



Principal Component Analysis in Kodo Millet (*Paspalum scrobiculatum*) under Salt Stress Conditions

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The study was carried out in a polyhouse using germination trays to examine the impact of salt stress on seedling growth and germination across 42 Kodo Millet genotypes. Conducted at the Research Farm of RVSKVV, Gwalior, the experiment followed a Completely Randomized Design (CRD) with three replications. To minimize variability and maintain uniform conditions, a standardized growing medium composed of compost, vermiculite, and cocopeat in a 1:1:1 ratio was employed. Salt stress levels were assessed using NaCl solutions at concentrations of 50 mM, 100 mM, 250 mM, and 500 mM. In this study, two principal components with eigen values greater than

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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. Scree plot and biplot 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; salt stress.

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 (Gyawali, 2021, Swapnil et al., 2024). Its ability to grow with minimal inputs supports sustainable, low-input farming systems (Ravikesavan et al., 2023, Sanodiya et al., 2023). 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 (Deshpande et al., 2015, Vetriventhan & Upadhyaya 2019, Arya & Shakya, 2021, Bunkar et al., 2021). As a gluten-free grain, it also supports dietary diversity and addresses micronutrient deficiencies (Priya et al., Yadav et al., 2024). 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 (Flowers & Colmer 2008, Shabala, 2013). 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 unreclaimed. 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 (Kumar et al., 2022). Cultivating salt-tolerant crops and varieties is a key strategy for soil reclamation and improving productivity (Ashraf & Munns 2022). 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 (Ashraf et al., 2008, Munns & Gilliam 2015).

Principal Component Analysis (PCA) is a widely used statistical technique in plant breeding that simplifies data analysis, identifies patterns, and guides decision-making (Khatun et al., 2023). 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 (Roka et al., 2024).

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 (Roka et al., 2024, Mehta et al., 2023). 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 (Füzy et al., 2019). 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. MATERIALS 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.

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 1).

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		

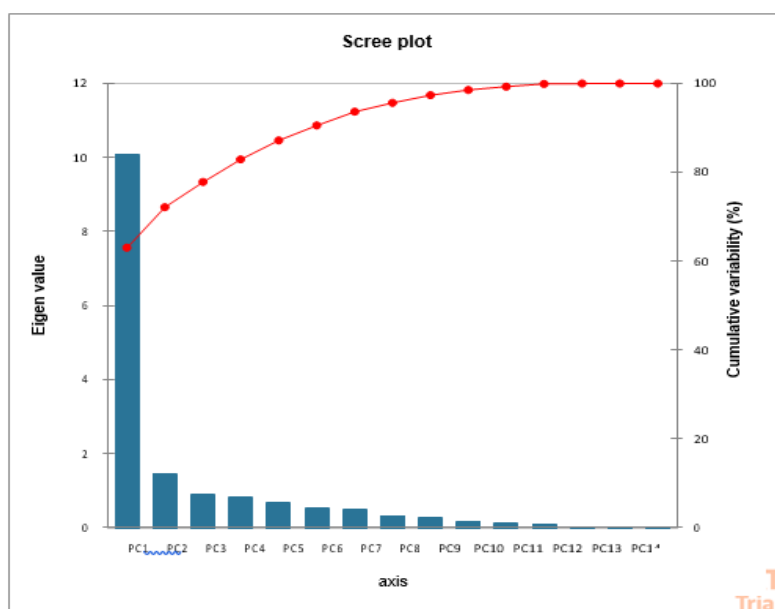


Fig. 1. Scree plot between eigen value and principal components

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 (Johnstone 2001, Danisman et al., 2014). 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 (Fig. 1).

Table 2 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 (Jolliffe, 2002, Winter & Dodou, 2016, Yamamoto et al., 2014).

