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HOLT'S EXPONENTIAL SMOOTHING AND ARIMA MODELS FOR FORECASTING COCONUT PRODUCTION TRENDS IN INDIA

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ABSTRACT

This study forecasts coconut production in India for the next decade using two time series forecasting models: Holt's Exponential Smoothing and ARIMA. By analysing historical production data from 1956 to 2021, both models indicate a consistent upward trend in coconut production. The study compares model performance using accuracy measures such as MAE, MAPE, and AIC. Results show that while both models forecast similar trends, ARIMA outperforms Holt's Exponential Smoothing in terms of accuracy, as reflected by lower MAPE values. Although Holt's method fitted the values slightly better, ARIMA produced more reliable predictions. The models did not perform well based on RMSE criteria, but residual analysis suggests that Holt's method produces more random, white noise residuals compared to ARIMA. The findings underscore ARIMA's superior predictive accuracy in forecasting coconut production, despite both models having potential for long-term forecasting.

Keywords: ARIMA,Coconut Production, Forecast, Holt Exponential Smoothing.

INTRODUCTION

India occupies a prominent position in the global coconut economy, contributing 31.45% of the world's production in 2021–22 with an output of 19,247 million nuts (India Trade Portal, 2025). The coconut sector plays a crucial socio-economic role by generating nearly 30,748 crore for the national GDP and supporting the livelihoods of around 12 million people. Approximately 600,000 workers are engaged directly in processing industries such as copra production, oil extraction and coir manufacturing (India Brand Equity Foundation). With an average productivity of 9,123 nuts per hectare - among the highest globally (Kalidas *et al*., 2014). India continues to be a key player in the international market.

Coconut cultivation in India is regionally concentrated, with Karnataka, Tamil Nadu, Kerala and Andhra Pradesh contributing nearly 89.13% of the national cultivated area and 90.04% of total production (Jayasekhar and Jacob, 2021; Narmada *et al*., 2022). Karnataka leads the country with 4,210.87 million nuts annually, followed by Tamil Nadu and Kerala (Narmada *et al.*, 2022). At the global level, India ranks third in production after Indonesia and the Philippines, with a cultivated area of

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approximately 2.19 million hectares (International Coconut Community, 2021).

However, production trends in the coconut sector are influenced by a combination of internal factors-such as cultivation techniques, labour availability, and management efficiency and external influences including climate change, natural disasters, pests and diseases, and volatile market conditions (Muyengi *et al*., 2015; Gurbuz and Manaros, 2019). These uncertainties highlight the necessity for accurate forecasting to support strategic decision-making. Reliable production forecasts play a vital role in planning resource allocation, stabilizing prices, ensuring livelihood security, guiding trade and export policies, and fostering value-added industries. Previous research has emphasized that fluctuations in production, area, and yield significantly affect long-term sectoral sustainability (Narmada and Karunakaran, 2022).

In this context, the present study aims to evaluate and compare the forecasting accuracy of two widely used timeseries models Holt's Exponential Smoothing and ARIMA using historical production data spanning 1956–2021. By analysing their performance and selecting the most reliable model, the study provides a scientific basis for forecasting coconut production in India for the next decade. The findings are expected to assist policymakers, agricultural planners, processing industries, and other stakeholders in adopting informed strategies to promote sustainability and growth in the coconut sector.

MATERIAL AND METHODS

This study focused on forecasting coconut production in India for the next ten years using historical production data from 1956 to 2021 (66 observations). Two time series models—Holt's Exponential Smoothing and ARIMA (Auto Regressive Integrated Moving Average)—were applied to capture trends, seasonality, and variations in the data. Both models relied on past values to predict future outcomes, but they approached the time series characteristics differently. Holt's method was suited for capturing trends and seasonality, whereas ARIMA addressed autocorrelation and more complex patterns.

Data analysis was carried out in RStudio. For Holt's Exponential Method, no differencing was required since the model inherently captured level and trend. In contrast, the ARIMA model required the series to be stationary, and the best fit was selected based on the Akaike Information Criterion (AIC). For Holt's method, model selection was guided by the values of the smoothing parameters Alpha (á) and Beta (β).

Holt's Exponential Smoothing Method

Holt's method, developed in 1957 as an extension of simple exponential smoothing, used weighted averages of past observations to forecast series with linear trends. It involved two main equations - level and trend - combined to generate forecasts.

