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Groundnut production forecasting in Odisha using ARIMA model

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Abstract
Groundnut is an important Oilseed crop in Odisha. Protein content is more in this crop which makes it more important for health. The present study aims the forecasting of Groundnut production in Odisha. Statistics data from 1970-71 to 2020-21 is taken for the present study. For trend estimation, Auto-Regressive Integrated Moving Average (ARIMA) model was used. Auto-Correlation function (ACF) and Partial Auto-Correlation function (PACF) were calculated for analysis purpose. Appropriate Box-Jenkins ARIMA model was fitted according to the Akaike Information Criteria (AIC) values. Validation of model was done by using Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE). ARIMA (0,1,1) model was used for forecasting the subsequent 5years' production. The result shows 391.54tonnes of groundnut production in the year 2025.

Keywords: ground nut, odisha, akaike information criteria (AIC), uto-regressive integrated moving average (ARIMA)

Introduction

Groundnut as a cash crop has been losing its shine in Odisha mainly because of lack of timely availability of quality seeds and high price volatility. Area allocation to groundnut in the state during the last two and half decades declined from 318 thousand hectares during triennium ending 1995-96 to 204.82 thousand hectares in 2019-20 registering negative growth of 0.93 percent per annum. Production of groundnut declined from 4.66 to 3.88 lakh tons during the same period. However, productivity of the crop has increased from 1465 kg/ha to 1894 kg/ha (different issues of Odisha Agricultural Statistics). Groundnut is grown in the state during kharif (the autumn crop sown at the beginning of the summer rains) as well as rabi (the grain crop sown in September and reaped in the spring) season. Area under rabi groundnut comprises of 67 percent of the total groundnut area and is mostly rainfed. Major decline in area was observed in kharif season where area decreased from 164 thousand hectares in 1993-94 to 68 thousand hectares in 2019-20. Rabi area under the crop declined from 166 thousand hectares to 137 thousand hectares during the period. Among the districts, Bargarh registered largest decline in production during the period. In fact all the major groundnut producing districts viz., Bolangir, Cuttack, Jagatsinghpur, Jajpur, Kendrapara, Dhenkanal, Angul, Ganjam and Bargarh experienced major shift in area allocation against groundnut during the period due to which the groundnut production decreases (Figure 1). Some of the non-traditional districts like Balasore, Subarnapur, Kalahandi, Kandhmal, Boudh, Keonjhar, Koraput, Nawarangpur, Deogarh and Mayurbhanj registered minute area escalation under the crop. Decline in production has been mainly attributed to unstable market and high price fluctuations. The premier agency has said it is focussing its seed and technological research to tap the unexplored resources of groundnut production in the State. The present study is focusing on forecasting of groundnut production which helps governments, farmers and policy makers to adopt new technologies for further increase the production.

Materials and Methods

Data Collection

The time series data on production of groundnut in Odisha for the period of 50 years from 1970-71 to 2020-21 were collected from India Stat website and statistical bulletin of Department of Agriculture, Odisha for present study.

Analytical Method

Forecasting of area, production and productivity using ARIMA Model

The annual data on groundnut crop cultivated area, production and yield of India for the period from 1970-71 to 2020-21 were used for forecasting the future values using ARIMA models. The ARIMA methodology is also called as Box-Jenkins methodology. The Box-Jenkins procedure is concerned with fitting a mixed Auto Regressive Integrated Moving Average (ARIMA) model to a given set of data. The main objective in fitting this ARIMA model is to identify the stochastic process of the time series and predict the future values accurately. These methods have also been useful in many types of situation which involve the building of models for discrete time series and dynamic systems. But, this method was not good for lead times or for seasonal series with a large random component (Granger and Newbold, 1970) [7].

The first thing to note is that most time series are non-stationary and the ARIMA model refer only to a stationary time series. Since the ARIMA models refer only to a stationary time series, the first stage of Box-Jenkins model is reducing non-stationary series to a stationary series by taking first order differences.

