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Forecasting of Rabi Pulse Production in Odisha (India) by Using Autoregressive Integrated Moving Average (ARIMA) Technique

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Authors' contributions

This work was carried out in collaboration among all authors. Authors AD and AM designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author Suman managed the analyses of the study. Author PM managed the literature searches. All authors read and approved the final manuscript.

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ABSTRACT

The present study was carried out to forecast the production of rabi pulse in Odisha by using the forecast values of area and yield of rabi pulses obtained from the selected best fit Autoregressive Integrated Moving Average (ARIMA) model. The data from 1971-72 to 2010-11 are considered as training set data and used for model building and from 2011-12 to 2015-16 are considered as testing set data and used for cross-validation of the selected model on the basis of the absolute percentage error. The ARIMA models are fitted to the stationary data which may be the original data and/or the differenced data. The different ARIMA models are judged on the basis of Autocorrelation Function (ACF) and Partial autocorrelation Function (PACF) at various lags. The possible ARIMA models are selected on the basis of significant coefficient of autoregressive and moving average components. The best fitted models are selected on the basis of residual diagnostics test and model fit statistics. The ARIMA model found to be best fitted for area under rabi pulse and yield of rabi pulse are ARIMA (2,0,0) with constant and ARIMA (0,1,1) without

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constant respectively which are successfully cross-validated with the testing set data. The excellent fit ARIMA model has been used to forecast the area and yield of rabi pulse for the years 2016-17, 2017-18 and 2018-19. The forecast value of area shows an increase, where as, the forecast values of yield shows a decrease. The forecast values of production of rabi pulse obtained from the forecast values of area and yield of rabi pulse shows an increase which is due to the increase in forecast value of area. Thus emphasis must be laid on increasing the future yield of rabi pulse so as to achieve sufficient increase in production of rabi pulses which could ensure nutritional security to more extent.

Keywords: Forecast; ARIMA; stationarity; pulse; production.

1. INTRODUCTION

Pulses are an important commodity group of crops that provide high quality protein complementing cereal proteins for pre-dominantly substantial vegetarian population of the country. Pulses are grown in all the thirty districts of Odisha. Odisha covers nearly about 9% area and 8% production of pulses as compared to the total area and production of pulses in India respectively.

The importance of pulses in present day agriculture of Odisha cannot be over emphasized because majority of people in Odisha, being vegetarians depend on pulses for their protein supply. To take various measures for increasing pulse production in Odisha and to fulfil the domestic need of the people, forecasting of production of pulse crops is necessary and important. Various approaches have been used for forecasting such agricultural systems. Several studies have been carried out on the univariate time series models known as Auto regressive integrated moving average (ARIMA) models. Naylor et al. [1] observed that the accuracy of Box-Jenkins' ARMA models was considerably better than the accuracy of Wharton econometric model. Nelson [2] concluded that the simple ARMA models are relatively more accurate with respect to post sample (future) predictions than the complex econometric models. Newbold and Granger [3] concluded that Box-Jenkins' approach of ARIMA models gave more accurate results than exponential smoothing or step-wise regression models. Vishawajith et al. [4], Sahu et al. [5] and Mishra et al. [6] used ARIMA model on Sugarcane production, rice & wheat in SAARC countries and fertilizer statistics for India. Dhekale et al. [7] used time series model in tea production. Mishra et al. [8] used arima modelling in milk production of India.

Pulse crops in Odisha is mainly grown in rabi season. Nearly 70% of total area and production of pulse crops in odisha during both the seasons (i.e. kharif and rabi) comes under during rabi pulse. So the present study is based on the pulse grown in Odisha during rabi season.

It is well known that production of a crop production depends on area and yield of crops. So in this study the forecasting of area and yield of rabi pulse crops of Odisha are obtained and from the forecast values of the area and yield, the forecast of production is obtained.

2. MATERIALS AND METHODS

The secondary data pertaining to the area and yield of rabi pulse of Odisha are collected for the period from 1971-72 to 2015-16 from various issues of Odisha Agricultural Statistics published by the Directorate Agriculture and Food Production, Government of Odisha. The area and yield are expressed in '000 ha and kg/ha respectively. (1 ha=10000 m^2).

ARIMA is a statistical analysis model that uses the time series data to forecast the future trends. This model is represented as ARIMA (p,d,q), where p represents order of auto-regression, d shows degree of differencing, q shows the order of moving average. The Auto Regressive Integrated Moving Average (ARIMA) methodology is also known as Box-Jenkin's methodology.

