

ASSESSMENT OF TIME SERIES MODELS FOR FORECASTING RICE PRODUCTION IN KERALA AND INDIA: ARIMA VERSUS HOLT'S EXPONENTIAL SMOOTHING

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ABSTRACT

The study conducted in 2023-24 compared two univariate time series forecasting models, ARIMA and Holt's Exponential Smoothing (HES), to predict rice production in India and Kerala from 1980-81 to 2022-23. The models were evaluated based on various model accuracy measures like Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE), Root Mean Squared Error (RMSE), Mean Absolute Percent Error (MAPE), and Akaike Information Criterion (AIC), with results showing that the ARIMA model had higher accuracy than HES. The forecast for India predicted steady growth, from 135,687.7 in 2024 to 150,444.4 in 2028, with HES slightly higher than ARIMA. Similarly, in Kerala, HES forecasted a higher increase, from 569.68 in 2024 to 581.08 in 2028, compared to ARIMA, which showed slightly lower values across the period. Overall, ARIMA demonstrated better predictive performance over HES for rice production.

Keywords: ARIMA, Forecasting, Holt's Exponential Smoothing Model, Production, Rice, Time Series.

INTRODUCTION

Rice played a pivotal role in India, not only as the backbone of its agrarian economy but also from the perspective of global food security. As the staple food for over 65% of the Indian population, rice held strategic importance in ensuring nutritional stability. It remained the dominant crop, occupying nearly a quarter of the total cultivated land, and was grown extensively across diverse agro-ecological zones, especially in tropical and rain-fed regions (Prasanna, 2018).

India emerged as the second-largest producer of rice globally and became the leading rice exporter (Kumar *et al.*, 2022), accounting for nearly 23% of global production

(FAO, 2024). In the agricultural year 2023–24, the country produced approximately 135.7 million tonnes of rice, cultivated across 43.79 million hectares (Ministry of Agriculture & Farmers Welfare, 2024). Rice alone accounted for about 33.9% of the total area under foodgrains and contributed 41.5% to the total foodgrain production during the same year (MoAFW, 2024).

Despite this growth, India's rice sector faced several challenges. Regional disparities in productivity persisted, and the positive impacts of successive generations of modern technology on rice yields appeared to decline. Even in high-productivity regions, trends showed stagnation and deceleration in yield

growth (Kumar *et al.*, 2022). Moreover, multiple agronomic constraints including insufficient soil moisture, waterlogging, low soil fertility, erosion, floods, erratic monsoons, and inadequate fertiliser use continued to affect rice production (Bhattacharya, 2022).

In contrast to the national trend of rising rice production, Kerala presented a unique and challenging scenario. Historically, rice occupied a central place in the state's agrarian culture and food habits. However, over the decades, Kerala witnessed a consistent decline in both the area under rice cultivation and total production. The state's share in national rice output reduced substantially, despite the crop once dominating its agricultural landscape. Several factors such as high population density, increasing urbanisation, labour shortages, and the conversion of paddy fields for non-agricultural purposes contributed to this decline. Nonetheless, recent trends indicated a marginal improvement in productivity, with an 8% increase recorded in 2022-23 compared to the previous year (Economic Review, 2023), suggesting that efforts to enhance per-hectare yield had yielded some positive results. This divergent trajectory between national expansion and regional contraction called for a deeper examination through time series analysis to forecast and plan future interventions effectively.

Given these contrasting trends at the national and state levels, it became essential to analyze past production patterns and forecast future trends. Time series modelling offered a valuable tool in this regard, providing a basis for making informed agricultural and policy decisions. Ramadhan *et al.*, (2024) emphasized the importance of time series models for estimating and forecasting agricultural production. Forecasting played a critical role in managing price volatility, planning

resource allocation, and adapting to climatic and market uncertainties. In states like Kerala, where cultivation declined, forecasting supported efforts to improve productivity and address the dynamics of agricultural land use.

Several researchers had applied time series models to agricultural forecasting. Sodha and Saha (2016) demonstrated their effectiveness in crop management. Annadanapu and Ravi (2017) fitted an ARIMA model to food production data from 1961 to 2013. Mgaya and Yildiz (2019) applied the ARIMA model to forecast livestock product consumption. Purohit *et al.*, (2021) forecasted agricultural product prices using hybrid methods involving both additive and multiplicative models, focusing on crops like tomato, onion, and potato. Mahto *et al.*, (2021) used ARIMA and Artificial Neural Networks (ANN) for short-term forecasting of agricultural commodities. Annamalai and Johnson (2023) applied ARIMA, Holt's exponential smoothing, and NNAR models to forecast rice cultivation area in India. Zelingher and Makowski (2023) explored machine learning models to forecast agricultural commodities and identify high-producing regions.

