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Forecasting of Arecanut in India using Time Series Model

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ABSTRACT

Background: Arecanut is popularly known as supari and is grown in many parts of the country. India maintained its first place in production among all the countries. In total world's area and production, India contributes about 49 per cent and 59 per cent respectively. The area has expanded to various states such as Tamil Nadu, West Bengal, Maharashtra, Andhra Pradesh, Goa, Meghalaya and Tripura *etc*.

Methods: The data from 1960-61 to 2015-16 is used to build the model, whereas data from 2016-17 to 2019-20 is used to validate the model. Appropriate statistical steps were adopted for model building and model validation. Holt's linear and Holt's exponential and ARIMA models is used in the study to forecast area, production and productivity for next five years from 2021 to 2025.

Result: The results from the study revealed that Holt's winter Exponential was the best model for predicating area and production whereas ARIMA (0, 1, 1) model was found best suited for predicating productivity.

Key words: Area, Arecanut, ARIMA, Forecasting, Modelling, Prediction, Productivity.

INTRODUCTION

The origin of the Arecanut is debated, but it is commonly thought to be either Malaysia or the Philippines. Areca nuts are grown and consumed primarily in India, which accounts for more than half of global production. After Brazil, Bangladesh and Sri Lanka are the world's leading producers of areca, each accounting for 14% and 10% of total production. Since half of the country's areca nut production area is in Bangladesh, the price of areca nuts in India skyrocketed after partition and the government has since prioritised policies aimed at reducing imports. Among the many fascinating points brought up by Ullal *et al*. (2021), one is that consumers in the north of India tend to view themselves as autonomous, while those in the south see themselves as a much more integral part of their families and communities.

Therefore, there was no Areca import in the 1970s. Due to its high profitability, many farmers in southern India began cultivating Areca at this time (Viswanath and Narappanavar, 1980).

Karnataka is responsible for producing over 65% of India's entire areca crop. We import roughly 18000 tonnes of areca nut annually, with our top two suppliers being Sri Lanka and Indonesia in 2017-2018 (Govt. of India, 2020). The Areca nut market has become more unstable in recent years due to fluctuations in trade volume on international and domestic marketplaces and the exchange rate of trading countries (Ramappa, 2013).

Areca nut traders, farmers and manufacturers all bear the brunt of the industry's pricing risk as a result of the current market climate. However, Pinto *et al*. (2020) claimed that the conventional theoretical approach lends credence to the idea that risks and stock returns are directly proportional to one another. The ARIMA method is commonly used in univariate time series forecasting and a good forecasting model will help the farmers and merchants in Meghalaya and Assam make a profit (Shil *et al*., 2013). In econometric research, it was common practise to make forecasts by analysing past data. However, the precision of such forecasts was quite low, which is what drove the widespread use of AR, MA, ARMA and ARIMA models in time series analysis (Cortez *et al*., 2018).

Backdrop

Arecanut is known as *Areca catechu* L., belongs to the Palmaceae family. It is popularly known as supari as well as fruit of divine origin in India. Arecanut is the major crop of

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South East Asia. Total arecanut production in the world was 14.15 lakh tonnes in 2017 which was increased to 14.29 lakh tonnes in 2018 (Govt. of India, 2020). The area and production under Arecanuthas increased from 113 thousand hectares to 777 thousand hectares from 1960-61 to 2020-21 (Govt. of India, 2022). India contributes about 49 per cent of the area and 59 per cent of the worlds'sArecanut production (Govt of India, 2020). In the total production, around 20 per cent consumed as ripe nuts and remaining 80 per cent is unripe, processed into red boiled type (Gupta *et al*., 2018). In India, cultivation of Arecanut is mainly limited to the states such as Karnataka, Kerala and Assam. The area under Arecanut production has expanded to Tamilnadu, West Bengal, Maharashtra andhra Pradesh, Goa, Meghalaya and Tripura *etc*. The main reason for increasing the area under cultivation is high return per rupee invested (Rabha, 2021). Arecanut is used as breath-freshener as well as have various digestive properties (Winstock, 2013).Along with this, it also helps togenerate additional employment and social security (Govt. of India, 2020). There is dearth of publications in relation to forecasting and modelling of Arecanut in India.Hence there is hunger need to carry out study on Arecanut.Area, output and efficiency in India's Arecanut industry have been projected using ARIMA, Holt's linear and Holt's exponential models for the period 2021-2025. The primary value of this research is that it accurately predicts what will happen in the future, allowing for proactive policymaking that will improve the area, production and productivity of Arecanut in India. Here is how the rest of the paper is structured. In Section 2, we see examples of the ARIMA and Holt-Winters linear and Exponential smoothing techniques in action. Predictions and model parameters are presented in Section 3.

