# Rice Production Trends and Forecasting in Manipur: A Time-Series Analysis

**Taibangjam Loidang Chanu* and S. Loidang Devi**

Department of Statistics, Dhanamanjuri University, Imphal - 795001 (India)

*Corresponding Author: loidangtt@gmail.com

**Abstract**

*This study investigates the fluctuations in rice production, cultivated area, and productivity, aiming to identify key contributing factors and develop strategies for future improvements. By analysing secondary time-series data from the* Economic Survey, Manipur 2021-2022, *published by the Directorate of Economics and Statistics, Government of Manipur, the research employs Univariate Auto-Regressive Integrated Moving Average (ARIMA) models, compound growth rate models, and exponential smoothing techniques to assess trends and forecast future patterns. The results reveal varying model performances, with the Compound Growth Rate model demonstrating the highest explanatory power for rice production and productivity, while the Exponential Smoothing model more effectively captures variations in cultivated area. The ARIMA model also provides useful insights but exhibits relatively lower R-square values across all parameters. Notably, while total rice production continues to increase, the cultivated area is shrinking over time, indicating enhanced productivity and efficiency in rice farming. These findings highlight the need for targeted policies to support sustainable agricultural practices, ensuring that increased yields do not come at the cost of long-term soil health and resource depletion.*

***Keywords:*** *Forecast, Modelling, Rice Yield, ARIMA, Compound Growth Rate, Exponential Smoothing.*

## Introduction

Rice is a fundamental staple for more than half of the world's population, particularly in Asia and Africa, where it serves as both a primary food source and an economic driver. Over 3.5 billion people rely on rice for daily sustenance, making it a critical component of global food security (Bin Rahman and Zhang, 2023). In India, rice plays an essential role not only in sustaining food production but also in contributing to economic stability (Mahajan et al., 2017). Within the north eastern state of Manipur, rice is the dominant crop, serving as the backbone of the state’s agriculture-dependent economy. Despite its small geographical area of 22,327 square kilometres and limited arable land, approximately 70.79% of the population depends on agriculture, highlighting its socio-economic significance (Singha and Mishra, 2015).

The Economic Survey of Manipur 2022-23 underscores the prominence of agriculture, particularly rice cultivation, which accounts for nearly 90% of the Gross Cropped Area (GCA) in the state (Manipur, 2021). The cropping intensity stands at 143.26%, reflecting frequent cultivation cycles, yet recent data indicate a decline in rice cultivation area from 180.72 thousand hectares in 2018-19 to 175.62 thousand hectares in 2019-20. Such reductions in cultivated land raise concerns regarding the sustainability of rice production and its long-term impact on food security in the region.

Several studies have investigated the factors influencing rice production and productivity in Manipur. Meitei and Sharma (2023) explored agro-climatic conditions and constraints faced by farmers, identifying climatic variations and resource limitations as significant contributors to production fluctuations. Similarly, Kumari et al. (2022) and Shafiya et al. (2023) emphasized the necessity of historical data analysis in selecting appropriate time-series models for forecasting rice production trends. Understanding these trends is crucial for policymakers and agricultural stakeholders to develop informed strategies for improving production efficiency and ensuring food security. Forecasting models play a vital role in agricultural planning. Thangjam and Jha (2020a) analysed the effectiveness of statistical models in predicting rice yields, while Chanu and Oinam (2023) demonstrated the significance of data-driven approaches in understanding production trends. Advanced statistical methods such as Univariate Auto-Regressive Integrated Moving Average (ARIMA) models, compound growth rate models, and exponential smoothing techniques have been widely used to assess trends and predict future production patterns. These models aid in formulating effective agricultural policies and optimizing resource allocation to enhance rice productivity.

Given the growing challenges in rice production, collaboration between researchers, agricultural experts, and government agencies is essential for ensuring that predictive models align with real-world farming conditions. Strengthening data-driven decision-making and policy implementation can help Manipur move towards self-sufficiency in rice production. This study aims to conduct a comprehensive analysis of rice production trends in Manipur using advanced time-series modeling techniques. By integrating statistical insights with policy recommendations, the research seeks to enhance forecasting accuracy and support sustainable agricultural development in the region.

## Materials and Methods

Present study is based on secondary data obtain from the economic survey of Manipur, Department of Agriculture, Government of Manipur for the year 2022-23. The time series data on rice production and area was collected for the period of 43 years from 1980 to 2022. For data analysis, the SPSS software package is utilized. The ARIMA model: ARIMA stands for Auto-Regressive Integrated Moving Average. A non-seasonal ARIMA model is represented as an ARIMA (p,d,q) model (Anggraeni et al., 2021; Dhaka and Poolsingh, 2023; Eyduran et al., 2022; Hemavathi and Prabakaran, 2018; Kathayat and Dixit, 2021; Mahajan et al., 2020). The notations are given as

p: Order of the autoregressive terms that is number of lagged values (past values used in the model

d: Order of the differencing to make stationarity of the variable

q: Order of the moving average terms that is the number of lagged error terms involved in the model.

The general ARIMA (p, d, q) model is presented in simple form as

$$\varphi(B)\nabla^d Y_t = \theta(B)U_t \qquad (1)$$

Where, $\varphi(B)$ is autoregressive operator of order ‘ p’ defined by

$$\varphi(B) = 1 - \varphi_1 B^1 - \varphi_2 B^2 - \cdots - \varphi_p B^p$$

$\nabla^d$ : the $d^{th}$ order difference values of the random variable $Y_t$.

$Y_t$ : rice production, area, or productivity at time t.

$\theta$(B): moving average operator of order ‘q’ defined by

$$\theta(B) = 1 - \theta_1 B^1 - \theta_2 B^2 - \cdots - \theta_q B^q$$

$U_t$: error component which is white noise.