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

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

Trend equation is $b_t = \beta(l_t - l_{t-1}) + (1\text{-}\beta)\, b_{t-1}$

Here, l_t denoted the level of the series, b_t denoted the trend, á was the level smoothing parameter, α was the trend smoothing parameter, and *h* represented the forecast horizon.

Auto Regressive Integrated Moving Average (ARIMA)

The ARIMA model predicted future values from past observations and error terms and effectively handled autocorrelation. It combined three components: autoregression (AR), differencing (I), and moving average (MA). The model was denoted as ARIMA(p,d,q), where *p* was the order of the AR part, *d* was the degree

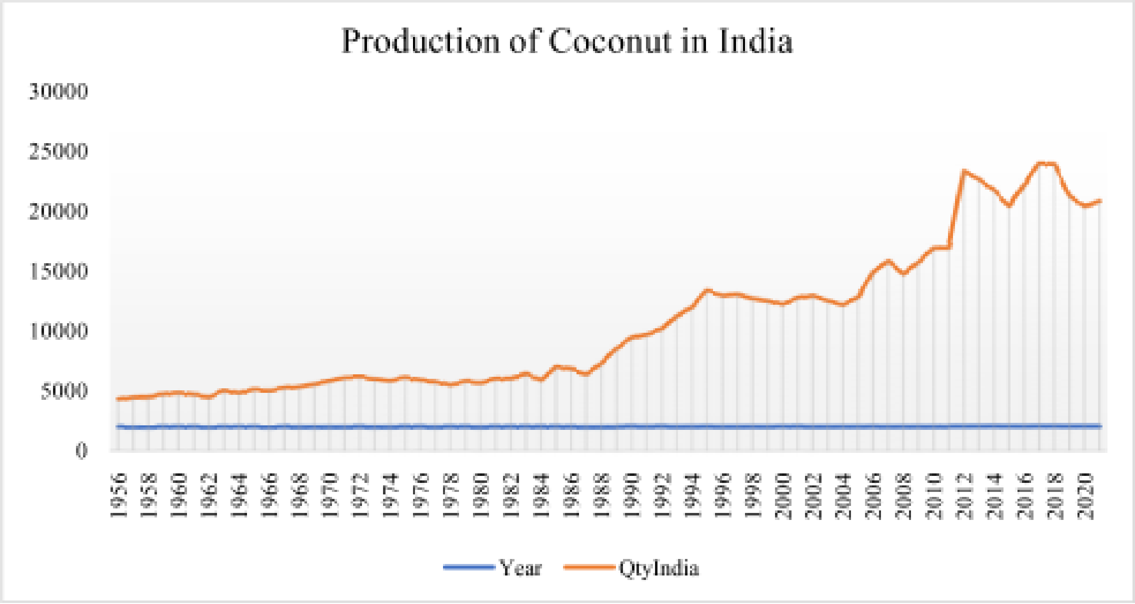

Fig 1. Coconut production in India.

of differencing, and *q* was the order of the MA part. The general form was:

$$y_t = c + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

where, y_t was the differenced series, ϕ represented the AR parameters, θ the MA parameters, and εt the error term.

RESULTS AND DISCUSSION

Before fitting a model to time series data, visualizing the data was essential to help reveal any underlying trends, seasonality, and other significant characteristics. Plotting allowed researchers to visually assess these elements, which were crucial for selecting and tuning an effective forecasting model. In this study, two univariate time series were examined: coconut production in India, aiming to forecast production over the next 10 years. Using statistical software to plot these time series provided insights into trends, seasonality, and stationarity, guiding the