MATERIALS AND METHODS

In the present study, annual data on Arecanut Area, production and productivity has been collected from 1960-61 to 2019-20 from the Ministry of Agriculture and Farmer's Welfare, GOI. As mentioned earlier, ARIMA, Holt's winter liner and Holt's winter exponential model is used to forecast the area, production and productivity of arecanut to find the best prediction model. Among several methodologies available for time series data, these two are well-established and pretty much applicable toour case.

The dataset is divided into two parts, comprising 80 per cent and 20 per cent of data for model specification and model validation. Thus, data from 1960-61 to 2015-16 is used for model building and annual data from 2016-17 to 2019-20 is used for model validation. Suitable statistical tools are used to estimate errors in test data. Finally, the Diebold-

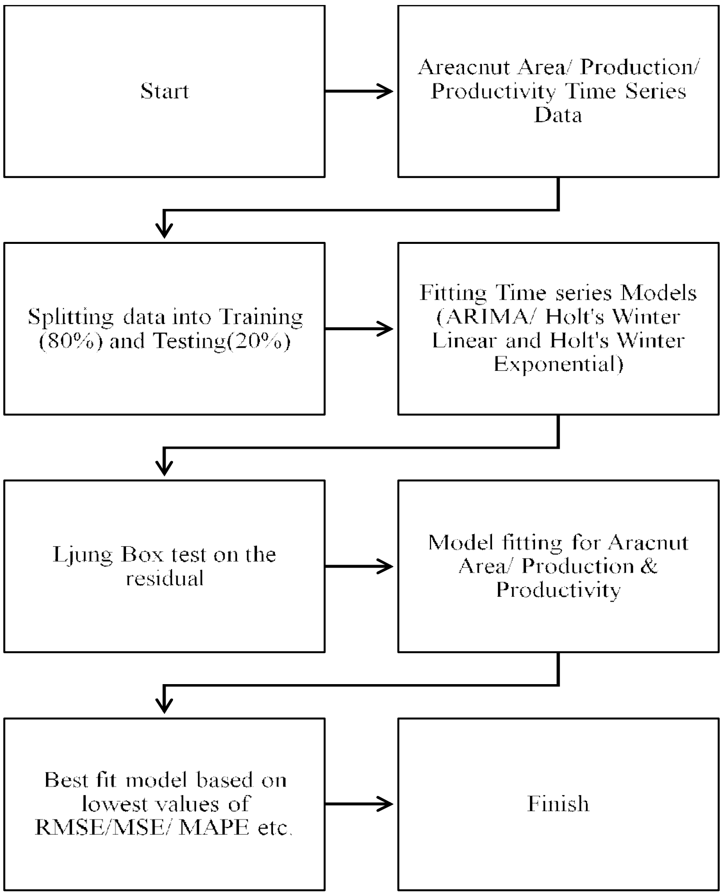

Fig 1: Schematic diagram of forecasting areacnut area/production/productivity.

Mariano Test results were compared to find any significant differences between the two forecasts from different models. The schematic flow of forecasting of area, production and productivity is presented in Fig 1.

Autoregressive integrated moving average (ARIMA)

The Box-Jenkins technique is another name for the autoregressive integrated moving average (ARIMA) model established by Box and Jenkins (1976). When an autoregressive (AR) model is combined with a moving average (MA), the resulting model is known as the autoregressive moving average model (ARMA). Although these models work well with stationary series, the ARIMA approach is used for analysing non-stationary data. First, the differences of the data from the stabilisation process at degree d are taken and then the ARMA (p, d, q) model is added. p indicates the AR model's degree, q the MA model's degree and d the number of differences to be used to stabilise the data in the ARIMA. The ARIMA (p, d, q) model can be defined as follows (equation 1):

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \ldots + \varphi_p Y_{t-p} + \alpha_1 \varepsilon_{t-1} + \alpha_2 \varepsilon_{t-2} + \ldots + \alpha_p \varepsilon_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_p \varepsilon_{t-p} \quad \text{(Equation 1)}$$

Where,

Y_t = Represents the value of the time series at time t.