An ARIMA (p,1,q) model is given by

$$\varphi(B)\nabla Y_t = \theta(B)U_t \qquad (2)$$

i.e. $w_t = \varphi_1 w_{t-1} + \varphi_2 w_{t-2} + \cdots + \varphi_p w_{t-p} + U_t - \theta_1 U_{t-1} - \theta_2 w_{t-2} - \cdots - \theta_q U_{t-q}$

Where, $w_t = Y_t - Y_{t-1}$

Whereas B is the backshift operator defined by

$$B^{m}Y_t = Y_{t-m} \text{ (m=0,1, 2,….p)}$$

$\nabla$ : backward difference operator

$$\nabla Y_t = Y_t - Y_{t-1} = (1 - B)Y_t$$

**The Dickey- Fuller test**

To identify the stochastic nature of a non-stationary series, the Dickey-Fuller test involves regressing the series on its first lag to assess if the regression coefficient of the lagged term is approximately equal to one and statistically significant (Box, 2013; Hipel et al., 1977). This is done under various conditions, including no constant, a non-zero constant, or a non-zero constant plus a deterministic trend coefficient. Examine the scenario known as the autoregressive no constant test. This model assumes that the regression equation does not include a significant constant term.

The initial regression model under examination is

$$y_t = \rho y_{t-1} + e_t$$

A regression model without an intercept indicates that this analysis tests for pure random walk without drift

$$y_t = \rho_1 y_{t-1} + e_t$$

and for $\rho_1 = 1$ then

$$y_t = y_{t-1} + e_t$$

(1-L) $y_t = e_t$

$$t = \frac{\rho_1 - 1}{se_{\alpha_1}}$$

$$|t| \geq \tau_t$$

Where, $\tau_t$ = the critical value of the first case.

The degrees of freedom are calculated as number of observation used in the test - number of lags included in then regression -1. The time series has a unit root, and is non-stationary. If the null hypothesis is not rejected, it suggests that the data-generating process has a unit root and is non-stationary. Consequently, a two-sided significance test is conducted to determine the statistical significance of $\rho_1 - 1$ , similar to a t-test. The null hypothesis that the series follows a non-stationary random walk is rejected if |t| exceeds $\tau_t$ , with $\tau_t$'s value depending on the sample size and the specific parameters included in the equation.

**Analysis**

a) Data: The time series data on rice for a period of 41 years (1980-2022) has been collected from the Directorate of Economic and Statistics, Government of Manipur, Imphal.

b) Implementing an ARIMA model involves four stages, which are:

i) Model identification: Stationarity was achieved by taking the first-order differences. Once the series became stationary, the p and q orders were identified using the correlogram of the ACF and PACF, respectively.

ii) Model Estimation: The parameters are estimated using the least squares method.

iii) Diagnostic evaluation: Diagnostic checking involved evaluating the model's assumptions using techniques such as the Ljung-Box statistic (autocorrelation test) and the ACF and PACF of the residuals (goodness-of-fit test). The model also met the criteria for having the lowest AIC/BIC.

**Ljung- Box test:**

It tests the null hypothesis that the residuals from the model are independently distributed. The test statistic Q is calculated based on the autocorrelations of the residuals (Jhade and Dagam, 2020).

The Ljung-Box Q statistics, denoted as Q, is computed as:

$$Q(m)=n(n+2)\sum_{j=1}^{m}\frac{r_j^2}{n-j}$$

Where, n: the sample size

$r_j$: is the autocorrelation at lag j

m: number of lag variables being tested

$H_0$: the residuals are white noise

We reject the null hypothesis $H_0$ that our model fits well and accept the alternative hypothesis $H_1$ that the model show lack of fit if

$$Q > \chi^2_{h,0.05}$$

where, $\chi^2_{p,0.05}$: table value of $\chi^2$ for h degrees of freedom at 5% level of significance.

The degrees of freedom h must be determined as m−p−q, where p and q denote the number of parameters in the estimated model.

iv) Forecasting: The model developed can be employed for predicting future values.

**Compound Growth Model:** The compound growth rate model calculates how a value grows over time when the growth is reinvested or compounded (Islam et al., 2023; Yadav et al., 2020). The equation for computing the compound growth rate is outlined below

$$Y_t = Y_0(1+r)^t \quad (3)$$

where, $Y_t$ = production/area/productivity at time t

$Y_0$ = constant (base year production/area/productivity)

t = time periods in years

r = compound growth rate

To simplify the analysis, we take the logarithm on both sides and obtain

$$L_n Y_t = L_n Y_0 + L_n(1+r) \quad (4)$$

$$\Rightarrow L_n Y_t = A + Bt$$

where, A = $L_n Y_0$,

B = $L_n(1+r)$ and

B = regression coefficient

Compound growth rate (%) = (Antilog B-1) *100

**Exponential Smoothing Model:** Exponential smoothing is a forecasting technique used to predict future data points by applying weighted averages to past observations, where the weights decrease exponentially over time (Dritsaki and Dritsaki, 2021; Kumari et al., 2022)**.**

The cumulative weighted mean up to period t for n data points $Y_t, Y_{t-1}, \ldots, Y_{t-(n-1)}$ *is*

$$S_t = \frac{1*Y_t + (1-\alpha)Y_{t-1} + (1-\alpha)^2 Y_{t-2} + \cdots + (1-\alpha)^{n-1} Y_{t-(n-1)}}{1 + (1-\alpha) + (1-\alpha)^2 + \cdots + (1-\alpha)^{n-1}}$$

$$S_{t+1} = \frac{1*Y_{t+1} + (1-\alpha)Y_t + (1-\alpha)^2 Y_{t-1} + \cdots + (1-\alpha)^{n-1} Y_{t-(n-1)}}{1 + (1-\alpha) + (1-\alpha)^2 + \cdots + (1-\alpha)^{n-1}}$$

