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Forecasting of Rice Production in India using Linear Time Series Models

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ABSTRACT: Time series analysis is a vital tool for examining agricultural production trends, enabling evidence-based planning, policymaking and efficient resource management. This study investigates the long-term production trends of rice in India from 1950–51 to 2022–23 using linear time series models. Among the models tested, Holt's Exponential Smoothing emerged as the most suitable for capturing the trend and variability in rice production. The analysis indicates a generally positive growth trajectory for rice, with moderate fluctuations over the years. Forecasts from 2024 to 2032 project continued growth in rice production, underscoring the need for strategic interventions. To sustain and amplify this growth, the adoption of high-yielding seed varieties, modern cultivation practices and improved agricultural infrastructure is essential. The study's findings provide a critical foundation for informed policy formulation and sustainable agricultural development aimed at ensuring long-term food security and meeting the rising demand of India's growing population.

Keywords: Time series analysis, Forecasting, ARIMA and Exponential Smoothing etc.

INTRODUCTION

India's economy is significantly reliant on agriculture, which contributes 18.20 per cent to the country's GDP and supports the livelihoods of approximately 42.30 per cent of the population (Anonymous, 2024). Agriculture is pivotal in ensuring food availability across global, national, and local levels, especially in agriculture-dependent countries. As the backbone of food security, it underscores the critical importance of sustained and efficient food production systems (Ray and Bhattacharyya 2020). India stands as the largest producer and exporter of cereal products globally, with rice accounting for 95 per cent of total cereal exports in the fiscal year 2023–24. The total value of cereal exports during this period was ₹9.10 lakh crore, underscoring rice's dominant role in India's agri-export portfolio. In 2023–24, rice production reached 136.7 million tonnes, reinforcing India's critical contribution to global food supply (APEDA, 2024).

As of 2024, India, with an estimated population of 1.48 billion, is the world's most populous country, and this figure is projected to reach 1.56 billion by 2025 (Chaurasia, 2020). This growing population highlights the urgency of maintaining and enhancing agricultural production systems to ensure food security, meet nutritional needs and support economic growth.

Rice holds a central position in India's agriculture and dietary systems, making the country the second-largest producer and consumer of rice globally, after China. India also leads the world in the area under rice cultivation. More than half of the population depends on rice as a staple food, particularly in the eastern and southern regions, where it is primarily cultivated during the Kharif season (Annamalai and Johnson 2023). Extensive research has been undertaken on rice production trends in India and globally, focusing on identifying challenges, opportunities, and pathways for improvement. Time series forecasting models such as ARIMA and Exponential Smoothing are widely used to predict agricultural production trends (Celik, 2016; Masood *et al.*, 2018; Biswas and Bhattacharyya 2019; Akanni and Adeniyi 2020; Dharmaraja *et al.*, 2020; Devi *et al*., 2021; Mishra *et al*., 2021; Annamalai and Johnson 2023; Bezabih *et al*., 2023).

Muhammed Irshad *et al.* (2024) developed a conventional linear model, ARIMA (2, 1, 1), and an advanced machine learning nonlinear model, NNAR (5, 3), based on proper model selection criteria. These models were then compared to determine the best one, and it was found that NNAR (5, 3) is the most effective model for forecasting the weekly black pepper prices in Kerala.

Such studies are critical for addressing challenges posed by climate change, resource constraints and evolving dietary patterns. Accurate forecasting of rice production is vital for ensuring food security, formulating sound agricultural policies and promoting sustainable practices. By employing predictive analytics, India can mitigate risks and strengthen the resilience of its rice production systems. In this context, the present study aimed to forecast rice production in India for the period 2024 to 2032 using ARIMA and Exponential Smoothing models. The findings offer a systematic understanding of production trends and support the development of data-driven strategies to ensure long-term food security.

METHODOLOGY

The production data for rice from 1950-51 to 2022-23, was obtained from Ministry of Agriculture & Farmers Welfare Government of India. Time series forecasting models were employed to analyze the production trends. The most suitable models were selected based on their performance metrics, including the Bayesian Information Criterion (BIC), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE).

