Modeling and Forecasting of Coconut Area, Production, and Productivity Using a Time Series Model

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Abstract. The study aimed to compare ARIMA and Holt's models for predicting coconut metrics in Kerala. The coconut data series was collected from the period 1957 to 2019. Of this, 80% of the data (from 1957 to 2007) is treated as training data, and the rest (20% from 2008 to 2019) is treated as testing data. Ideal models were selected based on lower AIC and BIC values. Their accuracy was evaluated through error estimation on testing data, revealing Holt's exponential, linear, and ARIMA (0,1,0) models as the best-fit choices for predicting coconut area, production, and productivity respectively. After using the testing data, we tried for the forecasting for 2020-2024 using these models, and the DM test confirmed their significant forecasting accuracy. This comprehensive analysis provides valuable insights into effective prediction models for coconut-related metrics, offering a foundation for informed decision-making and future projections.

1. Introduction

Coconuts, which are largely tropical plants, are farmed in over 90 countries through-out the world, with the majority of production concentrated in and around Asia and the Pacific [1]. Each portion of the plant, from the nut to the exocarp, has economic significance since it is a multi-utility crop with several uses [2]. The nut's flesh is consumed as food; the water is consumed as a healthy refresh-ing drink; the oil is consumed for cooking and skin and hair nourishment; the husks are used as a craft material and for ropes; the leaves are used for roof thatching; the sticks are used as brooms; the wood is used as firewood; and the flowers are consumed for their medicinal benefits.

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Coconut shell has indeed been employed in the manufacturing of structural lightweight concrete [3]. In recent years, there has been an upsurge in the demand for coconut goods on the worldwide market. In re-cent years, coconuts have increasingly been turned into high-value and specialized goods, necessitating more complicated processing and technological improvements along the worldwide value chain. A big part of this present trend is driven by non-traditional items such as coconut milk and coconut water, among others [4]. Historically, the cultivation and trade of coconuts were based on the manufacture and exchange of coconut oil. As of 2013, more than 40 coconut products are being manufactured and sold globally [5], and the number is steadily growing.

The countries with the highest consumption of coconuts in last years were Indonesia (18 million tonnes per year), the Philippines (15 million tonnes per year) and India (12 million tonnes per year). These countries were followed by Sri Lanka, Brazil, Vietnam, Papua New Guinea, Mexico and Thailand. From 2013 to 2019, Vietnam saw the most notable growth in coconut consumption among the major consuming countries ([6]. In last years, the global production of coconuts reached 62 million tons per year, which is roughly the same as in the previous years. The countries with the highest volumes of coconut pro-duction in 2019 were Indonesia, the Philippines and India. Sri Lanka, Brazil, Vietnam, Papua New Guinea and Mexico lagged slightly behind in terms of volume [7]. In last year, the area planted for coconuts worldwide was 13 million hectares, roughly in line with the previous year [8]. The average global coconut yield dropped to 5 tons per hectare, which was roughly the same as last year. In value terms, coconut exports rose to $ 527 million in 2019 [9]. Coconut production in India is one of the world's most im-portant; the country accounts for around 17 percent of total global production. Due to the extensive genetic composition and agronomic adaptability for climate change, co-conut farming in India is a profitable endeavor [10]. Coconuts are grown in Kerala, which is the country's leading producer and producer of coconuts and is commonly referred to as "the land of coconuts." There is an extremely low land-to-human ratio in Kerala, which has driven the area under major grains to fall behind and coconuts to rise to become a prominent player in the state's agricultur-al basket, as shown in the chart below [11]. However, it has been observed that the area and production of coconut in the state has declined over the years and the producers are struggling to earn profits from the crop [12,13]. It is grown over 760.78 thousand hectares, producing about 6980.30 million nuts in Kerala, which accounts for about 35 per cent of the total area and about 34 per cent of the total production in India (Horticulture division, Depart-ment of Agriculture and Cooperation, Ministry of Agriculture and Farmers Welfare, Government of India, 2019-2020). Despite being the highest producer in the country, the productivity of coconut in Kerala (9,175 nuts/ha (2019-2020)) is less than the na-tional average (9,345 nuts/ha (2019-2020); the highest being that of Maharashtra (17,485 nuts/ha (2019-2020). But it is expected that the changing climate will lead to an improvement in coconut productivity in Kerala, parts of Tamil Nadu and the North-east region, whereas other regions will witness a downfall [14]. Due to the lower yield of coconut in the state, it is necessary to examine the future of production of the crop in the state so that it is ensured that the topmost position of the state remains unchallenged. Therefore, the current study is being un-dertaken to forecast the production of coconuts in Kerala. In [15] se-lected the model for forecasting based on minimum root mean square error values and found ARIMA (1,1,1) as the most appropriate model for forecasting the production of coconut in India. The Box-Jenkins ARIMA method of modeling was used by [16] in a similar study to forecast coconut production in India, and the results showed that ARIMA (1,0,0) was the best appropriate model. In [17] ap-plied the unobserved component method (UCM) to forecast coconut production in Sri Lanka using non-stationary time series data, and the results were positive. Many addi-tional studies of a similar nature were conducted in order to forecast the production of coconuts in Sri Lanka

[18]. A regressor (area) model combined with ARIMA (2,1,0) was used to forecast the production of coconuts in Assam, and the re-searchers discovered that the production of coconuts increased over their forecasted time period [19]. In [20] utilized the ARIMA model to anticipate co-conut production in the Philippines, which he found to be accurate. As a result, it can be concluded that the ARIMA model was employed for forecasting in the majority of the investigations. The Autoregressive Integrated Moving Average (ARIMA) tech-nique of modeling was used to anticipate coconut production in Kerala in this study, which is based on the Box-Jenkins method of modeling.

