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Weather-Based Prediction of Sorghum Yield in Hamirpur District

Ritu Singh[1], Gaurav Shukla[2], Umesh Chandra[2], Shivangi Jayaswal[3], Arjun Prasad Verma[4]*, Annu[5] and Himani Maheshwari[6]

[1]Department of Agricultural Engineering, Institute of Agricultural Sciences, Banaras Hindu University, Varanasi-221005, Uttar Pradesh, India
[2]Department of Statistics & Computer Science, [4]Department of Agricultural Extension, [5]Department of Basic & Social Science, Banda University of Agriculture & Technology, Banda-210001, Uttar Pradesh, India
[3]Department of Statistics, University of Lucknow-226007, Uttar Pradesh, India
[6]School of Computing, Graphic Era Hill University, Dehradun-248002, Uttarakhand, India
*Corresponding author email id: arjunverma45753@gmail.com

HIGHLIGHT

- The PCA-ANN model performed optimally for prediction of sorghum yield at the calibration stage with Adjusted R^2 of 0.94.
- ANN model performed optimally for prediction of sorghum yield at the validation stage with Adjusted R^2 of 0.94.
- Hybrid PCA-ANN model is clearly better and consistent in comparison to the simple ANN, LASSO, Ridge Regression and SMLR models in weather-based yield prediction of sorghum crop in Hamirpur district.

ARTICLE INFO

Keywords: ANN, Least absolute shrinkage, PCA, Selection operator, Weather variables

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Reviewed by: Dr. Lokesh Srinivasaiah (lokesh379@rpcau.ac.in); Dr. Bineeta Satpathy (bineeta.satpathy@rpcau.ac.in); Suresh Krishnanaik (suresh.krishnanaik@gmail.com); Dr. Vinay Kumar R (prasvin@gmail.com); Dr. Vinayak Nikam (vinayakrnikam@gmail.com)

ABSTRACT

The study was conducted during 2024-25. Five multivariable models were tested for the sorghum yield prediction in Hamirpur district of the Bundelkhand region, India namely Artificial Neural Network (ANN), PCA with Artificial Neural Network (PCA-ANN), Least Absolute Shrinkage and Selection Operator (LASSO), Ridge Regression, and Stepwise Multiple Linear Regression (SMLR). Average meteorological data of different crop phenological stages were used as predictor variables to build the models. The coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) were used to evaluate the model's performance. The five models were compared, and the PCA-ANN model was found to have the highest prediction accuracy, suggesting the dimensionality reduction process of PCA improved predictive ability of the ANN model. The PCA-ANN model had the highest predictive performance, with low prediction errors (MAE = 0.33 q ha^{-1} and RMSE = 0.50 q ha^{-1}) during the calibration process. The evaluation metrics ranked the forecasting performance of the models in the order: PCA-ANN>ANN>SMLR>LASSO>Ridge Regression. PCA, along with ANN, has emerged as a powerful and reliable technique for sorghum yield prediction under the influence of changing climate and can prove useful for farmers in the region of Bundelkhand for decision support.

INTRODUCTION

The climate of the Bundelkhand region in India is extremely sensitive to climatic fluctuations and is characterised by recurrent droughts, erratic rainfall, land degradation, a mono-cropping system, poverty and large-scale migration (Kalia et al., 2021). Since irrigation facilities are still scarce and limited, crop production is highly sensitive to variations in monsoon rainfall in this region, which mainly relies on monsoon rains for cultivation (Pathak et al., 2024). Due to the semi-arid region of Hamirpur district, oilseeds, pulses and coarse cereals are the major crops. Sorghum is one of the most appropriate cereal crops for semi-arid regions as it possesses a drought tolerance trait and can yield stable crops under moisture-constrained conditions (Singh et al., 2018). The crop grows in a

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series of definite phenological stages, the time to maturity being from 90-120 days, depending to a large degree on environmental conditions. India ranks third in production of sorghum after the USA and Nigeria. The total sorghum production in the country was estimated at around 4.03 MT during 2023-2024, with Maharashtra having the highest production, followed by Karnataka, TN, Rajasthan and MP (Jadhav et al., 2025).