The literature made it evident that models like ARIMA, Holt-Winters, and NNAR were widely applied in forecasting agricultural variables such as price, production, area, and consumption. However, most studies focused either at the national or regional level—comparative forecasting studies across multiple geographic scales were relatively limited.

India provided a broad national context for examining long-term rice production trends, having seen a significant increase in cultivated area and output since the 1950s. In contrast, Kerala presented a unique case of declining area and production despite continued importance of rice. Interestingly, Kerala still ranked third in India in terms of income per

hectare from rice cultivation. This divergence between national expansion and state-level contraction, along with Kerala's economic efficiency, made a comparative forecasting study both relevant and necessary.

Therefore, the present study assessed rice production in India and Kerala using two popular time series models ARIMA and Holt's Exponential Smoothing. These models, known for their effectiveness in level forecasting, were applied to historical data to generate predicted values. The forecasts were then compared with actual values to evaluate and compare the predictive accuracy and performance of each model.

MATERIAL AND METHODS

The dataset for the study was the total quantity of production of rice in Kerala and India from 1981 to 2023. The data was sourced from the Directorate of Economics and Statistics, Thiruvananthapuram and National Accounts Statistics Publication Reports, Government of India. The study attempted to forecast the production of rice in Kerala as well as in India for the next five years using different time series forecasting methods/models. These models used historical data to predict the future values by incorporating the variations in the time, like trend, seasonality, etc. It was imperative to note that multiple models using the same dataset might not yield the same result, so it was critical to check which model best suited the dataset.

The study analysed the effectiveness of two popular time series forecasting methods known as Holt's Exponential Smoothing Method and ARIMA.

Holt's Exponential Smoothing Method/ Holt Winters Forecasting

Using weighted averages of past observations was the key to the exponential

smoothing technique, a tool used to generate reliable forecasting models for time series. Holt (1957) developed an extension of the simple exponential model to forecast a time series with a linear trend. This method involved two equations, one a smoothing equation and another a trend equation. The model could be written as:

Forecast equation is $y_{t+h} = l_t + hb_t$

Level equation is $l_t = \alpha y_t + (1-\alpha)(l_{t-1} + b_{t-1})$

Trend equation is $b_t = \hat{\alpha}(l_t - l_{t-1}) + (1-\hat{\alpha})b_{t-1}$

Where:

h is the time steps you want to forecast

l_t denotes an estimate of the level of the series at time t

b_t denotes an estimate of the trend (slope) of the series at time t

α is the smoothing parameter for the level and $\hat{\alpha}$ is the smoothing parameter for the trend.

Auto Regressive Integrated Moving Average (ARIMA)

Autoregressive models stemmed from the concept that future values of a time series could be predicted from the past values and past values of its errors. ARIMA models were relatively easy to implement and interpret and were a popular choice for both beginner and experienced time series analysts. The model accounted for patterns of growth/decline (trend), the rate of change and the relationship of 'noise' (error) between consecutive time points. ARIMA models addressed the autocorrelations in the data and combined the autoregression, differencing and moving average in the model. An ARIMA model could be written as ARIMA (p,d,q), where p was the order of the Auto Regressive (AR) term, d was the order of the Integrated (I) term and q was the order of the Moving Average (MA) term.

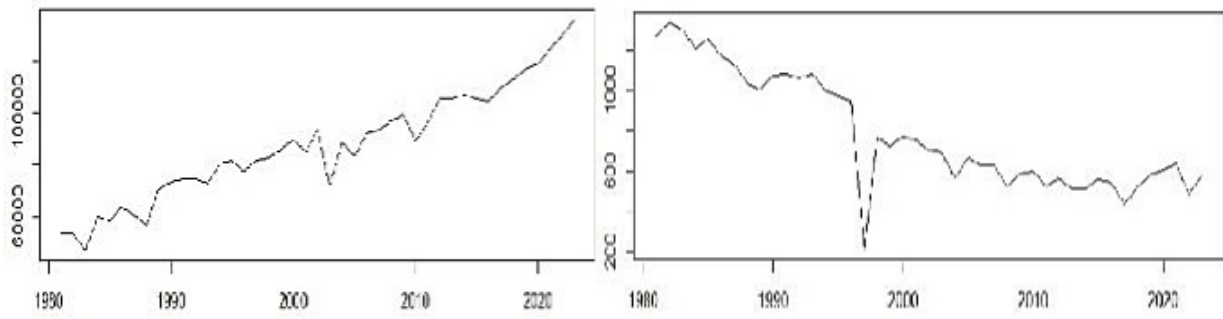


Fig 1. Rice production of Kerala and India.