The most basic version of exponential smoothing is expressed by the equation

$$S_{t+1} = \alpha Y_t + (1-\alpha)S_t \quad (5)$$

Where, $S_{t+1}$ = forecast value at time t+1

$S_t$ = current forecast value

$\alpha$ = Smoothing factor

$Y_t$= Actual value at time t

## Results and Discussion

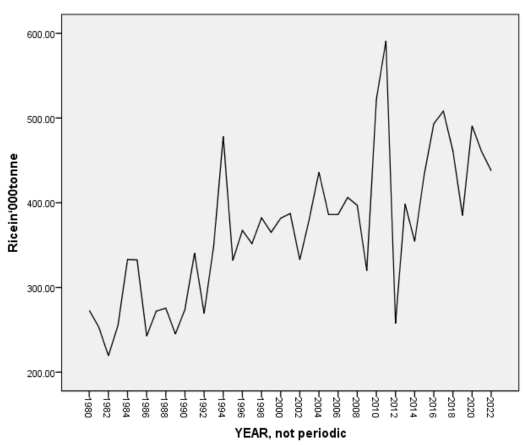
In this study, we utilized data on rice production, area, and productivity spanning from 1980 to 2022. To predict rice production, area, and productivity, the ARIMA model is applied only after converting the forecasted variable into a stationary series (Dhaka and

Poolsingh, 2023). The stationarity of the series is assessed by analyzing the differences or examining the time plot of the data. This test revealed that the time series of rice production, area, and productivity is non-stationary. The formal approach to testing the stationarity of a series, known as the Dickey-Fuller test (i.e., unit root test), is also employed to assess the stationarity of the time series for rice production, area, and productivity and found the data was nonstationary(Mamun et al., 2021; Pande and Ramesh, 2024).

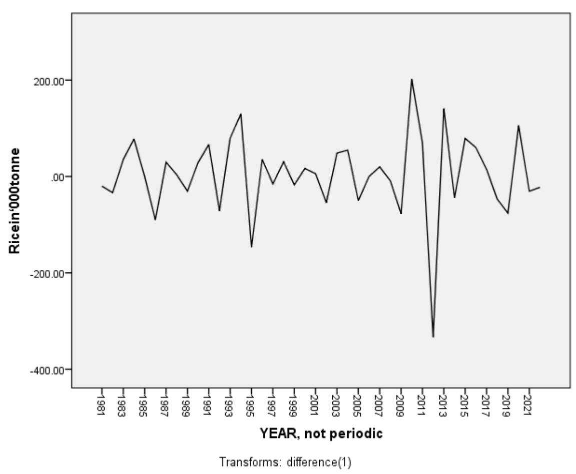
To achieve stationarity, applying a first-order difference (i.e., d=1) to the series for rice production, area, and productivity was sufficient. The graphical stationarity test, illustrated in Figure 1 clearly indicates that the original series for rice production, area, and productivity does not exhibit constant variance. However, the first-order differenced series displays a more stable variance compared to the original series. The Dickey-Fuller test statistic values were found to be 3.872, 4.971, and 4.736 for rice yield, cultivated land, and crop productivity respectively, each with a lag of 3. The Dickey-Fuller test revealed that the stationarity condition is met with a first-order difference, with a p-value of 0.01 for production, area, and productivity. This strongly indicates that there is no unit root in the first-order differenced series for rice production, area, and productivity at a 1% significance level.

By examining the orders of the ACF and PACF for the differenced series of rice production, area, and productivity in the correlogram in Figures 2, 3, and 4, the values of the parameters p and q are determined and estimated.

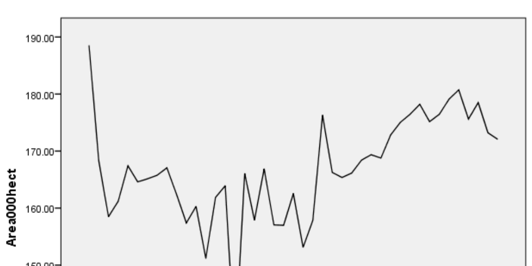
Original series (production)



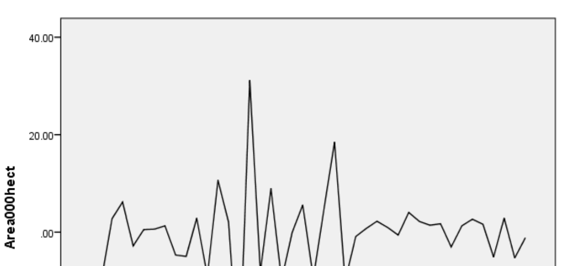

Difference series (production)




Original series (area)




Difference series (area)