$\varphi_1, \varphi_2, \ldots, \varphi_p$ = Autoregressive (AR) coefficients of lag p.

$\alpha_1, \alpha_2, \ldots, \alpha_p$ = Coefficients of the exogenous variables (if any) at lag p.

ε_t = Represents the error term at time t.

$\theta_1, \theta_2, \ldots, \theta_p$ = Moving average (MA) coefficients of lag q.

This equation demonstrates how the current value of the time series (Y_t) can be predicted based on its past values (lagged terms), the error terms (ε_t) and potentially the influence of exogenous variables ($\alpha_1, \alpha_2, \ldots, \alpha_p$). The autoregressive component captures the dependency on past values, the moving average component accounts for the dependency on past error terms and the exogenous variables can introduce additional explanatory factors.

Yt is the data with the difference of d degree from the original data (Brockwell *et al*., 2016; Gujarati and Porter 2012). The following steps can be applied for fitting a time series data to an ARIMA model (Hyndman and Khandakar 2007).

Step 1

Plotting the data, detecting any outlier and transforming the data (using the function of the log, sqrt…) to stabilise the variance if necessary.

Step 2

Taking differences of the data until the data are stationary.

Step 3

Finding the optimal values for the ARIMA model's p and q parameters by examining the Autocorrelation function (ACF) and Partial autocorrelation function (PACF) and then applying Akaike's Information Criterion with correction (AICc) to the set of candidate models.

Step 4

Examining residuals from the best model selected by plotting the ACF and PACF for residuals. A different model should be tried if the results do not resemble white noise (Mishra *et al*., 2021c).

Step 5

Calculating forecasts once the residuals look like white noise.

Holt's linear trend method

The exponentially weighted moving average is similar to the averages of smoothing random variability, but it has the added benefits of being (1) easy to calculate, (2) ever less weight is given to older data and (3) most importantly for data sets, requiring only a small initial sample. After Holt (1957) provided three equations for forecast, level and trend, Mishra *et al.* (2021a, b). Forecast equation:

$$Y_t = X_t + \rho.M_t + \rho.\theta_t \quad \text{(Equation 2)}$$

Level equation:

$$M_t = \upsilon.X_t + (1 - \omega).(M_{t-1} + \theta_{t-1}) \quad \text{(Equation 3)}$$

Trend equation:

$$b_t = \gamma.(M_t - M_{t-1}) + (1 - \gamma).\theta_{t-1} \quad \text{(Equation 4)}$$

Where,

Y_t = Forecasted value at time t.

X_t = Level component at time t.

p = Weight for the level component in the forecast equation.

M_t = Level component at time t.

υ = Weight for the current observation in the level equation.

ω = Weight for the previous level in the level equation.

θ_t = Trend component at time t.

b_t = Trend component at time t.

γ = Weight for the difference between current and previous levels in the trend equation.

RESULTS AND DISCUSSION

Descriptive statistics regarding the mean, median, mode and skewness are reported in Table 1. As Table 1 is

Table 1: Descriptive statistics of arecanut

	Area	Production	Productivity
count	61.000	61.000	61.000
Mean	279.163	348.524	1140.858
Std	150.168	263.089	232.298
Min	113.000	96.000	818.182
25%	178.000	165.000	918.182
50%	217.000	249.000	1145.000
75%	381.000	473.000	1235.142
Max	743.000	1209.000	1676.056
Skewness	1.431	1.652	0.632
Kurtosis	1.946	2.514	-.143

examined, we find the area of Arecanut increased by 558 per cent from 1960 to 2020. During the same duration, production increased by 1160 per cent. It shows a significant productivity improvement too. Productivity as bled during the study period with more than 100 per cent increase. The positive skewness of area, Production and productivity indicates the scope of future improvements in production too. A negative value of Kurtosis in productivity indicates a mesokurtic curve thatemphasises relatively stable productivity throughout the study period.

After seeing the arecanut area, production and productivity through descriptive statistics in Table 1, next step is model specification validation and forecast the area, production and productivity of Arecanut using the time series data. For projection purposes, we used different time series models. ARIMA, Holt's winter linear and Holt's winter exponential models were estimated and compared for best projection. The model selection for ARIMA Holt's winter linear and exponential for area, production and productivity of arecanut was obtained using some goodness of fit criteria like AIC and BIC. Following the autocorrelation function and partial autocorrelation Function charts, we were able to determine the various p and q values for the ARIMA model. (Fig 2 and 3).