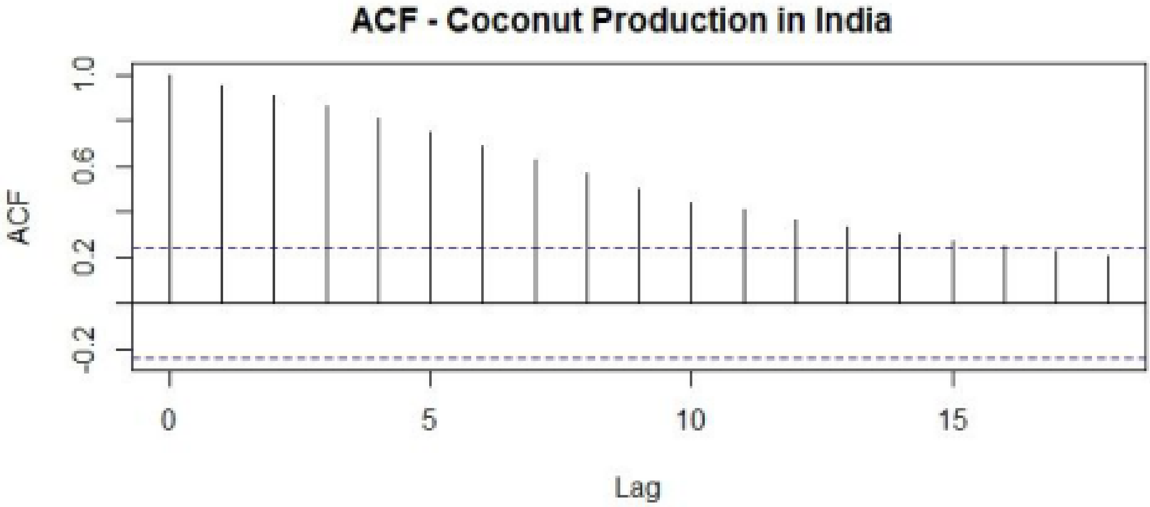

Fig 2. ACF – Coconut Production in India.

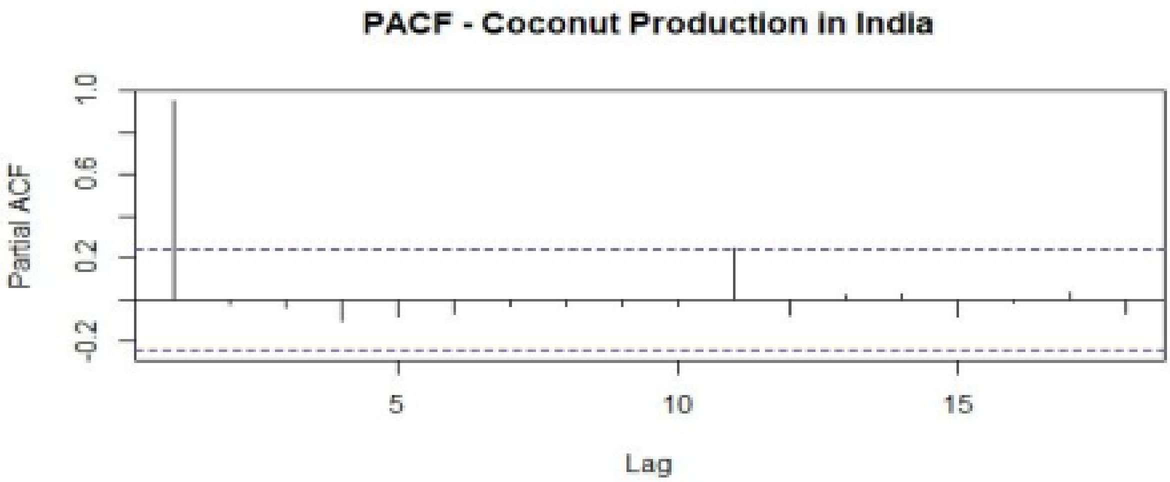

Fig 3. PACF – Coconut Production inIndia.