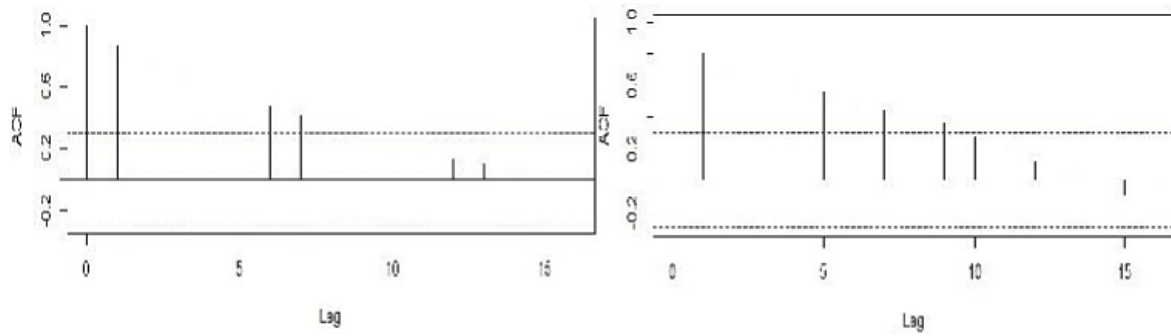


Fig 2. ACF – Rice Production of Kerala and India.

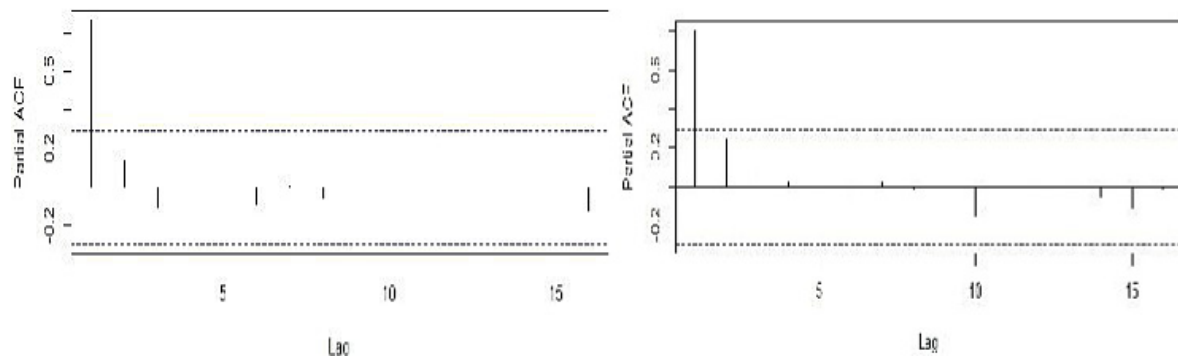


Fig 3. PACF – Rice Production of Kerala and India

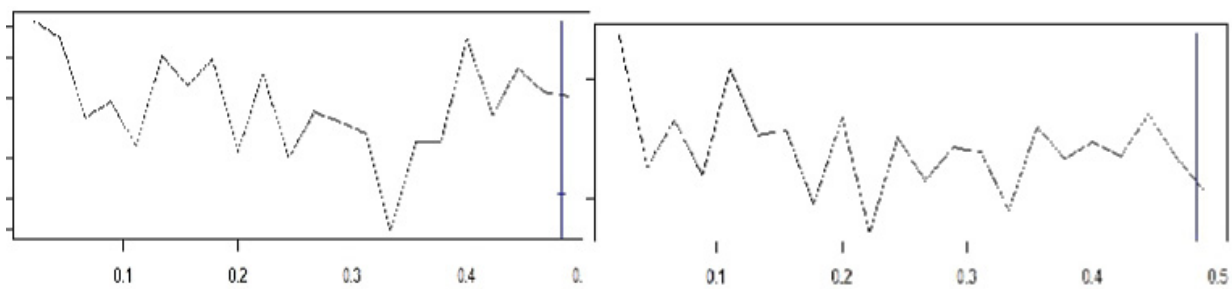


Fig 4. Periodogram – Rice Production of Kerala and India

The model could be written as:

$$y_t = c + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + \phi_1 \varepsilon_{t-1} + \dots + \phi_q \varepsilon_{t-q} + \varepsilon_t$$

where;

y is the differenced series

p is the order of the autoregressive part;

d is the degree of first differencing involved;

q is the order of the moving average part.

RESULTS AND DISCUSSION

Before fitting any model to the time series data, the first thing to do was to visualize the data, which could help to identify any trend, seasonality and other properties of time series data. Plotting the data was of utmost importance for any researcher of time series. As mentioned earlier, we were using the production of rice in Kerala and India as two different univariate time series and attempted to forecast the future production for the next five years for both the series. Plotting the data using a statistical package helped to identify trend, seasonality and stationarity.

While examining Figure 1 of both the series, one could easily identify the upward trend for rice production in India and the downward trend for rice production in Kerala.