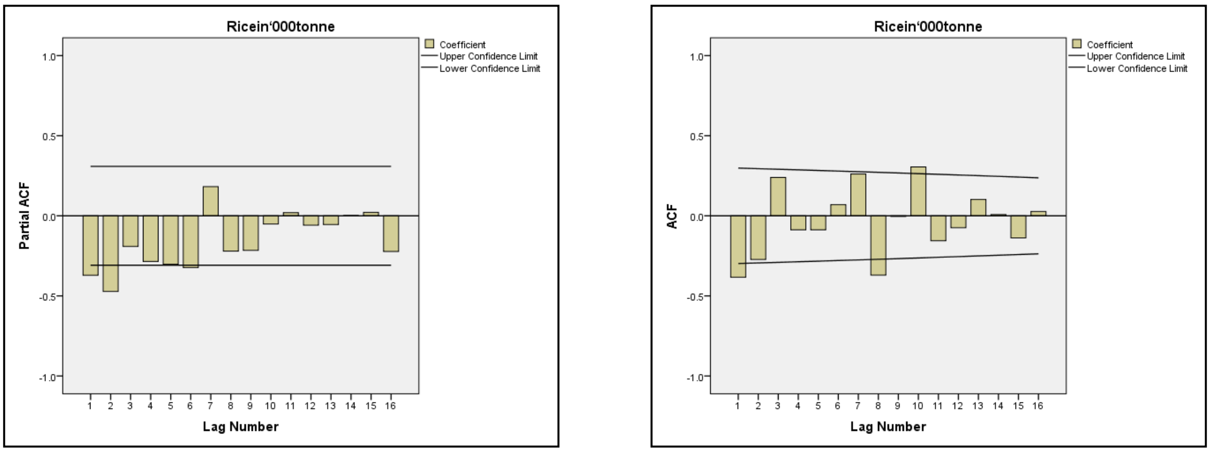



Figure 2. Graphical presentation of ACF and PACF of differenced data of rice production

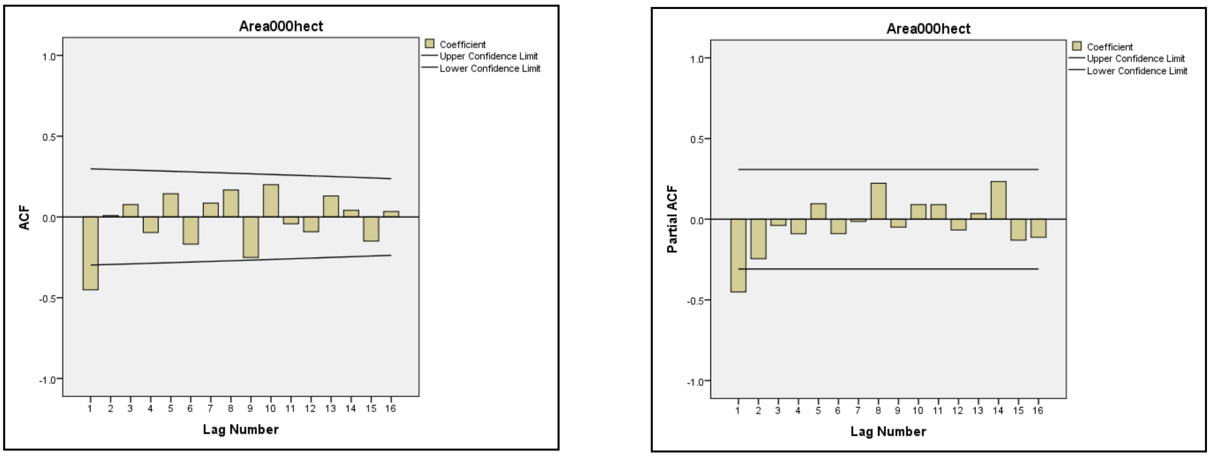



Figure 3. Graphical presentation of ACF and PACF of differenced data of rice area

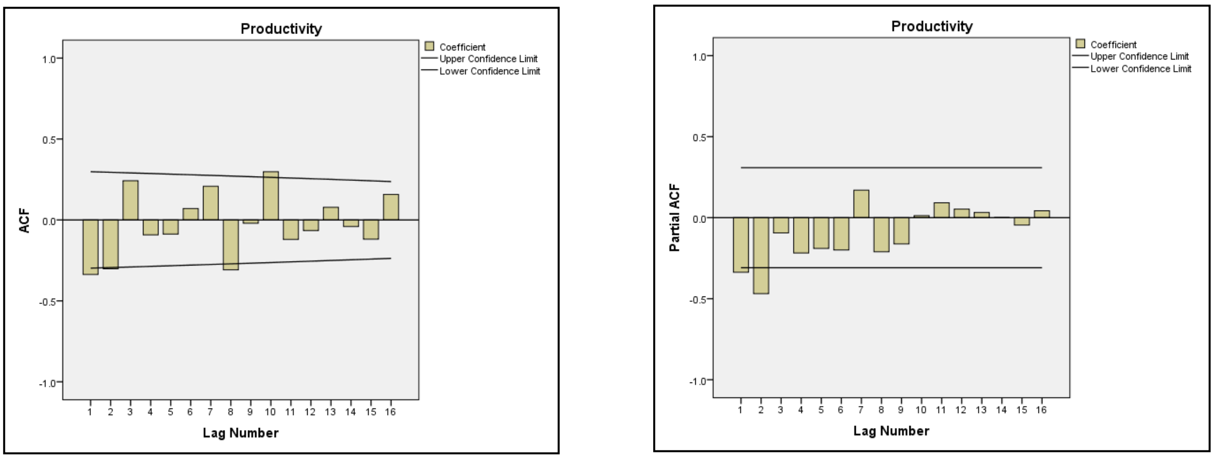



Figure 4. Graphical presentation of ACF and PACF of differenced data of rice productivity

Table 1: Summary of statistics of fitted ARIMA models

| Crop | Aspects | Model | Fit Statistics | | | | | | Ljung -Box Statistics | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Stationary $R^2$ | R-square | RMSE | MAPE | MAE | Normalized BIC | Statistics | Sig. |
| Rice | Production | ARIMA (1,1,2) | 0.521 | 0.545 | 1.578 | 5.742 | 1.081 | 1.268 | 23.747 | 0.07 |
| | Area | ARIMA (2,1,2) | 0.348 | 0.260 | 0.318 | 1.512 | 0.192 | -1.843 | 11.632 | 0.636 |
| | Productivity | ARIMA (2,1,2) | 0.389 | 0.422 | 0.121 | 5.335 | 0.077 | -3.786 | 12.840 | 0.539 |