2.1 Fitting of the Box-Jenkins Arima Model

Autoregressive integrated moving average (ARIMA) models are the ARMA models that includes the order of differencing (which is done to stationarise the data). The ARIMA model with parameter (p,d,q) is fitted by univariate Box-Jenkin's techniques [9]. This model includes Auto regression of order *p,* differencing to make stationary series of degree *d* and moving average of order *q*.

Here the data for the years from 1971-72 to 2010-11 are used for model building and is referred as training data. The data for the years from 2011-12 to 2015-16 that are held up and not used for model building are used for cross-validation and is referred as testing data.

The selection of best fit ARIMA model includes the following steps:

Checking of stationarity of the data: If the time series data has constant mean and variance over time then it is stationary. Checking of stationarity of the data initially done by line plot of the data obtained by using MS Excel and then confirmed from ACF and PACF plot of the data obtained by using SPSS 20.0. If the original data seems to be non-stationary then the differencing of the data is done and the line plot and ACF and PACF plot of the differenced data are obtained. This process is repeated till the data becomes stationary. The maximum order of differencing (d) is usually 2.

Determination of the order of auto regression (AR) and order of moving average (MA): The values of *p* (order of Auto regression) and *q* (order of moving average) can be determined by examining the ACF and PACF plots of the stationary value of the variables. The possible values of *p* and *q* are to be chosen from the ACF and PACF plots of either original values (if the original values seem to be stationary) or first or second differenced staionarised values. The coefficients of the order of autoregressive and moving average must be significant. If the constant is not significant then the model is again fitted with same value of *p* and *q* but without constant.

Selection of best fit model: Firstly, the model to be considered for selection as best fit model must have significant coefficients for all considered order(s) of auto regression and moving average. After that the residual diagnostic tests of the model are done.

The residual diagnostics test includes the (a) testing of independency of the residuals done by using Box-Ljung test [10].

(b) Testing of normality of the residuals done by using Shapiro-Wilk's test [11].

The model fit statistics used in selection of best fit model are:

1. Root Mean Square Error (RMSE)

$$\text{RMSE} = \frac{\sum_{t=1}^{n} e_t^2}{n-2} \qquad \text{Where, } e_t = Z_t - \hat{Z}_t$$

2. Mean absolute percentage error (MAPE)

Absolute Percent Error,

$$\text{APE}_t = \frac{\left|Z_t - \hat{Z}_t\right|}{Z_t} \times 100$$

Mean Absolute Percent Error, MAPE =

$$\frac{\sum_{t=1}^{n} \text{APE}_t}{n} \text{ ; Here } n = 40$$

The model which has lowest value of RMSE and MAPE among the model selected ARIMA are considered to be the best-fit model provided it satisfies the residual diagnostics test [12].

The forecasting tool of SPSS 20.0 is used for obtaining the coefficient(s) of various order(s) of AR and/or MA, the Box-Ljung test statistic and Shapiro-Wilk's test statistics and the model fit statistics such as RMSE and MAPE.

After selection of the best fit model, the model is cross-validated by using the testing data which are held up and not used in model building. For the cross-validation of the model the actual value the forecasted value of the left out period of the selected model are used.

The Absolute Percentage Error and hence the Mean Absolute Percentage Error is calculated from the above formula by using the observed value of the testing set data i.e. data held for cross-validation of the selected model.

3. RESULTS AND DISCUSSION

The result of analysis involves the selection of best possible ARIMA models and fitting of these ARIMA models and then selecting the best model among the fitted ARIMA models on basis of significance of the coefficients, residual diagnostics and value of model fit statistics. The selected model is also cross-validated and finally used for forecasting area and yield of rabi pulse. The forecasted values for production of rabi pulse are then obtained from the forecast values of area and yield. The tables and figures obtained from the analysis are presented at the end. The results for forecasting of area and yield of rabi pulse are discussed separately.

3.1 Forecasting of Area under Rabi Pulse by Fitting Appropriate ARIMA Model

In Fig. 1(a), the plot of original data on area under rabi pulse shows the data may be stationary i.e may have constant mean and variance. There is also some doubt of non-stationarity in the data. Thus, the first difference of the data is also plotted and shown in Fig. 1(b). From Fig. 1(b), it is seen that the first difference of data is stationary i.e. have constant mean and variance.

