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ARIMA models for forecasting production of cotton crop in selected districts of Karnataka

Ramesh, KN Krishamurthy, Shilpa M, Maruthi, Sharanabasappa and Channabasava

Abstract
Cotton is an important principal commercial fibre crop. It is one of the most leading and important cash crops in Indian economy. In the present study an attempt has been made using secondary data for forty six years (from 1970 to 2016) to understand the forecast in production of cotton crop in Dharwad, Ballari and Raichur districts of Karnataka. The results revealed that, ARIMA (2, 1, 2) model was appropriate for both Dharwad and Ballari districts while, ARIMA (1, 1, 1) model was found to be most suitable for forecasting production of cotton in Raichur district.

Keywords: Cotton, production, forecasting, ARIMA, RMSE and MAPE

Introduction
Cotton is the most essential natural fiber crop in the world for textile produce, accounting for about 50 per cent of all fibers used in the textile industry. It is more important than the various synthetic fibers, and it is grown all over the world in about 80 countries. Cotton is unique among agricultural crops, because it is the main natural fiber crop, and also provides edible oil and seed by-products for livestock feed, it also provides income for hundreds of millions of people. Cotton is one of the agro-industrial crops which are produced in both developing and developed countries. Cotton fibers are used in clothing and household furnishings. It has played an important role since the industrial revolution of the 17th century. Currently, it is an important cash crop especially for a number of developing countries at local and national levels (Gudeta and Egziabher, 2019) [4]. India is primarily an agriculture based country and its economy largely depends on agriculture. India cultivates the highest acreage under cotton in the world. It provides the basic raw material (cotton fiber) to the cotton textile industry (Rajan and Palanivel, 2018) [18]. It is the leading textile fiber in the world accounting for 35 per cent of the world fiber use. Cotton was first cultivated about 7,000 years ago, by the inhabitants of the Indus Valley Civilization. This civilization covered a huge swath of the north-western part of the Indian sub-continent, comprising today's parts of eastern Pakistan and north-western India (Mayilsami and Selvaraj, 2016) [9]. Cotton has been traditionally known as the backbone of nonfood crops of agricultural economy of India (Sharma, 2015) [20]. About 25 per cent of our country's Gross Domestic Product (GDP) comes from agricultural sector. Nearly 75 per cent of the country's population lives in villages and depends on agriculture (Parmar, *et al*., 2016) [11]. Cotton is an important principal commercial fiber crop. It is also known as 'White gold' or the "King of Fibers" due to its importance in agricultural as well as industrial economy throughout the world. Cotton is one of the leading and important cash crops in Indian economy (Mohammad, *et al*., 2018).India is the only country in the world growing all the four cultivated species of cotton, *viz*., *G. hirustum*, *G. arboretum*, *G. herbaceaum* and *G. barbadense*. The maximum area has been covered by the hybrids. India is unique among the major cotton growing countries because of the broad range of agro-climatic and soil conditions which permit cultivation of all varieties and staple lengths of cotton. (Samuel *et al*., 2013) [19]. Cotton is mainly grown in Punjab and Sindh provinces. This crop contributes significantly in Pakistan economy by providing raw material to textile industry as well as foreign exchange earnings through export of cotton lint (Ali, *et al*., 2017) [1]. Major Cotton producing countries are India, China, USA, Pakistan, Brazil, Australia, Uzbekistan, Turkey, Turkmenistan and Burkina (Rajan and Palanivel, 2017) [17]. In the recent period, cotton is gaining momentum in non-traditional areas such as Odisha, West Bengal and Tripura. India accounts for approximately 25 per cent of worlds total cotton area and 18 per cent of global cotton production (Kulkarni *et al*., 2017) [7].

India ranks first with respect to area and production and eighth rank with respect to productivity of cotton. Cotton in India occupies an area of 118.81 lakh hectares with a production of 345.82 lakh bales and productivity of 495 Kg/ha. Cotton is cultivated in a majority of the states in the country. The ten major cotton producing states of India are Gujarat, Maharashtra, Telangana, Karnataka, Andhra Pradesh, Haryana, Madhya Pradesh, Rajasthan, Punjab and Tamil Nadu and accounts for more than 95 per cent of the area under cotton. In Karnataka area under cotton is around 7.5 lakh hectares which is 7 per cent of country's area. The production of the crop is 28 lakh bales (around 4 per cent of country's production) while the productivity is 653 kg/ha. The main cotton growing districts in Karnataka are Dharwad, Ballari and Raichur. The Government of India has launched "Technology Mission on Cotton" in February 2000 with an objective of improving the production and productivity of cotton through development of high yielding varieties; enhance the income of the cotton growers by reducing cost of cultivation, appropriate transfer of technology and better farm management practices, cultivation of *Bt*-cotton hybrids etc. Area estimation and forecasting of production are essential procedures supporting in policy decisions with respect to production, land use allocation, food security, environmental issues price structures as well as consumption of cotton in the country. Increased global demand for cotton should induce higher production in the next decade. With these backgrounds, it is necessary to know the extent of cotton production in future with available resources. Various approaches have been used for forecasting such agricultural systems. Borkar Prema *et al*. (2016) [11] in their empirical study showed that ARIMA (2, 1, 1) is the appropriate model for forecasting the production of cotton in India. The study of Debnath *et al*. (2015) [2] revealed that area, production and yield of cotton in India would increase from 2016-17 to 2020-21. Similar studies have been conducted by Payyamozhil and Kachi (2017) and Rajan *et al*. (2018) [18] for forecasting cotton production in India, the analysis revealed that ARIMA (0, 1, 0) is the best model for forecasting cotton production. The present study has been undertaken with an objective to forecast the production of cotton in India in future using Box-Jenkins ARIMA model. Among the stochastic time series models ARIMA types are very powerful and popular as they can successfully describe the observed data and can make forecast with minimum forecast error. These types of models are very difficult to identify and estimate. Muhammad *et al*. (2018) [10] conducted an empirical study of modeling and forecasting time series data of rice production in Pakistan. Similar studies have been done by Rachana *et al*. (2010) [13] for forecasting pigeon pea production in India by using ARIMA Modeling and Rahman (2010) [14] for forecasting of boro rice production in Bangladesh. Iqbal *et al*. (2005) [6] also use the ARIMA Model for forecasting wheat area and production in Pakistan.

