

# FORECASTING RICE AREA, PRODUCTION AND PRODUCTIVITY IN INDIA USING ARIMA AND HYBRID ARIMA–ANN MODELS

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## Abstract

Rice is one of the most important food crops in India and plays a crucial role in national food security, agricultural growth and rural livelihoods. Accurate forecasting of rice area, production and productivity is therefore essential for agricultural planning and policy formulation. The present study evaluates the forecasting performance of the Autoregressive Integrated Moving Average (ARIMA) model and a hybrid ARIMA–Artificial Neural Network (ARIMA–ANN) model for India's rice area, production and yield. Annual time-series data covering the period 1961–2023 were analysed. The data from 1961–2018 were used for model development, while observations from 2019–2023 were reserved for out-of-sample validation. Descriptive statistics, normality tests, runs tests, Augmented Dickey–Fuller (ADF) tests and Ljung–Box tests were employed to investigate the statistical characteristics of the series. All three original series were found to be non-stationary, whereas first differencing achieved stationarity. Auto-ARIMA identified ARIMA(4,1,0) as the most suitable model for rice area and ARIMA(0,1,1) for both production and yield. Forecast accuracy was assessed using MAE, RMSE, MAPE,  $R^2$  and MASE. ARIMA performed marginally better than ARIMA–ANN for area and production, whereas the hybrid model showed slightly better performance for yield. Future forecasts for 2024–2033 indicate an overall increase in rice production and productivity, with comparatively slower growth in cultivated area. The findings suggest that productivity improvement will remain an important driver of future rice production growth in India. The study demonstrates the usefulness of both classical and hybrid time-series approaches for agricultural forecasting and provides evidence for informed agricultural planning.

**KEYWORDS:** Rice forecasting; ARIMA; Artificial Neural Network; Hybrid ARIMA–ANN; Time series; India; Agricultural production

## INTRODUCTION

Rice is a major staple crop and occupies a central position in India's agricultural economy. Changes in rice area, production, and productivity have direct implications for food availability, farm income, market stability, and national food security. Reliable forecasts of these indicators can support policymakers, agricultural scientists, and planners in making timely decisions regarding production planning, input management, storage, and food-security strategies.

Agricultural time series often exhibit trend, autocorrelation, and non-stationarity. These characteristics require systematic identification and transformation before appropriate forecasting models can be developed (Box et al., 2015; Montgomery et al., 2015). Classical autoregressive integrated moving average (ARIMA) models are widely used for time-series forecasting because of their ability to model linear temporal dependence after appropriate differencing and model identification procedures (Box & Jenkins, 1976; Box et al., 2015). Stationarity is a fundamental consideration in ARIMA modelling, and formal unit-root tests such as the Dickey–Fuller test are commonly used to examine this property (Dickey & Fuller, 1979). Model adequacy can subsequently be assessed using residual diagnostics, including the Ljung–Box test for remaining autocorrelation (Ljung & Box, 1978).

However, ARIMA models may not adequately represent nonlinear relationships that can occur in complex time-series processes. Artificial neural networks (ANNs), on the other hand, are flexible nonlinear modelling techniques capable of learning complex relationships from historical observations. Their application in agricultural and production forecasting has therefore received increasing attention (Ghosh & Kumar, 2021). Nevertheless, ANN models may sometimes be less effective in explicitly representing linear stochastic structures that are efficiently handled by conventional statistical models.

The hybrid ARIMA–ANN approach combines the strengths of linear and nonlinear modelling. Under this approach, ARIMA captures the linear component of the series, while ANN is intended to improve forecasting by modelling

nonlinear residual structures. This hybrid modelling philosophy was formally demonstrated by Zhang (2003), who showed the potential advantages of combining ARIMA and neural network models for time-series forecasting. More recently, comparative studies have continued to evaluate the relative performance of ARIMA, ANN, and hybrid ARIMA–ANN approaches across different forecasting applications (Alsuwaylimi, 2023). Comparing ARIMA with a hybrid ARIMA–ANN model can therefore provide useful evidence regarding the nature of agricultural time-series dynamics and the potential advantages of hybrid modelling.

The present study uses long-term annual data on rice area, production, and yield in India from 1961 to 2023. The major objectives were: (i) to examine the statistical and time-series characteristics of rice area, production, and yield in India; (ii) to test the stationarity and autocorrelation properties of the three series; (iii) to develop appropriate ARIMA models using the Auto-ARIMA procedure; (iv) to develop and compare ARIMA and hybrid ARIMA–ANN forecasting models; (v) to evaluate the out-of-sample forecasting performance of the competing models using established forecast accuracy measures such as MAE and RMSE (Willmott & Matsuura, 2005; Chai & Draxler, 2014; Hyndman & Koehler, 2006); and (vi) to forecast India's rice area, production, and yield for the period 2024–2033.

## 2. MATERIALS AND METHODS

### 2.1 Data Source and Study Period

The present study was based on secondary time-series data on rice area harvested, production, and yield in India. The data were obtained from the Food and Agriculture Organization of the United Nations (FAO) through the FAOSTAT database (Food and Agriculture Organization of the United Nations [FAO], 2024). Annual observations covering the period 1961 to 2023 were considered for the analysis, providing a total of 63 years of observations. The variables included in the study were area harvested, production, and yield (productivity) of rice in India.