Box-Jenkins Auto Regressive Integrated Moving Average (ARIMA) Models

Box-Jenkins methodology (Box and Jenkins of Time Series Analysis: Forecasting and Control) is used here for time series analysis which is technically known as the ARIMA methodology.

The ARIMA Model Includes:

The Autoregressive (AR) model.

The Moving Average (MA) Model

The ARMA Model

The Autoregressive (AR) Model

The Simplest form of the ARIMA model is called the autoregressive model. Let zt stand for the value of a stationary time series at time t, that is, a time series that has no trend, but fluctuates about a constant value referred to as the level of the series. (We deal with trends below.) By autoregressive, we assume that current zt values depend on past values from the same series. In symbols, at any t,

$$Z_t = C + \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \ldots\ldots + \varphi_p Z_{t-p} + \varepsilon_t$$

$$Z_t = C + \varepsilon_t + \sum_{i=1}^{p} \varphi_i z_{t-i}$$

Where C is the constant level, z_{t-1}, $zt_{-2,\ldots..}$, z_{t-p} are past series values (lags), the φ ‘s are coefficients (similar to regression coefficients) to be estimated, and ε_t is a random variable with mean zero and constant variance. The ε_ts are assumed to be independent and represent random error. Some of the‘s may be zero. If z_{t-p} is the furthest lag with a nonzero coefficient, the AR model is said to be of order p, denoted AR (p).

The Moving Average (MA) Model

z_t can also be modeled as a linear combination of white noise stochastic error terms. We call this type of model a moving average (MA) model. If z_t is considered as a weighted average of the uncorrelated ε_t's, MA(q) moving average component of order q, which relates each z_t value to the residuals of the q previous z estimates may be expressed as

$$z_t = e_t - q_1 e_{t-1} - q_2 e_{t-2} - \ldots - q_q e_{t-q}$$

The ARMA Model

The AR and MA models for stationary series to account for both past values and past shocks may be combined. Such a model is called an ARMA (p, q) model with p order AR terms and q order MA terms. Thus an ARMA (p, q) model is written as

$$z_t = C + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \ldots\ldots + \varphi_p z_{t-p} + \varepsilon_t - q_1 e_{t-1} - q_2 e_{t-2} - \ldots - q_q e_{t-q}$$

The main stages in setting up a Box-Jenkins forecasting model are Identification, Estimating the parameters, Diagnostic checking and Forecasting In ARIMA modeling, the order of AR(p) is identified by partial autocorrelation function (PACF) while the order of MA(q) is identified by autocorrelation function (ACF) (Tsay, 2002). The order of ARIMA (p, d, q) is also identified by model selection criteria’s i.e. Schwarz Bayesian information criteria (SBIC) and Akaike’s Information Criteria (AIC) (Casella *et al.*, 2008). These criteria’s are further explained in model specification section.

Model Specification: One of the important issues in time series forecasting is to specify model. Time series model is specified on the basis of some information criteria’s which includes AIC, BIC likelihood etc. Akaike’s (1973) introduced AIC criteria for model specification. AIC is mathematically defined as;

AIC= – 2log (maximum likelihood) + 2k

Where k = p+q+1 (if model includes intercept) otherwise k = p+q. model specified well if its AIC value is minimum as other fitted models (Tsay, 2005).

Forecasting Accuracy Measuring Techniques: After model selection, a next important step is to measure the accuracy to verify the reliability of forecasted value based selected model. Various tools are available in literature which includes Root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), mean error (ME) and mean percentage error (MPE). Further computation and literature of these accuracy measuring tools are given:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}|PE_t|$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_t^2$$

$$PE_t = \left(\frac{Y_t - F_t}{Y_t}\right) \times 100$$

Where Y_t is the present value for time t and F_t is the forecasted value for time t.

Results and Discussion

In this study, we used the data for groundnut crop cultivated production for the period 1970-71 to 2020-21. As we have earlier stated that development of ARIMA model for any variable involves four steps: Identification, Estimation, Verification and Forecasting. Each of these four steps is now explained for groundnut crop cultivated production as follows.