2. MATERIALS AND METHODS

Figure A represents the schema for modeling and forecasting of coconut area, production, and productivity using time series models.

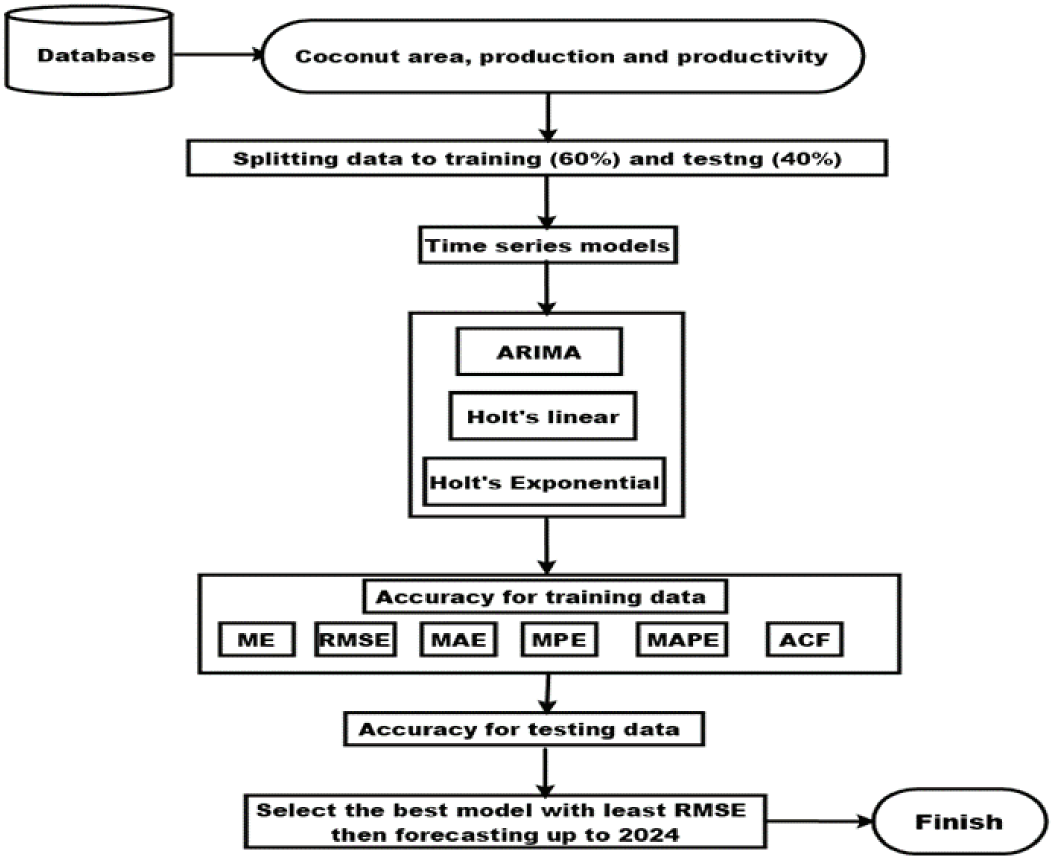

Fig. 1. Schema for Modeling and forecasting of Coconut area, production and productivity using time series models

2.1 ARIMA Model

There are three components to the ARIMA model. The initial component is (AR), denoting Autoregressive. The integrated portion (I) is the second. The model is called Autoregressive integrated moving average (ARIMA) because the third component is (MA) Moving Average. When data from time series are used to reduce seasonality, the integrated part of the ARIMA model equals zero ARIMA(p,0,q), which is represented as ARMA (p,0,q) (p,q). In these cases, the integrated part of the ARIMA model is equal to p, the order of the autoregressive part, and q, the order of the moving average. There are many studies that used the Arima model and developed its equations [21-29].
The first part is Autoregressive model.
Equation (1) the autoregressive model of order p is written as AR(p)

$$X_t = K + \sum_{i=1}^{P} \omega_i X_t + \varepsilon_t \qquad (1)$$

Where $\omega_1, \omega_2 \ldots . \omega_p$ are the parameters of the model, K is a constant and sometimes the constant term is avoided Equation is white noise.
The second part is Moving Average model.
Equation (2) the moving average model of order (q) is written as MA (q)

$$X_t = \mu + \varepsilon_t + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \qquad (2)$$

Where the θ1, ..., θq are the parameters of the model, μ is the expectation of Xt (often assumed to equal 0), and the $\varepsilon_t, \varepsilon_{t-1} \ldots$
Stationary time series can be modelled with ARIMA models.The non-seasonal ARIMA model can be written as in Equation 3.

$$V`_t = K + \emptyset_1 V`_{t-1} + \emptyset_2 V`_{t-2} + \ldots + \emptyset_p V`_{t-p} + e_t + \Theta_1 \varepsilon_{t-1} + \Theta_2 e_{t-2} + \cdots + \Theta_p e_{t-p} \qquad (3)$$

When necessary, the difference in the series to remove seasonality is what makes 〖V~〗_t significant. Lagged errors and lagged values of V_t are included in the "predictors" on the right-hand side. The ARIMA (p,d,q) model is the name given to this. The four main steps of ARIMA are model identification and construction, estimate, model diagnostics, and forecasting.First, the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) are used to identify the approximate model parameters. Next, MSE, MAPE, and other methods are used to establish the optimal coefficients for the model. The following stages entail forecasting, and at the end, validating and assessing the model's performance by looking at the residuals using the ACF plot of residuals and the Ljung Box test [30]. For instructions and details on how to analyze time series data using the Box Jenkins approach, see [31–34].