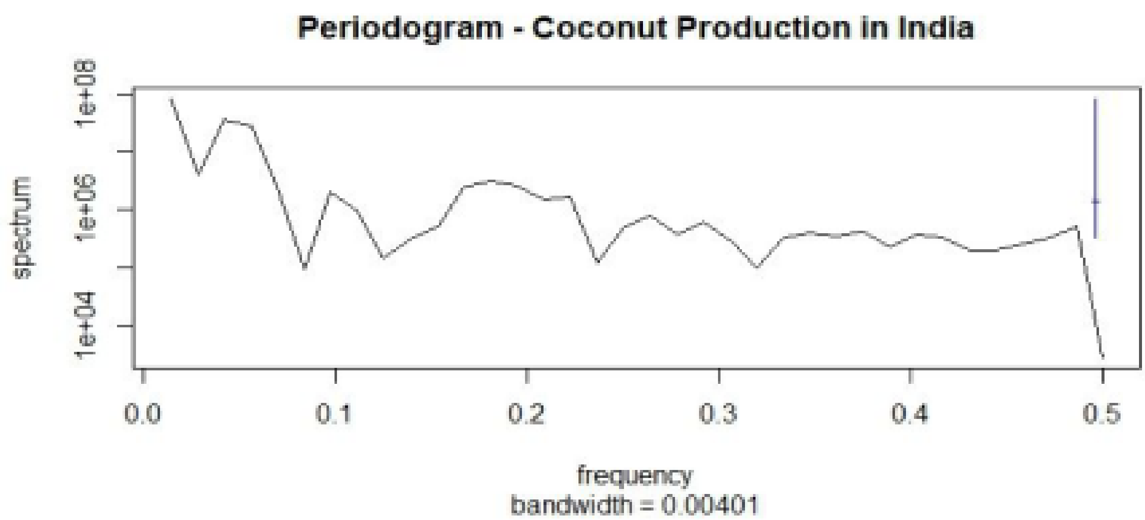

Fig 4. Periodogram – Coconut Production in India and Kerala.

identification of the most suitable approach for accurate prediction based on the observed patterns in the historical data.

The graph of the series (Fig. 1) clearly showed an upward trend in coconut production in India. To examine the presence of seasonality in the series, the Auto Correlation Function (ACF), Partial Auto Correlation Function (PACF), and the Periodogram were used.

The ACF, PACF, and periodogram analyses indicated the absence of seasonality in the series. Specifically, the ACF did not show strong lags at 1 or 12, and there were no prominent peaks in the periodogram, suggesting a non-seasonal nature. Additionally, the ACF lags and the general upward/downward trend suggested that the series was likely non-stationary. To confirm non-stationarity, the Augmented Dickey-Fuller test or the Phillips-Perron test was applied. If these tests confirmed non-stationarity, differencing the series helped achieve stationarity.

Table 1. ADF Test Results Before and After Differencing

Stationarity Test Results		
Remark	ADF Test	Phillips-Perron Test
Test Static	-1.8118	-7.3322
P-value	0.6514	0.6825
Result	Non-stationary	Non-stationary
Stationarity Test Results (after differencing)		
Remark	ADF Test	Phillips-Perron Test
Test Static	-4.2334	-54.742
P-value	0.01	0.01
Result	Stationary	Stationary

Table 2. Forecast of Coconut Production for Next Ten Years

Holt's		ARIMA	
Year	**Forecast**	**Year**	**Forecast**
2022	20969.72	2022	20990.15
2023	21203.32	2023	21244.17
2024	21436.92	2024	21498.2
2025	21670.52	2025	21752.23
2026	21904.12	2026	22006.25
2027	22137.72	2027	22260.28
2028	22371.32	2028	22514.31
2029	22604.92	2029	22768.33
2030	22838.52	2030	23022.36
2031	23072.12	2031	23276.38

The test results are presented below.

Table 1 presents the results of stationarity tests conducted using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron test, both before and after differencing the data. Initially, the test statistics for both the ADF (-1.8118) and Phillips-Perron (-7.3322) tests, along with their respective p-values (0.6514 and 0.6825), indicate non-stationarity as they fail to reject the null hypothesis of a unit root. However, after differencing the data, the test statistics significantly improve (ADF: -4.2334, Phillips-Perron: -54.742), with p-values dropping to 0.01 for both tests. This confirms stationarity, as the null hypothesis is now rejected at the 1% significance level. These results suggest that differencing the data was necessary to achieve stationarity, a critical assumption for time series modelling.