FAOSTAT was selected as the data source because it provides internationally standardized agricultural statistics covering countries and territories worldwide and disseminates data on crop area harvested, production quantity, and yield. The database compiles agricultural statistics primarily from official national sources, together with other validated sources where necessary, making it suitable for long-term comparative and time-series analyses.

The collected data were screened for completeness and consistency and arranged chronologically to construct separate annual time series for rice area, production, and yield in India. The resulting dataset was subsequently used for statistical analysis, model development, evaluation, and forecasting.

For model development and validation, the complete dataset was divided into two subsets. Data from 1961 to 2018 were used as the training dataset for model identification, parameter estimation and model development. The remaining observations from 2019 to 2023 were retained as an independent testing dataset to evaluate the out-of-sample forecasting performance of the developed models. The complete data analysis, time-series modelling, diagnostic testing and forecasting were carried out using R- Studio statistical and computational software. The ARIMA models were estimated using time-series analysis procedures, while the hybrid ARIMA–ANN models were developed using machine-learning and neural-network algorithms.

### 2.2 Data Pre-processing

The collected data were examined for completeness, consistency and chronological order before analysis. The variables were organized into three separate univariate time series representing rice area, production and yield. Preliminary exploratory analysis was conducted using graphical and descriptive statistical techniques to identify the general pattern, trend and variability of each series.

The basic descriptive measures calculated included mean, standard deviation, variance, minimum, maximum, coefficient of variation, skewness and kurtosis. The coefficient of variation was calculated as:

$$CV = \frac{SD}{\bar{X}} \times 100$$

where (SD) is the standard deviation and ( $\bar{X}$ ) is the arithmetic mean.

Normality and randomness tests were also performed to understand the distributional and sequential characteristics of the data. Time-series plots were used to visually examine long-term trends and fluctuations in rice area, production and productivity.

### 2.3 Stationarity Test

Stationarity is an important prerequisite for the development of ARIMA models. A stationary time series has statistical properties, such as mean and variance that remain relatively stable over time. The Augmented Dickey–Fuller (ADF) test was used to examine the stationarity of the rice area, production and yield series. The null hypothesis of the ADF test is that the series contains a unit root and is non-stationary.

H<sub>0</sub>: The Time series contains a unit root and is non-stationary

H<sub>1</sub>: The time series is stationary

The test was initially applied to the original series. Where the series was found to be non-stationary, differencing was applied. First-order differencing was calculated as:

$$\nabla Y_t = Y_t - Y_{t-1}$$

where  $Y_t$  represents the observation at time (t), and  $Y_{t-1}$  represents the observation in the preceding year. The ADF test was subsequently applied to the differenced series to confirm the achievement of stationarity.

## 2.4 Autocorrelation Analysis

The temporal dependence of the rice variables was examined using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). These plots were used to understand the relationship between current and past observations and to assist in identifying potential autoregressive and moving-average structures (Fig 1).