ARIMA (1,1,2), ARIMA (2,1,2), and ARIMA (2,1,2) models are the most suitable for rice production, area, and productivity, respectively, as they exhibit the highest number of significant coefficients along with the lowest AIC and normalized BIC values. The estimated parameters for the fitted ARIMA (1,1,2), ARIMA (2,1,2), and ARIMA (2,1,2) models for the production area and productivity of rice are presented in Tables 1. The Ljung-Box test reveals a p-value of 0.441, strongly indicating that there is no autocorrelation among the residuals of the fitted ARIMA (1,1,2) model for rice production at the 5% significance level. Similarly, for the area, the Ljung-Box test shows a p-value of 0.983, which strongly suggests no autocorrelation among the residuals of the fitted ARIMA (2,1,2) model at the 5% significance level. Additionally, for productivity, the Ljung-Box test yields a p-value of 0.776, again strongly suggesting the absence of autocorrelation among the residuals of the fitted ARIMA (2,1,2) model at the 5% significance level. Thus, these models are recommended for future forecasting. Additionally, the suitability and reliability of the fitted models are confirmed by the flat ACF and PACF of the residuals for rice production, area, and productivity, as shown in Figures 2,3 and 4, respectively. In the correlogram of the residuals, all lags fall within the confidence limits, indicating a good fit to the given data.

Graphical diagnostics for the residuals of the fitted ARIMA models for production, area, and productivity are presented in Figures 5,6 and 7 respectively. These figures show that nearly all points align closely with the Q-Q line, indicating that the residuals of the fitted ARIMA models are normally distributed for rice production, area, and productivity. Therefore, based on both graphical and formal tests, it is evident that the ARIMA (1,1,2), ARIMA (2,1,2), and ARIMA (2,1,2) models are the best choices for forecasting rice production, area, and productivity in Manipur. The future values predicted by the ARIMA models are shown in Table 2. The graphical representations of the observed and predicted values for rice production, area, and productivity are displayed in Figures 11,12 and 13, respectively. Table 3 shows that regression coefficient of rice area, production, and productivity by using compound growth rate model is significant at 5% level. Table 4 shows Summary report for the fitted compound growth rate model of rice production, area, and productivity. Table 5 shows Exponential smoothing approach to assess rice production, area, and productivity trends between 1980 and 2022. Table 6 overviews of the Statistics for Fitted Exponential Smoothing Models.

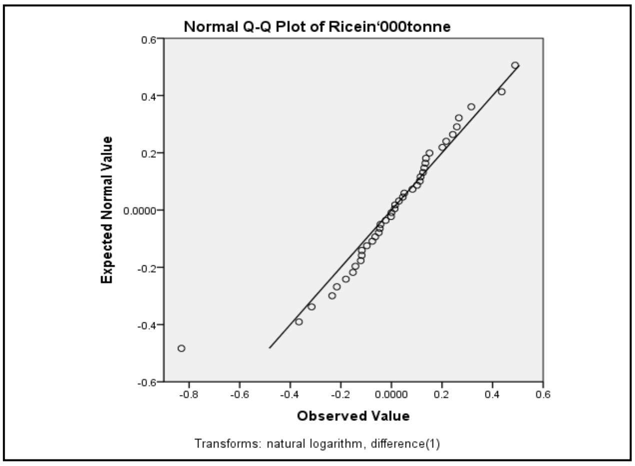



Figure 8. Showing of normality of residuals for ARIMA (1,1,2) model of rice production

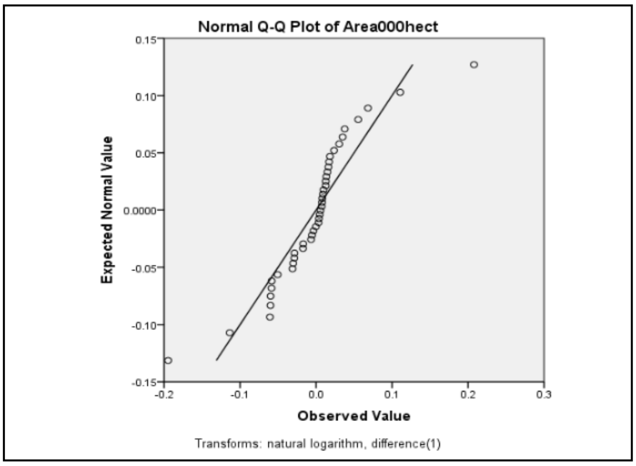



Figure 9. Showing of normality of residuals for ARIMA (2,1,2) model of rice area

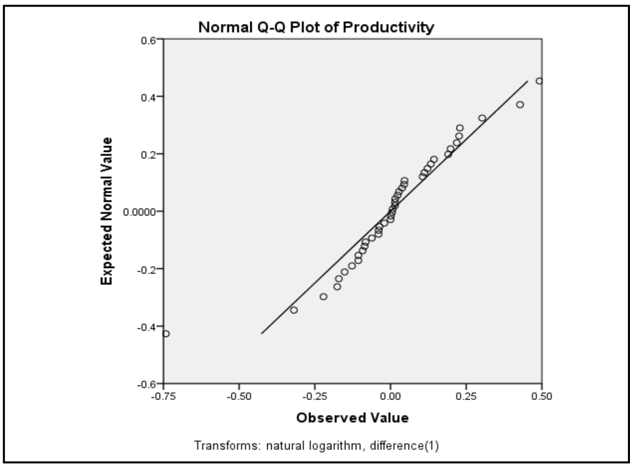



Figure 10. Showing of normality of residuals for ARIMA (2,1,2) model of rice productivity