ARIMA model. The Autoregressive Integrated Moving Average (ARIMA) model combines past values and past error terms to forecast time series data. The equation for the ARIMA(p, d, q) model can be expressed as follows:

$$Yt=\varphi_1 Y_{t-1}+\varphi_2 Y_{t-2}+\ldots+\varphi_p Y_{t-p}+\alpha_1-\theta_1\alpha_{t-1}-\alpha_2-\theta_2\alpha_{t-2}-\ldots-\alpha_q-\theta_q\alpha_{t-q},$$

Where φ_p represents the parameter values relating to the AR operator, α_q is the error term coefficient, θ_q represents the parameter values relating to the MA operator, and Y_t represents the data with d_{th} differences of the original data (Brockwell an Davis 2016; Gujarati *et al.,* 2012).

ARIMA (p, d, q) model building has different steps.

(i) *Stationarity:* Tested using the augmented Dickey-Fuller (ADF) test.

(ii) *Identification:* Orders p and q are determined via ACF and PACF plots.

(iii) *Estimation:* Parameters are estimated using nonlinear least squares.

(iv) *Diagnostic Checking:* Residuals are tested for white noise to assess model adequacy.

(v) *Forecasting:* If residuals are satisfactory, the model is used for prediction.

Exponential smoothing. Exponential smoothing generates forecasts by assigning exponentially decreasing weights to past observations, giving more importance to recent data (Hyndman, 2008). It is suitable for data without clear trend or seasonality. Basic equation for exponential smoothing

$$\mathbf{F_t = \alpha Y_t + (1-\alpha)F_{t-1}}$$

Where:

F_t = Forecast for the current period t

Y_t= Actual observation for the current period t

F_{t-1} = Forecast for the previous period t-1

α= Smoothing parameter ($0\leq\alpha\leq1$)

The value of alpha, ranging between 0 and 1, determines the weight assigned to the most recent observation. As α approach 1, greater weight is placed on the most recent data point, while as α approaches 0, more weight is given to the previous forecast. Exponential smoothing is a straightforward and adaptable forecasting technique applicable to a broad range of time series data. However, it does have limitations, such as the assumption of a constant level of trend and seasonality in the data. It may not perform well for time series with irregular patterns or extreme fluctuations (Hyndman, 2008).

Testing for Stationarity

Augmented Dickey Fuller Test. The standard Dickey Fuller unit-root test performs a simple regression in the form of equation

$$\Delta y_t = (a-1)\, y_{t-1} + \varepsilon_t$$

This test is applied when the underlying data-generating process is assumed to have no high-order lags. If higher-order lags are present, the Dickey-Fuller test becomes misspecified, and the standard errors are rendered unreliable. To address this issue, the augmented Dickey-Fuller test is commonly employed, which is represented by the following equation.

$$\Delta y_t = \beta_0 + (\alpha-1)\, y_{t-1} + \Sigma\alpha_i\, \Delta y_{t-1} + \varepsilon_t$$

A unit root in this context refers to the modulus of the roots of the AR polynomial to be smaller than unity and for the MA polynomial to lie inside the unit circle, which renders the MA part non-invertible. A time series is considered stationary if it does not contain a unit root. Stationarity can be achieved using the differencing method. To achieve stationarity in a time series, first-order differencing is applied if the series has one unit root. For series with two unit roots, second-order differencing is required, with higher-order differencing applied progressively based on the number of unit roots.

RESULTS AND DISCUSSIONS

Descriptive statistics, including measures such as mean, range, standard deviation, skewness and kurtosis, are essential tools for analyzing and understanding the fundamental characteristics of data (Das *et al*., 2019). The Table 1 presents the descriptive statistics for rice production in India from 1950 to 2023. During this period, rice production ranged from a minimum of 20.58 million tonnes to a maximum of 137.83 million tonnes, with a range of 117.25 million tonnes. The average production was 67.13 million tonnes, with a standard deviation of 31.94 million tonnes, indicating considerable variability over the years. The distribution of rice production was mildly right-skewed, as indicated by a skewness of 0.37, suggesting a tendency toward higher production values in more recent years. The kurtosis value of -0.95 indicates a distribution with flatter tails than the normal distribution, implying fewer extreme values.

Stationarity in a time series implies that its mean, variance and autocorrelation structure remain constant over time. To evaluate the stationarity of rice production data in India, the Augmented Dickey-Fuller (ADF) test was employed. The test statistic obtained for rice was 1.78, which is smaller than the critical values at the 1 per cent (4.10), 5 per cent (3.47), and 10 per cent (3.16) significance levels. Since the test statistic does not exceed any of the critical values, the null hypothesis of a unit root could not be rejected, indicating that the rice production series is non-stationary. Given the non-stationary nature of the data, first-order differencing was performed to make the data stationary. Subsequently, the correlogram for ACF and PACF was obtained, as shown in Fig. 1.