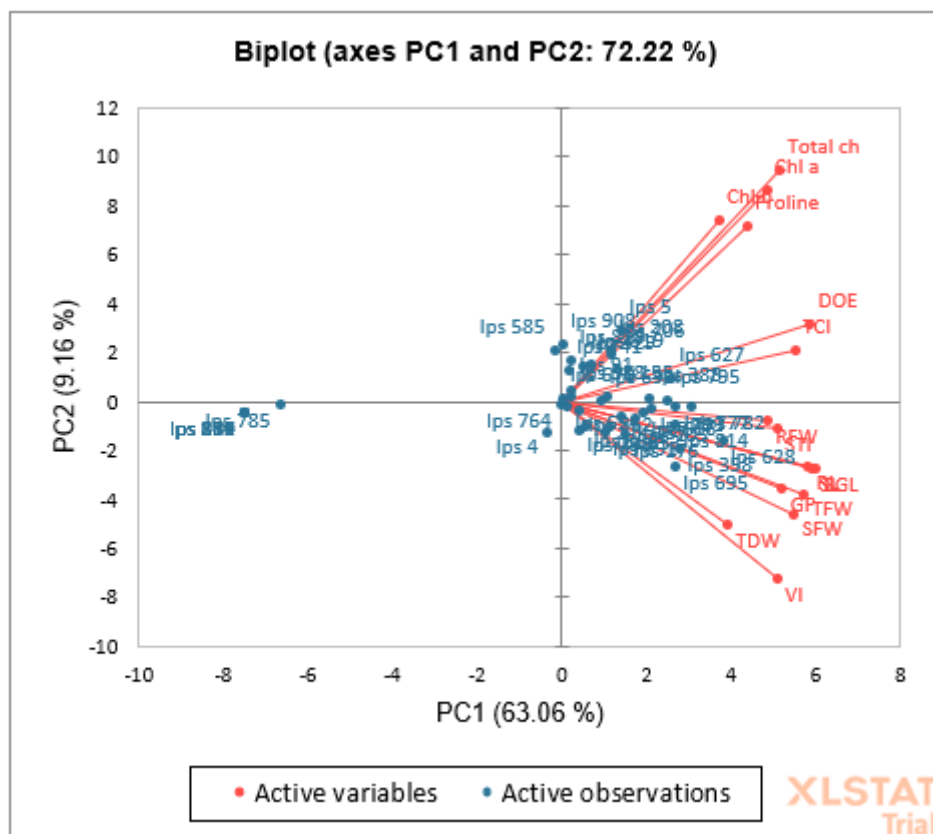
The factor score of the each component (PC1 and PC2) had positive and negative values. Factor scores greater than 1 are highlighted in bold in Table 3. Factor scores represent the transformed values of the original data points in the reduced dimensional space defined by the principal components. In PC1, 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 (Roka et al. 2024). 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 (Jolliffe, 2002, Abdi & Williams, 2010).

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. 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

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

Genotypes which are common in PC1 and PC2 are Ips 5, Ips 208 and Ips 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 (Shashibhushan et al., 2022, Vetriventhan & Upadhyaya, 2019). 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 (Fig. 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 (Shashibhushan et al., 2022, Gabriel, 1971). 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 (Wedlake, 2008, Gower & Hand, 1995, Holland, 2008).

4. CONCLUSION

Kodo millet, characterized by small floret size and a high degree of self-pollination, poses significant challenges for hybridization. Consequently, pure line and mass selection from high-yielding germplasm accessions are often preferred methods for varietal development. In India, most small millet varieties have been developed from existing germplasm. Evaluating preserved germplasm for salt stress tolerance offers significant potential to enhance Kodo millet yields (Sao et al. 2024). Principal Component Analysis (PCA) is a valuable tool in both pure line and mass selection, as it simplifies the assessment of genetic variability and trait significance. In pure line selection, PCA identifies traits contributing to variability, clusters similar lines, and highlights those performing well under specific conditions, such as stress. In mass selection, PCA evaluates population diversity, identifies critical traits, tracks selection progress, and examines environmental interactions. By reducing data complexity and focusing on traits

driving variability, PCA improves the efficiency and accuracy of breeding strategies in both approaches.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