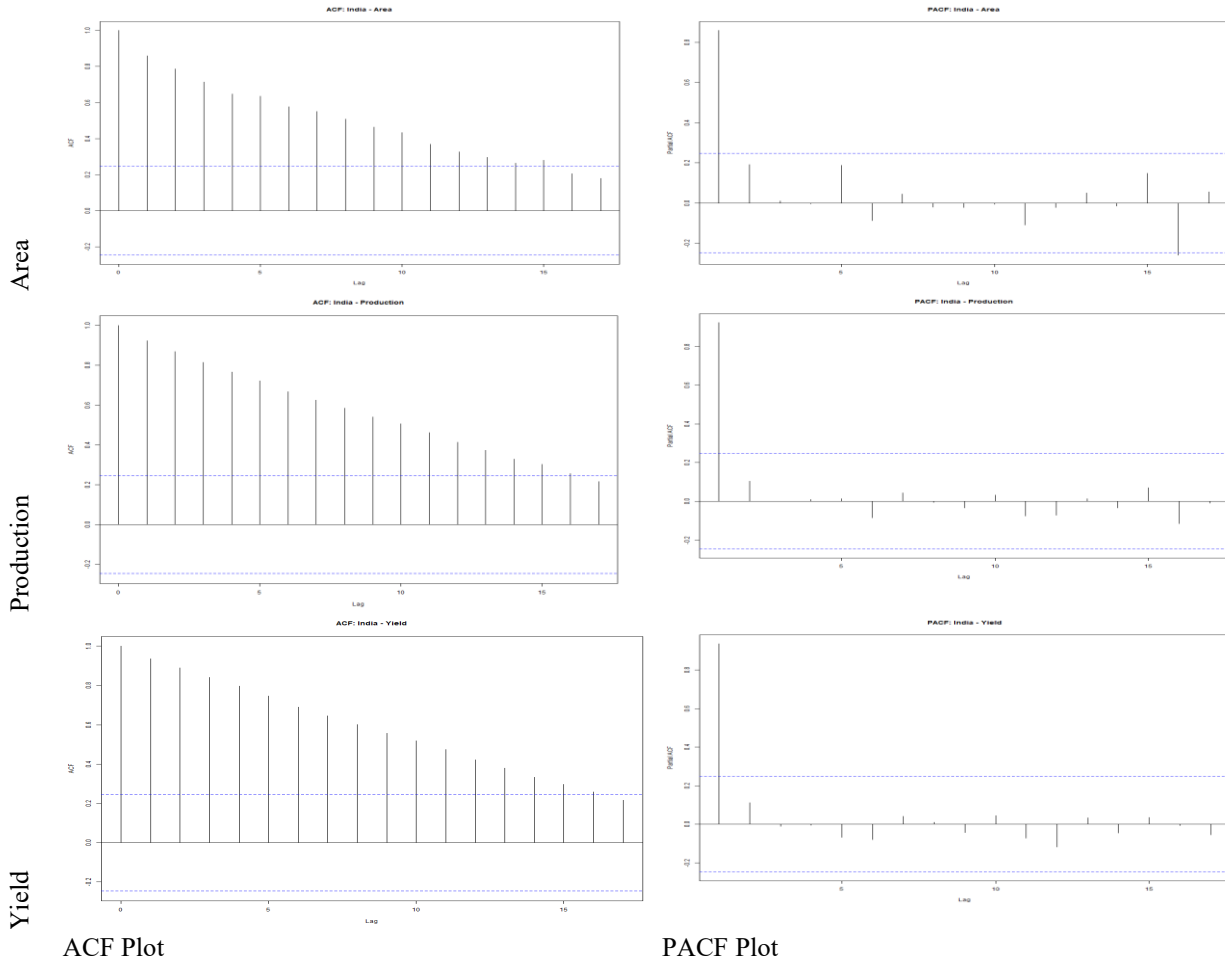


Fig. 1 ACF and PACF Plot

The Ljung–Box test was also used to test for the presence of significant autocorrelation in the time series and in the residuals of the fitted models. The null hypothesis of the test was that the autocorrelations up to a specified lag were jointly equal to zero.

A statistically significant result for the original series indicates the presence of serial dependence, whereas a non-significant result for model residuals indicates that the remaining errors approximately behave as white noise.

## 2.5 ARIMA Model Development

The Autoregressive Integrated Moving Average (ARIMA) model, introduced by Box and Jenkins (1976), remains one of the most widely used statistical approaches for univariate time-series forecasting. The ARIMA model is characterized by three parameters:

- **p**: the order of the autoregressive term,
- **d**: the degree of differencing, and
- **q**: the order of the moving average term.

Parameter identification was carried out by examining the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. The time series was differenced ( $d = 1$ ) to achieve stationarity, and model orders ( $p, q$ ) were determined by observing where the ACF and PACF tails decay. The general ARIMA model is expressed as:

$$Z_t - b_1 Z_{t-1} - \dots - b_p Z_{t-p} = U_t - \phi_1 U_{t-1} - \dots - \phi_q U_{t-q}$$

Where

$Z_t = Y_t - \bar{Y}$  (Deviation of  $Y_t$  from mean  $Y$ )

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to select the optimal (p, d, q) parameters. The model was implemented using the tseries package in R-Studio. The selected ARIMA models were further examined through residual diagnostics, including the Ljung–Box test, to ensure that significant autocorrelation was not retained in the residuals.

## 2.6 Hybrid ARIMA–ANN Model

To account for possible nonlinear patterns not completely captured by the ARIMA model, a hybrid ARIMA–Artificial Neural Network (ARIMA–ANN) model was also developed. The hybrid modelling approach assumes that an observed time series consists of linear and nonlinear components:

$$Y_t = L_t + N_t + e_t$$

where:

- $Y_t$  is the observed value at time (t);
- $L_t$  is the linear component;
- $N_t$  is the nonlinear component; and
- $e_t$  is the random error.

In the first stage, the ARIMA model was fitted to capture the linear temporal structure of the series. In the second stage, an Artificial Neural Network was employed to model the remaining nonlinear patterns. The final hybrid forecast was obtained by combining the forecasts generated from the linear ARIMA and nonlinear ANN components:

$$\hat{Y}_t = \hat{L}_t + \hat{N}_t$$

This hybrid approach was used to determine whether the incorporation of nonlinear modelling could improve forecasting accuracy compared with the conventional ARIMA approach.

## 2.7 Model Validation and Forecast Evaluation

The forecasting ability of the ARIMA and hybrid ARIMA–ANN models was evaluated using the independent testing period from 2019 to 2023. Forecasted values were compared with the actual observations reported in the FAOSTAT dataset. After parameter estimation, diagnostic checking was conducted to verify model adequacy and predictive performance. Competing models were compared based on the following evaluation criteria:

**Mean Absolute Error (MAE)** The Mean Absolute Error (MAE) is one of the most widely used performance metrics for evaluating the accuracy of time-series forecasting models. It quantifies the average magnitude of errors between predicted and actual observations, without considering their direction (i.e., whether over- or under-prediction occurs). MAE provides an easily interpretable measure of forecast accuracy in the same unit as the original data, Willmott, C. J., & Matsuura, K. (2005) and Chai, T., & Draxler, R. R. (2014). Mathematically, MAE is defined as:

$$MAE = \frac{1}{N} \sum_{i=1}^N |Y_i - \hat{Y}_i|$$

where:

- $Y_i$  = actual observed value at time i,
- $\hat{Y}_i$  = forecasted value at time i, and
- $N$  = total number of observations.

A lower MAE value indicates a more accurate forecasting model.