After ensuring stationarity, ARIMA and Exponential Smoothing models were applied to the transformed data. Various combinations of p, d, q values were determined from the ACF and PACF plots for fitting ARIMA model and the best-fitted model for each crop was identified, as shown in Table 3. The performance of forecasting models for rice production was evaluated using standard metrics, including Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Maximum Absolute Percentage Error (MaxAPE), Mean Absolute Error (MAE), Maximum Absolute Error (MaxAE), Bayesian Information Criterion (BIC), and the Ljung-Box test for residual autocorrelation. Among the models assessed, Holt's exponential smoothing model emerged as the best fit for rice, yielding the lowest BIC value of 3.31, along with a competitive RMSE of 5.00, MAPE of 6.20, and MaxAPE of 28.84. The residuals derived from the best-fitting model, were plotted as shown in Fig. 2 to examine whether they were white noise or uncorrelated, which is essential for reliable forecasting. The residual ACF and PACF plots indicate that autocorrelations and partial autocorrelations fall within the 95 per cent confidence limits, as depicted in Fig. 3. This confirms the models' good fit and adequacy for forecasting. Based on these models, the forecasts for rice obtained, as presented in Table 4 and Fig. 3. The forecasts showed a positive growth trend from 2024 to 2032, suggesting a steady increase in crop yields and production over the forecast period. This upward trend may be attributed to factors such as improvements in agricultural practices, advancements in crop management techniques and favorable climate conditions. Furthermore, technological innovations and policy interventions aimed at enhancing agricultural productivity are likely to contribute to this positive trajectory.

Table 1: Descriptive statistics for rice production (million tonnes) in India from 1950-2023.

Range	Minimum	Maximum	Mean	Standard dev	Skewness	Kurtosis
117.25	20.58	137.83	67.13	31.94	0.37	-0.95

Table 2: Augmented Dickey-Fuller Test for rice.

Test statistic	1% critical value	5% critical value	10% critical value
1.78	4.10	3.47	3.16

Table 3: Best time series model fitted under Rice production (million tonnes).

Model	RMSE	MAPE	Max APE	MAE	MaxAE	BIC	Ljung- Box (Q) statistics	Sig.
(Holt) Exponential Smoothing	**5.00**	**6.20**	**28.84**	**3.39**	**20.65**	**3.31**	**11.19**	**0.79**
ARIMA (0,1,1)	4.90	6.25	29.72	3.50	21.34	3.35	12.61	0.76
ARIMA (1,1,1)	4.92	6.29	29.44	3.42	21.14	3.42	11.71	0.76
ARIMA (2,1,0)	5.03	6.49	29.21	3.67	20.97	3.46	12.73	0.69

Table 4: Forecasted value of Rice production (million tonnes) from 2024-2032.

Model		2024	2025	2026	2027	2028	2029	2030	2031	2032
	Forecast	139.08	143.10	147.11	151.12	155.14	159.15	163.16	167.17	171.19
	UCL	149.07	153.66	158.48	163.54	168.81	174.29	179.96	185.79	191.78
	LCL	129.10	132.53	135.74	138.71	141.46	144.00	146.36	148.56	150.60

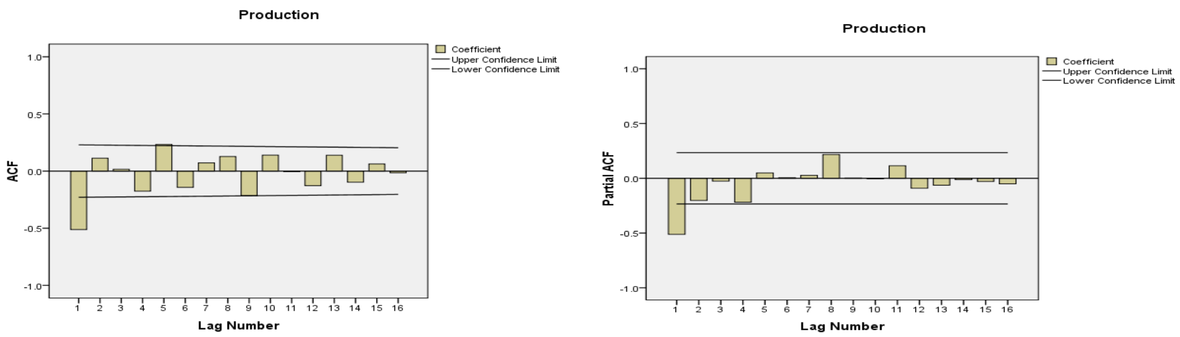

Fig. 1. Correlogram of ACF and PACF for first differenced production dataset.

