

Principal Component Analysis of Morphological and Physiochemical Traits in Kodo Millet (*Paspalum scrobiculatum*) Seedlings Under Salt Stress Conditions

ABSTRACT

Principal Component Analysis (PCA) is a powerful statistical technique used to simplify complex datasets by reducing them to a few key components, known as principal components (PCs). These components are combinations of the original variables that capture most of the variability in the data, providing a more interpretable representation while retaining essential information. In this study, two principal components with eigen values greater than one collectively accounted for 72.2% of the total variability among the analyzed traits. The first principal component (PC1) contributed the most, explaining 63.05% of the variation, while the second principal component (PC2) explained 9.15%. PC1 was primarily associated with traits such as days to emergence, final germination percentage, shoot length, seedling length, shoot fresh weight, root fresh weight, total fresh weight, total dry weight, and proline content. In contrast, PC2 was dominated by traits such as root length, vigor index, chlorophyll a, and chlorophyll b. The scores for PC1 ranged from 0.002 to 3.795 for positive values and -7.521 to -0.034 for negative values, while PC2 scores ranged from 0.061 to 2.894 for positive values and -2.687 to -0.089 for negative values. A scree plot was used to assess the relative importance of each principal component visually, and a biplot provided insights into the relationships among variables and observations. These tools collectively highlighted the major contributors to variability and their interrelationships under the salt stress condition in kodo millet genotypes.

Keywords: kodo Millet, Principal Component Analysis

1. INTRODUCTION

Kodo millet (*Paspalum scrobiculatum*) is increasingly important due to its resilience for biotic and abiotic stresses, making it ideal for regions facing climate change impacts [1] [2]. Its ability to grow with minimal inputs supports sustainable, low-input farming systems [3] [4]. Nutritionally, kodo millet is rich in protein, fiber, iron, and antioxidants, with a low glycemic index, making it beneficial for managing diabetes and promoting overall health [5] [6] [7] [8]. As a gluten-free grain, it also supports dietary diversity and addresses micronutrient deficiencies [9] [10]. Its role in ensuring food security, especially for smallholder farmers in marginal areas, and its contribution to biodiversity and sustainable agriculture make kodo millet a crucial crop in today's food systems.

Although kodo millet is generally tolerant to various stresses, its yield is adversely affected by salinity stress, as it is a glycophyte crop that can only tolerate low levels of salt [11] [12]. India incurs economic losses of approximately 249 billion Indian rupees each year due to around 6.73 million hectares of salt-affected soils (SAS) that remain un-reclaimed. These losses are projected to rise substantially, as future estimates suggest that SAS areas could expand to nearly 16 million hectares by 2050, driven by improper irrigation practices and the impacts of climate change [13]. Cultivating salt-tolerant crops and varieties is a key strategy for soil reclamation and improving

productivity [14]. Salt-tolerant cultivars are more effective in reclaiming salt-affected soils because they naturally adapt to high salinity, improving soil health over time without the high costs of physical or chemical interventions. By stabilizing soil structure, reducing erosion, and enhancing nutrient cycling, these cultivars sustainably improve both soil quality and agricultural productivity [15] [16].

Principal Component Analysis (PCA) is a widely used statistical technique in plant breeding that simplifies data analysis, identifies patterns, and guides decision-making [17]. Plant breeding to evaluate stress tolerance involves assessing numerous traits, including yield, quality, as well as morphological and physiological characteristics, which makes data management a complex task. PCA addresses this by reducing the dimensionality of datasets while retaining most of the variation, thereby simplifying interpretation. It groups correlated traits into principal components (PCs), helping breeders understand relationships among traits. For instance, traits like root length and yield might load heavily on the same component, indicating a strong association. This grouping also allows breeders to identify key traits contributing most to variation, enabling them to focus on the most impactful traits for selection [18].

PCA is essential for distinguishing between genotypes based on phenotypic or genotypic data, often through scatter plots that visually separate genotypes, aiding the identification of unique or promising candidates. It also plays a critical role in designing breeding programs by guiding the selection of parents with complementary traits, ensuring effective combinations [18][19]. Additionally, PCA is valuable in stress and adaptation studies, where it evaluates plant performance under different conditions by grouping traits or environments based on responses. This facilitates the selection of genotypes with broad adaptability or specific stress tolerance [20]. Its visualization capabilities in 2D or 3D plots enhance the intuitive understanding of complex datasets.