**Mean Squared Error (MSE)** The Mean Squared Error (MSE) is a fundamental and widely adopted statistical measure used to assess the accuracy of predictive and forecasting models. It quantifies the average squared difference between the actual and predicted values, providing an aggregate measure of model performance, Hyndman, R. J., & Koehler, A. B. (2006) and Chai, T., & Draxler, R. R. (2014). MSE evaluates how close the model's predictions are to the observed data and penalizes larger deviations more heavily due to the squaring operation. Mathematically, MSE is defined as:

$$MSE = \frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2$$

where:

- $Y_i$  = actual observed value at time i,
- $\hat{Y}_i$  = forecasted value at time i, and
- $N$  = total number of observations.

**Root Mean Square Error (RMSE):** Quantifies the average magnitude of forecast errors.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (Y_i - \hat{Y}_i)^2}{N}}$$

Where,  $Y_i$  is the Actual value,  $\hat{Y}_i$  is the predicted value and  $N$  is the number of observation

**Coefficient of Determination ( $R^2$ ):** Measures the proportion of variance in the dependent variable explained by the model. A value closer to 1 indicates a better fit, Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2015).

$$R^2 = \frac{SS_{\text{reg}}}{SS_{\text{total}}}$$

**Akaike Information Criterion (AIC)** The Akaike Information Criterion (AIC), introduced by Akaike (1974), provides a measure of model quality by estimating the relative amount of information lost when a model is used to represent a given dataset. AIC is calculated as:

$$AIC = -2\ln(L) + 2k$$

where L represents the maximum likelihood estimate of the model and k denotes the number of estimated parameters. The first term measures the goodness of fit, while the second penalizes model complexity. Lower AIC values indicate a model that achieves a better trade-off between fit and parsimony. Thus, among competing models, the one with the minimum AIC value is preferred.

**Bayesian Information Criterion (BIC)** The Bayesian Information Criterion (BIC), proposed by Schwarz (1978), is another metric used to compare and select the most suitable model, with an emphasis on penalizing model complexity more strongly than AIC. BIC is expressed as:

$$BIC = -2\ln(L) + k\ln(n)$$

where n is the number of observations, L is the likelihood of the model, and k is the number of model parameters. BIC favors simpler models when the dataset is large, as the penalty term  $k\ln(n)$  increases with sample size. Consequently, BIC tends to select models that are more parsimonious and generalizable compared to AIC.

### 3. RESULTS AND DISCUSSION

#### 3.1 Descriptive Statistics of Rice Area, Production and Yield

Table 1 presents the descriptive statistics of rice area, production and yield in India during 1961–2023.

**Table 1. Descriptive statistics of India's rice area, production and yield, 1961–2023**

| Variable   | N  | Mean    | SD     | Minimum | Median  | Maximum | CV (%) | Skewness | Kurtosis |
|------------|----|---------|--------|---------|---------|---------|--------|----------|----------|
| Area       | 63 | 41.401  | 3.255  | 34.694  | 41.918  | 47.832  | 7.861  | -0.312   | 2.210    |
| Production | 63 | 111.205 | 44.040 | 45.657  | 111.517 | 206.727 | 39.603 | 0.278    | 1.999    |
| Yield      | 63 | 26.245  | 8.721  | 12.936  | 26.163  | 43.223  | 33.228 | 0.225    | 1.847    |

The descriptive analysis reveals substantial long-term variation in rice production and yield. Rice area showed a coefficient of variation of only 7.86%, indicating comparatively limited variation in the cultivated area during the study period. In contrast, production had a CV of 39.60%, while yield had a CV of 33.23%. This result suggests that changes in rice production over the historical period were proportionately much larger than changes in cultivated area. The increasing contribution of technological progress and productivity improvement may therefore have been important in explaining long-term growth in rice output. The skewness values were relatively close to zero, although the normality tests indicated that none of the three series strictly followed a normal distribution.

#### 3.2 Normality and Randomness of the Series

The normality test results are presented in Table 2.

**Table 2. Normality test results**

| Variable   | Statistic | p-value | Decision     |
|------------|-----------|---------|--------------|
| Area       | 0.96195   | 0.04892 | Reject $H_0$ |
| Production | 0.95195   | 0.01539 | Reject $H_0$ |
| Yield      | 0.94550   | 0.00750 | Reject $H_0$ |

At the 5% significance level, the null hypothesis of normality was rejected for all three variables. Thus, rice area, production and yield did not follow a normal distribution according to the applied test.

The runs test also rejected the null hypothesis of randomness for all three series. The results indicate that the observations followed systematic temporal patterns rather than random sequences. This finding supports the use of time-series modelling.

#### 3.3 Stationarity Analysis

The ADF test results for the original series showed that all three variables were non-stationary.

**Table 3.1 ADF test results for the original series**

| Variable   | ADF Statistic | p-value | Decision             |
|------------|---------------|---------|----------------------|
| Area       | -2.72179      | 0.28263 | Fail to reject $H_0$ |
| Production | -1.97562      | 0.58479 | Fail to reject $H_0$ |

| Variable | ADF Statistic | p-value | Decision                      |
|----------|---------------|---------|-------------------------------|
| Yield    | -2.84335      | 0.23341 | Fail to reject H <sub>0</sub> |

Since all p-values exceeded 0.05, the null hypothesis of a unit root could not be rejected. Therefore, the original rice area, production and yield series were non-stationary. After first differencing, the series achieved stationarity according to the ADF procedure used in the analysis. Consequently, a differencing order of (d=1) was appropriate for the selected ARIMA models.