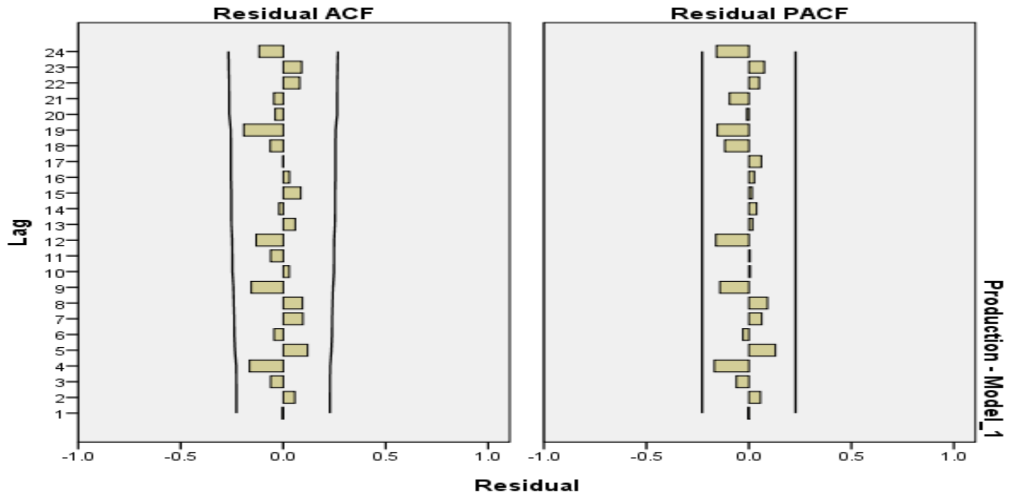

Fig. 2. Residual ACF and PACF of best fitted Exponential smoothing model.

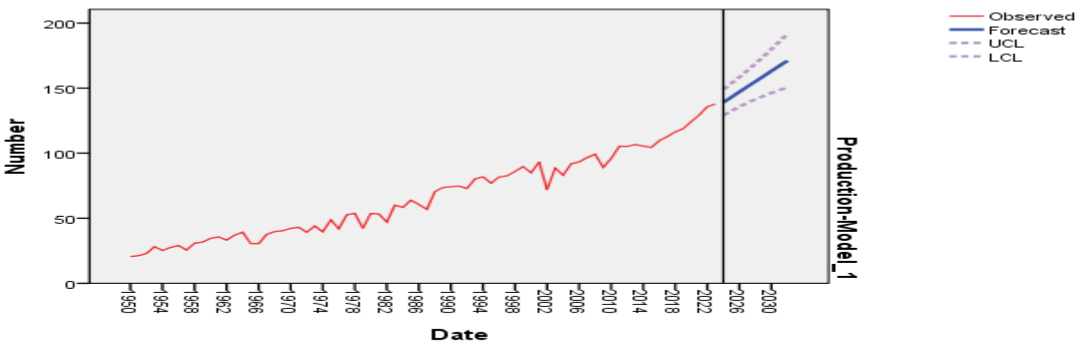

Fig. 3. Forecasting of Rice production (2024-2032).

CONCLUSIONS

Time series analysis for forecasting is a valuable tool for predicting future values based on historical data. The identification of the best-fitted time series model, along with the resulting forecasting patterns, can play a crucial role in addressing future food security challenges and guiding policy-making in India. These forecasts provide actionable insights for policymakers to develop strategic interventions. To sustain the projected growth in production, it is crucial to promote climate-resilient practices, adopt high-yield seeds and implement precision farming technologies. Additionally, strengthening farmer capacities through training and financial support will play a vital role in enhancing productivity and resilience. These findings serve as a crucial resource for researchers and policymakers, offering a roadmap for developing sustainable agricultural strategies that ensure long-term food security and agricultural growth.

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