Methodology
In the present study, major cotton growing districts of Karantaka *viz.*, Dharwad, Ballari and Raichur were selected. In order to fit theforecasting models for production of cotton crop, secondary data pertaining to the area, production and productivity of cotton crop for the period of 46 years (from 1970-71 to 2015-16) was obtained from the Directorate of Economics and Statistics, Bengaluru.

Forecasting using Auto Regressive Integrated Moving Average (ARIMA) Model
The Box-Jenkins procedure is concerned with fitting a mixed Auto Regressive Integrated Moving Average (ARIMA) model to a given set of data. A value below 1.5 and a value above 2.5 indicate the presence of autocorrelation in data. Auto Regressive (AR) models were first introduced by Yule in 1926. These were consequently supplemented by Slutsky who in 1937 presented Moving Average (MA) schemes. Wald (1938), combined both AR and MA schemes and showed that ARMA processes can be used to model all stationary time series as long as the appropriate order of p, the number of AR terms, and q, the number of MA terms stands.

a. Stationarity and non-stationarity
A Time series is said to be stationary if its underlying generating process is based on a constant mean and constant variance with its autocorrelation function (ACF) essentially constant through time. Otherwise it is called non-stationary. A statistical test for stationarity has been proposed by Dickey and Fuller (1979).$\Delta Y_{t-1} = \gamma Y_{t-1} + \varepsilon_t$
Where$\gamma = \Phi - 1$, Then, null hypothesis of $H_0: \gamma = 0$against the alternative hypothesis $H_1: \gamma < 0$. Acceptance of null hypothesis indicates that the series is stationary. Usually, differencing is applied until the ACF shows an interpretable pattern with only a few significant autocorrelations.

b. Seasonality
The seasonal pattern may additionally display constant change over the time as well. Just as regular differencing was applied to the overall trending series, seasonal differencing (SD) is applied to seasonal non-stationarity as well as autoregressive and moving average tools are available with the overall series, so too, they are available for seasonal phenomena using seasonal autoregressive parameters (SAR) and seasonal moving average parameters (SMA).

c. Autocorrelation Function (ACF)
The most important tools for the study of dependence is the sample autocorrelation function. The correlation coefficient between any two random variables X, Y, which measures the strength of linear dependence between X, Y, always takes values between -1 and 1. If stationarity is assumed and autocorrelation function ρ_k for a set of lags K = 1, 2..., is estimated by simply computing the sample correlation coefficient between the pairs, k units apart in time. The correlation coefficient between Y_t and Y_{t-k} is called the lag-k autocorrelation or serial correlation coefficient of Y_t and it is denoted by symbol ρ_k, under the assumption of weak stationarity, define as:

$$\rho_k = \frac{\sum_{t-k+1}^{r}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t-1}^{r}(Y_t - \bar{Y})} = \frac{\gamma_k}{\gamma_0}; for\ k = 1,2, \ldots where, \gamma_k = cov(Y_t, Y_{t-k})$$

It ranges from -1 to +1. Box and Jenkins has suggested that maximum number of useful ρ_k are roughly $N/4$where N is the number of period upon which information on $Y_t$is available.

d. Partial Autocorrelation Function (PACF)
The correlation coefficient between two random variables Y_t and Y_{t-k} after removing the impact of the intervening $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-k+1}$ is called (PACF) at lag k and denoted by ϕ_{kk}

$$\phi_{00} = 1, \phi_{11} = P_1$$

$$\phi_{kk} = \frac{P_k - \sum_{j-1}^{k-1} \phi_{k-1} P_{k-j}}{1 - \sum_{j-1}^{k-1} \phi_{k-1} P_j}, k = 2,3, \ldots \ldots where\ \phi_{k,j} = \phi_{k-1,j} - \phi_{k,k}\phi_{k-1,k-1}$$

e. Autocorrelation function (ACF) and partial autocorrelation function (PACF)
Theoretical ACFs and PACFs (Autocorrelations versus lags) are available for the various models chosen and for various values of orders of autoregressive and moving average components i.e. p and q. Thus comparing the correlograms (plot of sample ACFs versus lags) obtained from the given time series data with these theoretical ACF/PACFs, we find a reasonably good match and tentatively select one or more ARIMA models. The general characteristics of theoretical ACFs and PACFs are as follows:

Table 1: Pattern of ACF and PACF for AR, MA and ARMA processes

Process	ACF	PACF
AR (Auto Regressive)	Decays Towards zero	Cut Off to zero (lag length of last spike is the order of the process)
MA (Moving Average)	Cut off to zero (lag length of last spike is the order of the process)	Decays towards zero
ARMA (Auto Regressive and Moving Average)	Tails off towards zero	Tails off towards zero

f. White Noise (WN): A very important case of stationary process is called white noise. For a white noise series, all the ACFs are zero or close to zero. If {r_t} is normally distributed with zero mean and variance σ^2 and no autocorrelation, then it is said to be Gaussian white noise.