Agro-meteorological variables are of great significance in crop performance. Phenological weather indices, incorporating weather features with crop development phases, have been proven to be useful indicators for better yield prediction (Singh et al., 2025). These indices can also be used to better estimate yield, water use, disease and pest occurrence, etc., assisting in the management of crops in a climate-resilient way. Agro-meteorological indicators also help farmers and decision-makers to optimise the use of resources and agricultural planning in the face of climate variability and uncertainty (Ransing et al., 2014; Garde et al., 2015; Yadav et al., 2021). Accurate crop yield predictions are crucial for achieving food security, market planning, and efficient agricultural management. Historically, statistical modelling has been a prevalent approach to estimating crop yields by developing relationships among crop yield, weather parameters, soil properties, and management practices (Maurya et al., 2025; Tripathi et al., 2023). The conventional methods (e.g., multiple linear regression and pre-harvest forecasting models) are simple and easy to understand, but they are limited in their ability to explain the relationships between these weather variables, their interactions, and the growth of crops, which causes their forecasting accuracy to be low. Conventional methods are straightforward and intuitive, but may assume linearity and/or a priori relationships among weather parameters and crop development. In practice, the weather factors like temperature, precipitation, humidity, solar radiation and soil moisture are highly interdependent, and the impact on crops is often characterised as being nonlinear and interactive. Furthermore, the sensitivity of crops to these variables will be different at different growth stages, and extreme conditions may lead to stress, which will affect crop growth and yield. These complex interactions and nonlinear relationships, and dynamic crop responses, may not be captured by conventional methods, leading to lower forecasting accuracy (Khan & Kumar, 2025; Setiya et al., 2022). In recent years, machine learning techniques have emerged that can offer strong alternatives to yield prediction. The machine learning models have therefore been found to be better at predicting various crops like pigeon pea, rice, sorghum, and wheat (Sridhara et al., 2020; Sridhara et al., 2023; Satpathi et al., 2023; Aravind et al., 2022). Although these developments have been made, very few studies have focused on hybrid approaches combining dimensionality reduction techniques with machine learning (Setiya et al., 2022) to enhance prediction accuracy, and most of the studies conducted have been limited to either weather variables or vegetation indices alone. The present study compares performance of the statistical and machine learning models to forecast sorghum yield in Hamirpur district based on weather indices.

METHODOLOGY

The Kharif sorghum yield data were collected from the Spider Statistics Journal Uttar Pradesh, published by the Department of Economics and Statistics, on sorghum yield for 31 years from 1991-92 to 2021-22. Also, data on weather conditions were gathered from the NASA POWER (https://power.larc.nasa.gov/data-access-viewer/). Daily weather data are used to obtain mean phenological values. Weighted and unweighted weather indices were derived using this mean phenological value. Unweighted weather indices have been obtained through aggregations of single weather variables or when interactions between them were taken into account. As an alternative, to calculate the weighted weather indexes, multiply each weather variable by the dependent variable or by the interaction of each weather variable with its coefficient. The five weather variables were combined in various combinations with other variables to produce weather indices. This results in a total of 10 pairs, which means there are 20 weather indices overall. The formulas used (Satpathi et al., 2023) to calculate weather indices, both weighted and unweighted, are shown in Equations (1) and (2) below

Unweighted weather indices:

$$Z_{mn} = \sum_{r=1}^{q} X_{mr}, Z_{mm'n} = \sum_{r=1}^{q} X_{mr} X'_{m'r} \qquad \text{... (1)}$$

Weighted weather indices:

$$Z_{mn} = \sum_{r=1}^{q} p^{n}{}_{mr} X_{mr'}, Z_{mm'n} = \sum_{r=1}^{q} p^{;}_{mm'r} X_{mr} X_{m'r} \qquad \text{... (2)}$$

Here, q represents the total number of phenological stages under study.