2.2 Holt's Linear trend

The exponentially weighted moving average is also known as the smoothing random variability averages, and it has the following characteristics: (4) it is very important that older data have a declining weight; (5) it is very simple to calculate; and (6) the most important characteristic for data sets is that only the bare minimum of data is required. [26] has provided an equation for this.

Forecast Equation

$$\hat{y}_{t+h \backslash t} = m_t + h z_t \qquad (4)$$

Level Equation

$$m_t = \alpha\, y_t + (1 - \alpha)(m_{t-1} + z_{t-1}) \qquad (5)$$

Trend Equation

$$b_t = \beta^*(m_t - m_{t-1}) + (1 - \beta^*)z_{t-1} \quad (6)$$

where m_t represent an estimate of the level of 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 level, $0 \leq \alpha \leq 1$ and β^* is the smoothing parameter for the trend, $0 \leq \beta^* \leq 1$that's with simple exponential smoothing.

Fully additive combination

$$T_{(i+1)} = (L_i + B_i) + S_{(i+1-m)} + N_{(i+1)} \ (7)$$

We are predicting the value of the time series k time steps into the future, starting from an arbitrary step i, in the equation above. It is assumed that the seasonal variation has a known period length of m time steps. For instance, m=12 for an annual fluctuation.

Let's see how we can estimate *Li, Bi* and *S_i*.

Let's start with the estimate of trend *Bi* at step *i*

2.3 Holt-Winters Exponential Smoothing Equation

$$F_{(i+k)} = (L_i + K * B_i) + S_{(i+k-m)} \ (8)$$

Starting at an arbitrary step i, we are projecting the value of the time series k time steps into the future using the equation above. A known period length of m time steps is assumed for the seasonal change. For an annual variation, for instance, m=12.

$$B_i = \beta * [L_i - L_{(i-1)}] + (1 - \beta) * B_{(i-1)} \ (9)$$

L_i-L_((i-1)): This is the difference between two successive levels, and it shows how quickly the level at level L_((i-1)) is changing. This word can be conceptualized as the velocity of the data at level L_i, arriving at that level as it did from level L_((i-1)).

B_((i-1)): This is just the recursively expressed rate of change of level at L_((i-1)). Using the same formula for B_i and substituting i for (i-1) allows us to determine B_((i-1)). We repeat this process until we arrive at B_0, the value of which we take as an initial condition. In a moment, more on estimating initial conditions.

3. Results

Descriptive statistics for area, production, and productivity of coconut are presented in Table 1, and from Figure 1, it was observed that the data are approximately normally distributed.

Table 1. Descriptive Statistics of Coconut

Char.	Area (ha)	Production ('000ha)	Productivity (kg/ha)
mean	743.11746	4465.82143	5924.01286
std	126.845632	1270.16155	1240.3862
min	463.27	2602	3814
25%	668.07	3325.5	5008.5
50%	756.89	3981	5817

Char.	Area (ha)	Production (‘000ha)	Productivity (kg/ha)
75%	868.245	5507.5	6430
max	926	7631.35	10123
Skewness	-0.43533	0.556057	1.344054
Kurtosis	-0.575751	-0.730124	2.579566

The area of coconut varied from 463.27 to 926 with an average of 743.11746, where production ofcoconut varied from 2602 to 7631.35 with an average of 4465.82143 and productivity varied from 3814 to 10123 with an average of 5924.01286. Negative skewness (-0.43533) and negative kurtosis (-0.575751) for the area of coconut indicate that the area of coconut production was initially constant for a long time but increased in the later period, where production of coconut shows Positive skewness (0.556057) and negative kurtosis (-0.730124) indicate that there has been an increasing order of production during the early half of the study period and it has remained steady for a long time and Positive skewness (1.344054) and positive kurtosis (2.579566) indicates that there was a highly increased order during the early half of the study period and it remained steady for a long time, but later it decreased.

