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On Comparison of Classical and Machine Learning Models for Forecasting Rabi Green Gram Production in Odisha

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SUMMARY

Green gram is one of the major pulse crop of Odisha grown mostly during the Rabi seasons. Rabi green gram production accounts for approximately 51 percent of the total pulse production in Odisha. Data on production (in '000 MT) of rabi green gram are collected for the period from 1970-71 to 2023-2024. The entire data is splitted into two sets: training data set and testing/Cross validated data set. The data for the period from 1970-71 to 2019-20 for building training data set and 2020-21 to 2023-24 to be used as test data set/ cross validation data set. Classical Auto Regressive Integrated Moving Average (ARIMA) model and Artificial Neural Network (ANN) model is built for the training set data. Both the built-in models are compared on basis of Mean Absolute Percentage Error MAPE and Akaike Information Criteria Corrected (AIC_c) for the training set and test set data. The model performing better on basis of MAPE and AIC_c is selected for obtaining final forecast values of rabi green gram production.

ARIMA (2, 0, 0) fits best which after performing the BDS test for the residuals shows that both linearity and non-linearity is found in the data in ratio of 7:1. So hybrid ARIMA-ANN model is prescribed to be fitted with appropriate weightage to selected best fit ARIMA and ANN models. Out of the suitable NNAR models, NNAR (2, 3) model to be the best fit. So the hybrid ARIMA-ANN model is fitted with weightage of 0.875 to the selected best fit ARIMA (2,0,0) model and 0.125 to the selected best fit NNAR (2,3) model. The model fit statistics for the hybrid ARIMA-ANN model is found to be lower in case of training data set and testing data set. The forecast values of rabi green gram production obtained from the fitted hybrid ARIMA-ANN model are found to be decreasing in future years. Thus, it could be concluded that the advanced machine learning model definitely improves the accuracy of forecasting.

Keywords: Akaike Information Criteria Corrected; Forecasting; Hybrid ARIMA-ANN; linearity; Non- linearity.

1. INTRODUCTION

Pulses is regarded as vital sources of food, feed and fodder offering high quality protein at cheap rates to Indian vegetarians. Being the most important source of protein in Indian diet it is considered as a primary crop in farming. Odisha contributes 8 percent of pulse crop production in relation to India with Rabi season pulse crop contributing 31.77 percent, representing about 9 percent of the total land. Thus, production of green gram is crucial in the rural economy of the state of Odisha. This short-duration legume crop is typically produced in rotation with rice as a fallow crop.

In 2023-24, Odisha accounted for 82.4 per cent of the Rabi green gram cultivation in India. The area under green gram cultivation in Odisha decreased by 12.5 per cent in 2023-24 compared to the previous year. The average productivity of green gram in Odisha is 434 kg per hectare.

An efficient and precise prediction for area and output of significant green gram crops is crucial for agricultural policy-making, ensuring food and nutritional security for the population. Lagged values and stochastic error factors can be utilized to describe a time series using the ARIMA model. The linear component can be modelled by the ARIMA methodology (Rakshit and Paul, 2024). Using ARIMA approach, Sameerabanu (2024) forecast onion production in India. Employing a combination of classical statistical and machine learning models

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specifically ARIMA and NNAR Mishra *et al.* (2023) forecast pulse production in India and six major pulse producing Indian. The study by Devi *et al.* (2021) employs a hybrid time series model combining and ANN to forecast wheat production in Haryana, India. In order to represent series that incorporate nonlinear patterns, ANN model are widely used. ANNs can be used to describe time series structures that are both linear and nonlinear, although they are not equally effective at handling the two types. As a result, a hybrid method combining ANN and ARIMA models was employed. The goal of this study is to determine the best method for predicting the green gram production in Odisha. The study can help policymakers regarding understanding of future requirements, enabling them practice suitable policies for enhancing resource use efficiency, reduce risk of market volatility by anticipating supply and demand fluctuations, mitigate weather related adverse impacts on green gram production by forecasting climate variables

2. MATERIALS AND METHODS

Data on production (in '000 MT) of rabi green gram are collected for the period from 1970-71 to 2023-2024. The entire data is splitted into two sets: training data set and testing/Cross validated data set. The training data set have been used to build the model whereas, the testing/cross validated data set have been used to validate/test the selected built-in model. The data for the period from 1970-71 to 2019-20 for building training data set and 2020-21 to 2023-24 to be used as test data set/ cross validation data set.