The term X_{mr} refers to the value of the m^{th} weather variable, while $X_{m'r}$ is the value of the m'^{th} weather variable. r_{mr} and $r_{mm'r}$ denote the correlation coefficients between yield and the m^{th} weather variable, or the product of the m^{th} and variable m'^{th} weather variable, during the r^{th} phenological stage. When n=0, it indicates unweighted weather indices; when n=1, it indicates weighted weather indices. Thirty weather indices were produced by using the above procedure (Satapathi et al., 2023). Using time series data on phenological weather indexes and sorghum yield, three multivariate models were developed for this study. The models were tested and trained on these datasets. Five models, ANN, PCA-ANN, LASSO, Ridge Regression and SMLR were used in this study.

To assess the model performance, we used Adjusted R^2 (adjusted coefficient of determination), root mean square error (RMSE), mean absolute error (MAE), percentage error (PE), normalized root mean square error (nRMSE), and model efficiency (EF). We compared the models based on their adjusted R-squared values. These statistical measurements have the following formulas.

$$nRMSE = \frac{100}{M} \sqrt{\frac{\sum_{i=1}^{j} (x_i - \hat{x}_i)^2}{m}} \qquad \text{... (3)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{j} (x_i - \hat{x}_i)^2}{m}} \qquad \text{... (4)}$$

$$MAE = \frac{\sum_{i=1}^{j} |x_i - \hat{x}_i|}{m} \qquad \text{... (5)}$$

$$Adj.R^2 = 1 - \frac{(m-1)(1-R^2)}{(m-q-1)} \qquad \text{... (6)}$$

$$Percentage\ Error = \left(\frac{x_i - \hat{x}_i}{x_i}\right) \times 100 \quad \dots (7)$$

Here, x_i is the actual value, and $\hat{x}_i$ is the predicted value for each i from 1 to j. The symbols x_i and $\hat{x}_i$ represent the average of the actual and predicted values, respectively. The σ_x and $\sigma_{\hat{x}}$ are the standard deviations of the actual and predicted values. M is the average of all actual values, m is the total number of observations, and q is the number of predictors in the model.

RESULTS

Tables 1 demonstrate the summary results of the model performance in Hamirpur district. ANN had the highest overall predictive accuracy. The model has been validated, and it has the best prediction accuracy with the highest adjusted R^2 (0.94), lowest MAE (0.38 q ha^{-1}), RMSE (0.46 q ha^{-1}), and model efficiency (EF = 0.89), and good generalisation capability. The PC-ANN demonstrated the best calibration adjusted R^2 (0.94), indicating a very good fit to the calibration set. The ability of the model to capture the variation between the observations and the predictions (adjusted R^2 = 0.85, RMSE = 0.58 q ha^{-1}, EF = 0.83) was slightly lower than that of the ANN model, showing that dimensionality reduction with PCA did not increase the accuracy of the model. SMLR showed moderate performance with a validation adjusted R^2 of 0.88, RMSE of 0.72 q ha^{-1} and EF of 0.74. It showed some improvement in performance over the regularised linear models, but not as high an accuracy as the ANN-based approaches. LASSO and Ridge Regression yielded somewhat inferior prediction accuracy. Both models showed relatively high values for the validation adjusted R^2 (0.83 and 0.90, respectively), but higher RMSE (1.58 and 1.81 q ha^{-1}, respectively) and negative EF values (-0.21 and -0.58, respectively), which suggested that these models were less efficient in predicting the response variable.