Principal Component Analysis is a powerful statistical tool used to study salt stress tolerance in plants by identifying and summarizing key variables that contribute to phenotypic or physiological variations. Under salt stress conditions, plants exhibit complex responses involving multiple traits, such as growth rate, photosynthetic efficiency and osmotic adjustments. PCA helps reduce the dimensionality of such datasets by grouping correlated traits into principal components (PCs), each representing a distinct aspect of variation. By identifying these associations, one can get insights into which traits contribute to enhanced salt tolerance, which could guide breeding programs focused on improving resilience in kodo millet.

2. MATERIAL AND METHODS

The experiment was executed in a polyhouse at the Research Farm of the Department of Genetics & Plant Breeding, College of Agriculture, RVSKVV, Gwalior, MP, India. The study material consisted of 42 kodo millet genotypes, with 40 sourced from ICRISAT, Hyderabad, and two varieties, JK 137 and JK 155, obtained from Jawaharlal Nehru Krishi Vishwavidyalaya (JNKVV), Jabalpur, MP, India. A even growth medium of compost, vermiculite, and cocopeat in a 1:1:1 ratio was prepared to maintain consistency and avoid weed problem. The setup comprised nine plastic germination trays, each containing 112 cells with a height of 4 cm. Completely Randomized Design (CRD) was used with three replications across both control and stress conditions (NaCl concentrations of 50 mM, 100 mM, 250 mM, and 500 mM). Seeds were planted at a depth of 1 cm, with four seeds per cell. Salt stress tolerance was assessed by irrigating with specified NaCl concentrations from the first irrigation, while the control group received distilled water. Observations of morpho-physiochemical traits were logged 30 days post-germination. The ten morphological traits analyzed included days of emergence, final germination percentage, shoot length, root length, seedling length, shoot fresh weight, root fresh weight, total fresh weight, total dry weight, and vigor index. Physiochemical traits measured were proline content, chlorophyll a, chlorophyll b, total chlorophyll concentration, chlorophyll index, and salt tolerance index. Principal Component Analysis was performed using xlstat software.

Table 1: List of kodo millet genotypes used in the investigation

S.No.	Genotypes	S.No.	Genotypes	S.No.	Genotypes	S.No.	Genotypes
1.	IPs 4	12.	IPs 429	23.	IPs 706	34.	IPs 862
2.	IPs 5	13.	IPs 585	24.	IPs 730	35.	IPs 870
3.	IPs 91	14.	IPs 606	25.	IPs 741	36.	IPs 883
4.	IPs 105	15.	IPs 627	26.	IPs 764	37.	IPs 891
5.	IPs 176	16.	IPs 628	27.	IPs 777	38.	IPs 908
6.	IPs 181	17.	IPs 653	28.	IPs 782	39.	IPs 919
7.	IPs 208	18.	IPs 654	29.	IPs 785	40.	IPs 928
8.	IPs 287	19.	IPs 670	30.	IPs 793	41.	JK 137
9.	IPs 319	20.	IPs 694	31.	IPs 795	42.	JK 155
10.	IPs 358	21.	IPs 695	32.	IPs 814		
11.	IPs 388	22.	IPs 699	33.	IPs 828		

3. RESULTS AND DISCUSSION

At concentrations greater than 50 mM (namely 100 mM, 250 mM, and 500 mM), the impacts were intense, leading to total mortality and no germination. As a result, all observations were conducted for salt stress conditions solely at a concentration of 50 mM NaCl.

Out of the 12 principal components (PCs) analyzed, only two exhibited eigen values greater than 1, collectively accounting for 72.2% of the total variability among the studied traits. PC1 contributed the most to the variability, explaining 63.05% variation, followed by PC2, which accounted for 9.15% of the variation (Table 2). The eigen value of a component is the variance of the data explained by that component. A higher eigen value indicates greater importance of the component. If eigen value greater than 1 the component captures more variance than any single original variable and it contributes significantly in explaining the data variability. If eigen value is lesser than 1 the component captures less variance than a single variable, so it is usually discarded [21] [22]. Here scree plot is used as a visual tool to assess the importance of each principal component. It represents the proportion of the total variance explained by each principal component in descending order (Figure 1).

Table 2: Eigen values, variability percentage and cumulative variability percentage of 12 principal components

Particulars	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
Eigen value	10.08	1.46	0.89	0.81	0.68	0.53	0.49	0.32	0.27	0.19	0.12	0.09
Variability (%)	63.05	9.15	5.61	5.10	4.26	3.35	3.10	2.01	1.71	1.18	0.75	0.60
Cumulative variability (%)	63.05	72.21	77.83	82.93	87.19	90.54	93.65	95.67	97.38	98.56	99.32	99.93

Table 3 reveals that each principal component is separately loaded with various morphological and physiochemical traits under investigation known as factor loadings. Value for factor loading revealed that the first principal component (PC1) which accounted for the highest variation was related with traits *viz.*, days of emergence, final germination percentage, shoot length, seedling length, shoot fresh weight, root fresh weight, total fresh weight, total dry weight and proline. The second principal component (PC2) was dominated by traits *viz.*, root length, vigor index, chlorophyll a and chlorophyll b. Factor loadings represent the relationship between the original variables and the principal components. These values indicate how strongly each variable contributes to or correlates with a specific principal component. Factor loadings range from -1 to 1, where values close to 1 or -1 signify a strong positive or negative correlation, respectively, and values near 0 indicate little to no relationship with the component. They are crucial for understanding the structure of the data because they describe the weight of each variable in forming a principal component [23] [24][25].