Compound Annual Growth Rate:

$Y_t = ab^t$ (Dash, *et al.,* 2017)

Where, Y_t = Production of rabi green gram in years

t = time period (t=1, 2, 3…n)

a = intercept

b = regression coefficient

b = 1 + r/100

Where r = percentage rate of compound growth rate of production per annum

CAGR = (b - 1)* 100

2.1 Coppock's Instability Index:

The Coppock Instability Index (CII) is a statistical instrument that measures variability in agricultural variables such as area, production and yield while accounting for underlying trends. Unlike traditional measurements, the CII provides a "trend-free" view of fluctuations, successfully differentiating them from any persistent growth and decline in the agricultural sector. An elevated CII score indicates a greater degree of instability, providing important insights into the volatility of agricultural output across time. This makes it an important statistic for understanding agricultural dynamics in terms of both short-term fluctuations and long-term trends (Dash and Hansdah, 2020).

Coppock Instability Index (CII) =Antilog ($\sqrt{\log V}$ - 1)* 100

$$\log V = \frac{1}{N-1}\sum_{t=1}^{n}\left(\log\frac{X_{t+1}}{X_t} - m\right)^2$$

Where, log V = log variance

$$m = \frac{1}{n-1}\sum_{t=1}^{n}\log\frac{X_{t+1}}{X_t}$$

An ARIMA (p, d, q) model is a non-seasonal ARIMA model, where p is the number of autoregressive terms, d is the number of non-seasonal differences required for stationarizing the data, and q is the number of moving average terms.

Methodology for ARIMA model consists of:

(a) Determining values of p and q on the number of lagged observations of the response variable and the number of lagged errors. Parameter (d) indicates the appropriate number of differencing required to stationarise the data

(b) The AR and MA parameters of ARIMA models are estimated using maximum likelihood estimation (MLE).

(c) Model verification and accuracy measures suggest that model with the lowest MAPE, Akaike Information Criterion Corrected (AICc) and Bayesian Information Criterion (BIC) values is selected.

(d) After fitting the model, the presence of independency and white noise are tested from examination of the residuals. Model exhibiting white noiseis considered suitable for forecasting; otherwise, it is re-fitted until white noise is achieved. (Yeasin *et al.,* 2014)

The general forecasting equation for ARIMA model:

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \quad \text{(Garai } et\ al., \text{ 2024)}$$

Where, μ = mean of the stationary series

ϕ_1, ϕ_2..., ϕp = parametric coefficients of autoregressive terms

θ_1, θ_2 … θ_q = parametric coefficients of moving average terms

ε_t = error term at time t

N nonlinear least square and maximum likelihood methods are used for estimation of the parametric coefficients.. These techniques help in accurately capturing the underlying patterns by optimizing the model by minimizing the error between observed and predicted values. In this study, parameter estimation is performed using the R programming language.

2.2 Model Evaluation Criteria:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{\left| Y_i - \hat{Y} \right|}{Y_i} \times 100 \quad \text{(Dash } et\ al., \text{ 2020)}$$

Where, Y_i is the observed value or actual value of i^{th} year

$\hat{Y}$ is the forecasted value of i^{th} year

n is the number of observations

A lower MAPE indicates better model accuracy and reliability. (Paul *et al.,* 2023; Mitra and Paul, 2017)

Corrected Akaike Information Criterion (AICc):

AICc can introduce an extra penalty term that accounts for sampling bias

$$AIC_c = AIC + \frac{2k(k+1)}{n-k-1} \quad \text{(Sahu and Dash, 2022; Dibya and Dash, 2022)}$$

Where*n* is the total number of observations and *k* denotes the number of estimated parameters in the model. This adjustment makes AICc a more reliable choice for model comparison in case of limited data. The model having lower AIC_cvalue is selected as the best fit model.