The ACF and PACF plot of the original values of area under rabi pulses shown in Fig. 2, gives the tentative value of q and p suitable for the area which are found to be *q*=0 and *p*=2. Thus the ARIMA model found to be suitable for area is ARIMA(2,0,0). As there is also a possibility of non-stationarity in the line plot of original data in Fig. 1(a), the ACF and PACF plot of the first difference data on area under rabi pulses is also obtained and shown in Fig. 3. The plot gives the tentative value of *q* and *p* suitable for the area under rabi pulses which are found to be *q*=0 and *p*=1. Thus ARIMA(1,1,0) model is also found to be suitable for area under rabi pulse.

The selected ARIMA models with constant are fitted for the data on area under rabi pulse and the result is shown in Table 1 which shows the AR and MA components of the fitted ARIMA model. The Table 1 shows that the constant is significant in case of ARIMA(2,0,0) but in (1,1,0) it is not significant. So, ARIMA(1,1,0) is also fitted without constant. The autoregressive coefficients are also significant for all the ARIMA models fitted to the data.

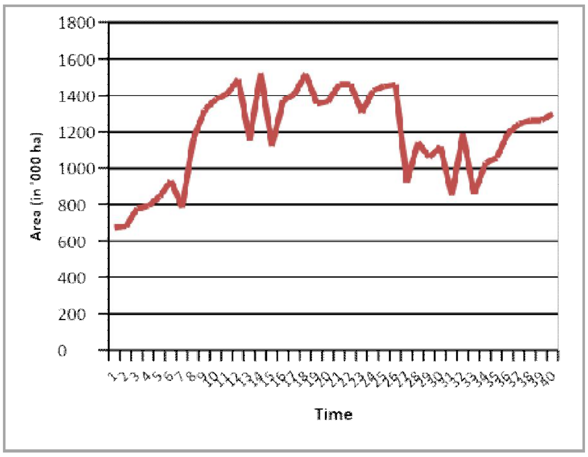

Fig. 1(a). Plot of original values of area under rabi pulse Vs time

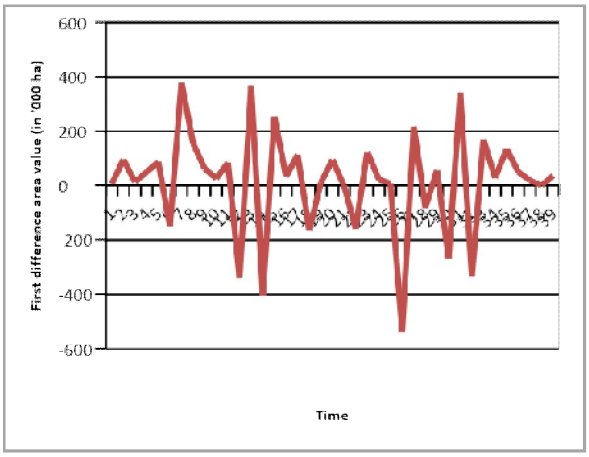

Fig. 1(b). Plot of first difference value of area under rabi pulse Vs time

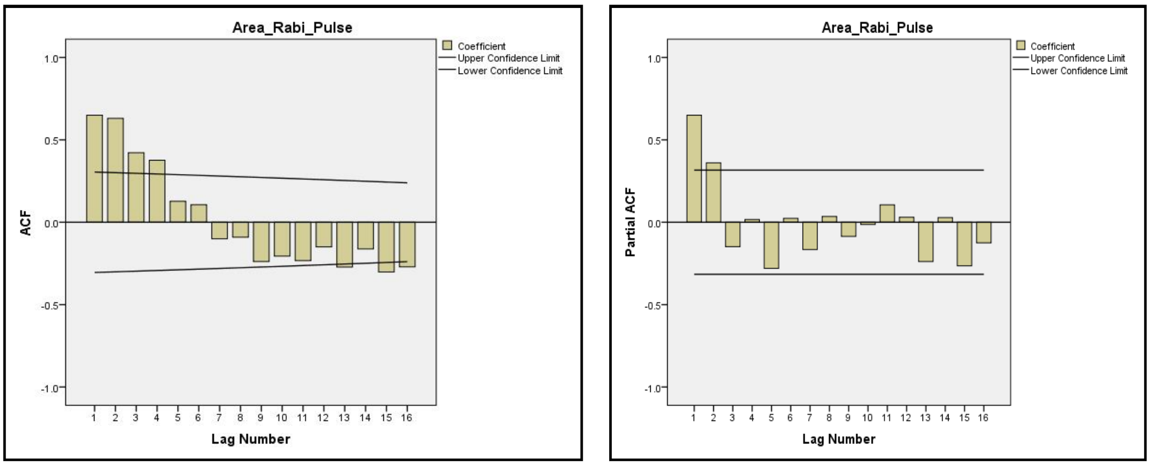

Fig. 2. ACF and PACF plot of original values of area under rabi pulse

Table 1. Coefficients of the AR and MA components and the constant of the fitted ARIMA model selected for forecasting area under rabi pulse in Odisha