Autoregressive process (AR)
A stochastic model that can be extremely useful in the representation of certain practically occurring series is the autoregressive model. In this model, the current value of the process is expressed as a finite, linear aggregate of previous values of the process and a errorε_t.
A model written in the form$r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + \cdots + \phi_p r_{t-p} + \epsilon_t$is called autoregressive model of order p and abbreviated as AR (p), where ϕ is autoregressive coefficient and ε_t is white noise.
In general, a variable r_t is said to be autoregressive of order p [AR (p)], if it is a function of its p past values and can be represented as:

$$r_t = \sum_{i-1}^{P} \phi_i r_{t-i} + \epsilon_t$$

Moving Average process (MA)
A second type of Box-Jenkins model is called a "moving average" model. Although these models look very similar to the AR model, the concept behind them is quite different. Moving average parameters relate what happens in period t only to the random errors that occurred in past time periods. A series {r_t} is called moving average of order q and abbreviated as MA (q), expressed in following form of equation:

$$r_t = \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots - \theta_q \epsilon_{t-q}$$

Where, θ is moving average coefficient and ε_t is white noise
The above equation can be written as,

$$r_t = \epsilon_t - \sum_{i-1}^{q} \theta_i \epsilon_{t-i}$$

Autoregressive Moving Average process (ARMA):
An autoregressive moving average is expressed in the form:

$$r_t = \phi_1 r_{t-1} + \phi_2 r_{t-2} + \ldots + \phi_p r_{t-p} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \ldots - \theta_q \epsilon_{t-q}$$

A stationary solution to above mentioned equation exists if and only if all the roots of the AR characteristic equation $\phi(x) = 0$ are outside the unit circle. For invariability, the roots of $\theta(x) = 0$ lie outside the unit circle, Where ε_t is a sequence of uncorrelated variables, also referred to as a white noise process, and $(\phi_1, \ldots, \phi_p, \theta_1, \ldots, \theta_q)$ are unknown constants or parameters. The above equation can be written as:

$$(1 - \phi_1 B^1 - \phi_2 B^2 - \ldots - \phi_p B^p) r_t = (1 - \theta_1 B^1 - \theta_2 B^2 - \cdots - \theta_q B^q) \epsilon_t$$

Where B is the backshift operator, that is $B\ (X_t) = X_{t-1}$ and

$$\phi(B) = (1 - \phi_1 B^1 - \phi_2 B^2 - \ldots - \phi_p B^p)$$

$$\theta(B) = (1 - \theta_1 B^1 - \theta_2 B^2 - \ldots - \theta_p B^p)$$

Autoregressive Integrated Moving Average process (ARIMA)
ARIMA is one of the most traditional methods of non-stationary time series analysis. In contrast to the regression models, the ARIMA model allows r_t to be explained by its past, or lagged values and stochastic error terms. These models are often referred to as "mixed models". Although this makes forecasting method, more complicated, but the structure may indeed simulate the series better and produce a more accurate forecast. Pure models imply that the structure consists only of AR or MA parameters - not both. The models developed by this approach are usually called ARIMA models because they use a combination of autoregressive (AR), integration (I) - referring to the reverse process of differencing to produce the forecast, and moving average (MA) operations. An ARIMA model is usually stated as ARIMA (p, d, q). An autoregressive integrated moving average is expressed in the form:
If $w_t = \nabla^d r_t = (1 - B)^d r_t$then

$$w_t = \phi_1 w_{t-1} + \phi_2 w_{t-2} + \cdots + \phi_p w_{p-1} + \epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \cdots - \theta_p \epsilon_{t-p}$$

If $\{W_t\}$ follows the ARMA (p, q) model, and $\{r_t\}$ is an ARIMA (p, d, q) process. For practical purposes, we can take is usually d = 1 or 2 at most. Above equation is also written as:

$$\phi(B)w^t = \theta_0 + \theta(B)\epsilon_t$$

Where, $\phi(B)$ is a stationary autoregressive operator, $\theta(B)$ is a stationary moving average operator, and ϵ_t is white noise and θ_0 is a constant. In the case of the pattern of seasonal time series ARIMA model is written as follows:

$$\phi(B)\Phi(B)\nabla^d \nabla_s^D r_t = \theta(B)\Theta(B)\epsilon_t$$

Where

$w_t = \nabla^d \nabla_s^D r_t$, $\nabla^d = (1-B)^d$ is number of regular differences and $\nabla_s^D = (1-B^s)^D$ is number of seasonal differences.

Seasonal ARIMA model is denoted by (p, d, q) (P, D, Q), where p denotes the number of autoregressive terms, q, number of moving average terms and d, number of times a series must be differenced to induce stationarity. P, number of seasonal autoregressive components, Q, number of seasonal moving average terms and D denotes the number of seasonal differences required to induce stationary.

The main stages in setting up a Box-Jenkins forecasting model are described below:

1. Identification

The foremost step in the process of modelling is to check for the stationarity of the series, as the estimation procedures are available only for stationary series. If the original series is non-stationary, then first of all it should be made stationary. Stationarity is achieved by differencing the data for required number of times they could be obtained by looking for significant autocorrelation and partial autocorrelation coefficients. Say, if second order auto correlation coefficient is significant, then an AR (2), or MA (2) or ARMA (2) model could be tried to start with. This is not a hard and fast rule, as sample autocorrelation coefficients are poor estimates of population autocorrelation coefficients. Still they can be used as initial values while the final models are achieved after going through the stages repeatedly. Stationarity can be analyzed graphically using a ACF plot. A slow decay over the period indicates non-stationarity. A sudden change in lags of ACF plot shows the data has become stationary. Further, if the sequence graph of data is stationary over mean or variance we say as stationarity is achieved. Order of AR i.e. p and MA i.e., q is obtained by the examination of PACF and ACF plots respectively. Number of lagged values outside the limit is the order of the model.

2. Estimation of parameters

The model is said be good fit for the data if the Ljung Q statistics is non-significant. At the estimation stage, the coefficients of the identified models are estimated. Generally, method of least squares is used to estimate the parameters which utilizes the concept of minimizing the sum of squares due to residuals. At the estimation phase, Stationarity and invariability are checked for the coefficient obtained at the same time checking is also done in order to know, whether the model fit the data satisfactorily or not? If the model is significant and estimates of the parameters are non-significant suitable transformation can be done depending on the data. Outliers can be detected and removed in order to get an appropriate model.

Outlier in time series

Time series observations may sometimes be affected by unusual events, disturbances, or errors that create spurious effects in the series and result in extraordinary patterns in the observations that are not in according with most observations in the time series. Such unusual observations may be referred to as outliers. They may be the result of unusual external events such as strikes, sudden political or economic changes, sudden changes in a physical system, and so on, or simply due to recording or gross errors in measurement. The presence of such outliers in a time series can have substantial effects on the behavior of sample autocorrelations, partial autocorrelations, estimates of ARMA model parameters, forecasting, and can even affect the specification of the model.