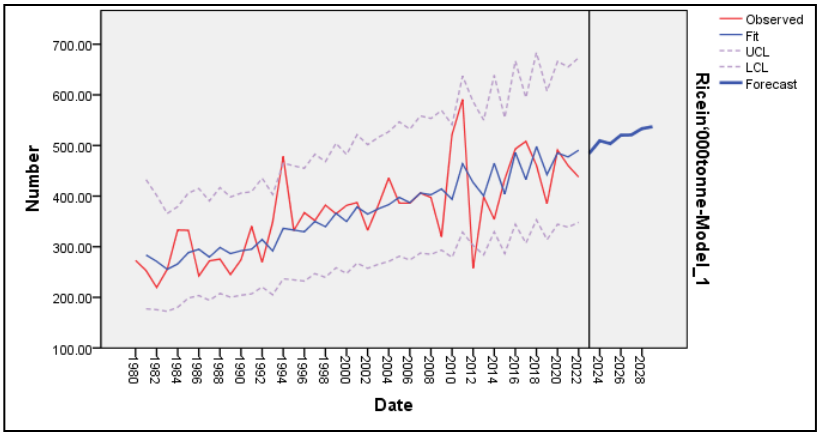



Figure 11. Graphical representation of original and forecasted rice production

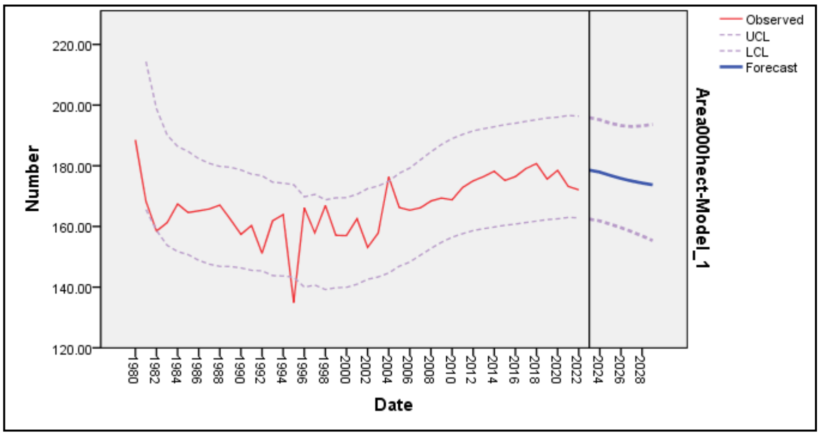



Figure 12. Graphical representation of original and forecasted rice area

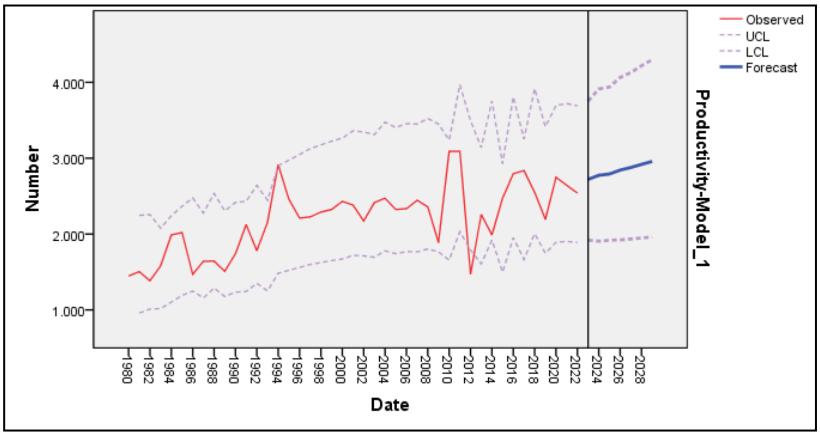





Figure 13. Graphical representation of original and forecasted rice productivity

Table 2: Future Forecasting of Rice Production, Area, and Productivity in Manipur Using the ARIMA Method

| Year | Future prediction for rice | | |
|---|---|---|---|
| | **Forecasted value for Production (tonne)** | **Forecasted value for Area (ha)** | **Forecasted value for Productivity (t/ha)** |
| 2023 | 484.25 | 178.55 | 2.72 |
| 2024 | 509.42 | 177.90 | 2.77 |
| 2025 | 503.56 | 176.79 | 2.79 |
| 2026 | 520.42 | 175.81 | 2.84 |
| 2027 | 520.82 | 174.99 | 2.88 |
| 2028 | 533.39 | 174.30 | 2.92 |
| 2029 | 537.25 | 173.72 | 2.96 |

Table 3: Regression parameters estimated for rice production, area, and productivity from 1980 to 2022.

| Crop | Aspect | | Value | T value | Sig. |
|---|---|---|---|---|---|
| Rice | Production | Constant | 2.419 | 117.034 | 0.000 |
| | | Coefficient(B) | 1.002 | 2956.116 | 0.000 |
| | Area | Constant | 2.201 | 309.502 | 0.000 |
| | | Coefficient(B) | 1.000 | 78160.68 | 0.000 |
| | Productivity | Constant | 0.212 | 12.697 | 0.000 |
| | | Coefficient(B) | 1.018 | 320.706 | 0.000 |

** denotes statistical significance at the 0.05 level.

Table 4: Summary report for the fitted compound growth rate model

| Crop | Aspect | R | $R^2$ | SE |
|---|---|---|---|---|
| Rice | Production | 0.746 | 0.557 | 0.028 |
| | Area | 0.445 | 0.198 | 0.010 |
| | Productivity | 0.669 | 0.447 | 0.254 |

** denotes statistical significance at the 0.05 level.

Table 5: Exponential smoothing approach to assess rice production, area, and productivity trends between 1980 and 2022

| Crop | Aspect | $\alpha$ estimate | SE | t value | Sig. |
|---|---|---|---|---|---|
| Rice | Production | 0.142** | 0.040 | 3.553 | 0.001 |
| | Area | 0.150** | 0.041 | 3.662 | 0.001 |
| | Productivity | 0.175** | 0.045 | 3.918 | 0.000 |