Artificial Neural Networks (ANNs) are data-driven models capable of learning complex nonlinear relationships in time series data. An ANN model mimics the structure of biological neural systems, where interconnected neurons process inputs and transmit outputs through weighted links. In time series applications, the most commonly used ANN is the **single hidden layer feedforward network,** comprising

An input layer representing lagged values of the time series,

A hidden layer with a specified number of neurons processes the data through weighted sums and activation functions and

An output layer that produces the forecast/ final prediction.

The units are linked by different connection strengths known as weights. The input data is fed into the first layer, and the values are passed forward from each neuron to all neurons in the subsequent layer. The final output is produced by the output layer.

General equation for a multi-layer feed forward model is given by

$$Y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j g\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-p} \right) + \varepsilon_t \quad \text{(Pradhan and Dash, 2024)}$$

Where, α_j (j = 0, 1, 2, …, q) and β_{ij} (i = 0, 1, 2, …, p, j = 0, 1, 2, …, q) are model parameters/connection weights, p is the number of input nodes, q is the number of hidden nodes and g represents the activation function

Among the various activation functions, the logistic sigmoid function is widely employed, particularly within the hidden layers, and given by

$$g(x) = \frac{1}{1 + \exp(-y)}$$

The ANN model is represented by the following equation

$$Y_t = f\left(Y_{t-1}, Y_{t-2}, .., Y_{t-p}, w\right) + \varepsilon_t$$

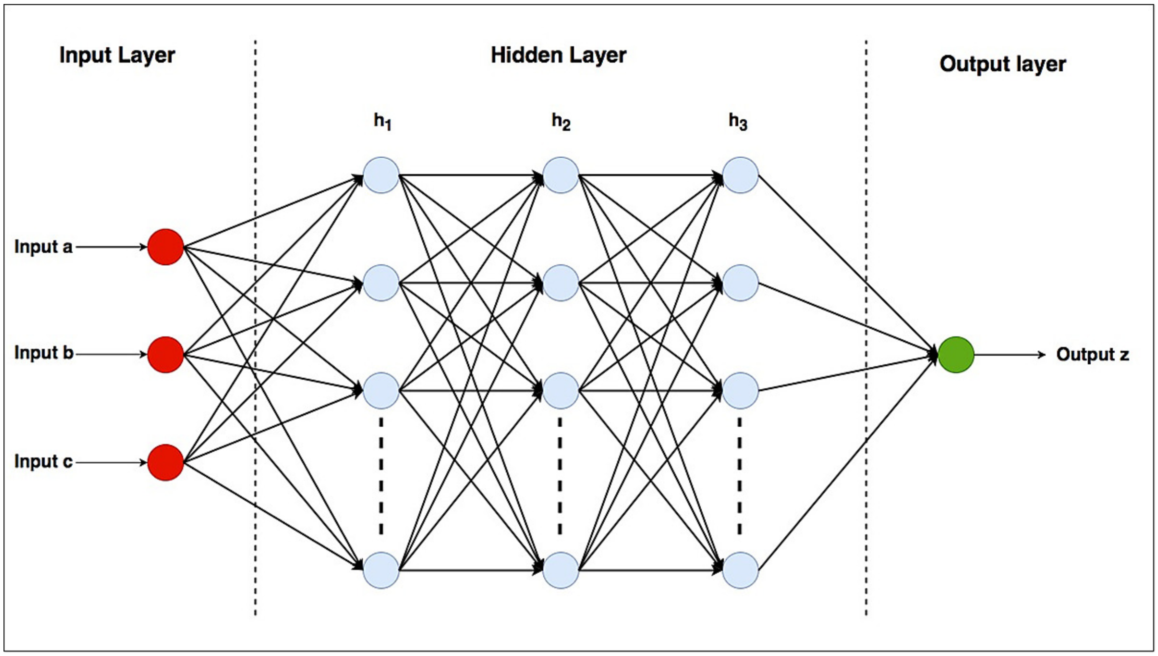

Fig. 1. BDS Test for Linearity of Residuals

Where, f captures the relationship based on the architecture and weights of the network, where presents the vector of model parameters, and ε_t denotes the error term or random noise.