Types of Outliers

- **Additive Outlier (AO):** An outlier that affects a single observation. For example, a data coding error might be identified as an additive outlier.
- **Level shift (LS):** An outlier that shifts all observations by a constant, starting at a particular series point. A level shift could result from a change in policy.
- **Innovational Outlier (IO):** An outlier that acts as an addition to the noise term at a particular series point. For stationary series, an innovational outlier affects several observations. For non-stationary series, it may affect every observation starting at a particular series point.
- **Local Trend (LT):** An outlier that starts a local pattern at a particular series point.
- **Transient:** An outlier whose impact decays exponentially to 0.
- **Seasonal additive:** An outlier that affects a particular observation and all subsequent observations separated from it by one or more seasonal periods. All such observations are affected equally. A seasonal additive outlier might occur in beginning of a certain year, if sales are higher every January.
- **Additive patch:** A group of two or more consecutive additive outliers. Selecting this outlier type results in the detection of individual additive outliers in addition to patches of them.

Detection of outliers

These outliers are detected one by one using SPSS 20 software. The outliers are removed until the parameter estimates are significant. In most of the cases 10 per cent of the more influential observations are deleted to obtain a significant parameter estimate. The importance of the coefficients is measured by their statistical significance. Each estimated coefficient has a sampling distribution with a certain standard error that is to be estimated. Most ARIMA estimation routine automatically tests the hypothesis that the true coefficient is zero. If the coefficients are highly correlated the estimates are of poor quality. To check the closeness of the fit, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and some more were calculated.

3. Diagnostic checking

Having chosen a particular ARIMA model and having estimated its parameters, the next step is to check whether the chosen model fits the data reasonably well, as it is possible that another ARIMA model might do the job well. Here selection of model will be done by criteria like R-square and MAPE (Mean Absolute Percent Error).

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error (MAPE), also known as mean absolute percentage deviation (MAPD), is a measure of accuracy of a method for constructing fitted time series values in statistics, specifically in trend estimation. It usually expresses accuracy as a percentage, and is defined by the formula:

$$M = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

Where, A_t is the actual value and F_t is the forecast value. The difference between A_t and is divided by the actual value A_t again. The absolute value in this calculation is summed for every fitted or forecasted point in time and divided again by the number of fitted points n. multiplying by 100 makes it a percentage error.

Forecasting accuracy checking

Among the best fitted ARIMA and exponential smoothing technique a best model is used for forecasting based on the accuracy of the testing. The accuracy is checked using two measures namely RMSE and MAPE. A major part of the data used for model fitting is called as training set and a smaller portion (usually 10%) of data used for checking forecasting accuracy is called as testing set.

Results and Discussion

Time series models for forecasting the production cotton crop in Dharwad district

ARIMA model

An ARIMA model was computed using the SPSS 20.0 statistical package. The first step in time series analysis is to plot the given data. Fig. 1shows the plot of production of cotton crop from 1970-71 to 2015-16. An examination of Fig. 1 revealed a positive trend over time which indicates the non stationary nature of series. This was confirmed, through the Autocorrelation Function (ACF) Partial Autocorrelation Function (PACF).

ACF of the time series presented in Fig. 2 shows a slow linear decay of the autocorrelation coefficients. Fig. 3 represents the PACF plot which shows significant at lags 1. It indicates the non-stationarity of time series. To make the series stationary, it was first differenced after which the data attained stationarity as shown in Fig. 4.

Identification of the model

ARIMA (2,1,2) model was fitted based on the Autocorrelation function and Partial autocorrelation function of the differenced series as shown in Fig 3 and Fig. 4.It was observed that all the lagged values were within the limit in both ACF and PACF plots. Further, outliers were detected and removed to get a significant model. Based on R^2, RMSE and MAPE values, we found that ARIMA (2, 1, 2) was the best fit after eliminating two significant outliers. The two significant outliers which were detected are shown in Table 1. The estimates of the parameters are given in Table 2. The adequacy of the model was also appraised based on the values of L' jung-Box Q statistics as shown in in Table 3, which was found to be non-significant. The R^2, RMSE and MAPE values for ARIMA (2, 1, 2) model are given in Table 3. The residual analysis was carried out to check the adequacy of the selected model. The residuals of ACF and PACF were obtained from the tentatively identified model. All the lags were found to be non-significant which as per Fig. 4. So, it was inferred that the model ARIMA (2, 1, 2) was adequate for forecasting future production of cotton in Dharwad district.

Forecasting accuracy and forecasting

The forecasting adequacy was checked using the RMSE and MAPE values. The predicted values using ARIMA with the model fit statistics like RMSE and MAPE values are given in Table 3. It was found that ARIMA (2, 1, 2) model was the best fit with lower RMSE (25.143) and lower MAPE (19.845). Forecasting was done for the next four years using the ARIMA (2, 1, 2) model. Forecasted values are given Table 4. ARIMA (2, 1, 2) was selected as a model for forecasting in ARIMA technique after analyzing the ACF and PACF plots as given in Fig. 3 and Fig. 4 respectively. Thus, ARIMA (2, 1, 2) model was observed to be the best fit with R^2 value of 81.70 per cent. Iqbal *et al.* (2005) [6] have also obtained ARIMA (2, 1, 2) model for production of wheat in Pakistan.