** denotes statistical significance at the 0.05 level.

Table 6: Overview of the Statistics for Fitted Exponential Smoothing Models

| Crop | Aspect | Fit statistics | | | | | Ljung -Box Statistics | |
|---|---|---|---|---|---|---|---|---|
| | | R-square | RMSE | MAPE | MAE | Normalized BIC | Statistics | Sig. |
| Rice | Production | 0.398 | 1.755 | 6.640 | 1.242 | 1.212 | 26.563 | 0.110 |
| | Area | 0.295 | 7.997 | 13.684 | 0.282 | 4.169 | 15.550 | 0.556 |
| | Productivity | 0.307 | 0.385 | 11.359 | 0.238 | -1.823 | 22.662 | 0.182 |

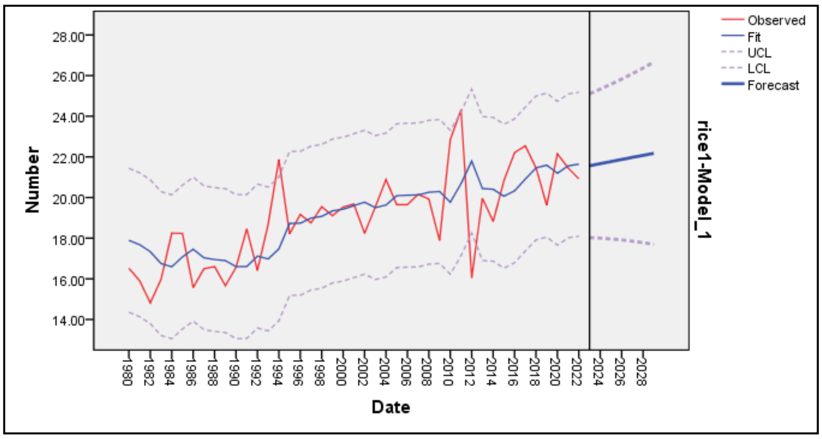



Figure 14. Forecasting rice production using the exponential smoothing model

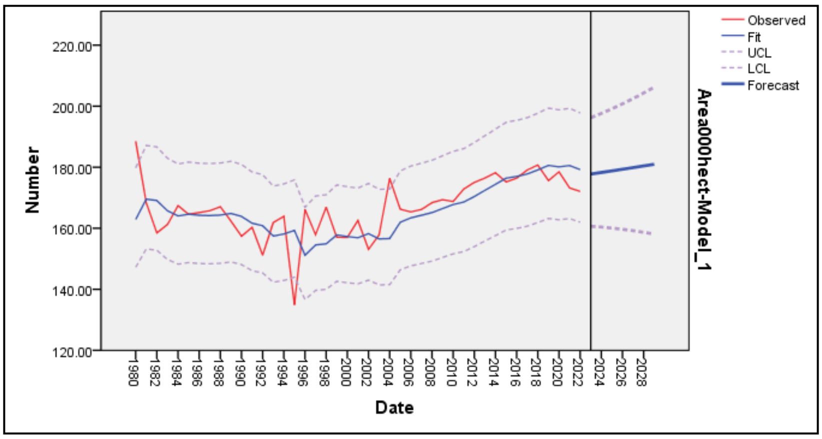



Figure15. Forecasting rice area using the exponential smoothing model

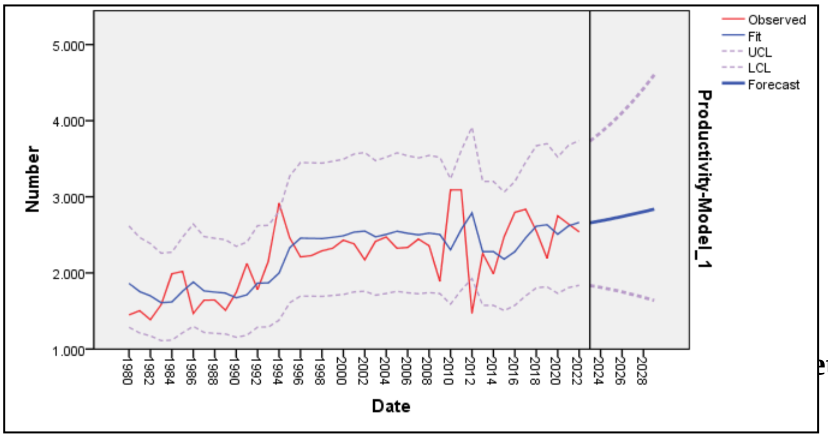





Figure 16. Forecasting rice productivity using the exponential smoothing model

Table 7 presents a comparison between the compound growth rate model, the exponential smoothing model, and the ARIMA model. It was found that the compound growth rate model performs better compared to the ARIMA and exponential smoothing models, as it has the highest $R^2$ value among the three.

Table 7: Comparison of $R^2$ values for the ARIMA model, compound growth rate model and exponential smoothing model

| **Particulars** | **$R^2$ value** | | |
|---|---|---|---|
| | **ARIMA model (1,1,2)** | **Compound growth rate** | **Exponential growth rate** |
| Production | 0.545 | 0.557 | 0.398 |
| Area | 0.260 | 0.198 | 0.295 |
| Productivity | 0.422 | 0.447 | 0.307 |

The study reveals that the ARIMA model explains 54.5% of the variation in rice production, as indicated by the R-square value, based on the independent variables used. In comparison, the compound growth rate model accounts for 55.7% of the variation in production with the same variables. Similarly, the exponential smoothing model explains 39.8% of the variation in production. For area and productivity, the ARIMA model accounts for 26.05% and 42.2% of the variation, respectively. The compound growth rate model explains 19.8% of the variation in area and 44.7% in productivity, while the exponential smoothing model captures 29.5% of the variation in area and 30.7% in productivity using the same independent variable.