Best fit ARIMA model	Constant (μ)	Coefficient of autoregressive components		Coefficient of moving average components	
		α_1	α_2	θ_1	θ_2
(1,1,0) With Constant	51.336 (0.17)	-0.564** (0.001)	-	-	-
(1,1,0) Without Constant	-	-0.540** (0.001)	-	-	-
(2,0,0) With Constant	870.1** (0.001)	0.369* (0.015)	0.474** (0.002)	-	-

(Figures in the parentheses indicate the p-value)
** Significant at 5% level of significance; ** Significant at 1% level of significance*

The study of model fit statistics represented in Table 2 shows that the RMSE and MAPE value for all the three nos of fitted ARIMA models are very close to each other lying between 165 to 168 and between 10.208% to 11.061% respectively which is lowest for AIMA(1,1,0) with constant model. The residual diagnostics shown in Table 2 for the fitted ARIMA models to data on area shows that the Ljung Box- Statistics is insignificant for all the models. Thus the residuals obtained from all the three models are independent. But the Shapiro-Wilk's statistic is insignificant only for ARIMA(2,0,0) with constant model and for other two fitted models, it is significant. Thus the residuals obtained only from ARIMA(2,0,0) with constant model follows normal distribution while for the other two models they do not follow normal distribution. Thus it is concluded that ARIMA(2,0,0) with constant model is found to be the best fit model for data on area under rabi pulse. The adequacy of the best fit model is further confirmed from the Fig. 4 which shows that the ACF and PACF plot of residuals obtained by fitting ARIMA(2,0,0) with constant model are within the significant limits.

Table 3 shows the result of cross validation of the selected best fit ARIMA (2,0,0) with constant model fitted to data on area under rabi pulse. The result shows that the MAPE values obtained are less than 5% for all the years except for the year 2015-16 where it is around 11% which results in a low MAPE value of 4.33%. This shows the successful cross validation of the selected best ARIMA (2,0,0) with constant model for data on area under rabi pulse.

3.2 Forecasting of Yield of Rabi Pulse by Fitting Appropriate ARIMA Model

In Fig. 5(a), the plot of original data on yield of rabi pulse shows the data is non-stationary. Thus, the first difference of the data is also plotted and shown in Fig. 5(b). From Fig. 5(b), it is seen that the first difference of data is stationary.

The ACF and PACF plot of the first difference data on yield of rabi pulses is obtained and shown in Fig. 6. The plot gives the tentative value of q and p suitable for the yield of rabi pulses which are found to be q=1 and p=0. Thus ARIMA(0,1,1) the ARIMA model is also found to be suitable for yield of rabi pulse.

Table 2. Model fit statistics and residual diagnostics of the ARIMA models fitted for area under rabi pulse and in Odisha

Model	Model Fit Statistics		Residual diagnostics	
	RMSE	MAPE (in%)	Ljung – Box Q Statistic	Shapiro-Wilk's Statistic
(1,1,0) With Constant	165.208	10.208	12.114 (0.793)	0.929* (0.016)
(1,1,0) Without Constant	167.315	10.811	11.971 (0.781)	0.928* (0.016)
(2,0,0) With Constant	167.432	11.061	13.606 (0.608)	0.963 (0.21)

(Figures in the parentheses indicate the p-value) (Models highlighted as bold are the best fit models)

Table 3. Cross validation of the selected best fit ARIMA (2,0,0) with constant model for area under rabi pulse in Odisha

Year	Actual value (in '000 ha)(Z)	Forecasted value (in '000 ha) $\left(\hat{Z}\right)$	Error $\left(Z-\hat{Z}\right)$	Absolute Percentage Error
2011-12	1359.55	1309.39	50.16	3.689
2012-13	1274.17	1332.44	-58.27	4.573
2013-14	1319.05	1347.32	-28.27	2.143
2014-15	1368.12	1365.64	2.48	0.181
2015-16	1243.37	1381.37	-138	11.099
Mean Absolute Percentage Error				4.337

Table 4. Coefficients of the AR and MA components and the constant of the fitted ARIMA model selected for forecasting yield of rabi pulse in Odisha