**Table 3.2 ADF test results after differencing**

| Variable   | ADF Statistic | P Value | Decision              | Interpretation |
|------------|---------------|---------|-----------------------|----------------|
| Area       | -5.97447      | 0.01    | Reject H <sub>0</sub> | Stationary     |
| Production | -6.00389      | 0.01    | Reject H <sub>0</sub> | Stationary     |
| Yield      | -6.33711      | 0.01    | Reject H <sub>0</sub> | Stationary     |

### 3.4 Autocorrelation Structure

The Ljung–Box test at lag 10 strongly rejected the null hypothesis of no autocorrelation for the original series. The test statistics were 278.67 for area, 358.08 for production and 378.14 for yield, with p-values effectively equal to zero. Therefore, all three variables contained significant serial dependence. The presence of strong autocorrelation confirms that current observations are related to previous observations and that time-series forecasting models are appropriate for analysing these data.

### 3.5 Selection of ARIMA Models

The Auto-ARIMA procedure identified different optimal structures for the three rice indicators.

**Table 4. Selected ARIMA models**

| Variable   | Training Period | Test Period | Selected Model | AIC     | BIC     |
|------------|-----------------|-------------|----------------|---------|---------|
| Area       | 1961–2018       | 2019–2023   | ARIMA(4,1,0)   | 174.641 | 186.899 |
| Production | 1961–2018       | 2019–2023   | ARIMA(0,1,1)   | 399.182 | 405.311 |
| Yield      | 1961–2018       | 2019–2023   | ARIMA(0,1,1)   | 210.430 | 216.559 |

Rice area was best represented by ARIMA(4,1,0), whereas production and yield were both represented by ARIMA(0,1,1). The residual Ljung–Box p-values were 0.6556 for area, 0.4291 for production and 0.6035 for yield. Since these values exceeded 0.05, the residuals did not show statistically significant remaining autocorrelation. This indicates that the selected ARIMA models adequately captured the major linear temporal dependence present in the training series.

### 3.6 Comparison of ARIMA and ARIMA–ANN Models

The forecasting performance during the 2019–2023 test periods is presented in Table 5.

**Table 5. Out-of-sample forecasting accuracy of ARIMA and ARIMA–ANN models**

| Variable   | Model     | MAE     | RMSE    | MAPE (%) | MASE   |
|------------|-----------|---------|---------|----------|--------|
| Area       | ARIMA     | 1.9128  | 2.1056  | 4.0789   | 2.1002 |
|            | ARIMA–ANN | 1.9197  | 2.1119  | 4.0937   | 2.1077 |
| Production | ARIMA     | 17.8481 | 19.3835 | 9.0181   | 2.3876 |
|            | ARIMA–ANN | 17.9887 | 19.5249 | 9.0901   | 2.4064 |
| Yield      | ARIMA     | 1.8994  | 1.9415  | 4.5184   | 1.3551 |
|            | ARIMA–ANN | 1.8828  | 1.9335  | 4.4775   | 1.3433 |

For **rice area**, the ARIMA model performed slightly better than the hybrid ARIMA–ANN model across all reported accuracy measures. The ARIMA model achieved an MAE of 1.9128 and RMSE of 2.1056 compared with 1.9197 and 2.1119, respectively, for ARIMA–ANN. For rice production, ARIMA again produced marginally better forecasts, with MAE of 17.8481, RMSE of 19.3835 and MAPE of 9.0181%. The corresponding values for the hybrid model were slightly higher. For rice yield, the hybrid ARIMA–ANN model showed a small improvement. It achieved MAE of 1.8828, RMSE of 1.9335, MAPE of 4.4775% and MASE of 1.3433, compared with MAE of 1.8994, RMSE of 1.9415, MAPE of 4.5184% and MASE of 1.3551 for ARIMA. Thus, the comparison indicates that there was no universal superiority of the hybrid model. The conventional ARIMA approach was more accurate for area and production, while the ARIMA–ANN approach was marginally superior for yield. The differences between the two

models were generally small. This suggests that the nonlinear component captured by the ANN was limited for area and production, whereas yield may contain slightly more nonlinear variation.