The combination with least AIC and BIC criteria were selected for model validation and forecasting. After estimating all the possible combinations, the best model for area and production was Holt's exponential model (Table 2) with least AIC and BIC values. However, we did consider ARIMA (2, 2, 1) for area and production validation and forecasting as it was having least AIC and BIC values among all combinations of ARIMA. In case of productivity, ARIMA (0, 1, 1) is the best model for forecasting as it possessleast AIC and BIC values (Table 2).

However, in all these three cases, finally we proceed with ARIMA, Holt's linear and exponential models and tried

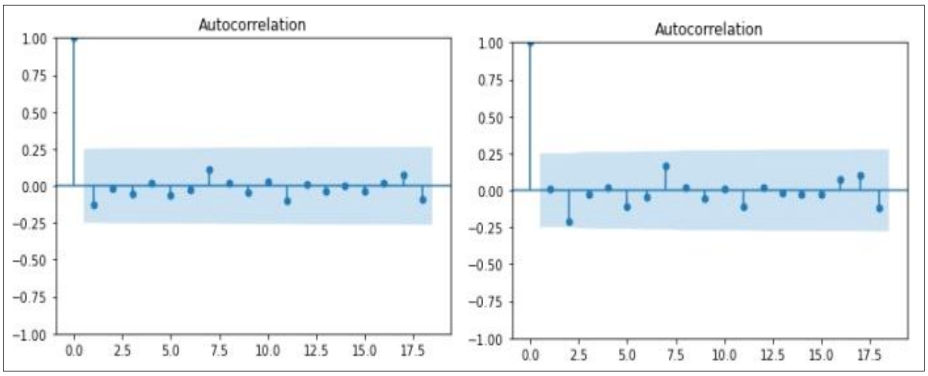

Fig 2: Autocorrelation plots.

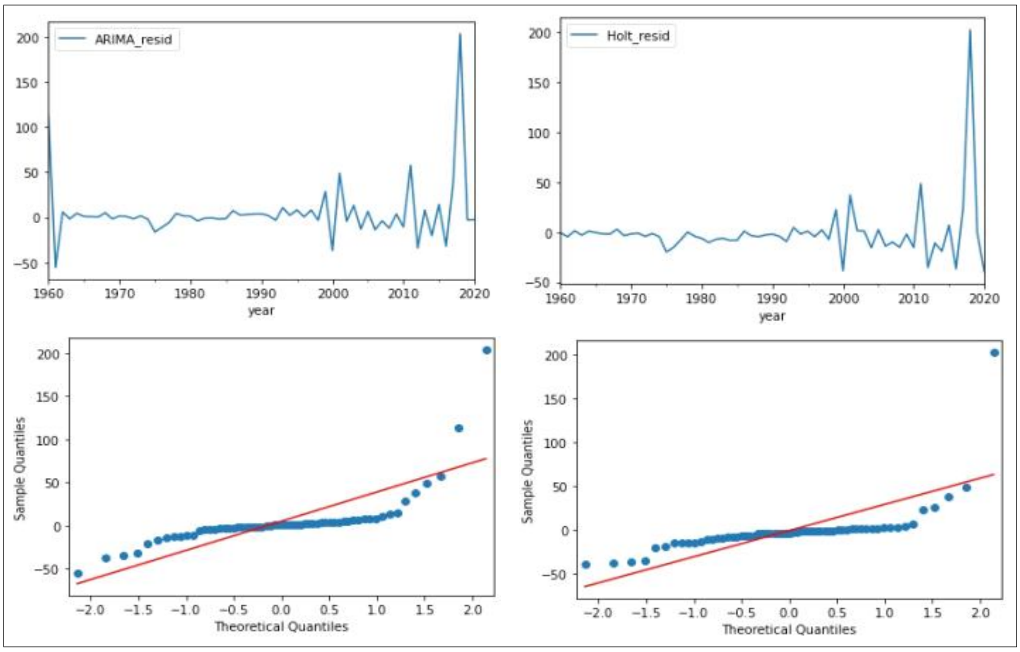

Fig 3: Residual estimation of ARIMA and holt's model in area.

to capture the best forecasts possible for area, production and productivity of arecanut.