Table 3: Factor loadings for traits under study

Characters	PC1	PC2
Days of emergence (days)	0.896	0.185
Final germination percentage (%)	0.795	-0.206
Shoot length (cm)	0.901	-0.158
Root length (cm)	0.156	0.529
Seedling length (cm)	0.918	-0.161
Shoot fresh weight (g)	0.839	-0.266
Root fresh weight (g)	0.742	-0.046
Total fresh weight (g)	0.873	-0.219
Total dry weight (g)	0.599	-0.291
Vigor index	-0.421	0.775
Proline ($\mu\text{g g}^{-1}$ fresh weight)	0.667	0.417
Chlorophyll a (mg g^{-1} tissue fresh weight)	0.509	0.739
Chlorophyll b (mg g^{-1} tissue fresh weight)	0.430	0.566
Total chlorophyll (mg g^{-1} tissue fresh weight)	0.785	0.548
Chlorophyll index	0.839	0.121
Salt tolerance index (%)	0.776	-0.063

The factor score of the each component (PC1 and PC2) had positive and negative values. Factor scores greater than 1 are highlighted in bold in Table 4. Factor scores represent the transformed values of the original data points in the reduced dimensional space defined by the principal components. In PC1, the positive scores ranged from 0.002 (lps 670) to 3.795 (lps 628), while negative value ranged from -7.521 (lps 870) to -0.034 (lps 764). In PC2, the positive value of the component arrayed from 0.061(lps 795) to 2.894 (**lps 5**) and negative value ranged from -2.687 (lps 695) to -0.089 (lps 764). Studying factor scores in principal component analysis is crucial as they represent individual genotypes in the reduced-dimensional space [18]. Derived from the linear combination of original variables weighted by component loadings, factor scores help reveal patterns, groupings, and outliers in the dataset, enabling a clearer understanding of the distribution and clustering of data based on the most significant variance dimensions [23] [26].

Genotypes which are common in PC1 and PC2 are lps 5, lps 208 and lps 706 indicating that these genotypes contribute significantly to the variability captured by multiple principal components and thus for all the principal components under study. This suggests that these genotypes are influential and well-represented in the reduced-dimensional space, as they align strongly with the

dominant patterns or structures in the dataset [6] [27]. Such genotypes may exhibit attributes that are central to the underlying relationships among variables, reflecting a strong, consistent presence in the most important dimensions of variance. Identifying these genotypes can help highlight key patterns or representative observations in the data.

The biplot (Figure 2) typically displays the first two principal components (PC1 and PC2) as the axes, as these components capture the most of the variability. Each data point (observation) is plotted in the reduced-dimensional space using its factor scores. Variables in a biplot are represented as vectors (arrows) radiating from the origin [27] [28]. The direction of the arrows indicates how each variable contributes to the principal components, while the length reflects the strength of this influence. Longer arrows signify a stronger contribution of the variable to the principal components, highlighting its importance in explaining the variance within the data. The angle between arrows in a biplot indicates the correlations between variables. Small angles suggest a high positive correlation, perpendicular arrows imply no correlation, and opposite directions signify a negative correlation. Additionally, the projection of observations onto the arrows represents how strongly an observation is associated with a particular variable, providing insight into the relationships between observations and variables [29] [30] [31].

4. CONCLUSION

Principal Component Analysis (PCA) is valuable for developing salt-tolerant crop varieties as it identifies key traits contributing to variability under salt stress conditions. By reducing complex datasets into a few principal components, PCA highlights traits strongly associated with stress tolerance, such as germination rate, seedling growth and physiological responses like proline content and chlorophyll levels. This allows breeders to prioritize these traits in selection programs, enabling efficient screening and identification of genotypes with superior performance. PCA also aids in understanding trait interrelationships, guiding targeted breeding strategies for developing robust, salt-tolerant crop varieties.