Table 1: Detected outliers of the ARIMA models for production of Cotton in selected districts of Karnataka

Districts	ARIMA Models	Year	Type of outlier	Estimate	SE	t statistic	p-value
Dharwad	2,1,2	2007	Additive	-82.016**	21.211	-3.867	0.000
		2008	Additive	-70.670**	21.238	-3.328	0.002
Ballari	2,1,2	1997	Local Trend	12.055**	1.252	-9.626	0.000
		2011	Local Trend	37.967**	1.252	30.328	0.000
Raichur	1,1,1	2014	Additive	-131.759**	23.416	-5.627	0.000

** Significant at 1% level

Table 2: Estimate of the ARIMA Model parameter for production of Cotton in selected districts of Karnataka

Districts	Transformation	Parameters	Lag	Estimate	SE	t statistic	p-value
Dharwad	No Transformation	Constant		421.307**	118.996	3.541	0.001
		AR	Lag 1	-1.213**	0.161	-7.557	0.000
			Lag 2	-0.613**	0.154	-3.989	0.000
		Difference		1			
		MA	Lag 1	0.020^{NS}	2.564	0.008	0.994
			Lag 2	0.972^{NS}	2.541	0.383	0.704

Ballari	No Transformation	Constant		-743.30**	105.204	-7.065	0.000
		AR	Lag 1	-1.538**	0.119	-12.87	0.000
			Lag2	-0.719**	0.142	-5.06	0.000
		Difference		1			
		MA	Lag 1	-0.199^{NS}	32.612	-0.006	0.995
			Lag2	0.801^{NS}	26.184	0.031	0.976
Raichur	No Transformation	Constant		-810.507**	188.289	-4.305	0.000
		AR	Lag 1	0.418*	0.179	2.337	0.025
		Difference		1			
		MA	Lag 1	0.989*	0.543	1.820	0.076

** Significant at 1% level, NS-Non-significant

Table 3: Model fit statistics and Ljung-Box Q statistics for production of Cotton in selected districts of Karnataka

Districts	Model Fit statistics			Ljung-Box Q			Number of Outliers detected
	R^2	RMSE	MAPE	Statistic	DF	p-value	
Dharwad	0.817	25.143	19.845	8.550^{NS}	14	0.859	2
Ballari	0.977	9.117	13.660	19.859^{NS}	14	0.135	2
Raichur	0.872	24.961	20.309	18.396^{NS}	16	0.301	1

NS-Non-significant

Table 4: Forecasted values for production of cotton crop in selected districts of Karnataka

Districts	Year	Forecasted Value for production ('000 t)	95% Confidence interval	
			Lower	Upper
Dharwad	2017	159.09	109.31	208.87
	2018	148.43	97.49	199.36
	2019	218.07	164.96	271.19
	2020	129.06	69.42	188.71
Ballari	2017	318.73	283.81	353.64
	2018	355.68	316.68	394.68
	2019	391.04	335.31	446.77
	2020	424.51	350.81	498.20
Raichur	2017	256.45	185.91	327.00
	2018	253.17	177.70	328.63
	2019	256.40	178.29	334.51
	2020	260.63	180.21	341.06