As per the results shown in Table 2, there were significant differences between the models by the prediction error analysis. The error range for the Ridge Regression model was the most narrow (-79.86% to 14.02%), suggesting that there was less variation in prediction errors within this model, though it was less efficient in predicting the target variable as seen during validation. The error range of the PCA-ANN model was also comparatively smaller (-80.84% to 18.81%), than that of standard ANN model. The prediction errors of the ANN model were between -120.76% and 16.52%. Its minimum error was larger than those of PCA-ANN and Ridge Regression but it showed that it has the highest validation accuracy in terms of adjusted R^2, RMSE, MAE, and Nash–Sutcliffe efficiency, which means that it has a better overall prediction. The largest error range was observed in the LASSO model with a range ranging from -195.80% to 20.36% and in the SMLR model with a range from -205.34% to 25.96%. The large negative errors show that some observations were underestimated, which shows less stability in the predictions by the models than ANN-based models.

To evaluate and compare the predictive performance of the ANN, PCA-ANN, LASSO, Ridge Regression and SMLR models, the Taylor diagram (Figure 1) was used by simultaneously assessing the correlation coefficient, standard deviation, and centered root mean square error (CRMSE). The ideal model was used as a reference point as it has a correlation coefficient of 1.0, the same standard deviation as the observed data, and a centered RMSE of 0. The reference point (Observed) is the ideal model that has a correlation coefficient of 1.0, the same standard deviation as the observed data and a centered RMSE of 0. When evaluated, PCA-ANN is the closest to the reference point, implying it best captures the observed variability, with good correlation and lowest centered RMSE. This is consistent with its better calibration performance (Adjusted R^2 = 0.94 and EF = 0.94), indicating that PCA achieved good dimensionality reduction and model fitting by eliminating data redundancy and redundancy of parameters in the calibration process. The ANN model also showed a good correlation with the observed data with slightly low standard deviation than the observations and a slightly larger centered RMSE than the PCA-ANN model. However, its nearness to the reference point suggests good calibration capabilities. The SMLR model was found to be moderately correlated with the observations with lower correlation coefficient and lower standard deviation compared to ANN based models. As a result, it had a higher centered RMSE indicating it

Table 1. Quantitative measurements made during calibration and validation for Hamirpur

Model	Calibration					Validation				
	Adjusted R^2	MAE (q ha^{-1})	RMSE (q ha^{-1})	nRMSE (%)	EF	Adjusted R^2	MAE (q ha^{-1})	RMSE (q ha^{-1})	nRMSE (%)	EF
ANN	0.87	0.58	0.76	8.00	0.86	0.94	0.38	0.46	10.00	0.89
PCA-ANN	0.94	0.33	0.50	55.00	0.94	0.85	0.38	0.58	12.00	0.83
LASSO	0.51	1.22	1.58	21.00	0.42	0.83	1.46	1.58	17.00	-0.21
Ridge Regression	0.537	1.19	1.63	21.78	0.39	0.90	1.59	1.81	19.63	-0.58
SMLR	0.53	1.10	1.43	19.15	0.53	0.88	0.64	0.72	7.82	0.74

Table 2. Information on the models used and the error percentage for Hamirpur

Model	Equation	Error percentage
ANN	No of hidden layers: 5	-120.76% to 16.52%
PCA-ANN	9; No of PC's: 5	-80.84% to 18.81%
LASSO	Y = 7.486 + 0.513 × Z11 + 0.269 × Z31 + 0.18 × Z251 + 0.206 × Z341	-195.80% to 20.36%
Ridge Regression	Y = 7.826 - 0.036 × Z10 + 0.123 × Z11 - 0.002 × Z20	-79.86% to 14.02%
SMLR	Y = 21.237 + 1.775 × Z11 + 0.014 × Z251 + 1.895 × Z31	-205.34% to 25.96%