Best fit ARIMA model	Constant (μ)	Coefficient of autoregressive components		Coefficient of moving average components	
		α_1	α_2	θ_1	θ_2
(0,1,1) With Constant	-4.709(0.639)	-	-	0.498**(0.002)	-
(0,1,1) Without Constant	-	-	-	0.500**(0.002)	-

(Figures in the parentheses indicate the p-value)
** Significant at 5% level of significance; ** Significant at 1% level of significance*

Table 5. Model Fit statistics and residual diagnostics of the ARIMA models fitted for yield of rabi pulse and in Odisha

Model	Model Fit Statistic		Residual diagnostics	
	RMSE	MAPE (in %)	Ljung – Box Q Statistic	Shapiro-Wilk's Statistic
(0,1,1) With Constant	173.159	11.111	29.637* (0.029)	0.919** (0.008)
(0,1,1) Without Constant	154.397	8.971	19.036 (0.326)	0.953 (0.107)

(Figures in the parentheses indicate the p-value) (Models highlighted as bold are the best fit models)

Table 6. Cross validation of the selected best fit ARIMA (0,1,1) without constant model for yield of rabi pulse in Odisha

Year	Actual value (in '000 ha) (Z)	Forecasted value (in '000 ha) $\left(\hat{Z}\right)$	Error $\left(Z-\hat{Z}\right)$	Absolute Percentage Error
2011-12	450	457.23	-7.23	1.607
2012-13	414	456.62	-42.62	10.295
2013-14	477	455.99	21.01	4.405
2014-15	483	455.35	27.65	5.725
2015-16	481	454.7	26.3	5.468
Mean Absolute Percentage Error				5.499

The ARIMA(0,1,1) model with constant is fitted for the data on yield of rabi pulse and the result is shown in Table 4 which shows the AR and MA components of the fitted ARIMA model. The Table 4 shows that the constant is insignificant in case of ARIMA(0,1,1). So, ARIMA(0,1,1) is also fitted without constant. The moving average coefficient is also significant for both the ARIMA models fitted to data on yield of rabi pulse.

Table 7. Forecasted values for area and yield of rabi pulse obtained from best fit ARIMA model

	Year	Forecasted value	Lower Confidence Limit (95%)	Upper Confidence Limit (95%)
Area (in '000 ha)	2016-17	1397.77	926.35	1869.19
	2017-18	1413.19	928.52	1897.86
	2018-19	1428.57	934.26	1922.88
Productivity (in kg/ha)	2016-17	454.03	289.98	618.07
	2017-18	453.34	280.42	626.27
	2018-19	452.64	271.27	634.02

Table 8. Forecasted values for production of rabi pulse in Odisha

	Year	Forecasted value	Lower Confidence Limit (95%)	Upper Confidence Limit (95%)
Production (in'000 tonnes)	2016-17	634.63	268.62	1155.29
	2017-18	640.66	260.38	1188.57
	2018-19	646.63	253.44	1219.14

