-8585, Santhi, Kalabhutia, Jaladhi II, Swarnaprabha, TRB 451			
V	TRB 468, TRB 467, Laxmichura, Ambika, Bhasamanik, Chamarmani, TRB 466,Purnandu	8	2.17	0.47

the efficacy of the CSTSI metric, demonstrating a strong correlation with RY and YSI evidenced by R-squared values of 0.897 and 0.791, respectively (Fig. 6). These correlations imply that CSTSI can explain nearly 90% of the variance in RY and 80% in YSI, with a highly significant regression coefficient, underscoring CSTSI as a reliable predictor of yield performance under stress conditions (Draper and Smith 1998). Such analytical findings advocate the potential of CSTSI as an instrumental tool in breeding programs aimed at enhancing stress tolerance. The analysis of yield stability index (YSI), relative yield (RY), and combined tolerance stress and stability index (CSTSI) revealed that several genotypes outperformed Swarnaprabha (YSI: 0.74, RY: 1.17, CSTSI: 1.91) under low light stress conditions. Nine genotypes, such as Purnandu, Ambika, Laxmichura, Chamarmani, Bhasamanik, TRB-466, TRB-468, TRB-467, and TRB-451, exhibited higher YSI, RY, and CSTSI values, showing greater ability to maintain yield under stress. Similarly, another nineteen genotypes showed slightly lower CSTSI (> 1.60), but 15 of them showed slightly higher YSI values than Swarnaprabha (Table 3), indicating similar/slightly lower ability to maintain yield under LL stress like Swarnaprabha. On the other hand, 29 genotypes like Kunti, SanwalBasumati, Khandagiri, Golaka, Pusa-834, Ratanagiri-4, TRB-448, CSR-35, Pantdhan-19, IRCTN91-85, BVS-1, Rajendra Dhan102, CO-48, Danteswari, Radhunipagal, SahabhagiDhan, Srabani, Sinsatsu, TRB-439, etc., showed lower CSTSI than the susceptible check variety IR8 (YSI: 0.24, RY: 0.19, CSTSI: 0.43) (Table 3), indicating lower tolerance to low light stress. These findings align with previous research that suggests genotypes with higher CSTSI values are better suited for environments with fluctuating light conditions, as they tend to maintain better photosynthetic efficiency and grain filling under stress (Peng et al. 2013; Wang et al. 2013). The strong performance of genotypes like Purnandu, Ambika, Laxmichura, Chamarmani, Bhasamanik, TRB-466, TRB-468, etc. emphasizes their potential use in breeding programs aimed at enhancing stress tolerance in rice, particularly for regions frequently impacted by environmental challenges. Similarly, Rawte et al. (2021) utilized crop yield indices and

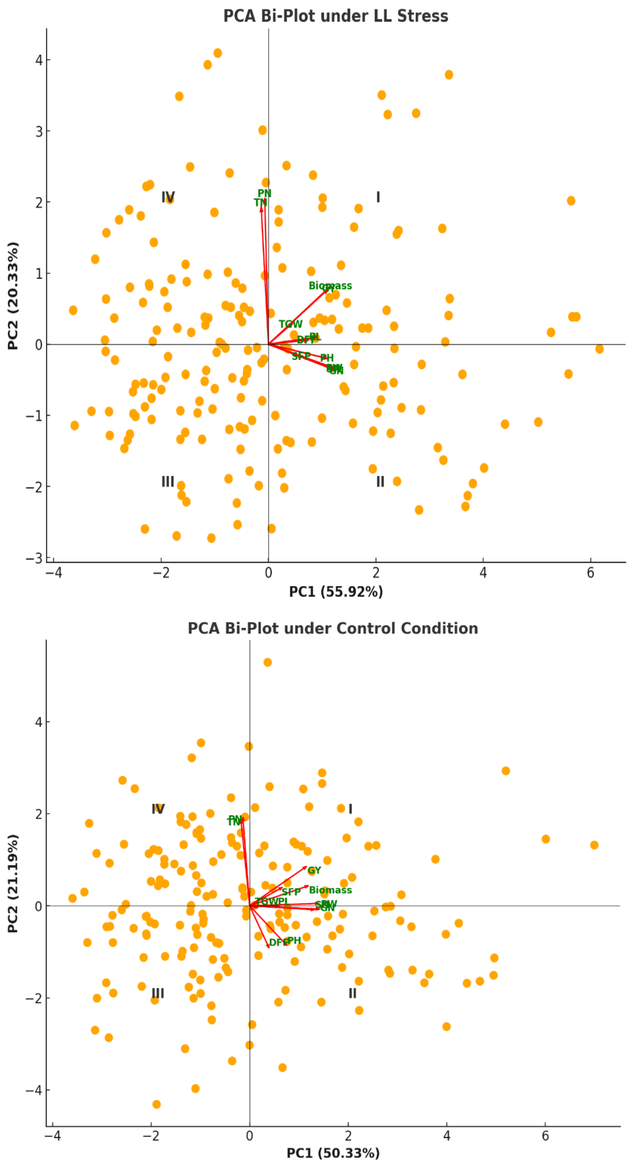

Fig. 5. Principal component analysis for 12 agro-morphological traits under control (open) and low light (LL) stress conditions

the Eberhart and Russell model to evaluate the stability of various rice genotypes under different conditions and also used the Drought Susceptibility Index (DSI) to assess year-to-year drought resistance variability among genotypes. These results underscore the importance of selecting genotypes with robust stress tolerance indices to develop resilient rice varieties capable of sustaining high yields under challenging conditions.