Comparison of the Performance of the Two Methods

Table 2 compared the forecasts of coconut production in India for the next ten

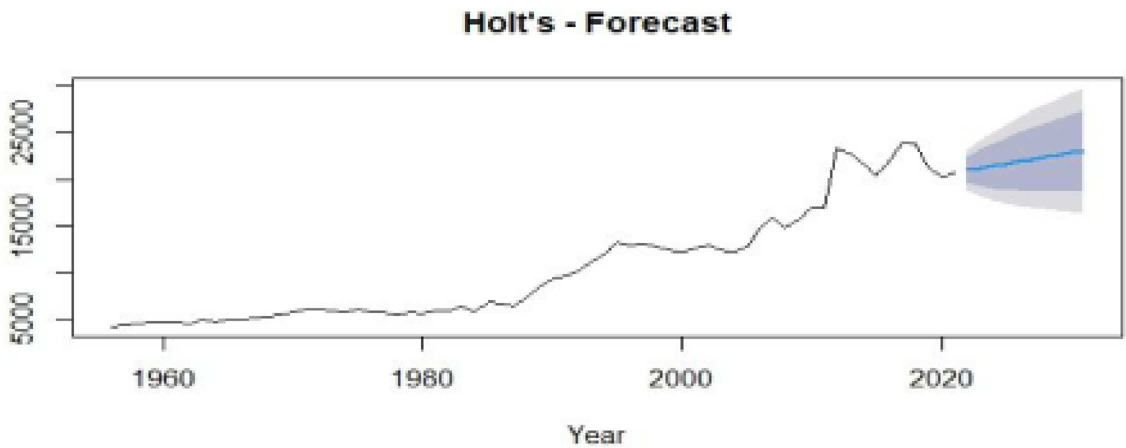

Fig.5. Forecast of Coconut Production in India: Holt's Method.

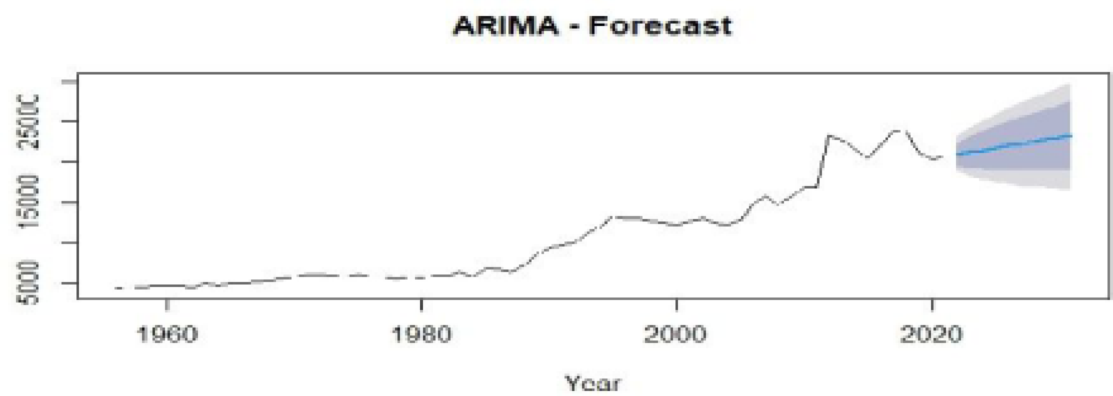

Fig 6. Forecast of Coconut Production in India: ARIMA.

years (2022–2031) using Holt's Exponential Smoothing method and the ARIMA model. Both models projected an increasing trend in production over the forecast period, but there were subtle differences in their predictions in specific years. Holt's method, an extension of simple exponential smoothing, focused on capturing trends and seasonality. On the other hand, the ARIMA model accounted for past values and errors in the time series, emphasizing autocorrelation and modelling complex seasonal patterns.

Holt's Exponential Smoothing provided slightly lower forecasts for most years compared to ARIMA. In 2022, Holt's predicted a production of 20,969.72 units, which was slightly lower than ARIMA's 20,990.15 units. This trend continued in subsequent years, with both models gradually increasing their estimates. By 2026, Holt's forecast reached 21,904.12 units, compared to ARIMA's slightly higher 22,006.25 units, indicating a difference of about 102 units. Similarly, by 2030, Holt's predicted 22,838.52 units, while ARIMA estimated 23,022.36 units, maintaining a consistent gap. Overall, while the forecasts were closely aligned, ARIMA's projections consistently edged higher than those of Holt's, suggesting a marginally more optimistic outlook for coconut production. This comparison underscored the reliability of both methods in capturing growth trends, with ARIMA offering a nuanced advantage in accounting for historical patterns.

Table 3. Fitted Vs Actual Values

Year	Actual Value	Fitted Values	
		Holt's	ARIMA
2016	22167	20673	20693
2017	23904	22401	22421
2018	23798	24137	24158
2019	21288	24031	24052
2020	20308	21521	21542
2021	20736	20542	20562

Fig. 5 indicates a general upward trend in production, with some fluctuations over the years.

Fig. 6 illustrates the forecast of India's coconut production using the ARIMA, an upward trend with notable fluctuations over time.