Model identification and Validation: For forecasting groundnut crop production ARIMA model estimated only after transforming the variable under forecasting into a stationary series. The stationary series is the one whose values vary over time only around a constant mean and constant variance. There are several ways to ascertain this. The most common method is to check stationarity through Augemented Dickey-Fuller test of the data. As result of Augemented Dickey-Fuller test the production data for Odisha is not stationary, so one differencing is required to make the data stationary.

The next step is to identify the values of p and q. The Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) show that the order of p and q can. Basing on the p, d, q values from the ACF and PACF graph (figure 1) we entertained four tentative ARIMA models for production and chose that model which has minimum AIC (Akaike Information Criterion), RMSE (Root Mean Square Error) & MAPE. The models and corresponding AIC, RMSE & MAPE values are given in Table 1.

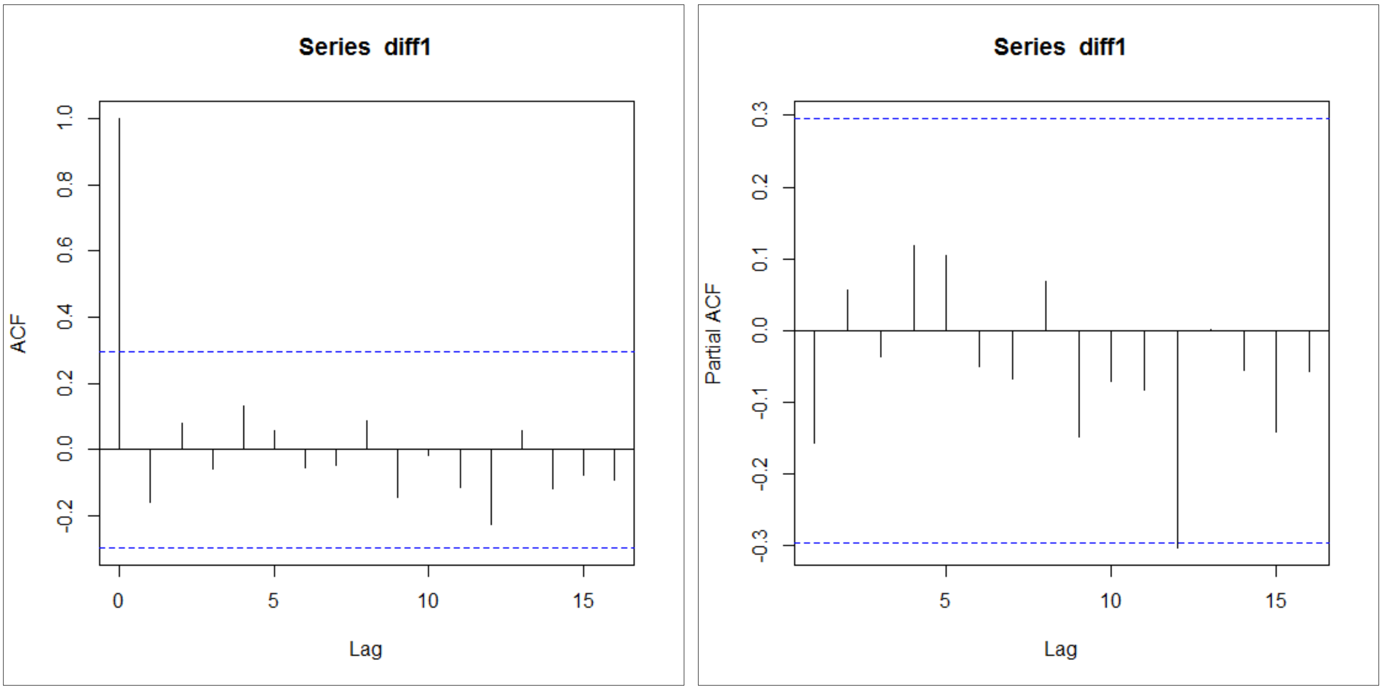

Fig 1: ACF & PCF graph for Groundnut Production of Odisha

Table 1: ARIMA models with AIC, RMSE & MAPE values

	ARIMA (p,d,q)	AIC	RMSE	MAPE
Groundnut production in India	1,1,0	334.80	108.0	135.827
	1,0,0	342.04	107.8	143.691
	0,1,1	333.91	103.7	133.771
	0,1,0	334.88	110.5	133.988