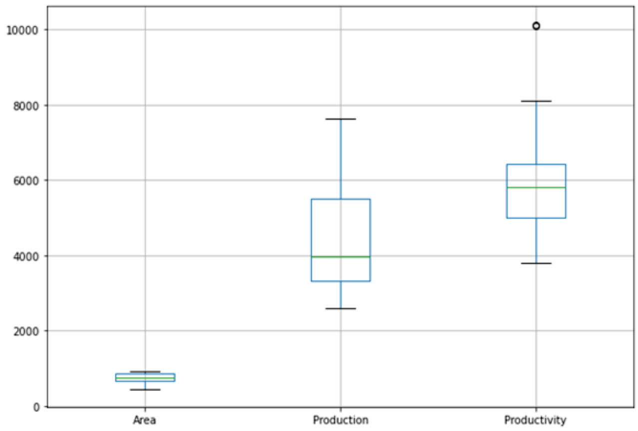

Fig. 2. Boxplot

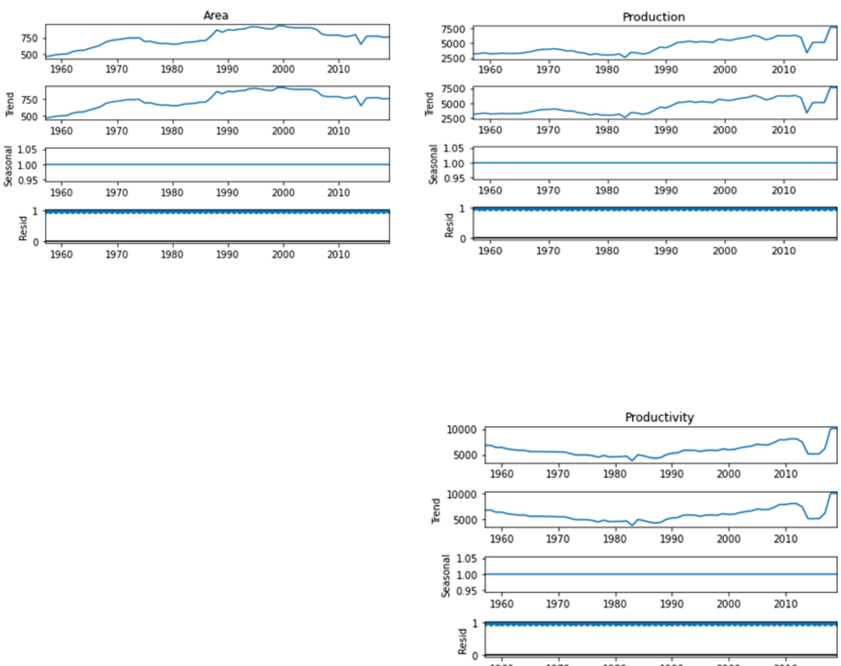

Fig. 3. Presenting the decomposition of data.

Present study was undertaken in the paper based on forecasting of area, production, and productivity of coconut with respect to the parametric regression model along with the Auto Regressive Integrated Moving Average (ARIMA) model. Some stochastic nature observed on trending components in the data series, which confirmed to take a decision to choose ARIMA and Holt’s model for farther study. The best model has been selected based on the model performance criteria, and it (i.e., the best model) has been used to determine the forecast value for the next five years. It is required to check the nature of the data series by using the decomposition process (Ray et. al. 2021) (Figure 2). From the figure, it confirmed that there is no seasonality behavior observed in the data series. Some stochastic nature observed on trending Table 2 represents the performance of the forecasting model for area, production and productivity of coconut in the state of Kerala. It was revealed that Halt’s exponential model gives the good fit because of having the lower AIC (449.1315) and BIC (459.8472) value for area of coconut.

Table 2. Model Estimation of ARIMA and Holt's Model

Area			Production		
	Estimation Criteria			Estimation Criteria	
Model	AIC	BIC	Model	AIC	BIC
ARIMA(0,1,0)	619.034	623.288	ARIMA(0,1,0)	965.219	969.473
ARIMA(1,1,0)	619.439	625.821	ARIMA(1,1,0)	965.408	970.79
ARIMA(0,1,1)	619.725	626.107	ARIMA(0,1,1)	964.113	970.495
ARIMA(1,1,1)	621.293	629.801	ARIMA(1,1,1)	966.111	974.619
Holt's linear	552.1744	460.7469	ARIMA(0,1,2)	965.82	974.328
Holt's Exponential	449.1315	459.8472	ARIMA(1,1,2)	965.257	975.892
Productivity			Holt's linear	801.8789	810.451
	Estimation Criteria		Holt's Exponential	804.3187	815.0344
Model	AIC	BIC			
ARIMA(0,1,0)	983.734	987.988			
ARIMA(1,1,0)	983.801	990.182			
ARIMA(0,1,1)	983.784	990.166			
ARIMA(1,1,1)	985.783	994.292			
Holt's linear	823.8951	832.4677			
Holt's Exponential	826.2362	836.952			

Forecasting production and productivity of coconut in Kerala Holt's linear model gives the best fit because it’s having the lowest AIC(801.8789 & 823.8951) and BIC (810.451 & 832.4677) values compare to other models presented in table 2. Table 3 also confirms that Holt's Exponential model has the lowest RMSE (95.1442), MAPE (11.8134) and MAE (88.6377) values.

Table 3. M0

easure of Error estimation on testing data

	Model	RMSE	MAPE	MAE
Area	ARIMA(0,1,0)	172.765	21.666	163.469
	Holt's linear	172.66	21.653	163.372

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	Model	RMSE	MAPE	MAE
	Holt's Exponential	95.1442	11.8134	88.6377
Production	ARIMA(0,1,1)	1229.1257	0.1849	878.7609
	Holt's linear	1191.702	0.1771	844.866
	Holt's Exponential	1428.965	0.21705	1015.9618
Productivity	ARIMA(0,1,0)	1636.9084	0.1872	1353.604
	Holt's linear	1679.3465	0.2066	1276.7999
	Holt's Exponential	1695.342	0.2081	1277.3987

So this model can be used for forecasting the area of coconuts in Kerala. In the case of the production of coconut, Holt's linear model having the lowest RMSE (1191.702), MAPE (0.1771), and MAE (844.866) values indicates that the model can be used further for forecasting the production of coconut. For forecasting the productivity of coconu Statistical significance of the parameters of the selected best fitted model for area, production, and productivity was tested through the Lung-Box Q test, depicted in Table 4, and it was observed that the null hypothesis was accepted and it can be concluded that the model gives a good fit. In the forecasting area of coconut, Holt's linear and Holt's exponential show statistically significant (P value 0.05) through the DM test (table 5), but in the case of production and productivity, ARIMA (0,1,1) and Holt's linear are statistically significant ($P > 0.05$), which indicates that both models are equally precise and can be used for forecasting of production and productivity of coconut in the state of Kerala.Holt's linear model gives the best fit because it also has the lowest MAE value (1276.7999). From the correlogram of ACF, it was observed that for the forecasting area there was only one significant spike (Figure 3), and for production and productivity, two significant spikes (Figure 4 & Figure 5) were found for both the ARIMA and Holt's Exponential model.