Table 3 compared the actual coconut production values from 2016 to 2021 with the fitted values from Holt's Exponential Smoothing and ARIMA. In 2016, the actual production was 22,167 units, and both models underpredicted the value, with Holt's at 20,673 and ARIMA at 20,693. In 2017, the actual production of 23,904 units was closely estimated by both models, with Holt's predicting 22,401 and ARIMA 22,421. In 2018, the actual value was 23,798, and both models slightly overestimated, with Holt's at 24,137 and ARIMA at 24,158. The actual production dropped to 21,288 in 2019, but both models overestimated again, with Holt's at 24,031 and ARIMA at 24,052. In 2020, the actual value of 20,308 was overestimated by both models, with Holt's at 21,521 and ARIMA at 21,542. Similarly, in 2021, the actual value of 20,736 was predicted by Holt's as 20,542 and ARIMA as 20,562. It was evident from the above table that both models fitted the data as well as the trend while comparing the actual values to fitted values. Overall, while both models followed a similar pattern, ARIMA generally provided slightly more accurate predictions, especially in matching the actual values more closely in most years.

Table 4. Residual Analysis – Ljung Box Test

Ljung-Box Test		
Remarks	**Holt's**	**ARIMA**
Test Statistic	20.311	20.857
P-Value	0.2211	0.02645
Total Lags used	10	10

Residual Analysis

We further analysed the residuals and measures of accuracy of the model to support the above statement. Residual analysis and accuracy measures were essential for evaluating model performance and selecting the most suitable model. In residual analysis, plotting residuals over time allowed us to visually assess whether they maintained a constant mean and variance. Additionally, a histogram of residuals revealed whether they followed a normal distribution. This step helped determine if the model effectively captured the data's underlying patterns. The Autocorrelation Function (ACF) plot further assisted in verifying the independence of residuals. If the ACF plot showed no significant spikes, it indicated a lack of correlation, suggesting that residuals were uncorrelated. For further validation, the Ljung-Box Pierce statistic was used to statistically