The BDS (Brock-Dechert-Scheinkman) test is a nonparametric test used to detect the presence of nonlinearity present in time series data or in residuals obtained from ARIMA model. It helps determine whether a series is independently and identically distributed. It is used to evaluate whether the residuals left unexplained by a linear model contain hidden non-linear structure. The test is carried out at multiple embedding dimensions (m = 2, 3) and distance thresholds ($\varepsilon = 0.5\sigma_R$, σ_R, $1.5\sigma_R$, $2\sigma_R$, where σ_R is the standard deviation of residuals. For each combination, the BDS test statistic is computed, and a corresponding p-value is obtained. If all p-values are greater than 0.05, it indicates that the residuals exhibit linear behaviour, suggesting no significant nonlinear patterns and the ARIMA model is alone employed. If all p-values are less than 0.05, suggesting presence of nonlinearity in residuals then only the ANN model is used for forecasting. However, a mixed result indicates a combination of linear and nonlinear patterns in the residual series where a hybrid ARIMA-ANN model is very effective.

2.3 Hybrid ARIMA-ANN Model:

Time series data often exhibit a combination of linear and nonlinear patterns. The ARIMA model is effective for handling linear components in time, while ANN model are very efficient at modelling complex nonlinear relationships. Hybrid model consisting the features of both ARIMA and ANN model is very effective in forecasting / predictive analysis in such cases. In hybrid ARIMA–ANN framework, the ARIMA model is first employed to capture the linear component of the series. Then ANN model is employed to the residuals captured from the ARIMA model, which contain the nonlinear structure. The final forecast is obtained by combining the forecasts of both models. This approach leverages the strengths of both ARIMA and ANN, making it more capable of handling datasets that often contain both types of patterns. BDS test is applied to assess the presence of nonlinear structure in the ARIMA residuals and justify the use of ANN. Hybrid ARIMA-ANN model enhance the overall forecasting accuracy and outperform individual ARIMA and ANN model in various application.

2.4 Diagnostic Checks of Model Residuals

The residuals generated from ARIMA model is subjected to diagnostic testing to examine whether they meet the fundamental assumptions of normality and independence of error. The Shapiro–Wilk test is employed to evaluate the normality of the residuals, while the Box–Pierce test is used to examine the independence or lack of autocorrelation in the error terms.

2.5 Shapiro-Wilk's test for Normality:

Shapiro–Wilk test is applied to assess whether the residuals from the time series models follow a normal distribution. This test evaluates whether a given sample denoted by x_1, x_2, $x_{3...}x_n$ originates from a normally distributed population.

Null Hypothesis (H_0): The residuals are normally distributed.

Alternate Hypothesis (H_1): The residuals are non-normally distributed.

Test statistic:

$$W = \frac{\left(\sum_{i=1}^{n} a_i x_{(i)}\right)^2}{\sum_{i-1}^{n}\left(x_i - \bar{x}\right)^2}$$

Where $x_{(i)}$ represents the ordered sample values (from smallest to largest),

$\bar{x}$ is the sample mean and

a_i are coefficients derived from the expected values of the order statistics of a normal distribution

P value less than the fixed level of significance confirms rejection of null hypothesis

2.6 Box-Pierce Test:

The Box-Pierce test is employed to assess whether the residuals from a time series model are uncorrelated i.e. exhibit independence over time. This diagnostic tool helps verify if the model has successfully captured the temporal structure of the data, leaving random noise in the residuals.

Null Hypothesis (H_0): Data is distributed independently i.e. absence of autocorrelation

Alternate Hypothesis (H_1): Data is not independently distributed i.e. data possess autocorrelation

The test statistics is represented by the following formula:

$$BP(k) = N\sum_{k=1}^{h}\hat{\rho}_k^2$$

Where, $\hat{\rho}_k^2$ is the sample autocorrelation of the residuals at lag k

N ad k are number of observations and maximum number of lags respectively

P value less than the fixed level of significance confirms rejection of null hypothesis.