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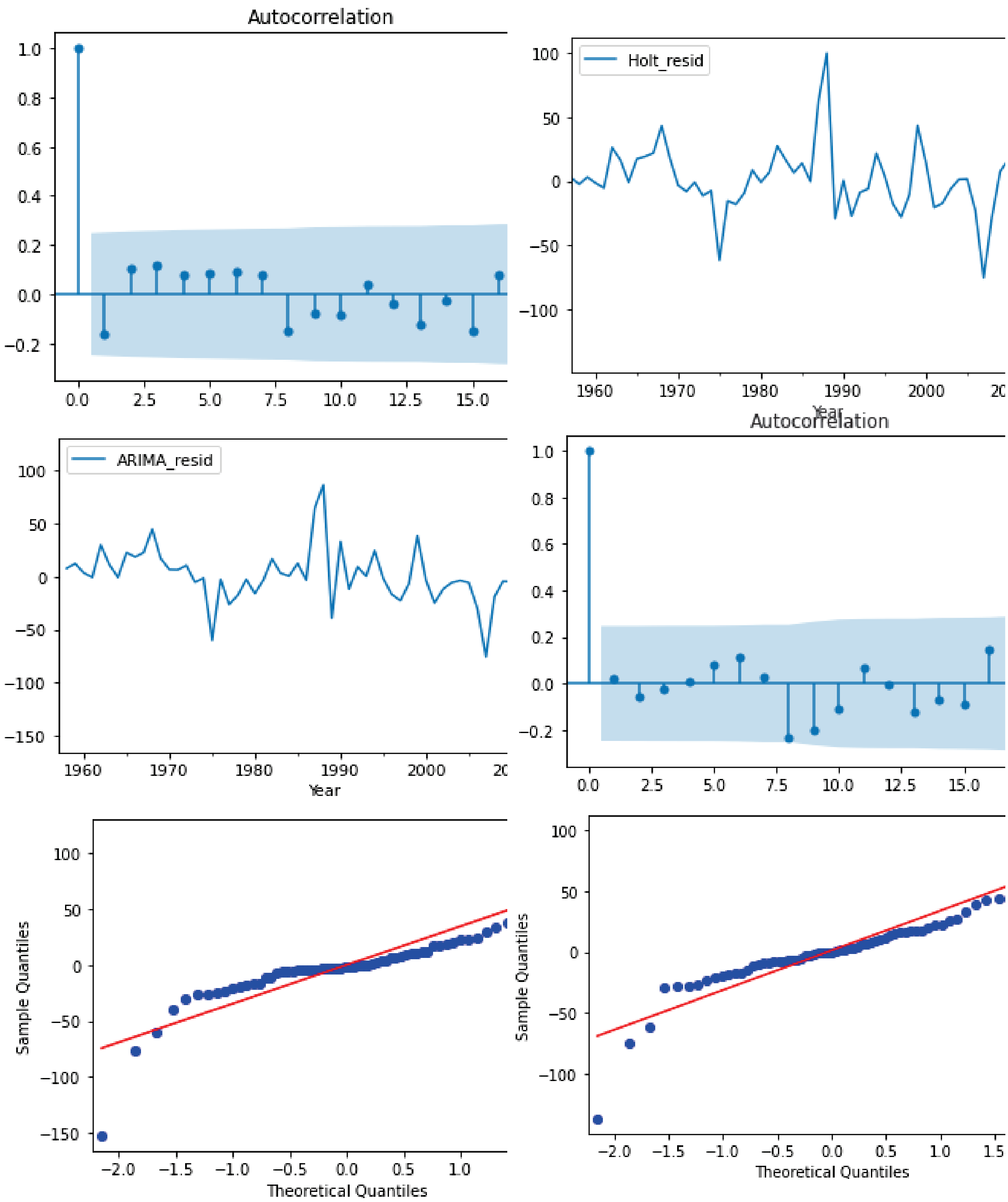
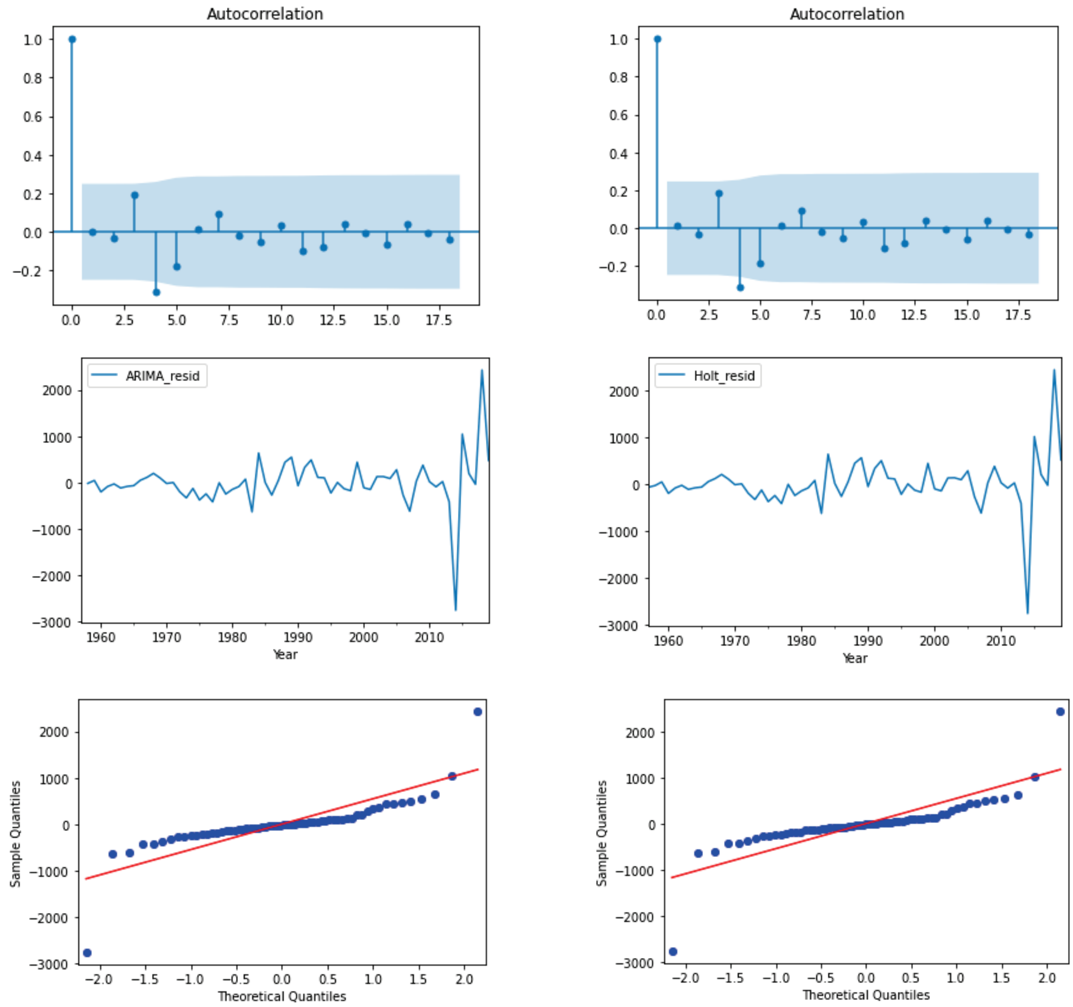