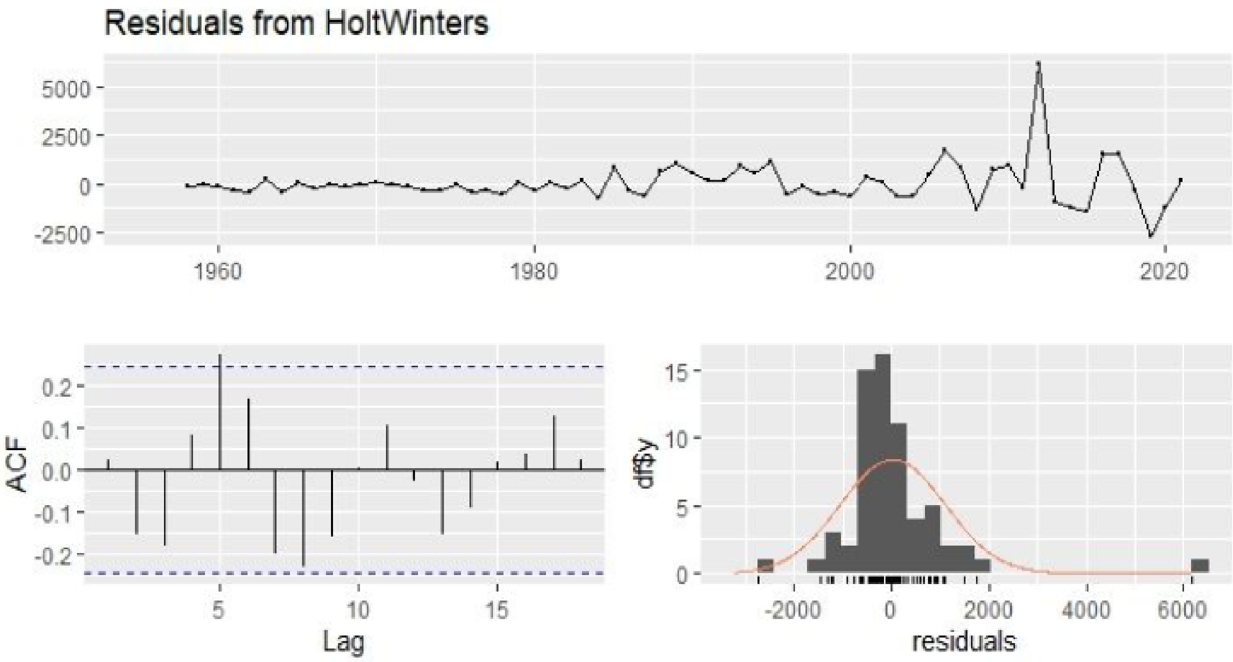

Fig7. Residuals from Holt's Exponential Model: Coconut Production in India

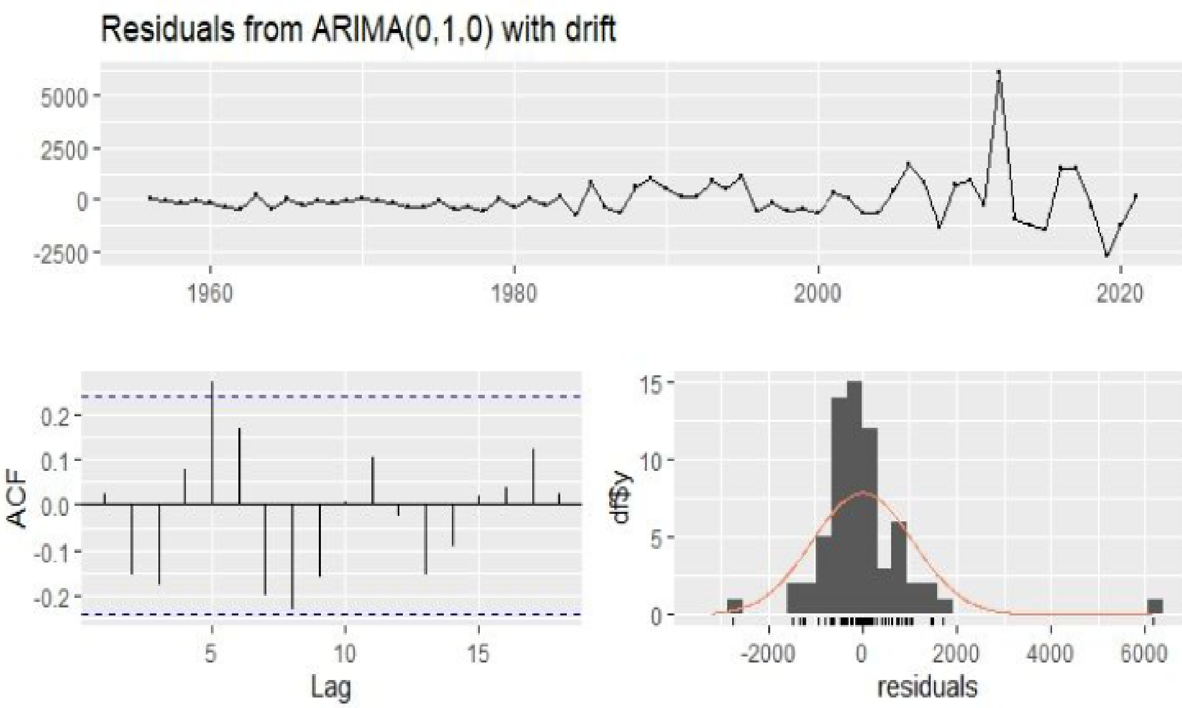

Fig 8. Residuals from ARIMA Model: Coconut Production in India

confirm residual independence. Together, these methods provided a comprehensive check, confirming that the model's assumptions held and that it had adequately captured the data structure.

The Ljung-Box test results presented in Table 4 assessed the autocorrelation of the residuals from both Holt's Exponential Smoothing and ARIMA models. For both models, the test was applied to 10 lags, with the test statistic for Holt's being 20.311 and for ARIMA being 20.857. The p-value for Holt's was 0.2211, which was greater than the common significance level of 0.05, indicating that the residuals from Holt's did not exhibit significant autocorrelation and were likely random (i.e., the model had captured the underlying structure of the data well). However, for ARIMA, the p-value was 0.02645, which was less than 0.05, suggesting that there was significant autocorrelation in the residuals. This indicated that the ARIMA model had not fully captured all the patterns in the data, and further refinement might have been needed. In conclusion, Holt's appeared to have produced residuals that were more adequately white noise compared to ARIMA.

For both models, Holt's Exponential Smoothing and ARIMA, the time plot of the residuals (Fig. 7 and 8) showed that the variation of the residuals stayed within a range and remained consistent across the historical data, indicating that the variance could be treated as constant. The histogram suggested that the residuals might not have been normal — the left tail seemed a little too long. Consequently, forecasts from these methods were likely to be quite good, but prediction intervals computed assuming a normal distribution might have been inaccurate.