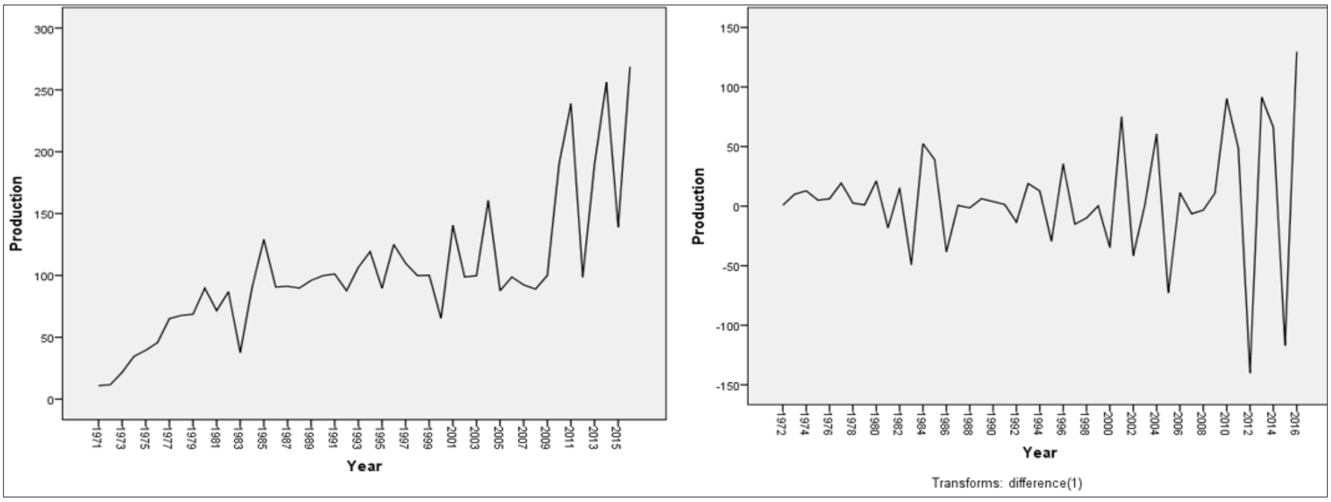

Fig 1: Time plot for production of cotton in Dharwad district

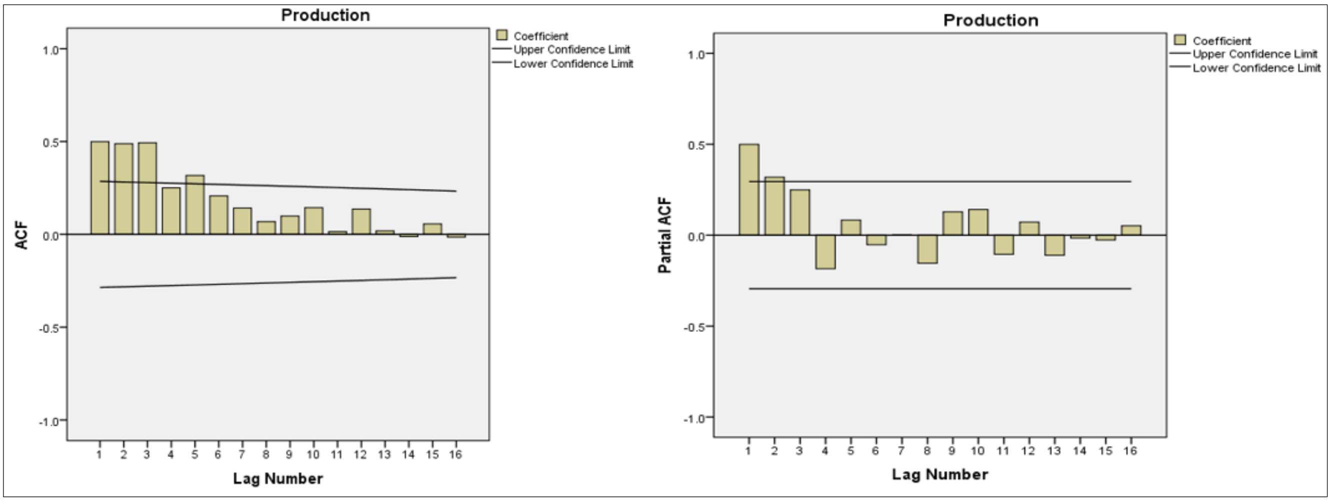

Fig 2: ACF AND PACF of cotton in Dharwad district

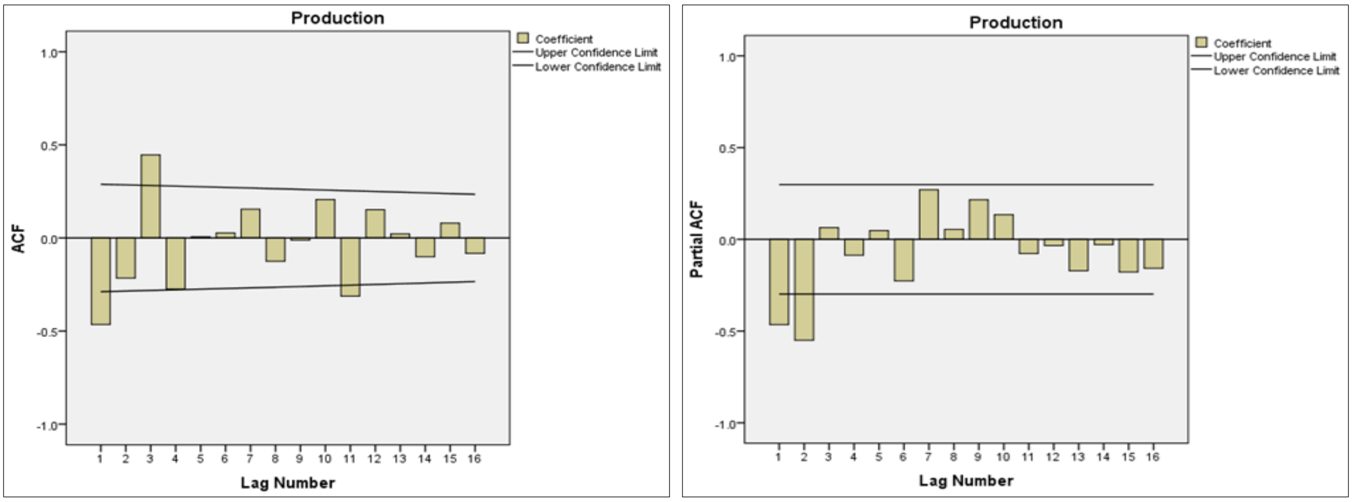

Fig 3: Autocorrelations and Partial autocorrelations at different lags of 1st differenced time series for production of cotton in Dharwad district

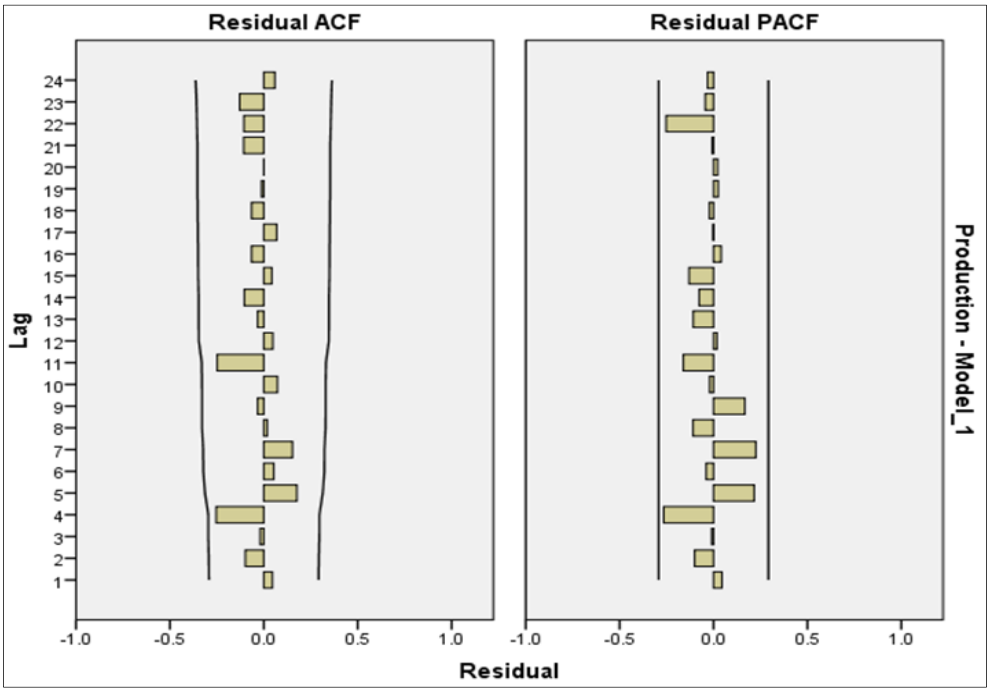

Fig 4: Residual autocorrelation and partial autocorrelations for production of cotton in Dharwad district