Fig. 4. Residual estimation of ARIMA and Holt’s model in Area.

The residual plot also shows that there are no significant differences found among the two models for forecasting area, production, and productivity of coconut. Theoretical quantile plots show a similar trend in the case of coconut production and productivity, where minor differences were observed for area, as shown in Figure 3. All the residuals were situated around the straight line in the case of Holt’s exponential model, which indicates it may be suitable for forecasting the area of coconut in the state of Kerala. Finally, forecasting of coconut was done for area using ARIMA (0,1,0) and Holt's Exponential model, where for production it was done.

Table 4. Final Model parameter and LungBox Q test for residuals

		Parameter estimation				LungBox Q test		
	Model	Coefficient	Estimates	SE		Residual	Statistic	P Value
Area	ARIMA(0,1,0)	Constant	4.786	4.382		Lag upto 5	4.254242	0.513422
						Lag upto 10	7.888438	0.639733
						Lag upto 15	11.320754	0.729543
	Holt's Exponential	smoothing_level	0.5715029			Lag upto 5	0.733119	0.981102
		smoothing_trend	0.4305077			Lag upto 10	9.754128	0.462323
		initial_level	441.87731			Lag upto 15	12.336933	0.653368
		initial_trend	1.0420604					
		damping_trend	0.8					
Production	ARIMA(0,1,1)	Constant	69.6656	54.106		Lag upto 5	11.420057	0.053659
		ma1	-0.2277	0.126		Lag upto 10	12.414161	0.258294
						Lag upto 15	14.144926	0.514567
	Holt's Linear	smoothing_level	0.7582796			Lag upto 5	11.549444	0.051511
		smoothing_trend	0.0011046			Lag upto 10	12.54066	0.250499
		initial_level	3198.8652			Lag upto 15	14.315439	0.501753
		initial_trend	54.557609					
Productivity	ARIMA(0,1,0)	Constant	53.0806	82.978		Lag upto 5	12.130899	0.145458
						Lag upto 10	12.671014	0.242652
						Lag upto 15	13.276504	0.58095
	Holt's Linear	smoothing_level	0.99505			Lag upto 5	12.468737	0.131483
		smoothing_trend	0.000099			Lag upto 10	13.020904	0.222505
		initial_level	6831.9875			Lag upto 15	13.641099	0.552905
		initial_trend	66.0575					



ARIMA(0,1,1) Residual representation Holt's Linear residual representation

Fig. 5. Residual estimation of ARIMA and Holt's model in Production.

Table 5. Measure of Forecasting accuracy using DM test

	Model Compared	DM test Statistic	P Value
Area	Holt's linear	7.282696	<0.01
	Holt's Exponential		
Production	ARIMA(0,1,1)	1.61341	0.1066
	Holt's linear		
Productivity	ARIMA(0,1,0)	0.2753	0.78304
	Holt's linear		

Table 6 reveals that the last 13 years of data were used for validation of the model, which can be regarded as an in-sample forecast, and the last five years of data were used for prediction purposes, which is popularly known as an out-of-sample forecast. From Figure 6, it was clearly observed that the predicted values were closely related to both the models. No significant differences were observed (Figure 6) for the forecasting area, production, and productivity of coconut in the state of Kerala, which indicates that both the models are equally efficient.