3. RESULTS AND DISCUSSION

Result are shown in form of tables and figure with the discussion as per below. Table 1 shows indicates positive growth forgreen gram production from 1970-71 to 2023-24 with high instability index. This shows that though production of green gram shows acceleration in Odishaduring rabi season, the high instability can be a matter of concern which may be due to substitution of green gram cultivation with other legume crops.

Study of Table 2 regarding estimates of coefficients for the various parameters involved in the modelconfirms ARIMA (2,0,0) and ARIMA (1,0,1) for having all the estimated coefficients significant. So these two models are considered for selection among the group of fitted ARIMA models.

The model validation test and accuracy measures for the fitted ARIMA models presented in table 3 shows that both the selected ARIMA models from table 2 satisfy the normality and independency of residuals. The ARIMA (2,0,0) with intercept is found to be bettere model than ARIMA (1,0,1) with intercept as it has lower MAPE and lower AIC value for the training set data. So ARIMA (2,0,0) with intercept is considered to the best fit ARIMA model fitted to production of rabi green gram in Odisha.

Table 4 represents the model validation test and accuracy measuresof the NNAR model fitted to the training and test dataset of rabi green gram production at lag 2 and one hidden layer with 1 to 4 nodes. Among all the models satisfying both the assumption of normality of residuals and independence of errors, the NNAR (2, 2) is selected as the as the best fitted model as it shows good performance with respect to both training and test data, and can be a robust choice for predicting rabi green gram production in Odisha. The diagnostic results from the NNAR (2,4) model have the lowest training error, indicating better fit but, the error of NNAR (2,4) is highest among all other models suggesting overfitting of dataset.

Table 5 shows the result of BDS test applied to the residuals obtained from ARIMA (2, 0, 0) with intercept model for production of rabi green gram in Odisha. The BDS test was performed at embedding dimensions 2, 3,4,5,6 and 7, for 0.5σ, σ, 1.5σ, and 2σ shows that eleven out of twenty-four epsilon values were significant (p-value < 0.05) for production. These findings suggest residual nonlinearity. Therefore, Hybrid ARIMA-ANN model could be fitted with weights 0.46 and 0.54 assigned to the best fit ARIMA (2, 0,0) with intercept and NNAR (2,2) model respectively.

Table 6 displays MAPE value for both train dataset and test dataset of the selected best fit ARIMA, ANN and Hybrid model. ARIMA (2, 0, 0) with intercept, a linear model that effectively captures linear relationship in data set as reflected by moderate MAPE values on training (18.76%) and test (18.55%) set data. NNAR (2,2), a nonlinear neural network model, fits training data better as represented by lower MAPE (15.97%) but suffers from over fitting, shown by a higher test MAPE (25.88%). The combined ARIMA-ANN model leverages the linearity and non-linearity in data setwith improved generalization with the lowest training MAPE (15.74%) and lowest test MAPE (16.62%). Therefore, for robust and accurate forecasting in agricultural research, the hybrid ARIMA-ANN model is recommended due to its superior predictive performance and ability to capture diverse data behaviours.

The results from the Hybrid ARIMA-ANN model forecasts given in Table 7 indicate a rise in production of rabi green gram in 2024-25 followed by gradual from 2025-26 to 2027-28. The upper 95 per cent confidence interval is higher in 2024-25 and lower 95 per cent confidence is lowest in 2026-27.

Figure 1 shows that the actual, fitted with forecast production of rabi green gram of the state. The study of figure shows that the actual and fitted values obtained from selected Hybrid ARIMA-ANN model run close to each other. The forecast value shows a rise in the first future year i.e. 2024-25 with gradual decline in the next three future years.