### 3.7 Validation Forecasts for 2019–2023

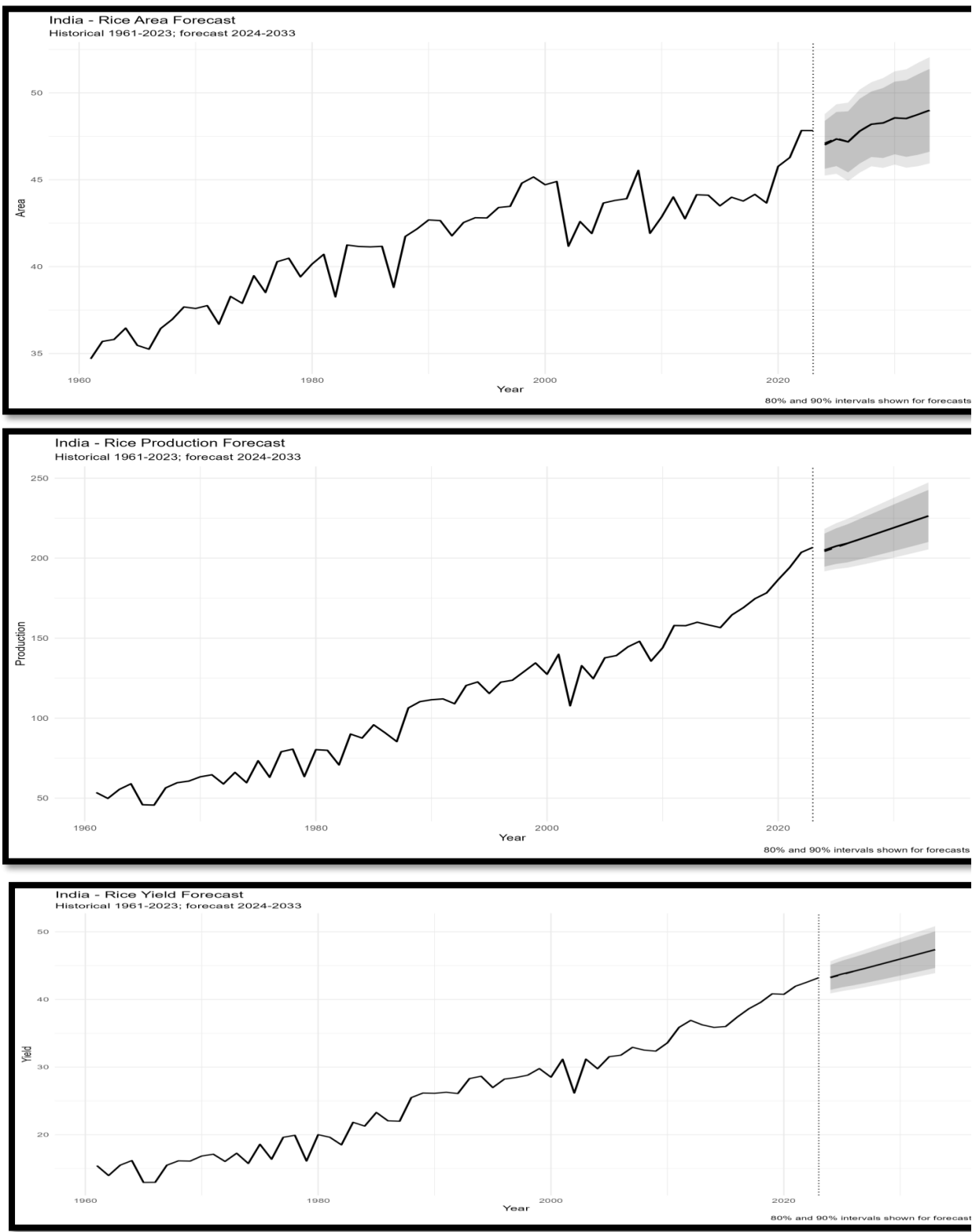
The models were evaluated using observations withheld from model estimation. For example, the forecasts for rice area showed that both models closely followed the general level of the observed series, although deviations increased when actual area rose substantially in the later test years. Similarly, both ARIMA and ARIMA–ANN models captured the overall upward movement in rice production during the validation period. However, the rapid observed growth in production created forecasting challenges, particularly for longer horizons within the five-year test sample. The results demonstrate the importance of evaluating agricultural forecasting models using an independent test period rather than relying solely on in-sample goodness-of-fit measures.

### 3.8 Future Forecasts for 2024–2033

Based on the final fitted models with drift and Hybrid models forecasts were generated for the next ten years.