Table 6. Final Model Forecast of ARIMA and Holt's Model

	Area			Production			Productivity		
Year	Actual	ARIMA (0,1,0)	Holt's Exponential	Actual	ARIMA (0,1,1)	Holt's Linear	Actual	ARIMA (0,1,0)	Holt's Linear
2007	802.00	877.79	877.31	5564.00	6187.22	6170.56	6935.00	6988.08	6950.47
2008	787.77	806.79	816.05	5802.00	5775.54	5764.90	7365.00	6988.08	6949.77
2009	788.00	792.56	780.51	6239.50	5865.64	5847.35	7918.00	7418.08	7378.42
2010	788.00	792.79	771.00	6239.50	6224.06	6199.36	7918.00	7971.08	7931.85
2011	766.00	792.79	773.06	6211.21	6305.65	6284.48	8109.00	7971.08	7934.45
2012	773.00	770.79	761.61	6321.00	6302.38	6283.54	8107.00	8162.08	8124.75
2013	797.21	777.79	764.44	5968.01	6386.43	6366.60	7486.00	8160.08	8123.54
2014	649.85	802.00	786.74	3370.00	6132.93	6118.67	5185.81	7539.08	7504.18
2015	770.62	654.64	686.63	5113.14	4068.66	4086.43	5161.00	5238.89	5207.54
2016	772.49	775.41	733.62	5137.04	4945.03	4917.84	5187.00	5214.08	5171.20
2017	773.00	777.28	762.87	5123.00	5162.99	5137.11	6211.00	5240.08	5196.84
2018	756.89	777.79	776.40	7631.35	5201.77	5179.46	10083.00	6264.08	6217.79
2019	760.00	761.68	767.59	7621.00	7147.91	7093.78	10123.00	10136.08	10083.34
2020		764.79	763.63		7582.97	7549.10		10176.08	10195.85
2021		769.57	763.93		7652.63	7604.64		10229.16	10268.41
2022		774.36	764.18		7722.30	7660.19		10282.24	10340.76
2023		779.14	764.37		7791.96	7715.73		10335.32	10412.89
2024		783.93	764.52		7861.63	7771.27		10388.40	10484.79

Table 7. Forecast accuracy improvement percentage

Series	Model	RMSE	RMSEimprovement percent	MAPE	MAPE improvement percent	MAE	MAE improvement
Area	Holt's Linear	172.66	44.895	21.65	45.442	163.372	45.7449
	Holt's Exponential	95.144		11.813		88.6377	
Production	ARIMA(0,1,1)	1229.12	3.045	0.1849	4.218	878.7609	3.8571
	Holt's linear	1191.702		0.1771		844.866	
Productivity	Holt's linear	1679.346	2.527	0.2066	9.390	1276.799	-6.0154
	ARIMA(0,1,0)	1636.908		0.1872		1353.604	

4. DISCUSSION

From the findings of this research paper, it is clear that different statistical time series model can be used to estimate the forecasting nature of agricultural crop commodities based on the data availabilities. We focused on to find the best time series model (ARIMA & Holt’s) for area, production and productivity of coconut in Kerala. As the stochastic nature of the data observed in trend component, we choose ARIMA and Holt’s model in our study.

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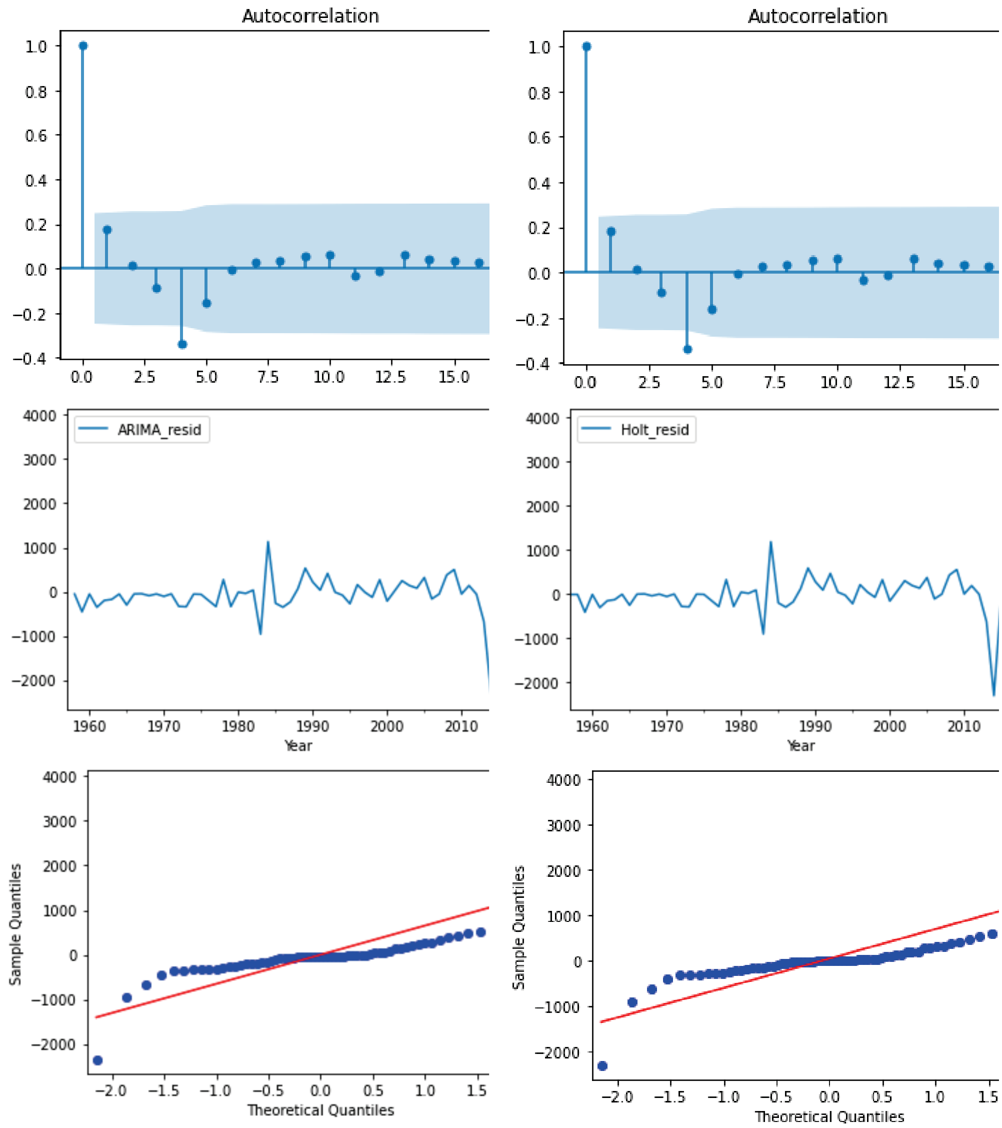
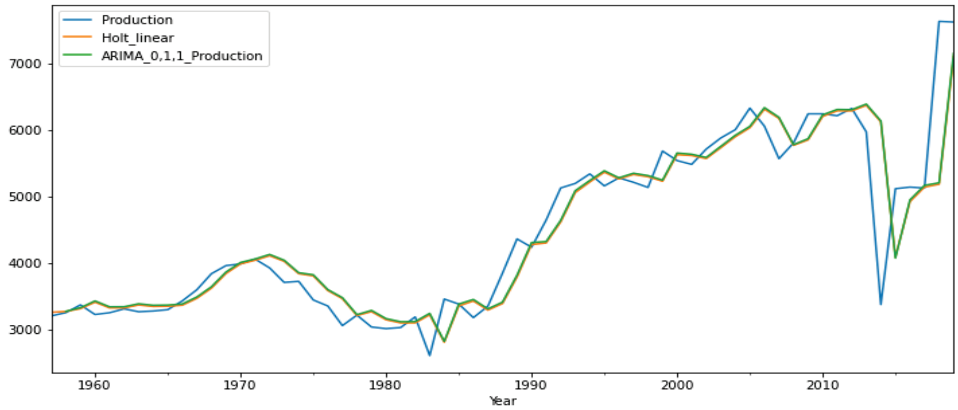