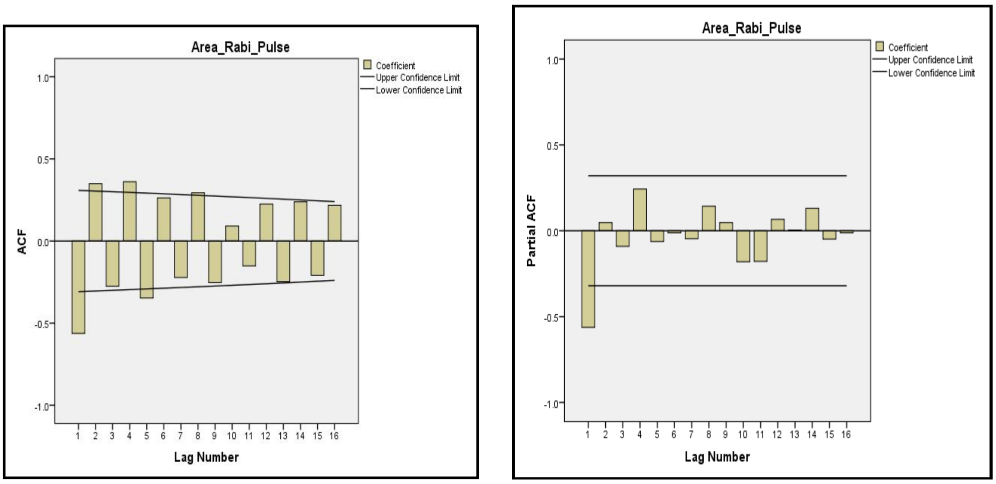

Fig. 3. ACF and PACF plot of first difference values of area under rabi pulse

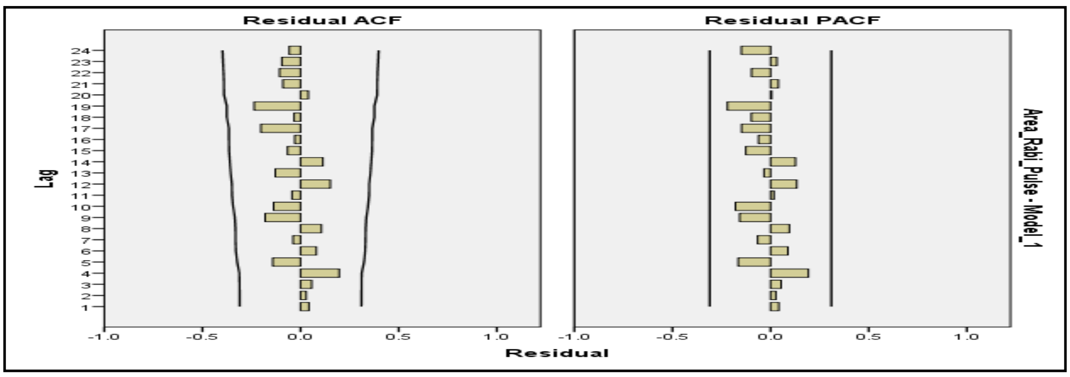

Fig. 4. ACF and PACF plot of residuals obtained by fitting ARIMA(2,0,0) with constant to data on area under rabi pulse

The study of model fit statistics presented in Table 5 shows that the fitted ARIMA(0,1,1) without constant model has low value of RMSE and MAPE than ARIMA(0,1,1) with constant model. The residual diagnostics shown in Table 5 for the fitted ARIMA models to data on yield of