**Table 6.1 Selected ARIMA forecasts for India's rice Area, Production and Productivity**

| Variable   | Year | Final ARIMA Model       | ARIMA Forecast | Lo80   | Hi80   | Lo90   | Hi90   |
|------------|------|-------------------------|----------------|--------|--------|--------|--------|
| Area       | 2024 | ARIMA(4,1,0) with drift | 47.10          | 45.72  | 48.48  | 45.33  | 48.87  |
|            | 2025 |                         | 47.38          | 45.83  | 48.94  | 45.39  | 49.38  |
|            | 2026 |                         | 47.19          | 45.44  | 48.95  | 44.94  | 49.45  |
|            | 2027 |                         | 47.81          | 45.95  | 49.67  | 45.42  | 50.19  |
|            | 2028 |                         | 48.20          | 46.32  | 50.09  | 45.79  | 50.62  |
|            | 2029 |                         | 48.27          | 46.26  | 50.29  | 45.69  | 50.86  |
|            | 2030 |                         | 48.56          | 46.48  | 50.65  | 45.88  | 51.25  |
|            | 2031 |                         | 48.53          | 46.33  | 50.74  | 45.70  | 51.36  |
|            | 2032 |                         | 48.76          | 46.45  | 51.08  | 45.79  | 51.74  |
|            | 2033 |                         | 49.01          | 46.63  | 51.39  | 45.95  | 52.06  |
| Production | 2024 | ARIMA(0,1,1) with drift | 204.26         | 193.97 | 214.56 | 191.05 | 217.48 |
|            | 2025 |                         | 206.72         | 195.60 | 217.84 | 192.45 | 220.99 |
|            | 2026 |                         | 209.18         | 197.30 | 221.06 | 193.93 | 224.43 |
|            | 2027 |                         | 211.64         | 199.03 | 224.24 | 195.46 | 227.81 |
|            | 2028 |                         | 214.09         | 200.81 | 227.38 | 197.05 | 231.14 |
|            | 2029 |                         | 216.55         | 202.62 | 230.48 | 198.67 | 234.43 |
|            | 2030 |                         | 219.01         | 204.46 | 233.56 | 200.34 | 237.68 |
|            | 2031 |                         | 221.47         | 206.33 | 236.61 | 202.03 | 240.90 |
|            | 2032 |                         | 223.92         | 208.21 | 239.64 | 203.76 | 244.09 |
|            | 2033 |                         | 226.38         | 210.12 | 242.65 | 205.51 | 247.26 |
| Yield      | 2024 | ARIMA(0,1,1) with drift | 43.22          | 41.37  | 45.07  | 40.85  | 45.60  |
|            | 2025 |                         | 43.68          | 41.72  | 45.65  | 41.16  | 46.20  |
|            | 2026 |                         | 44.14          | 42.07  | 46.21  | 41.49  | 46.80  |
|            | 2027 |                         | 44.61          | 42.44  | 46.78  | 41.82  | 47.39  |
|            | 2028 |                         | 45.07          | 42.80  | 47.34  | 42.16  | 47.98  |
|            | 2029 |                         | 45.53          | 43.17  | 47.89  | 42.50  | 48.56  |
|            | 2030 |                         | 45.99          | 43.54  | 48.44  | 42.85  | 49.13  |
|            | 2031 |                         | 46.45          | 43.92  | 48.99  | 43.20  | 49.71  |
|            | 2032 |                         | 46.92          | 44.30  | 49.53  | 43.56  | 50.28  |
|            | 2033 |                         | 47.38          | 44.68  | 50.08  | 43.91  | 50.84  |



**Fig 2. Forecast Plot of Area Production and Productivity of Rice in India**

**Table 6.2 ARIMA-ANN forecasts for India's rice Area, Production and Productivity**

| Variable | Year | ARIMA ANN | Lo80  | Hi80  | Lo90  | Hi90  |
|----------|------|-----------|-------|-------|-------|-------|
| Area     | 2024 | 47.01     | 45.63 | 48.39 | 45.24 | 48.78 |

|            |      |        |        |        |        |        |
|------------|------|--------|--------|--------|--------|--------|
|            | 2025 | 47.34  | 45.79  | 48.90  | 45.35  | 49.34  |
|            | 2026 | 47.18  | 45.42  | 48.94  | 44.93  | 49.43  |
|            | 2027 | 47.80  | 45.94  | 49.66  | 45.41  | 50.19  |
|            | 2028 | 48.19  | 46.31  | 50.08  | 45.78  | 50.61  |
|            | 2029 | 48.26  | 46.25  | 50.28  | 45.68  | 50.85  |
|            | 2030 | 48.55  | 46.47  | 50.64  | 45.87  | 51.24  |
|            | 2031 | 48.52  | 46.32  | 50.73  | 45.69  | 51.35  |
|            | 2032 | 48.75  | 46.44  | 51.07  | 45.78  | 51.73  |
|            | 2033 | 49.00  | 46.62  | 51.38  | 45.94  | 52.05  |
| Production | 2024 | 205.01 | 194.72 | 215.31 | 191.80 | 218.23 |
|            | 2025 | 207.50 | 196.38 | 218.61 | 193.23 | 221.76 |
|            | 2026 | 209.29 | 197.41 | 221.18 | 194.04 | 224.55 |
|            | 2027 | 211.71 | 199.10 | 224.31 | 195.53 | 227.88 |
|            | 2028 | 214.11 | 200.83 | 227.40 | 197.07 | 231.16 |
|            | 2029 | 216.56 | 202.63 | 230.49 | 198.68 | 234.44 |
|            | 2030 | 219.02 | 204.47 | 233.57 | 200.34 | 237.69 |
|            | 2031 | 221.47 | 206.33 | 236.62 | 202.04 | 240.91 |
|            | 2032 | 223.93 | 208.22 | 239.64 | 203.76 | 244.10 |
|            | 2033 | 226.39 | 210.13 | 242.65 | 205.51 | 247.26 |
| Yield      | 2024 | 43.28  | 41.43  | 45.13  | 40.90  | 45.65  |
|            | 2025 | 43.77  | 41.81  | 45.73  | 41.25  | 46.29  |
|            | 2026 | 44.18  | 42.11  | 46.25  | 41.52  | 46.83  |
|            | 2027 | 44.61  | 42.44  | 46.78  | 41.82  | 47.39  |
|            | 2028 | 45.07  | 42.80  | 47.34  | 42.16  | 47.98  |
|            | 2029 | 45.53  | 43.17  | 47.89  | 42.50  | 48.56  |
|            | 2030 | 45.99  | 43.54  | 48.44  | 42.84  | 49.13  |
|            | 2031 | 46.45  | 43.91  | 48.98  | 43.20  | 49.70  |
|            | 2032 | 46.91  | 44.29  | 49.53  | 43.55  | 50.27  |
|            | 2033 | 47.37  | 44.67  | 50.07  | 43.91  | 50.84  |