4. CONCLUSION

A brief summary of the analysis for rabi green gram is presented. Based on the BDS test and model evaluation statistics like MAPE, RMSE, AIC, the best fit models ARIMA, ANN, or hybrid ARIMA-ANN were selected for forecasting. In case of rabi green gram, the selected best fit model for data on production is ARIMA (2, 0, 0) with intercept as confirmed by the diagnostic tests. However, BDS results indicated presence of nonlinearity in the dataset. Thus, NNAR and Hybrid ARIMA-NNAR models were also evaluated. The NNAR (2, 2) is selected as the best fitted model as it shows good performance on both training and test data. The hybrid ARIMA(2,0,0)-NNAR(2,2) model outperformed others, achieving the lowest train error (MAPE 15.74 Per Cent) and lowest test error (MAPE 16.62%) for the data set, apprehending both patterns and can be the most robust choice for predicting rabi green gram production in Odisha. Forecast for 2024-2027 indicate that the production of rabi green gram slightly increases upton2024 and then gradually decreases over the years. The study also estimated the compound annual growth rate (CAGR) at 0.76%, highlighting marginal growth in production of rabi green gram. However, the Coppock's Instability Index (CII) was high at 48.27%, reflecting substantial fluctuations and volatility in production over the period. This high instability points to significant vulnerability and inconsistency in rabi green gram output despite the slight positive growth trend that can be attributed to substitution and green gram cultivation with other legume crops.

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TABLES AND FIGURES

Table 1. Estimate of CAGR (Compound Annual Growth Rate) and CII (Coppock's Instability Index) for production of rabi green gram in Odisha

Variable	CAGR (%)	CII (%)
Production	0.76*	48.27

* Significant at 5% level of probability

Table 2. Parameter estimates of the ARIMA Model fitted to production under rabi green gram

ARIMA(p,d,q)	Intercept	ϕ1	ϕ2	Θ1	Θ2
ARIMA(2,0,0)	236.02*** (0.0001)	0.44*** (0.0007)	0.33* (0.015)		
ARIMA(1,0,1)	236.63*** (0.0001)	0.87*** (0.0001)		-0.39** (0.005)	
ARIMA(1,0,2)	236.59*** (0.0001)	0.85*** (0.0001)		-0.45* (0.011)	0.14 (0.32)
ARIMA(2,0,1)	236.46*** (0.0001)	0.59 (0.08)	0.22 (0.37)	-0.17 (0.06)	

*** Significant at 0.1 % ** Significant at 1 % * Significant at 5 %

Table 3. Model diagnostic test with model fit statistics of the ARIMA Model fitted to production of rabi green gram

ARIMA (p,d,q)	Model Diagnostic Test		Model Fit Statistics		
	Shapiro-Wilk Test Statistic	Box-Pierce Test Statistic	Training Set Data		Test Set Data
			MAPE	AICc	MAPE
ARIMA (2,0,0)	**0.96 (0.072)**	**6.87 (0.73)**	**18.76**	**540.32**	**18.55**
ARIMA (1,0,1)	0.96 (0.072)	10.97 (0.94)	18.95	540.86	23.72
ARIMA (1,0,2)	0.95 (0.065)	12.07 (0.81)	18.67	542.38	22.01
ARIMA (2,0,1)	0.98 (0.081)	12.13 (0.91)	18.74	542.57	23.47

Table 4. Model Diagnostic test with Model Fit Statistics of the ANN Model fitted to production of rabi green gram in Odisha

NNAR Model	Shapiro-Wilk Test	Box-Pierce Test	Model Fit Statistics of training data		Model Fit Statistics of test data	
			RMSE	MAPE	RMSE	MAPE
NNAR(2,1)	0.95 (0.065)	0.008 (0.93)	44.01	16.34	106.58	26.15
NNAR(2,2)	**0.97 (0.081)**	**0.0002 (0.98)**	**40.18**	**15.97**	**106.76**	**25.88**
NNAR(2,3)	0.96 (0.072)	0.019 (0.88)	35.24	12.57	111.05	26.64
NNAR(2,4)	0.94 (0.061)	0.009 (0.92)	34.48	11.96	113.48	26.31