The ACF, PACF and Periodogram of both the series (fig. 2, 3, and 4), however, referred to no seasonality as there were no strong lags at 1 and 12 for ACF and no dominant spikes in the periodogram. Hence, it was interpreted that the series was non-seasonal. The lags of ACF and upward/downward trend of the series also denoted the data was non-stationary. We could use the Augmented Dickey Fuller test to check if the series was non-stationary. If the series was non-stationary, we could differentiate it to make the series stationary. The results of the test were mentioned in table 3.

Rstudio software was used to analyse the data and interpret Holt's Exponential method and ARIMA. As the data exhibited no seasonality, Holt's Exponential method was run with the seasonality option as 'FALSE' (gamma = FALSE). It was also noted that as Holt Exponential method would take care of trend and seasonality, there was no need to differentiate the series before fitting the Holt Exponential model. However, the time series had to be stationary for fitting the ARIMA model. The statistical package would fit the best model based on AIC model (for ARIMA) and based on Alpha and Beta values (for Holt's Exponential Smoothing model).

Table 4. was the forecast of rice production for India and Kerala using ARIMA

Table 3. ADF Test Results Before and After Differencing

ADF Test Results	India	Kerala
Test Static	-1.5351	-1.787
P-value	0.7574	0.6579
Result	Non-stationary	Non-stationary
ADF Test Results (after differencing)	India	Kerala
Test Static	-5.1486	-4.7686
P-value	0.01	0.01
Result	Stationary	Stationary

Source: Computed

Table 4. Forecast for Next Five Years: India and Kerala

Year	INDIA		KERALA	
	Holt's Exponential Smoothing	ARIMA	Exponential Holt's Smoothing	ARIMA
2024	135687.7	132115.4	569.68	507.15
2025	139376.9	133994.5	572.53	488.73
2026	143066	135873.7	575.38	470.3
2027	146755.2	137752.9	578.23	451.88
2028	150444.4	139632	581.08	433.46

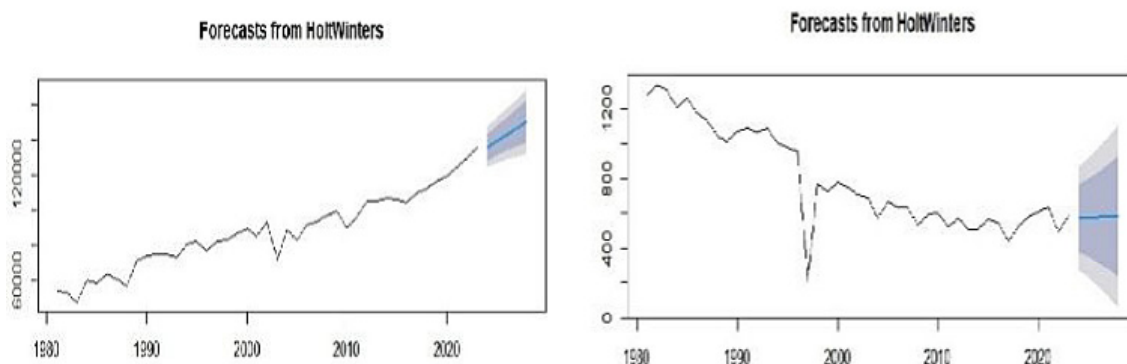
Source: Computed

and Holt's Exponential Model for a period of 5 years from 2024 to 2028. The forecasted data revealed a clear divergence between Holt's Exponential Smoothing and ARIMA methods. At the national level (India), Holt's model predicted consistently higher values, rising from 135687.7 thousand tonnes in 2024 to 150444.4 thousand tonnes in 2028, compared to ARIMA's forecasts, which ranged from 132115.4 thousand tonnes in 2024 to 139632.0 thousand tonnes in 2028, indicating a more optimistic growth trajectory. Conversely, at the state level (Kerala), ARIMA forecasted a decline from 507.15 0 thousand tonnes in 2024 to 433.46 0 thousand tonnes in 2028, while Holt's model showed a steady increase from 569.68 0 thousand tonnes in 2024 to 581.08 0 thousand tonnes in 2028. This contrast highlighted ARIMA's sensitivity to

potential downturns versus Holt's focus on long-term trends.

The figure 5 showed the forecasted coconut production in India and Kerala using Holt-Winters' method, demonstrating a steady upward trend from 1980 to 2023 at the national level and showing a declining trend from 1980 until stabilizing in recent years in the case of Kerala.