Clustering of genotypes

The cluster analysis using Euclidean distance classified 192 rice genotypes into five distinct clusters based on agro-morphological traits under low-light stress (Table 4, Fig. 7). Clusters Vcontained highly tolerant genotypes such as Purnandu, TRB 466, Chamarmani, Bhasamanik, Ambika,

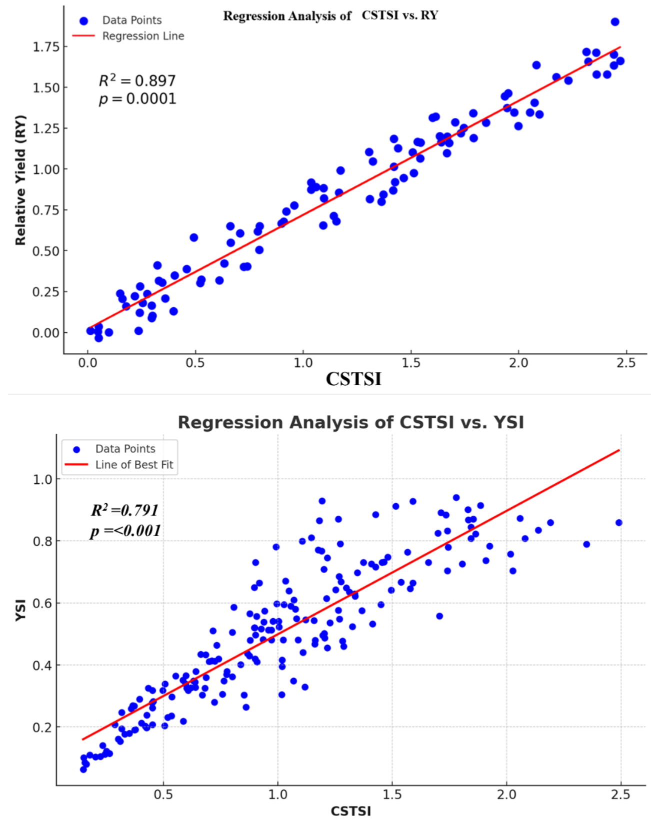

Fig. 6. Regression analysis between CSTSI, and RY and YSI

Laxmichura, TRB 467, and TRB 468, which demonstrated higher CSTSI values. Clusters IV included tolerant genotypes like VL Dhan 209, RR-8585, Santhi, Kalabhutia, Jaladhi II, Swarnaprabha, TRB 451, etc., which also demonstrated higher CSTSI values. These genotypes performed well under low light stress, confirming their suitability for breeding programs focused on enhancing stress resilience in rice. Conversely, Cluster I contained genotypes like Kunti, SanwalBasumati, Khandagiri, Golaka, Pusa-834, IR8, IR64, Srabani, Golaka, SahabhagiDhan, Khandagiri, BVS-1, CSR-35, etc., all of which exhibited lower CSTSI values, indicating weaker adaptation to stress conditions. The strong performance of genotypes in clusters IV and V further supports their potential for use in breeding programs. Integrating clustering analysis with performance metrics such as YSI, RY, and CSTSI is vital for developing stress-tolerant rice varieties. Clusters IV and V, featuring key genotypes like Swarnaprabha and Purnandu as well as VL Dhan-209 and Laxmichura, are distinguished for their low-light tolerance and superior performance, while Cluster I, which includes sensitive genotypes like IR8 and IR64, showed significantly lower YSI, RY, and CSTSI values (Ganguly et al. 2020).This clustering supports earlier studies that highlight the rich genetic diversity and variable stress responses among rice genotypes—according to Touthang et al. (2024) categorized 32 Ahu rice genotypes into four significant clusters based on their