We estimated the errors on the forecasted values of testing data using some well-established measures like RMSE (root mean square errors), MAPE (mean absolute percentage errors), MAE (Mean Absolute Error) and MSE (Mean Square Error) to obtain the best model which is presented in Table 3.

In case of area, all the indicators suggest Holts Exponential as the best suited model for forecasting. In the case of production, two indicators suggest ARIMA (2, 2, 1) and rest two suggests Holts exponential as best fit model for prediction. Again, in case of productivity, both ARIMA (0, 1, 1) and Holt's Linear model was found to be best fit for future prediction. The models predicted values are reported later in Table 6. To further verify our models, we ran a Ljung box q test on the data we had collected as residuals. Based on the results of the tests, we know that the residuals are white noise series and so lack autocorrelation. The detailed results of the model parameter of the best fit models and Ljung box Q test are presented in the Table 4.

Table 2: Model estimation of ARIMA and holt's model.

Model	Estimation criteria	
	AIC	BIC
Area		
ARIMA (2,2,1)	423.755	431.637
Holt's linear	282.670	292.707
Holt's exponential	281.070	291.107
Production		
ARIMA (2,2,1)	642.275	650.586
Holt's linear	489.253	497.696
Holt's exponential	485.003	493.447
Productivity		
ARIMA (0,1,1)	528.054	536.498
Holt's linear	528.389	537.829
Holt's exponential	620.693	624.671

The mathematical model for Area prediction using ARIMA (2, 2, 1) is specified as:

$$Y_t = c + (-0.032)\, Y_{t-1} + (-0.2416)Y_{t-2} - (-0.848)e_{t-1} + e_t$$

Where,

Y_t = Value of the time series at time t.

c = Constant term or the intercept.

(-0.032) and (-0.2416) = Autoregressive (AR) coefficients for the lagged terms Y_{t-1} and Y_{t-2}, respectively.

(-0.848) = Moving average (MA) coefficient for the lagged error term e_{t-1}.

e_t = Error term at time t.

The mathematical model for prediction of production using ARIMA (2,2,1) is specified as:

$$Y_t = c + (-0.341)Y_{t-1} + (-0.332)Y_{t-2} - (-0.718)e_{t-1} + e_t$$

Where,

Y_t = Value of the time series at time t.

c = Constant term or the intercept.

(-0.341) and (-0.332) = Autoregressive (AR) coefficients for the lagged terms Y_{t-1} and Y_{t-2} respectively.

(-0.718) = Moving average (MA) coefficient for the lagged error term e_{t-1}.

e_t = Represents the error term at time t.

The mathematical model for prediction of Productivity using ARIMA (0, 1, 1) is specified as:

$$Y_t = c + (-0.373)Y_{t-1} + e_t$$

Where,

Y_t = The differenced value of the time series at time t.

c = Constant term or the intercept.

(-0.373) = Moving average (MA) coefficient for the lagged differenced value ΔY_{t-1}.

e_t = Represents the error term at time t.

The selected model lead to fewer errors in predicting the future and the difference in the accuracy among the selected models were tested with the help of DM test (Table 5). The DM test results show that there is a significant difference among the predicted values of ARIMA and Holt's Exponential in case of arecanut area.

Table 3: Measure of error estimation on testing data.

	Model	RMSE	MAPE	MAE	MSE
Area	ARIMA (2,2,1)	165.684	17.480	123.948	27451.308
	Holt's linear	161.959	17.060	120.949	26230.965
	Holt's exponential	147.264	15.3922	109.203	21686.779
Production	ARIMA (2,2,1)	183.894	14.351	150.932	33817.209
	Holt's linear	215.674	15.408	168.499	46515.547
	Holt's exponential	192.847	13.409	147.969	37190.198
Productivity	ARIMA (0,1,1)	68.773	3.6301	57.089	4729.861
	Holt's linear	72.836	3.528	54.441	5305.181
	Holt's exponential	85.5145	4.933	67.819	7312.745

Table 4: Final model parameter and lung box Q test for residuals.