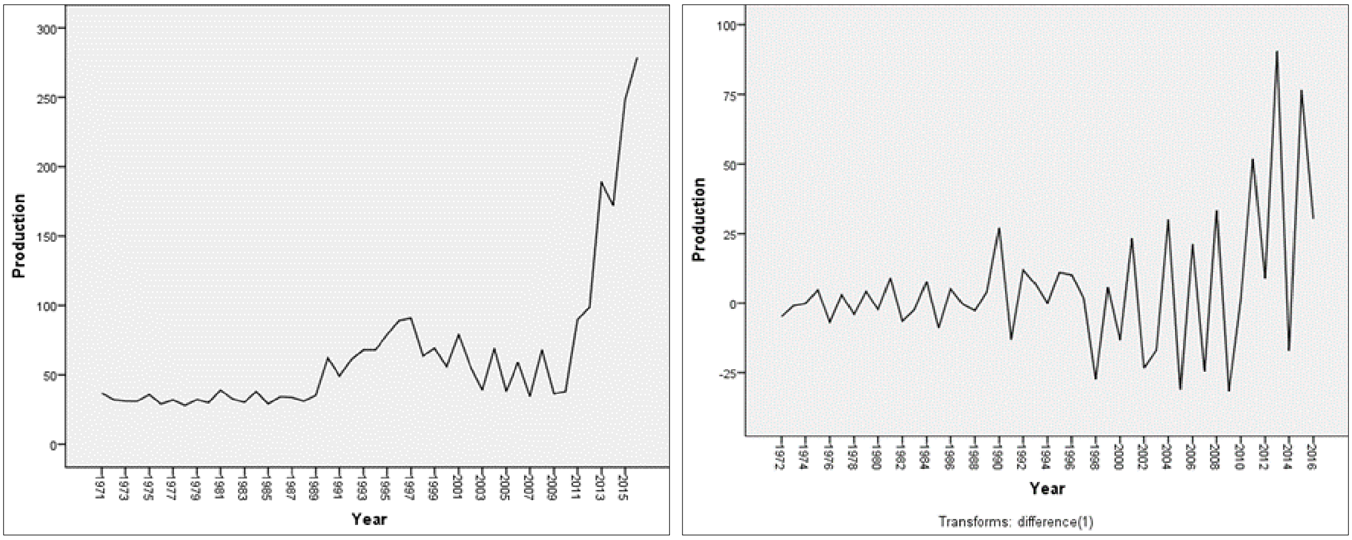

Fig 5: Time plot for production of cotton in Ballari district

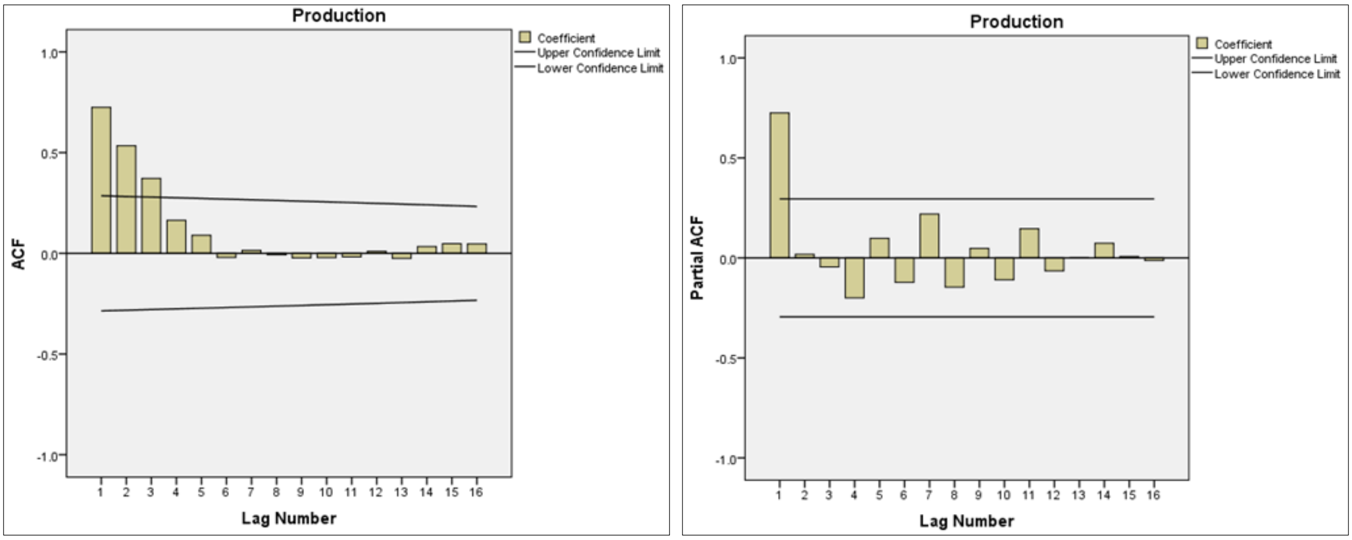

Fig 6: ACF AND PACF of cotton in Ballari district

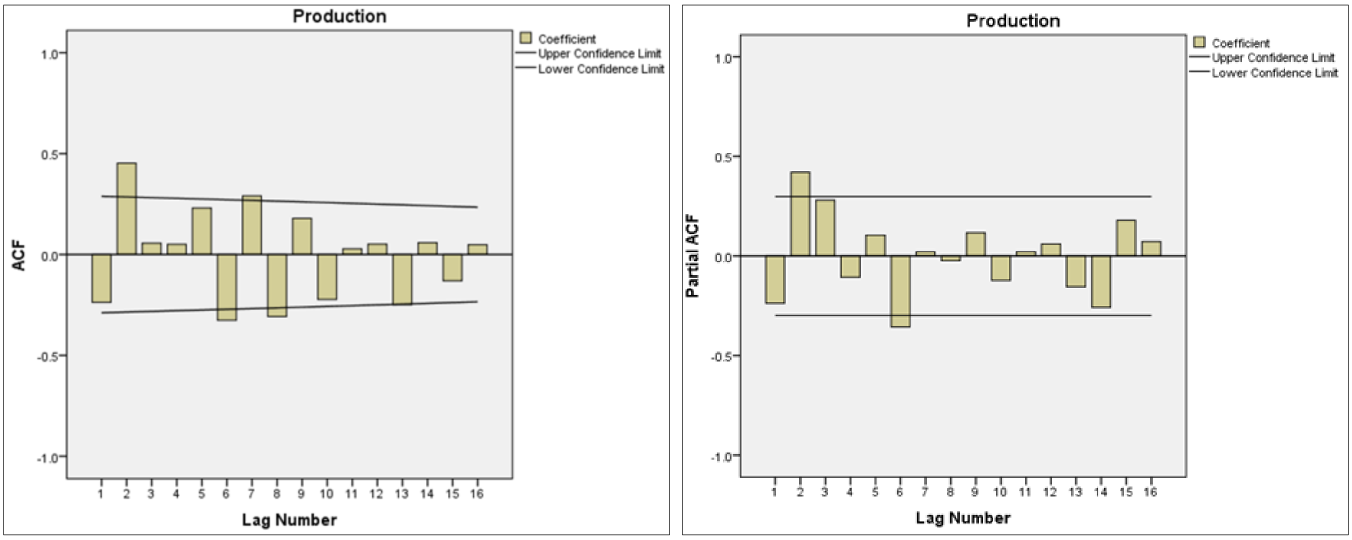

Fig 7: Autocorrelations and Partial autocorrelations at different lags of 1st