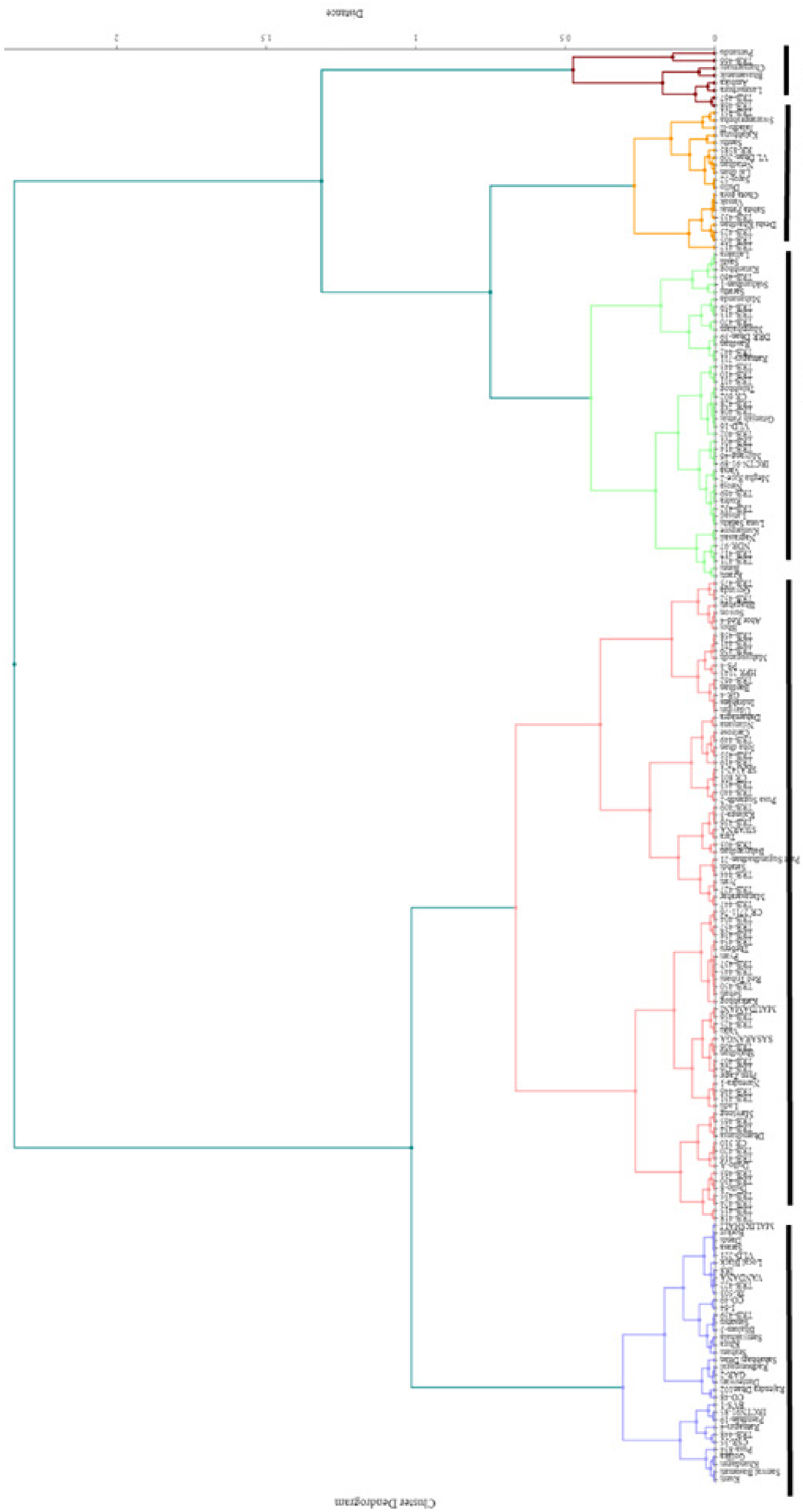

Fig. 7. Dendogram showing five distinct clusters among192 genotypes based on 12 agro-morphological Ftraits under low light stress condition

response to varying phosphorus levels, with each cluster exhibiting distinct trait expressions and potential breeding implications, as detailed in a heatmap and hierarchical clustering analysis.

Our study assessed the effects of low light conditions on rice during the *Kharif* seasons of 2021 and 2022, analyzing variations in photosynthetically active radiation (PAR) and their impact on 12 agro-morphological traits across 192 rice genotypes. Significant findings highlighted that reduced PAR during monsoon periods substantially affects key traits like tiller number, grain number, spikelet number, spikelet fertility percent, panicle number, TGW, biomass, and grain yield, which experienced significant declines. The Combined Stress Tolerance and Stability Index (CSTSI) effectively identified nine genotypes like Purnandu, Ambika, Laxmichura, Chamarmani, etc., as highly low-light-tolerant. These genotypes offer valuable resources for the identification of QTLs/genes and molecular breeding programs for developing rice varieties that maintain high productivity under low-light conditions.

Authors' contribution

Conceptualization of research (SD, SM); Designing of the experiments (LB, RP, KS); Execution of field/lab experiments and data collection (SD,BM,NC,RJ); Analysis of data and interpretation (SM.DP); Preparation of the manuscript (SD, SM, LB), Critical suggestions (AK, SS, SKP, MB).

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