	Parameter estimation					Lung box Q test		
	Model	Coefficient	Estimates	SE	Optimise	Residual	Statistic	P value
Area	ARIMA (2,2,1)	ar1	-0.032	4.382		Lag upto 5	1.520	0.910
		ar2	-0.2416	0.659		Lag upto 10	2.719	0.910
		ma1	-0.848	0.511		Lag upto 15	3.6521	0.998
		Sigma 2	940.258	116.533				
	Holt's exponential	Smoothing_level	0.997		True	Lag upto 5	3.923	0.560
		Smoothing_trend	0.001		True	Lag upto 10	6.157	0.801
		Initial_level	108.088		True	Lag upto 15	7.252	0.950
		Initial_trend	1.051		True			
		Damping_trend	0.995		True			
Production	ARIMA (2,2,1)	ar1	-0.341	0.200		Lag upto 5	3.569	0.612
		ar2	-0.332	0.211		Lag upto 10	11.636	0.310
		ma1	-0.718	0.191		Lag upto 15	13.290	0.579
		Sigma 2	2653.641	234.837				
	Holt's exponential	Smoothing_level	0.617		True	Lag upto 5	7.911	0.161
		Smoothing_trend	0.1132		True	Lag upto 10	17.541	0.063
		Initial_level	91.914		True	Lag upto 15	19.189	0.205
		Initial_trend	1.0356		True			
Productivity	ARIMA (0,1,1)	ma1	-0.373	0.099		Lag upto 5	0.993	0.963
		Sigma 2	5647.2626	663.228		Lag upto 10	1.7077	0.998
						Lag upto 15	2.020	0.990
	Holt's linear	Smoothing_level	0.506		True	Lag upto 5	4.919	0.426
		Smoothing_trend	0.000		True	Lag upto 10	9.953	0.444
		Initial_level	848.720		True	Lag upto 15	13.427	0.569
		Initial_trend	12.506		True			

Table 5: Measure of forecasting accuracy using DM test.

	Model compared	DM test statistic	P value
Area	ARIMA (2,2,1) Holt's exponential	2.456	0.014
Production	ARIMA (2,2,1) Holt's exponential	0.197	0.843
Productivity	ARIMA (0,1,1) Holt's linear	0.2753	0.78304

Table 6: Final model forecast of ARIMA and holt's model.

Year	Area			Production			Productivity		
	Actual	ARIMA (2,2,1)	Holt's exponential	Actual	ARIMA (2,2,1)	Holt's linear	Actual	ARIMA (0,1,1)	Holt's linear
2016	455	487.02721	491.6945	723	727.1986	769.359	1589.011	1528.89898	1544.63027
2017	497	458.281308	472.030085	833	773.157822	774.499	1676.056	1566.57384	1579.598
2018	718	514.565673	515.2901	1144	851.890754	852.032014	1593.315	1635.19115	1640.931
2019	743	745.89147	743.9145	1107	1143.71184	1111.01	1489.906	1608.94552	1629.34867
2020	731	733.5632	770.4547	1209	1147.65851	1192.794	1653.899	1534.33819	1571.2796
2021		769.7192	760.5142		1335.22315	1295.452		1609.272	1625.59783
2022		815.733	790.9022		1407.1578	1395.2429		1618.7289	1638.10533
2023		849.2586	822.34334		1489.46091	1502.7207		1624.1272	1650.61283
2024		881.4268	854.86767		1586.247	1618.4778		1629.2728	1663.12033
2025		916.655	888.506		1674.687	1743.15186		1649.4539	1675.62783

No significant differences were found in the predicted values of production and productivity when we used ARIMA v/s Halt's Exponential and ARIMA v/s Holt's linear model. Either of the models give forecast with least errors. The final forecasts for the next five years, starting from 2021 to 2025 is presented in Table 6.

CONCLUSION

The study uses arecanut area, production, annual data from 1960-61 to 2019-20 to forecast Area, Production and Productivity for India. Autoregressive Integrated Moving Average (ARIMA), Holt's winter linear model and Holt's winter exponential model was used for forecasting. Based on suitable selection criteria, Holt's exponential model was found best for predicting both Area, Production whereas ARIMA (0, 1, 1) model was found best for predicting productivity. Only in case of Area prediction, the two alternative models gave significantly different whereas in case of production and productivity, the forecasts were found non-significantly different to each other. The forecasts of area, production and productivity suggests that all three variables will increase in future in India but the productivity growth will be subtle as compared to area and production. The limitation of the study is that it uses annual data for autocorrelated time series modelling. Increasing the frequency of the dataset by either increasing the number of years or by incorporating monthly data may lead to decreased results' robustness. However, incorporating more advanced methodology like machine learning technique may increase the accuracy of the forecasts and future studies can aim in this direction. The methodology of Arecanut forecasts can even be utilized for other crops and in other countries.

Conflict of interest: None.

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