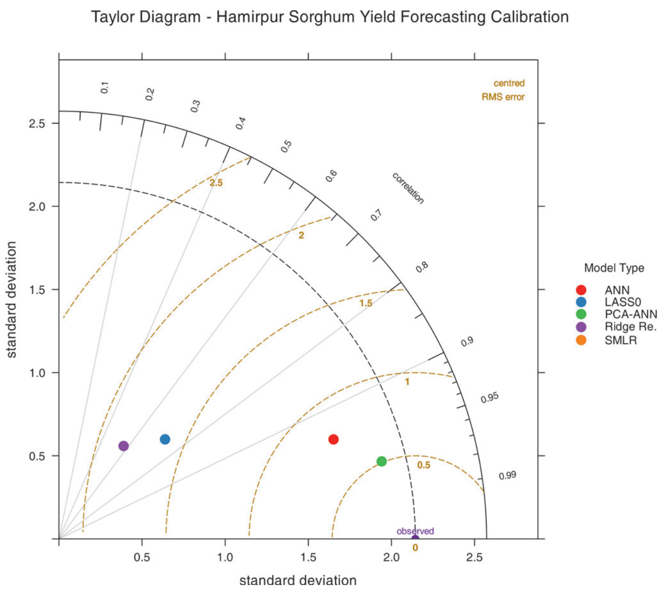

Figure 1. Taylor diagram for calibration

was less able to capture the observed variability. Both LASSO and Ridge Regression are found further away from the reference point, and have relatively smaller standard deviations and correlation. The higher RMSE values of their centered values suggest that they are less in agreement with the observed data and less able to calibrate as compared to the ANN-based approaches.

The performance of the validation was shown by the Taylor diagram in Figure 2. In all the models tested, the ANN model is closest to the reference point, which shows the greatest correspondence with the observed sorghum yield. It has a high correlation coefficient (about 0.94), standard deviation near that of the observed data and the lowest centered RMSE, indicating that it is the best model to reproduce the magnitude and variability of the observed yields. Validation statistics between these observations are in line with those for ANN, which had the highest adjusted R^2

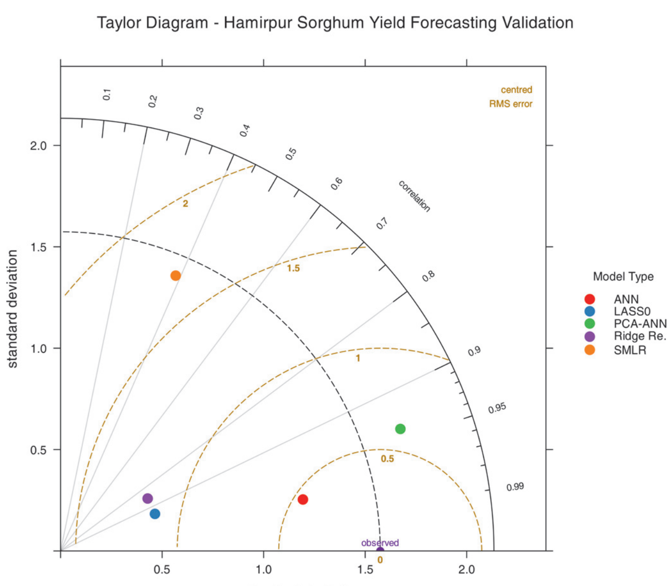

Figure 2. Taylor diagram for validation

(0.94), lowest RMSE (0.46 q ha^{-1}) and highest model efficiency (EF = 0.89). It can be seen that the PCA-ANN model is located slightly away from the reference point than ANN model, which means the correlation is slightly lower with a centered RMSE slightly higher than that of ANN. It was equally able to encompass the range of the observed data but its predictive ability was somewhat less than that of the ANN model in line with the statistical validation results. The SMLR model had moderate performance as it had a lower correlation coefficient and larger centered RMSE than the ANN based models. Also, its standard deviation was lower than the standard deviation of the observations, which indicated that it underestimated the yield variation of sorghum. The LASSO and Ridge Regression are the two farthest from the reference point, having comparatively low correlation coefficients, and very low standard deviations with higher centered RMSE values. performance, as they were not as effective as a constant (the observed mean) predictor.