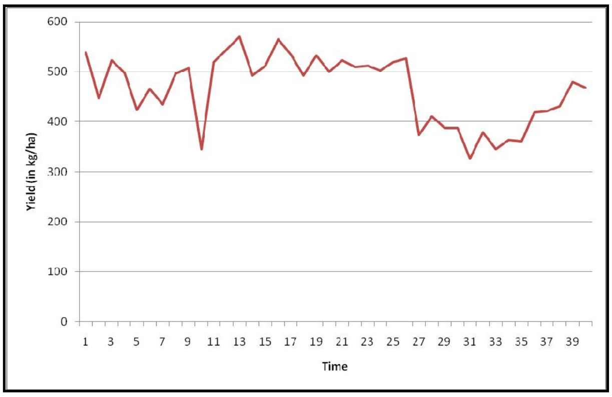

Fig. 5(a). Plot of original value of yield of rabi pulse Vs time

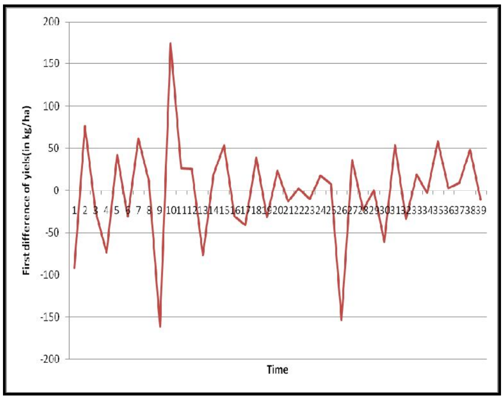

Fig. 5(b). Plot of first difference value of of yield of rabi pulse Vs time

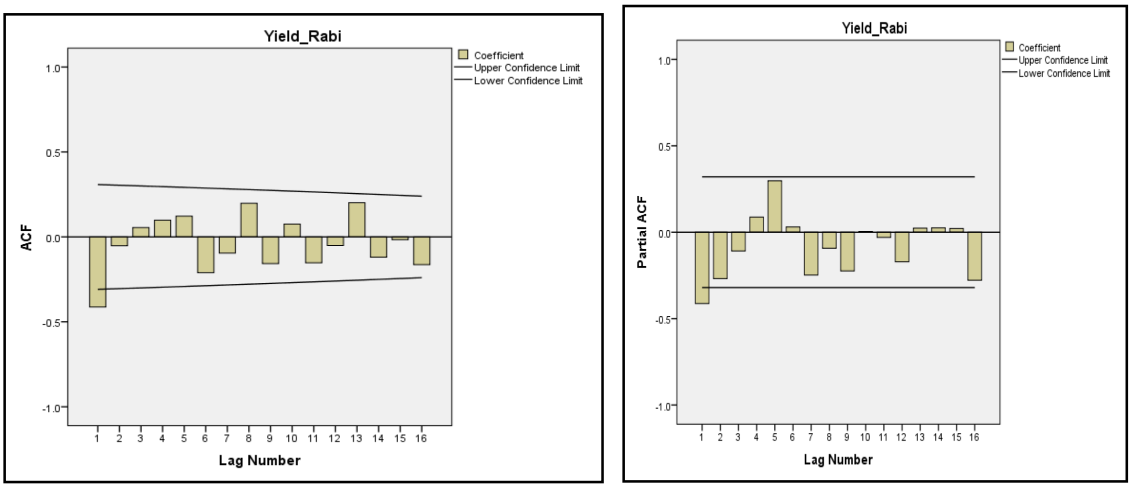

Fig. 6. ACF and PACF plot of first difference values of yield of rabi pulses

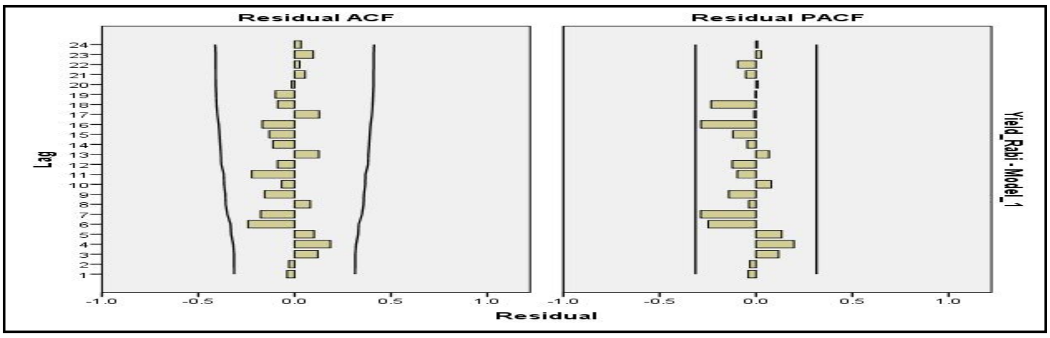

Fig. 7. Residual ACF and Residual PACF plot for best fit ARIMA (0,1,1) without constant model for yield of rabi pulses

rabi pulse shows that the Ljung Box Statistic and the Shapiro-Wilk's statistic are both significant for ARIMA(0,1,1) with constant model. Thus the residuals obtained from this model are neither independent nor normally distributed. But both of these statistic are found to be insignificant for ARIMA(0,1,1) without constant model which shows that the residuals obtained from this model are independent and normally distributed. Thus it is concluded that ARIMA(0,1,1) without constant model is found to be the best fit model for data on yield of rabi pulse. The adequacy of the best fit model is further confirmed from the Fig. 7 which shows that the ACF and PACF plot

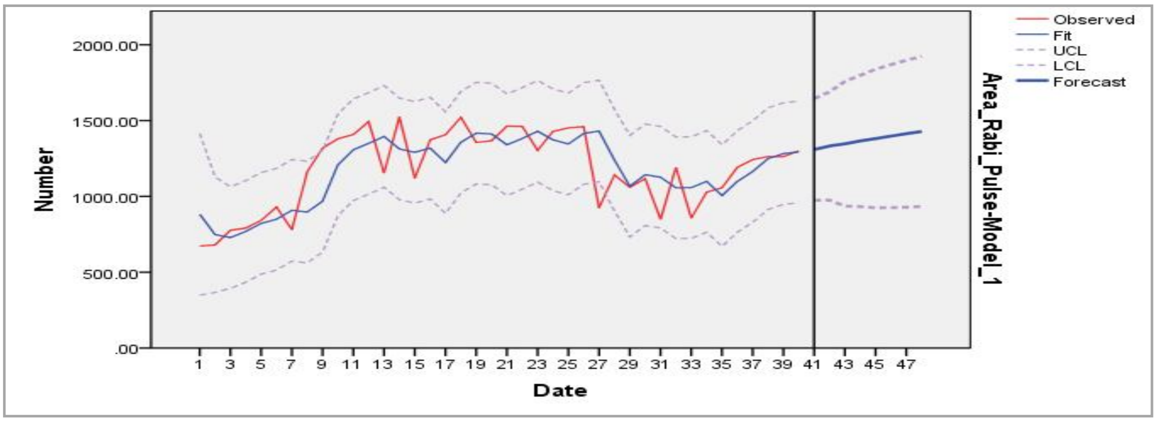

Fig. 8. Observed and Fit values of area under Rabi Pulse along with upper and lower limit by using selected best fit ARIMA (2,0,0) with constant model