REFERENCES

- Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2(4), 433–459.
<https://doi.org/10.1002/wics.101>
- Arya, S. S., & Shakya, N. K. (2021). High fiber, low glycaemic index (GI) prebiotic multigrain functional beverage from barnyard, foxtail, and kodo millet. *LWT*, 135, 109991.
<https://doi.org/10.1016/j.lwt.2020.109991>
- Ashraf, M., & Munns, R. (2022). Evolution of approaches to increase the salt tolerance of crops. *Critical Reviews in Plant Sciences*, 41(2), 128–160.
<https://doi.org/10.1080/07352689.2022.2065136>
- Ashraf, M., Athar, H. R., Harris, P. J. C., & Kwon, T. R. (2008). Some prospective strategies for improving crop salt tolerance. *Advances in Agronomy*, 97, 45–110.
[https://doi.org/10.1016/S0065-2113\(07\)00002-8](https://doi.org/10.1016/S0065-2113(07)00002-8)
- Bunkar, D. S., Goyal, S. K., Meena, K. K., & Kamalvanshi, V. (2021). Nutritional, functional role of kodo millet and its processing: A review. *International Journal of Current Microbiology and Applied Sciences*, 10(01), 1972–1985.
<https://doi.org/10.20546/ijcmas.2021.1001.229>
- Danisman, Y., Yilmaz, M. F., Ozkaya, A., & Comlekçiler, I. (2014). A comparison of eigenvalue methods for principal component analysis. *Applied and Computational Mathematics*, 13, 316–331.
- De Winter, J. C., & Dodou, D. (2016). Common factor analysis versus principal component analysis: A comparison of loadings by