Table 5. Measures of Accuracy

Model Performance – Measures of Accuracy		
Remarks	**Holt's**	**ARIMA**
MAE	636.8156	621.6017
MAPE	5.431846	5.353232
MASE	1.010142	0.9860087
RMSE	1071.639	1055.082

Measures of Accuracy

Various model accuracy measures, such as Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE), Root Mean Squared Error (RMSE), Mean Absolute Percent Error (MAPE), and Akaike Information Criterion (AIC), provided insight into model performance using historical data. These metrics helped gauge how well the model fitted past data, though it was important to note that they might not have directly translated to future forecasting accuracy. MAE, which indicated the average absolute difference between actual and forecasted values, was straightforward and useful; a lower MAE suggested a more accurate model. MASE, when above 1, implied that the model performed worse than a naive forecasting approach, with lower values indicating better accuracy relative to this benchmark. RMSE was valuable for understanding the model's prediction error; an RMSE of 0 would have signified perfect alignment between expected and actual values, while lower RMSE values generally reflected a better-fitting model. MAPE, meanwhile, enabled comparison of forecast accuracy across models, with lower MAPE values indicating superior forecasting performance. Finally, the AIC assisted in model selection, balancing goodness of fit with model complexity. Collectively, these metrics offered a comprehensive approach to assessing model accuracy and comparing models effectively.

The model performance metrics presented in the table, including MAE, MAPE, MASE, and RMSE, provided a comparison of the accuracy of Holt's Exponential Smoothing and ARIMA models. The Mean Absolute Error (MAE) was slightly lower for ARIMA (621.60) compared to Holt's (636.82), indicating that ARIMA had a marginally smaller average prediction error. Similarly, the Mean Absolute Percentage Error (MAPE) for ARIMA (5.35%) was also slightly better than Holt's (5.43%), suggesting that ARIMA's forecasts were more accurate in terms of percentage error. The Mean Absolute Scaled Error (MASE) was very close for both models, with Holt's at 1.01 and ARIMA at 0.99, indicating similar scaling of errors relative to the benchmark model. Lastly, the Root Mean Square Error (RMSE) was also lower for ARIMA (1055.08) compared to Holt's (1071.64), further highlighting that ARIMA offered slightly better performance in terms of reducing large errors. Overall, both models showed similar accuracy, but ARIMA marginally outperformed Holt's in most accuracy measures.

CONCLUSION

This study set out to analyse coconut production in India and to forecast future production using two univariate time series models: Holt's Exponential Smoothing and the ARIMA model. The visual examination of the data revealed a clear and consistent upward trend in coconut production from 1956 to 2021, supporting the historical data suggesting a consistent increase in demand. Forecasts for the period 2022–2031 from both methods indicated a continued rise in coconut production, with ARIMA consistently projecting slightly higher value, 23,022.36 units in 2030 compared to Holt's 22,838.52. When evaluated against the actual values from 2016 to 2021, both models broadly captured the underlying trend, though ARIMA provided marginally closer estimates in most years. Residual analysis offered an important contrast: Holt's model produced residuals that were uncorrelated and behaved more like white noise, as indicated by a statistically insignificant Ljung–Box p-value (0.2211). In contrast, the ARIMA model showed some residual autocorrelation (p = 0.02645), suggesting incomplete modelling of the underlying data structure. However, despite this limitation, the accuracy metrics: MAE, MAPE, MASE, and RMSE indicated that ARIMA performed slightly better than Holt's. ARIMA recorded a lower MAE (621.60 versus 636.82), lower MAPE (5.35% versus 5.43%), lower MASE (0.986 versus 1.01), and a lower RMSE (1055.08 versus 1071.64), confirming its marginally superior forecasting accuracy across all measures. Overall, the study concludes that both Holt's Exponential Smoothing and the ARIMA model are suitable for forecasting coconut production in India, effectively capturing the long-term growth trend observed in the historical data. While Holt's demonstrates stronger residual behaviour, ARIMA achieves marginally superior forecasting accuracy, making it the more reliable model for predicting future coconut production in this case. The forecasts from both models indicate a steady rise in coconut output over the next decade, offering valuable insights for policymakers, agricultural planners, and stakeholders in the coconut sector.

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