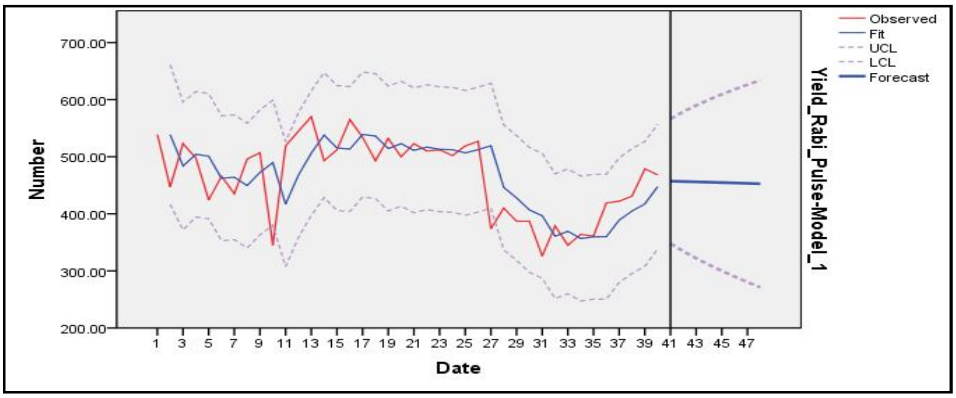

Fig. 9. Observed and Fit values of yield under Rabi Pulse along with upper and lower limit by using selected best fit ARIMA (0,1,1) without constant model

of residuals obtained by fitting ARIMA(0,1,1) without constant model are within the significant limits.

Table 6 shows the result of cross validation of the selected best fit ARIMA (0,1,1) without constant model fitted to data on yield of rabi pulse. The result shows that the MAPE values obtained are less than 6% for all the years except for the year 2012-13 where it is around 11% which results in a low MAPE value of 5.499%. This shows the successful cross validation of the selected best ARIMA (0,1,1) without constant model for data on yield of rabi pulse.

In Table 7, the forecasted values for area and yield of rabi pulse are obtained from the respective best fit ARIMA model. The table shows that there is an increase in the forecasted values of area under rabi pulse but the forecasted values of yield of rabi pulse decreases from 2016-17 to 2018-19.

Figs. 8 and 9 show the plot of observed values and the fit values of area and yield of rabi pulse respectively along with their upper and lower limit as obtained from the respective selected best fit ARIMA(2,0,0) with constant model and ARIMA(0,1,1) without constant model. The observation of Figs. 8 and 9 reveal that the observed values and the fit values of area and yield of rabi pulse are in accordance to each other with very less difference.

Table 8 shows the forecast values of production of rabi pulses for the year 2016-17, 2017-18 and 2018-19 by using the forecasted values for area and yield of rabi pulse in these years obtained from the respective best fit ARIMA model. It is seen in the Table 8 that there is an increase in the forecast values of production from 2016-17 to 2018-19.

4. CONCLUSION

ARIMA(2,0,0) with constant model is found to be the best fit model for forecasting area under rabi pulse of Odisha which after successful cross validation is used for forecasting the area under rabi pulse of Odisha for the years 2016-17, 2017-18 and 2018-19. The forecast values for area shows an increase in area under rabi pulse of Odisha. ARIMA(0,1,1) with constant model is found to be the best fit model for forecasting yield of rabi pulse of Odisha which after successful cross validation is used for forecasting the yield of rabi pulse of Odisha for the years 2016-17, 2017-18 and 2018-19. The forecast values for yield shows a decrease in yield of rabi pulse of Odisha. The increase in forecast value of area under rabi pulse in Odisha can be attributed to two reasons: (i) increasing demand for pulse crops for nutritional requirement and (ii) improvement in irrigation facilities. But the decrease in forecast value of yield can be a matter of concern and to be taken care of by the agricultural planners and policy makers. The forecast value of production of rabi pulse obtained from forecast values of area and yield of rabi pulse shows an increase in production of rabi pulse in Odisha. This increase in production may be due to increase in area though there is decrease in forecast value of yield. But if the future yield could be increased then the increase in production would be sufficiently more and this would add to our goal of achieving nutritional security.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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