Figure 6 explained national-level data, showing a consistent upward trend with growing values over time, suggesting steady growth or improvement in the forecasted metric. The state-level data showed a declining trend initially, followed by stabilization and modest recovery in the forecast, indicating localized challenges or slower growth compared to the nation. The contrasting trends

**Fig. 5. Holt's Exponential Smoothing Forecast – Kerala and India**

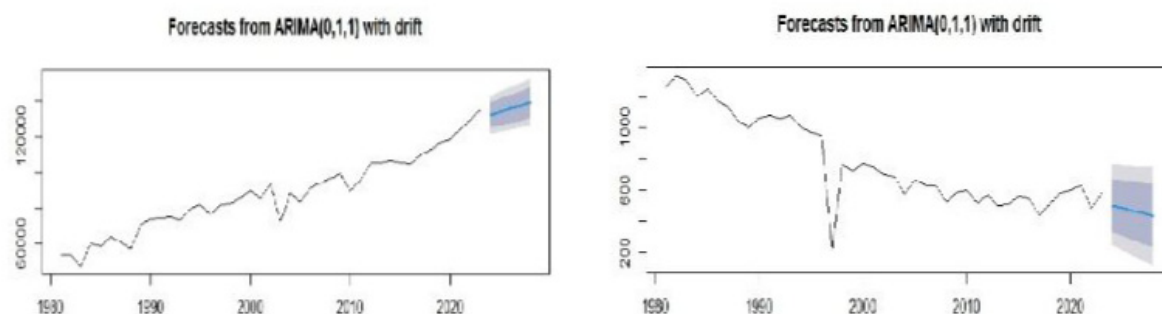


Fig. 6. ARIMA Forecast – Kerala and India.

highlighted differences in performance or development patterns between the national and state levels.

Table 5 presented the comparison between fitted values and true values of the outcome variable for India and Kerala using ARIMA and Holt's Exponential Smoothing Model. At the national level, actual values increased from 116500 thousand tonnes in 2019 to 135500 thousand tonnes in 2023, with Holt's predictions ranging from 113386.31 to 129627.46, and ARIMA closely following, from 11369.43 to 127249.95. In Kerala, actual production increased from 578.3 thousand tonnes in 2019 to 581.4 thousand tonnes in 2023. Holt's model showed consistent growth, from 486.29 to 552.55, while ARIMA captured

variability, starting at 459.08 and ending at 497.01. Both models aligned reasonably well with actual trends, but Holt's smooth predictions contrasted ARIMA's sensitivity to fluctuations.

Residual Analysis and Measures of Accuracy

Residual analysis and verifying the measures of accuracy helped to analyse the performance of the model and also to select the best model.

In terms of residual analysis plotting (Fig. 7, 8, 9, and 10), the residuals against time were a visual method to check for constant mean and variance. The histogram plot helped to identify whether the residuals were

Table 5. Fitted Values: India and Kerala

Year	Actual Value	INDIA Fitted Values		Actual Value	KERALA Fitted Values	
		Holt's Exponential Smoothing	ARIMA		Holt's Exponential Smoothing	ARIMA
2019	116500	113386.31	11369.43	578.3	486.29	459.08
2020	118900	116739.7	116589.12	605.6	531.68	481
2021	124400	119903.55	119304.74	633.8	575.17	504.73
2022	129500	124417.3	123028.22	487	616.69	529.98
2023	135500	129627.46	127249.95	581.4	552.55	497.01

Source: Computed

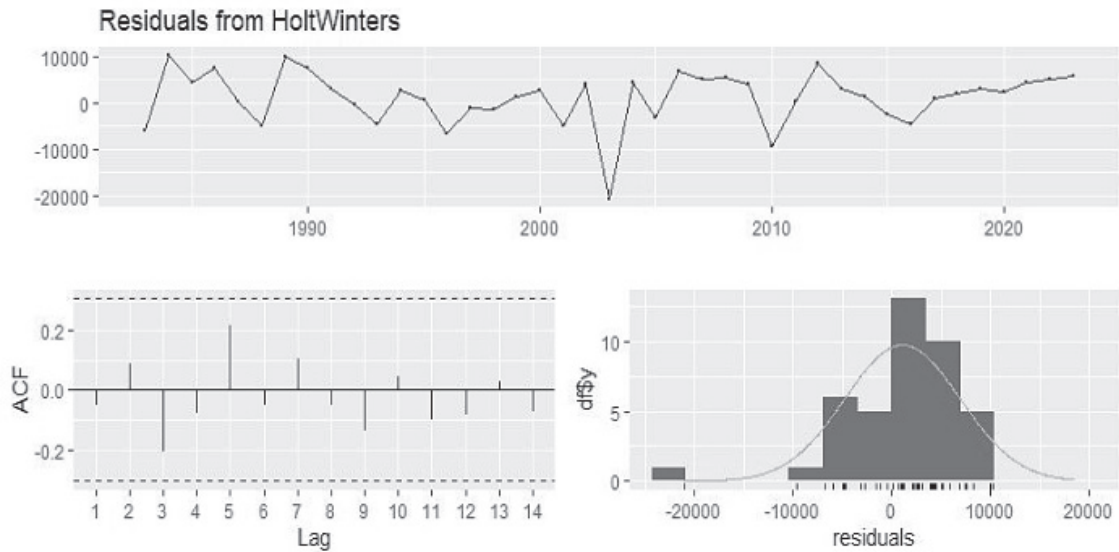


Fig. 7. Residuals from Holt Exponential Smoothing Model – Rice production in India