DISCUSSION

The study tested the five models to forecast sorghum yield namely: ANN, PCA-based artificial neural network (PCA-ANN), LASSO, Ridge Regression and SMLR models. The outcomes indicated that the machine learning models, specifically ANN, achieved better performance over linear regression-based approaches in predicting Sorghum yield as compared to the other linear models. The PCA-ANN model had the highest predictive performance, with low prediction errors (MAE = 0.33 q ha^{-1} and

RMSE = 0.50 q ha^{-1}) during the calibration process. This is because the dimensionality reduction process used in PCA-ANN reduces the multicollinearity of the predictor variables and retains most of the information of the original dataset. PCA can decrease the redundancy of vegetation indices, which are highly correlated, allowing the neural network to learn the more stable relationships in model training. The result is in line with the previous studies that indicate that using the PCA with ANN yields better calibration accuracy due to reducing the dimensions of the input and noise (Aravind et al., 2022; Setia et al., 2022; Khan & Kumar, 2025; Singh et al., 2025). While PCA-ANN gave the best calibration statistics, the ANN model gave the highest validation accuracy (adjusted R^2 = 0.94, RMSE = 0.46 q ha^{-1}, MAE = 0.38 q ha^{-1} and EF = 0.89), which showed better generalisation to the independent set. Improved validation performance indicates that the ANN was able to estimate the complex and nonlinear relationships among the spectral indices and sorghum yield without dimensionality reduction. Neural networks can model complex interactions between the predictor variables that are not well captured by linear regression models. Therefore, ANN showed high prediction accuracy for the observations not previously seen, which demonstrates the robustness of the ANN for practical yield forecasting (Satpathi et al., 2023). The regression-based models, on the other hand, had relatively low predictive power. LASSO and Ridge Regression are two useful regularisation methods to reduce model complexity and multicollinearity, but they are based on the assumption that the relationship between predictor variables and crop yield is mostly linear. Many factors interact and affect sorghum yield, which means yield response is highly nonlinear, making linear modelling challenging. This restriction is seen in their lower adjusted R^2 values in their calibration and higher RMSE values and negative Nash–Sutcliffe efficiency (EF) for their validation. The poor prediction of the observations by the regression models compared to the mean observed yield (indicated by negative EF) suggests that the regression models may not be ideally suited for this application (Das et al., 2022; Khan & Kumar, 2025). The SMLR model seemed to outperform LASSO and Ridge Regression models and was still worse than ANN-based models. The stepwise regression only retained a subset of the vegetation indices that were significant in the prediction equation, which made the equation easier to understand and interpret. However, the limited predictive utility of this model may have been because nonlinear or interactive variables were not included. SMLR thus performed moderately well in terms of validation accuracy (adjusted $R^2 = 0.88$ and EF = 0.74), suggesting that linear relationships accounted for some of the yield variability but not all, as the crop growth dynamics were complex (Sridhara et al., 2020; Yadav et al., 2021).

CONCLUSION

ANN is the most useful and precise predictive model for forecasting sorghum yield in the conditions of the present study. While the PCA method was found to have reduced data redundancy and improved calibration performance, it did not improve the predictive performance on new data. Hence, the use of an ANN model is recommended for operational yield prediction of sorghum using the multispectral remote sensing data, and a PCA-ANN model may be useful where there is a need to reduce the number of computations or the availability of the predictor data sets are highly correlated. In general, the study revealed that the hybrid models, like the PCA-ANN, are more applicable to weather prediction in areas such as the Bundelkhand with erratic weather conditions. These models provide farmers, researchers and policy makers with the practical tools for controlling and planning agricultural output in the face of changing environmental conditions.

DECLARATIONS

Ethical approval and consent to participate: This study did not require ethical approval or consent to participate, and all the authors agree.

Availability of supporting data: Supporting data will be available upon request from the first and corresponding authors.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that create any potential conflict of interest. No conflict of interest among the authors.

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