The projected values indicate that rice production is on the rise, while the area under cultivation is gradually declining. Factors contributing to this trend could include:

- Improved agricultural techniques: Use of better seeds, fertilizers, or farming methods.
- Technological advancements: Implementation of modern machinery or irrigation systems.
- Shifts in land use: Land previously used for rice cultivation might be repurposed for other crops, urban development, or other uses.
- Intensification of farming practices: Higher yields achieved through focused, intensive farming on smaller areas.

This pattern reflects a transition towards more efficient use of agricultural land, but it might also raise concerns about long-term sustainability, soil health, or the risks of overreliance on intensive practices. To ensure self-sufficiency in rice production, it is essential for the relevant authorities to take timely and appropriate measures.

## References

1. Anggraeni, L., Nugroho, S. B. and Kurniawan, M. A. (2021). *Forecasting agricultural production using ARIMA models: A case study in Indonesia*. Journal of Agricultural Data Science, 12(3), 145–160.

2. Bin Rahman, S. and Zhang, J. (2023). Rice production and food security: Challenges and opportunities in Asia and Africa. Agricultural Systems, 205, 103481.

3. Box, G. E. P., Jenkins, G. M. and Reinsel, G. C**.** (2013). *Time Series Analysis: Forecasting and Control* (4th ed.). John Wiley & Sons.

4. Chanu, T. L. and Oinam, P. (2023). Statistical analysis of rice production trends in Manipur: A data-driven approach. Journal of Agricultural Research, 45(2), 150-163.

5. Department of Agriculture, Government of Manipur. (2022). Economic survey of Manipur 2022-23. Directorate of Economics and Statistics, Government of Manipur.

6. Dhaka, V. and Poolsingh, S. (2023). *Time series analysis of crop yield prediction using ARIMA models in India*. International Journal of Agricultural Statistics, 28(1), 55–72.

7. Dritsaki, C. and Dritsaki, M. (2021). Forecasting Agricultural Production Using Exponential Smoothing Methods. *Advances in Agriculture*, 2021, 1–10.

8. Economic Survey of Manipur. (2021). Manipur economic survey 2022-23. Directorate of Economics and Statistics, Government of Manipur.

9. Eyduran, S. P., Öztürk, C. and Eyduran, E. (2022). *Application of ARIMA models in forecasting agricultural production: A comparative approach*. Agricultural Statistics Review, 19(2), 98–112.

10. Hemavathi, D. and Prabakaran, R. (2018). *An ARIMA-based approach for forecasting crop yield trends in Tamil Nadu, India*. Indian Journal of Agricultural Research, 52(4), 324–331.

11. Hipel, K. W., McLeod, A. I. and Lennox, W. C. (1977). Advances in Box–Jenkins modeling: 2. Applications. *Water Resources Research*, 13(3), 577–586.

12. Islam, M. S., Hossain, M. I. and Rahman, M. M. (2023). Application of Compound Growth Rate Model in Agricultural Production Analysis. *International Journal of Agricultural Research*, 18(2), 45–53.

13. Jhade, S. and Dagam, S. (2020). Growth Status and ARIMA Model Forecast of Area, Production of Wheat Crop in India. *Journal of Scientific Research & Reports*, 26(5), 117–125.

14. Kathayat, B. and Dixit, A. (2021). *Statistical modeling and forecasting of food grain production using ARIMA techniques*. Journal of Agricultural Economics and Forecasting, 17(3), 210–225.

15. Kumari, R., Singh, P. and Verma, S. (2022). Time-series modeling for rice production forecasting in India: A comparative analysis. Indian Journal of Agricultural Sciences, 92(6), 345-359.

16. Mahajan, G., Chauhan, B. S. and Johnson, D. E. (2017). Sustainable rice production in India: Challenges and solutions. Field Crops Research, 213, 145-159.

17. Mahajan, S., Sharma, R., and Singh, P. (2020). *A study on ARIMA models for predicting agricultural output: Evidence from Northern India*. Advances in Agricultural Sciences, 27(5), 110–125.

18. Mamun, M. A. A., Rahman, M. M. and Hasan, M. M. (2021). Application of Dickey-Fuller Test in Time Series Data: An Approach to Investigate the Stochastic Nature of Non-Stationary Series. *Journal of Statistical Research*, 55(1), 1–12.

19. Meitei, N. S. and Sharma, H. (2023). Agro-climatic conditions and rice production in Manipur: A critical analysis. Asian Journal of Agricultural Economics, 17(1), 78-92.

20. Pande, A. and Ramesh, K. (2024). Unit Root Testing in Time Series Data: The Dickey-Fuller Approach. *Journal of Quantitative Economics*, 22(1), 123–145.

21. Shafiya, M., Ramesh, K. and Prakash, P. (2023). Predicting rice production trends using time-series models: Evidence from Northeast India. Agricultural Economics Review, 31(4), 289-305.

22. Singha, K. and Mishra, R. N. (2015). Agriculture and rural economy of Manipur: An empirical analysis. Economic and Political Weekly, 50(30), 78-86.

23. Thangjam, N. and Jha, R. (2020a). Forecasting rice yield in Manipur using ARIMA models: A case study approach. International Journal of Agricultural Statistics, 15(3), 210-225.

24. Thangjam, N. and Jha, R. (2020b). Rice production and consumption patterns in Northeast India: An economic perspective. Indian Journal of Economics and Development, 18(2), 92-107.

25. Yadav, S. K., Singh, R. and Kumar, A. (2020). Estimation of Compound Growth Rate in Area, Production and Productivity of Major Crops in Uttar Pradesh. Journal of AgriSearch, 7(1), 45-49.