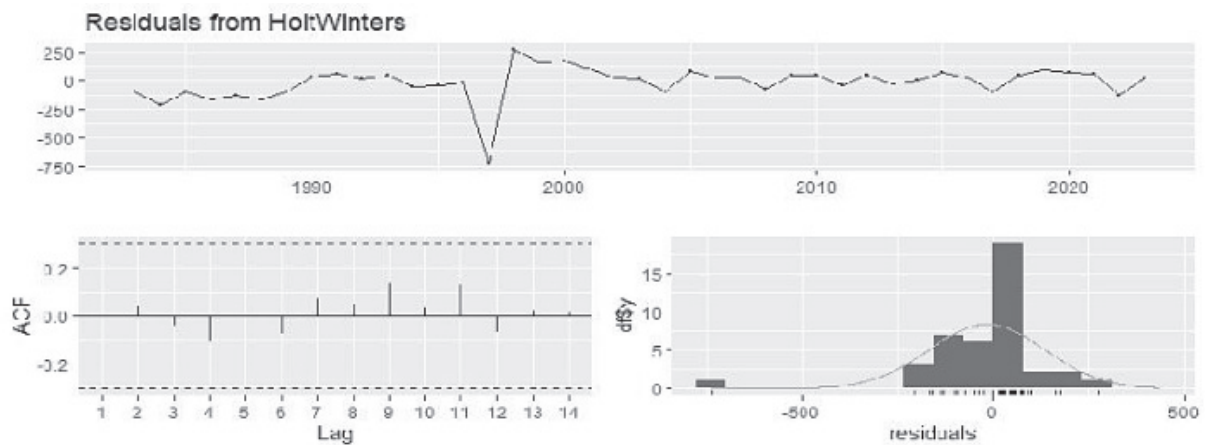


Fig 8. Residuals from Holt Exponential Smoothing Model – Rice production in Kerala