The forecasts indicate a broadly positive long-term outlook for India's rice sector. The cultivated rice area is forecast to increase gradually from approximately 47.10 in 2024 to 49.01 by 2033. The increase is relatively modest, indicating that future expansion of rice output may not depend primarily on substantial increases in cultivated land. Rice production is projected to increase from approximately 204.26 in 2024 to 226.38 by 2033. The forecast therefore indicates a sustained upward trend in national rice output. Rice yield is also forecast to increase steadily from approximately 43.22 in 2024 to 47.38 by 2033. The simultaneous increase in production and productivity, combined with comparatively slower growth in area, suggests that future production growth may increasingly depend on productivity improvement. The ARIMA–ANN forecasts showed very similar long-term trajectories. For 2033, the hybrid model projected approximately 49.00 for area, 226.39 for production and 47.37 for yield. The close correspondence between the two forecasting approaches strengthens confidence in the general direction of the projected trends, although prediction intervals should be considered when using the estimates for policy purposes.

#### 4. DISCUSSION

The statistical analysis demonstrates that India's rice area, production and yield possess clear temporal dependence and non-stationary behaviour. This is expected for long-term agricultural series affected by technological change, policy interventions, changes in input use, irrigation development, climate variability and structural transformation in agriculture.

The rejection of randomness and the significant Ljung–Box statistics indicate that historical observations contain substantial information relevant to future forecasting. The ADF results further demonstrate the importance of differencing before fitting conventional ARIMA models. The selected models differed among variables. Rice area required a higher-order autoregressive structure, ARIMA(4,1,0), suggesting that multiple past movements in the

difference area series contributed to forecasting. In contrast, production and yield were adequately represented by ARIMA(0,1,1), indicating that a first-difference moving-average structure was sufficient to capture their principal linear dynamics. An important finding is that hybridisation did not automatically improve forecast accuracy. ARIMA was slightly superior for both area and production, whereas ARIMA–ANN was marginally better for yield. This result has methodological implications because hybrid models are sometimes assumed to be universally superior to conventional models. The present analysis shows that additional model complexity should be justified by measurable improvements in out-of-sample forecasting accuracy. The negative out-of-sample  $R^2$  values for the short five-year validation period also warrant careful interpretation. They indicate that the models faced difficulty in reproducing some deviations from the benchmark mean over this particular holdout period. Therefore, MAPE, MAE, RMSE and MASE should be jointly considered rather than relying exclusively on  $R^2$  for time-series forecast evaluation. The future projections suggest continued growth in India's rice production and yield through 2033. Since the projected increase in area is comparatively modest, productivity enhancement appears to be an important pathway for sustaining production growth. These findings have relevance for research investments in improved varieties, efficient water management, precision agriculture, climate-resilient production systems and dissemination of improved crop-management technologies.

## 5. CONCLUSION

The present study compared ARIMA and hybrid ARIMA–ANN models for forecasting rice area, production, and yield in India using annual time-series data from 1961 to 2023. The findings demonstrated that all three series were non-stationary in their original form and became suitable for ARIMA modelling after first differencing. Furthermore, the series exhibited significant autocorrelation and systematic temporal behaviour, confirming the relevance of time-series modelling for forecasting these agricultural indicators.

The Auto-ARIMA procedure selected ARIMA(4,1,0) for rice area and ARIMA(0,1,1) for both rice production and yield. The selected models successfully passed the residual white-noise diagnostics, indicating that the major temporal structures in the respective series were adequately captured. The results are consistent with previous studies demonstrating the usefulness of ARIMA and related time-series approaches for agricultural and livestock production forecasting (Mishra et al., 2020; Patel et al., 2020).

In terms of forecasting performance, the ARIMA model performed marginally better than the hybrid ARIMA–ANN model for forecasting rice area and production, whereas the ARIMA–ANN model showed marginally better performance for forecasting rice yield. These findings suggest that hybridisation does not necessarily guarantee superior forecasting performance for every agricultural variable. The relative performance of conventional statistical and machine-learning approaches may vary according to the underlying linear and nonlinear characteristics of individual agricultural time series (Patel et al., 2020; Singh et al., 2022). Therefore, model selection should be based on rigorous out-of-sample evaluation rather than assuming that either conventional ARIMA or hybrid models will universally provide the best forecasts.

The forecasts for the period 2024–2033 indicate continued growth in India's rice production and productivity, while the expansion of cultivated rice area is expected to remain comparatively gradual. This suggests that future growth in rice production may increasingly depend on improvements in productivity rather than substantial expansion of the area under cultivation. Such forecasts can provide useful evidence for agricultural planning, resource allocation, production strategies, and long-term food-security planning.

Overall, both ARIMA and hybrid ARIMA–ANN models provide useful forecasting frameworks for agricultural production analysis. The present findings reinforce earlier evidence that the comparative performance of statistical and artificial intelligence-based forecasting methods is context- and variable-specific (Mishra et al., 2020; Sonkar et al., 2025; Dipti et al., 2025). Consequently, agricultural forecasting studies should systematically evaluate competing models using appropriate validation procedures and forecast accuracy measures before selecting the final model for operational forecasting.

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