Table 2: ARIMA models with RMSE, MAPE & MAE values for validation of data

Arima (p,d,q)	Rmse	Mape	Mae
1,1,0	107.23	117.64	98.25
1,0,0	108.45	119.25	103.16
0,1,1	102.54	113.24	101.47
0,1,0	107.63	120.54	111.89

As the result of Augemented Dickey-Fuller the value of “d” is one i.e. the data is stationary after first differentiation. From the figure 1 (ACF and PACF graph) the value of p and q are taken. Four different ARIMA models (1,1,0), (1,0,0), (0,1,1) and (0,1,0) are tested.

From this table, most suitable model is ARIMA (0, 1, 1), which has the lowest AIC, RMSE and MAPE values. So this model is taken for forecasting of future values groundnut production in Odisha.

For the validation of model last 5years of data has taken. Table 2 shows ARIMA (0,1,1) is the best fit model for forecasting the groundnut production having minimum RMSE, MAPE, and MAE values.

Table 3: Forecasted values of groundnut production, area and yield with 95% Confidence Level (CL)

Ground nut production in Odisha			
Year	Production	LCL	UCL
2021	388.69	278.92	537.47
2022	389.58	243.28	531.74
2023	388.86	248.81	542.92
2024	390.89	258.32	586.47
2025	391.52	269.90	578.15

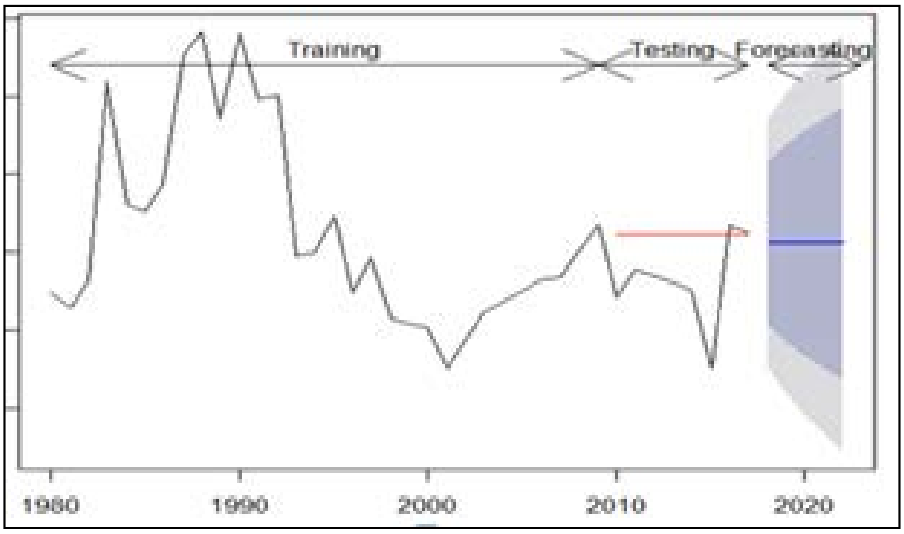

Fig 2: Forecasting of Ground nut production

By using the suitable ARIMA (0,1,1) models forecasted values of Ground nut production of Odisha are given in table 3. From the table it shows that the Ground nut production will increase in the year 2025, it will reach to 391.52 tonnes. In this table along with the forecast value lower and upper confidence values of 95% confidence are given. The production may be increase as per application of inputs and improved package of practices but the production will lie between the forecasted limits.

Conclusion

A careful study of the forecasting of Groundnut production of Odisha shows that there was an increase in production. Out of all tested models ARIMA (0,1,1) is best suitable model for forecasting of Groundnut production in this state. The production of groundnut can be increased by timely supply of inputs, available of fiancé to the farmers and use of improved technology .This forecasting is useful for planning different practices and recommended different strategies to improve groundnut production, also useful for Government for preparing budget & implementing new policies.

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