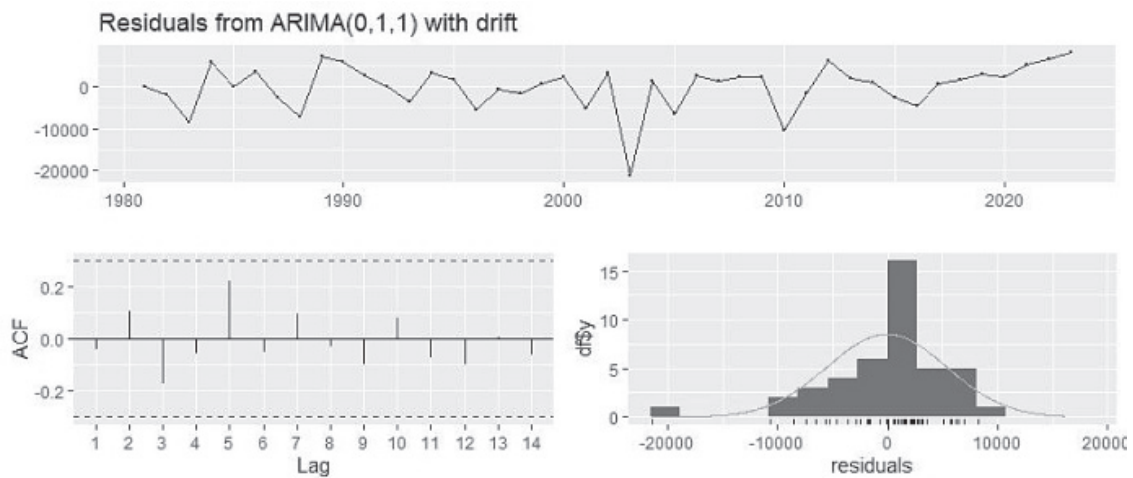


Fig. 9. Residuals from ARIMA Model – Rice production in India

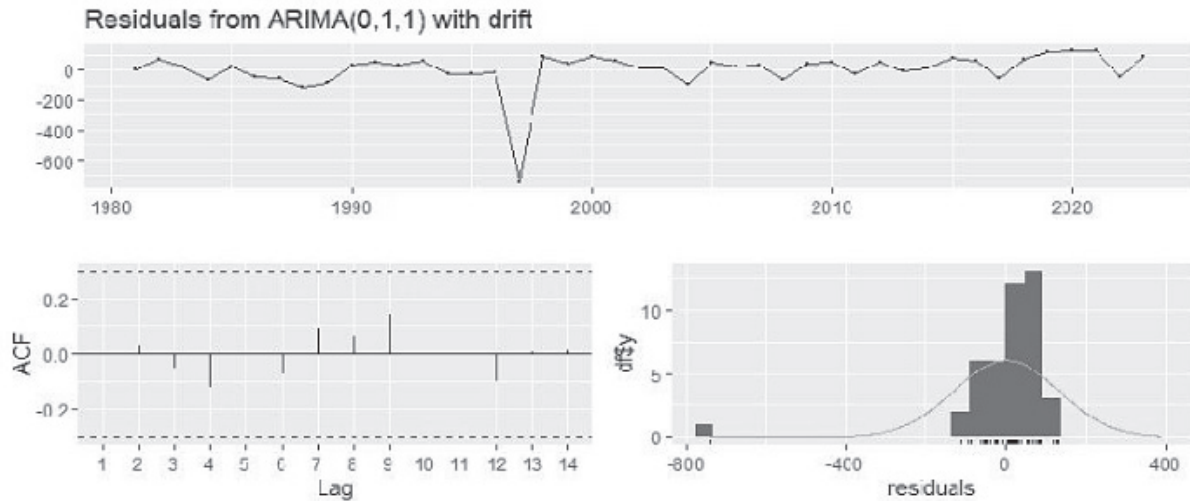


Fig. 10. Residuals from ARIMA Model – Rice production in Kerala

Table 6. Residual Analysis Ljung Box Test

Ljung-Box Test	Holt Winters		ARIMA	
	India	Kerala	India	Kerala
P-Value	0.6367	0.983	0.6602	0.9357

distributed normally. Residual analysis was a method to identify if the model had captured the information in the data adequately. ACF plot of the residuals helped to check whether the residuals were independent. No spikes from zero points indicated a lack of correlation and thus it could be assumed that the residuals were not correlated. The below visual implementation methods were rechecked using Ljung-Box Pierce statistic (Table: 6) to ascertain the independence of the residuals.

Various model accuracy measures (Table 7) like Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE), Root Mean Squared Error (RMSE), Mean Absolute Percent Error (MAPE) and Akaike Information Criterion (AIC) were accuracy measures based on the historical data. Care was taken that though these measures could be used as an indicator of the forecast accuracy, they did not carry over to future values. A lower MAE indicated

superior model accuracy and was the simplest measure of forecast accuracy. For India, the MAE for Holt's Exponential Smoothing was 4553.62, while for ARIMA, it was 3866.89, showing that ARIMA had better accuracy. If MASE was greater than 1, then the model was worse than the naive model. For India, the MASE for Holt Exponential Smoothing was 0.8949, and for ARIMA, it was 0.7599, showing ARIMA performed better. The lower the MASE, the better the model. RMSE helped to gauge the degree of inaccuracy in a model, and 0 indicated that the expected and actual values matched precisely. For India, RMSE for Holt Exponential Smoothing was 5873.25, while for ARIMA, it was 5362.52, indicating that ARIMA made more accurate predictions. Low RMSE values showed that the model made more accurate predictions and fit the data well. MAPE

Table 7. Measures of Accuracy

Parameters	Holt Winters		ARIMA	
	India	Kerala	India	Kerala
MAE	4553.62	93.9066	3866.89	68.4133
MAPE	5.6603	18.7406	4.8241	15.5673
MASE	0.8949	1.149	0.7599	0.8327
RMSE	5874.25	150.11	5352.52	128.39

of different models could be compared to evaluate the superiority of model performance in terms of forecasting accuracy. The MAPE for Holt Exponential Smoothing in India was 5.6603, while for ARIMA, it was 4.8241, showing ARIMA indicated higher accuracy with a lower MAPE value. Lower values of MAPE indicated higher accuracy.

CONCLUSION

For both models, the time plot of the residuals showed that the variation of the residuals stayed within a range and much the same across the historical data and hence the variance could be treated as constant. The histogram suggested that the residuals might not be normal the left tail seemed a little too long. Consequently, forecasts from this method would probably be quite good, but prediction intervals that were computed assuming a normal distribution might have been inaccurate. The comparative analysis of forecasting performance clearly establishes that the ARIMA model is more effective than the Holt's Exponential Smoothing model in predicting rice production in both India and Kerala. This is evident across all accuracy metrics. For India, ARIMA recorded lower errors with a MAE of 3866.89, MAPE of 4.8241%, MASE of 0.7599, and RMSE of 5362.52, compared to Holt's MAE of 4553.62, MAPE of 5.6603%, MASE of 0.8949, and RMSE of 5873.25. In Kerala, the pattern was similar. ARIMA had a MAE of 68.4133, MAPE of 15.5673%, MASE of 0.8327, and RMSE of 128.39, while Holt-Winters showed higher values across the board (MAE: 93.9066, MAPE: 18.7406%, MASE: 1.143, RMSE: 150.11). These results confirm that ARIMA not only provides better forecast accuracy but also fits the historical data more effectively, making it the more robust and reliable model for rice production forecasting in both regions.