Table 5. BDS Test results for production of rabi green gram in Odisha

ARIMA(2,0,0) with non-zero mean fitted to production of rabi green gram of Odisha				
Embedding Dimension	**Standard normal value of epsilon for close point**			
	0.5σ = 24.6176	**σ = 49.2352**	**1.5σ = 73.8528**	**2σ = 98.4704**
2	4.31* (0.0001)	1.86 (0.06)	1.67 (0.09)	0.33 (0.74)
3	2.76* (0.0057)	1.65 (0.09)	2.11* (0.03)	0.41 (0.67)
4	2.77* (0.0056)	1.25 (0.21)	1.94 (0.052)	0.35 (0.72)
5	6.11* (0.0001)	1.15 (0.25)	2.04* (0.04)	0.43 (0.66)
6	6.34* (0.0001)	1.35 (0.17)	2.22* (0.02)	0.45 (0.65)
7	-3.09* (0.0019)	2.08* (0.037)	2.50* (0.01)	0.52 (0.60)

* Significant at 5 %

Table 6. Comparison of performance of selected ARIMA, ANN and Hybrid ARIMA-ANN model fitted to the data on rabi green gram production

Model	**Weights**		**Model Fit Statistics**	
			MAPE	
	ARIMA	**NNAR**	**Training Set Data**	**Test Set Data**
ARIMA(2,0,0) with intercept	-	-	18.76	18.55
NNAR(2,2)	-	-	15.97	25.88
Arima(2,0,0) with intercept **+NNAR(2,2)**	**0.46**	**0.54**	**15.74**	**16.62**

Table 7. Forecasted value of Hybrid ARIMA-ANN model

Year	**Point Forecast**	**Lo 95**	**Hi 95**
2024-25	271.52	142.69	401.53
2025-26	268.79	134.04	398.36
2026-27	266.47	127.06	395.25
2027-28	264.56	121.59	392.41

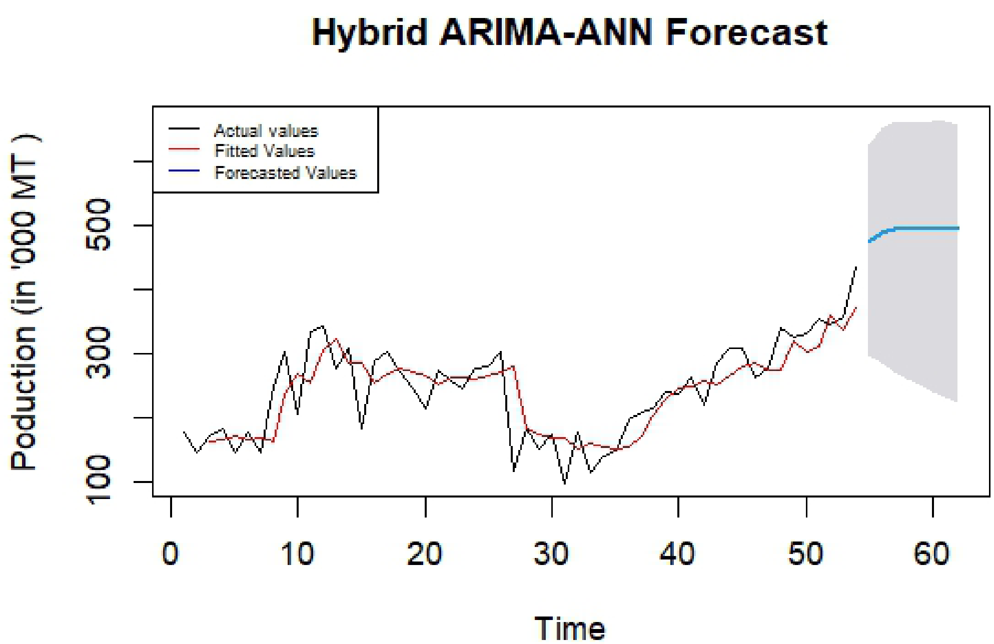

Fig. 1. Actual, fitted and forecasted values of production of rabi green gram