- means of simulations. *Communications in Statistics-Simulation and Computation*, 45(1), 299–321.
- Deshpande, S. S., Mohapatra, D., Tripathi, M. K., & Sadvatha, R. H. (2015). Kodo millet—nutritional value and utilization in Indian foods. *Journal of Grain Processing and Storage*, 2(2), 16–23.
- Flowers, T. J., & Colmer, T. D. (2008). Salinity tolerance in halophytes. *New Phytologist*, 177(4), 945–963. 10.1111/j.1469-8137.2008.02531.x
- Füzy, A., Kovács, R., Cseresnyés, I., Parádi, I., Szili-Kovács, T., Kelemen, B., ... & Takács, T. (2019). Selection of plant physiological parameters to detect stress effects in pot experiments using principal component analysis. *Acta Physiologiae Plantarum*, 41, 1–10. <https://doi.org/10.1007/s11738-019-2842-9>
- Gabriel, K. R. (1971). The biplot graphic display of matrices with application to principal component analysis. *Biometrika*, 58(3), 453–467. <https://doi.org/10.1093/biomet/58.3.453>
- Gower, J. C., & Hand, D. J. (1995). *Biplots* (Vol. 54). CRC Press.
- Gyawali, P. (2021). Production trend, constraints, and strategies for millet cultivation in Nepal: A study from review perspective. *International Journal of Agricultural and Applied Sciences*, 2(1), 30–40. <https://doi.org/10.52804/ijaas2021.213>
- Holland, S. M. (2008). Principal components analysis (PCA). *Department of Geology, University of Georgia*, 2501.
- Johnstone, I. M. (2001). On the distribution of the largest eigenvalue in principal components analysis. *The Annals of Statistics*, 29(2), 295–327. <https://doi.org/10.1214/aos/1009210544>
- Jolliffe, I. T. (2002). Principal component analysis and factor analysis. In *Principal Component Analysis* (pp. 150–166).
- Khatun, M., Islam, M. R., Khan, M. A. R., Hossain, M. K., & Islam, A. K. M. A. (2023). Principal component analysis and estimated breeding values for selecting suitable parental genotypes in rice (*Oryza sativa* L.). *Sabao Journal of Breeding & Genetics*, 55(6). <http://doi.org/10.54910/sabao2023.55.6.3>
- Kumar, R., Singh, A., Bhardwaj, A. K., Kumar, A., Yadav, R. K., & Sharma, P. C. (2022). Reclamation of salt-affected soils in India: Progress, emerging challenges, and future strategies. *Land Degradation & Development*, 33(13), 2169–2180. <https://doi.org/10.1002/ldr.4320>
- Mehta, A., Sengupta, P., Garg, D., Singh, H., & Diamand, Y. S. (2023). Benchmarking the effectiveness of classification algorithms and SVM kernels for dry beans. *arXiv preprint arXiv:2307.07863*. <https://doi.org/10.48550/arXiv.2307.07863>
- Munns, R., & Gilliam, M. (2015). Salinity tolerance of crops—What is the cost? *New Phytologist*, 208(3), 668–673.
- Priya, K., & Gakkhar, A. (n.d.). Nutritional importance of millet in India.
- Ravikesavan, R., Jeeva, G., Jency, J. P., Muthamilarasan, M., & Francis, N. (2023). Kodo millet (*Paspalum scrobiculatum* L.). In *Neglected and Underutilized Crops* (pp. 279–304). Academic Press. <https://doi.org/10.1016/B978-0-323-90537-4.00019-3>
- Roka, P., Shrestha, S., Adhikari, S. P., Neupane, A., Shreepaili, B., & Bista, M. K. (2024). A review on genetic parameters estimation, trait association, and multivariate analysis for crop improvement. *Archives of Agriculture and Environmental Science*, 9(3), 618–625. <https://doi.org/10.26832/24566632.2024.0903029>
- Sanodiya, L. K., Sanodiya, P. K., Prajapati, A., Kumawat, P., & Singh, A. (2023). The sustainability of millets and the advantages they bring for human health. *Research Gate*. <https://doi.org/10.5281/zenodo.7947530>
- SAO, A., PALI, V., & PATIL, H. E. (2024). Genetic improvement for yield, quality, biotic, and abiotic stresses in little millet (*Panicum sumatrense* Roth. Ex Roem. and Schult.). In *Genetic Improvement of Small Millets* (pp. 571–599). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-7232-6_28
- Shabala, S. (2013). Learning from halophytes: Physiological basis and strategies to improve abiotic stress tolerance in crops. *Annals of Botany*, 112(7), 1209–1221. <https://doi.org/10.1093/aob/mct205>
- Shashibhushan, D., Kumar, C. S., & Kondi, R. K. R. (2022). Principal component analysis for yield and yield-related traits in pearl millet cultivars. *Ecology, Environment and Conservation*, 28, S104–S107. <http://doi.org/10.53550/EEC.2022.v28i06s.017>

- Swapnil, Parveen, R., Singh, D., Imam, Z., & Singh, M. K. (2024). Breeding Kodo Millet for Biotic and Abiotic Stress Tolerance. In *Genetic improvement of Small Millets* (pp. 613–635). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-7232-6_30
- Vetriventhan, M., & Upadhyaya, H. D. (2019). Variability for productivity and nutritional traits in germplasm of kodo millet, an underutilized nutrient-rich climate smart crop. *Crop Science*, 59(3), 1095–1106. <https://doi.org/10.2135/cropsci2018.07.0450>
- Wedlake, R. S. (2008). Robust principal component analysis biplots (Doctoral dissertation, Stellenbosch University).
- Yadav, M., Bansal, C., Shukla, U., & Zainab, S. (2024). A critical review on the efficacy of Kodo, Sorghum, and foxtail millets in the management of type 2 diabetes mellitus. *Indian Journal of Health Sciences and Biomedical Research KLEU*, 17(3), 200–208. https://doi.org/10.4103/kleuhsj.kleuhsj_243_24
- Yamamoto, H., Fujimori, T., Sato, H., Ishikawa, G., Kami, K., & Ohashi, Y. (2014). Statistical hypothesis testing of factor loading in principal component analysis and its application to metabolite set enrichment analysis. *BMC Bioinformatics*, 15, 1–9. <https://doi.org/10.1186/1471-2105-15-51>

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