REFERENCES

- Annadanapu, P. K., & Ravi, B. 2017. Time series data analysis on agriculture food production. *Advanced Science and Technology Letters*. 147, 520–525. <https://doi.org/10.14257/astl.2017.147.73>.
- Annamalai, N., & Johnson, A. 2023. Analysis and forecasting of area under cultivation of rice in India: Univariate time series approach. *SN Computer Science*, 4, 193. <https://doi.org/10.1007/s42979-022-01604-0>
- Bhattacharya, U. 2022. Rice cultivation in India – Challenges and environmental effects. In *Proceedings of the Workshop on NLP in Agriculture and Livestock Management* (pp. 1–4). Association for Computational Linguistics.
- Department of Agriculture and Farmers Welfare. 2022. *Agricultural statistics at a glance*. Government of India.
- Directorate of Economics and Statistics. 2023. *Agricultural statistics 2022–23*. The Government of Kerala, Thiruvananthapuram.
- FAO. (2024). FAOSTAT statistical database. Food and Agriculture Organization of the United Nations. <https://www.fao.org/faostat/>
- Holt, C. C. 1957. Forecasting seasonals and trends by exponentially weighted moving averages (ONR Memorandum No. 52). Carnegie Institute of Technology, Pittsburgh. (Available from the Engineering Library, University of Texas, Austin.)
- Kerala State Planning Board. 2023. *Economic Review 2022–23*. Government of Kerala. Retrieved from <https://spb.kerala.gov.in>

- Kumar, A., Singh, R. K. P., Mishra, J. S., Singh, D. K., Raman, R. K., & Kumar, U. 2022. Changing pattern of rice production in eastern India: An economic analysis. *Indian Journal of Agricultural Economics*, 58(2), 71–76. <https://doi.org/10.5958/2454-552X.2022.00058.5>
- Ministry of Agriculture & Farmers Welfare (MoAFW). 2024. Agricultural statistics at a glance 2024. Government of India.
- Mahto, A. K., Alam, A. M., Biswas, R., Ahmed, J., & Alam, S. I. 2021. Short-term forecasting of agricultural commodities in the context of the Indian market for sustainable agriculture by using the artificial neural network. *Hindawi Journal of Food Quality*, 1–13. <https://doi.org/10.1155/2021/9939906>
- Mgaya, J. F., & Yildiz, F. 2019. Application of ARIMA models in forecasting livestock products consumption in Tanzania. *Cogent Food & Agriculture*, 5(1). <https://doi.org/10.1080/23311932.2019.1607430>
- National Accounts Statistics Publication Reports. 2023. Government of India.
- Prasanna, L. P. A. 2018. Dynamics of rice production in India – Emerging sustainability issues and options available. *Journal of Rice Research*, 11(2), 63–72.
- Purohit, S. K., Panigrahi, S., Sethy, P. K., and Behera, S. K. 2021. Time series forecasting of price of agricultural products using hybrid methods. *Applied Artificial Intelligence*, 35(15), 1388–1406. <https://doi.org/10.1080/08839514.2021.1981659>
- Ramadhan, A. J., Biswas, T., Ray, S., Anjanawe, S. R., Rawat, D., Kumari, B., Yadav, S., Mishra, P., Abotaleb, M., Alkattan, H., and Albadran, Z. 2024. Modeling and forecasting of coconut area, production, and productivity using a time series model. *BIO Web of Conferences*, 97, 00113. <https://doi.org/10.1051/bioconf/20249700113>
- Sodha, D., and Saha, G. 2016. Crop management of agricultural products using time series analysis. In *IEEE International Conference on Recent Trends in Electronics Information Communication Technology* (pp. 1456–1460). <https://doi.org/10.1109/RTEICT.2016.7808073>
- Zelingher, R. and Makowski, D. 2023. Investigating and forecasting the impact of crop production shocks on global commodity prices. *Environmental Research Letters*, 19. <https://doi.org/10.1088/1748-9326/ad0dda>.

Smitha, P. 2025. Assessment of the Time series Models for Forecasting Rice Production in Kerala and India: ARIMA Versus Holt's Exponential Smoothing. *The Journal of Research ANGRAU*, 53(2), 118-128. <https://doi.org/10.58537/jorangrau.2025.53.2.14>