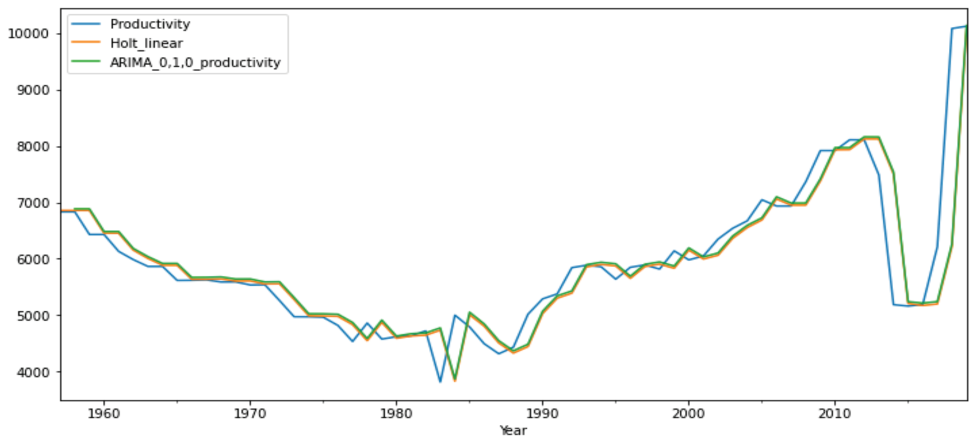
ARIMA(0,1,0) Residual representation   Holt's Linear residual representation

Fig. 6. Residual estimation of ARIMA and Holt's model in Productivity.

Area



Production



Productivity

Fig. 7. Prediction graph of ARIMA and Holt's model.

Holt's exponential model gave best performance for area data series in terms of model selection as well as forecast accuracy prediction, confirmed from the DM test.On the other hands, for production and productivity data series, both ARIMA and Holt's linear model gave a significantly same performance in forecasting accuracy. We also document an interesting finding that, for area data series, Holt's exponential model performed superior with an improvement of RMSE (44.895%), MAPE (45.442%) and MAE (45.7449%). For production, Holt's linear model get slightly improvement than ARIMA in error estimation; RMSE (3.045%), MAPE (4.218%) and MAE (3.8571%). And for productivity, ARIMA and Holt's linear have the same performance about error estimation. As the Holt's model was the dominating model of coconut in Kerala, we also suggest that machine learning forecasting model can be used over statistical time series model for future aspect.

5. CONCLUSIONS

Our main objective in this research paper is to estimate the forecasting behavior after developing the best ARIMA and Holt's models. First, we tried to find the best three time series models on ARIMA and Holt's model based on lower AIC and BIC criterion. Then we evaluated the measure of error estimation of testing data based on the lower RMSE, MAPE, and MAE values of these three models for all data series. It is confirmed that Holt's exponential model for area, Holt's linear model for production, and the ARIMA (0,1,0) model for productivity act as the best fitted models. The best models obtained from the data series were found to have well fitted residuals, which were confirmed by the Lung-Box Q test. Also, we compared the measure of forecasting accuracy by using the DM test. From the DM test, we confirmed that the forecasting accuracy from ARIMA (0,1,1) and Holt's linear model for production and ARIMA (0,1,0) and Holt's linear model for productivity is significantly at par. Holt's exponential model performed better than the ARIMA (0,1,0) model for area data series. This manuscript has successfully exposed the importance of coconut production studies. Wearer is also hopeful that this study will provide an advantage to farmers, different stakeholders, and policymakers by providing an accurate crop production forecast.

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