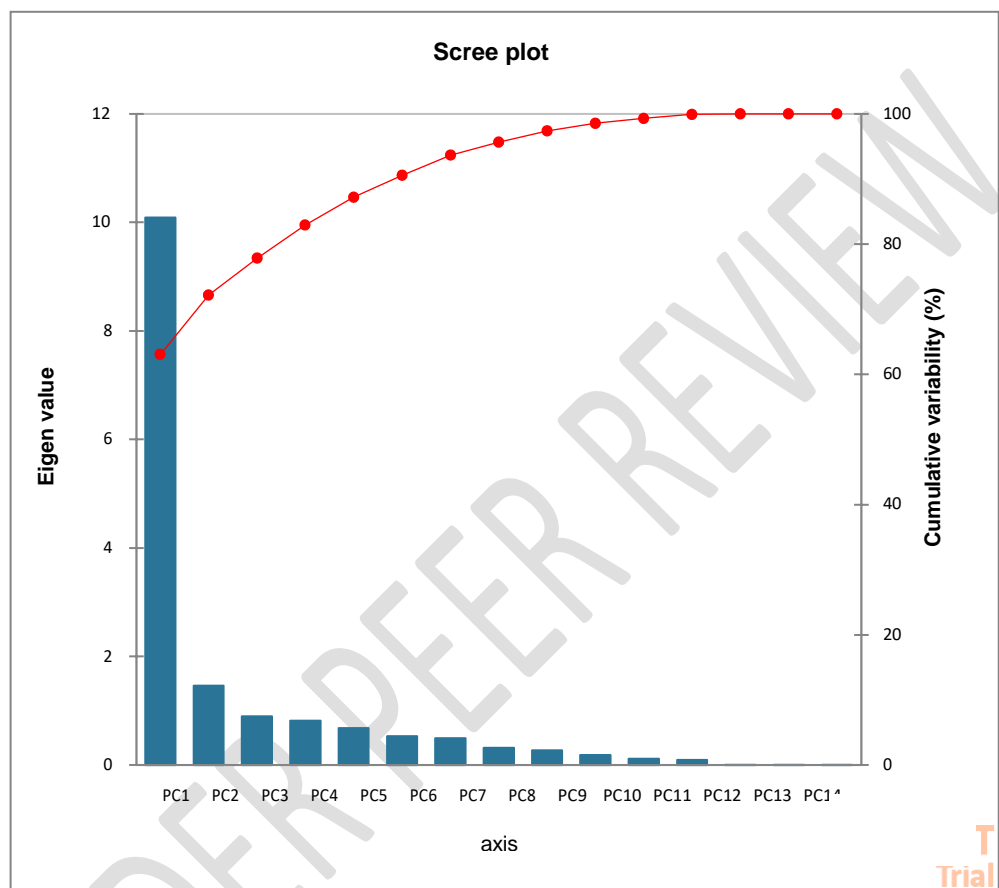


FIG.1. Scree plot between Eigen value and Principal components

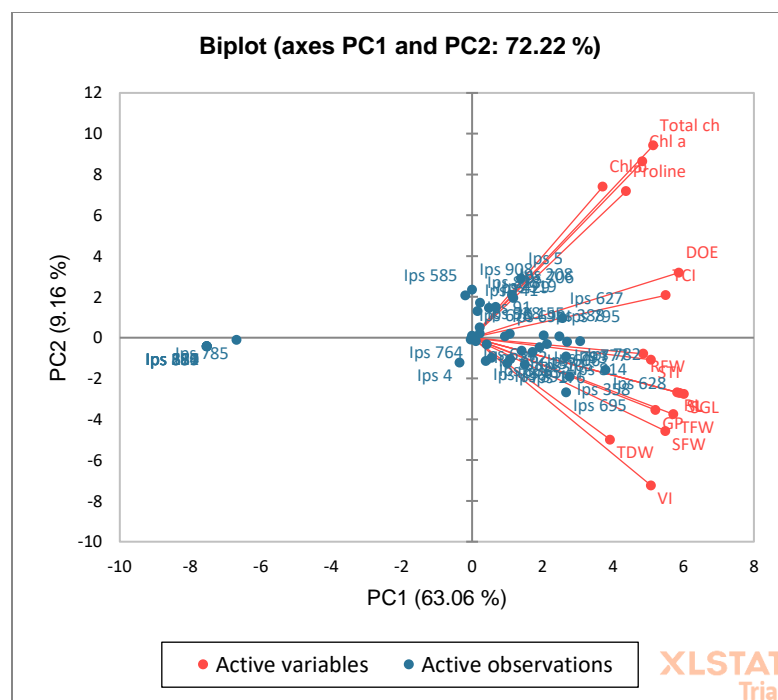


FIG.2. Biplot against PC1 and PC2 for studied characters of 42 genotypes

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