differenced time series for production of cotton in Ballari district

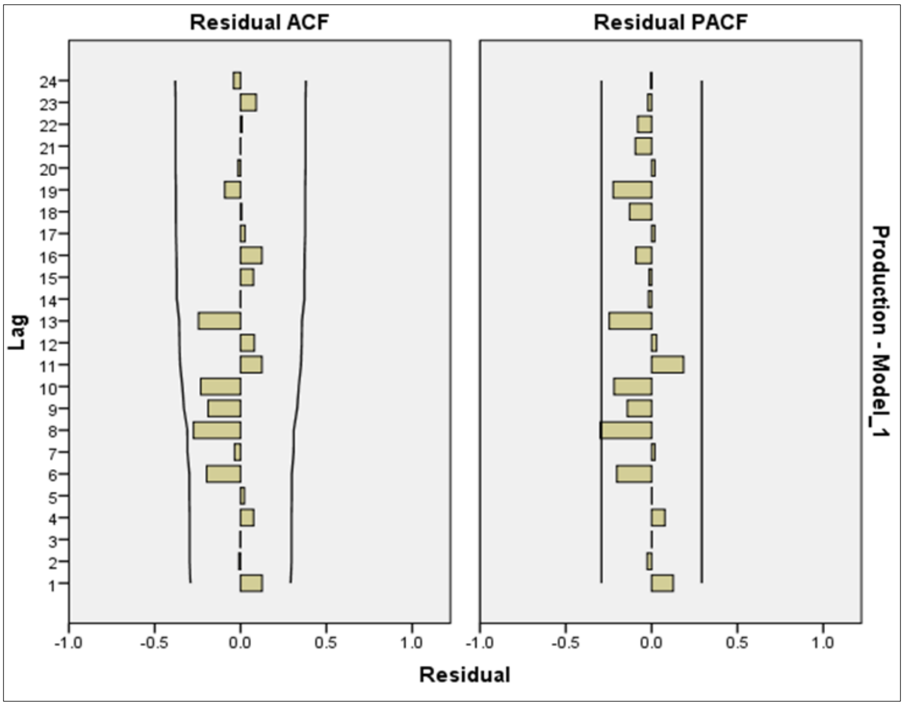

Fig 8: Residual autocorrelation and partial autocorrelations for production of cotton in Ballari district

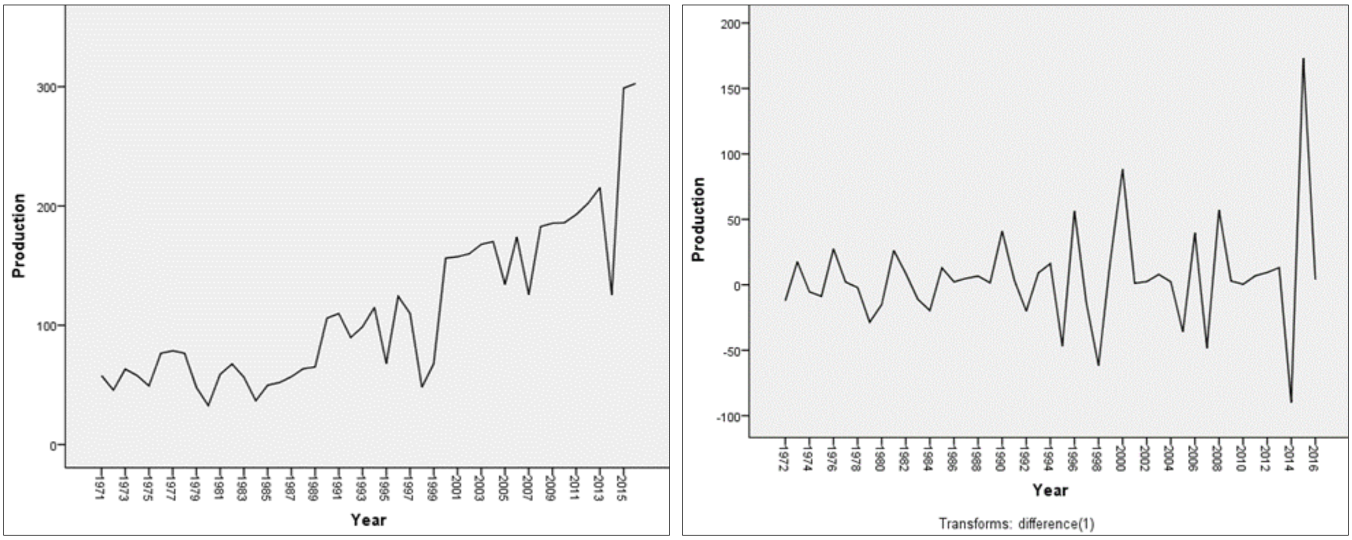

Fig 9: Time plot for production of cotton in Raichur district

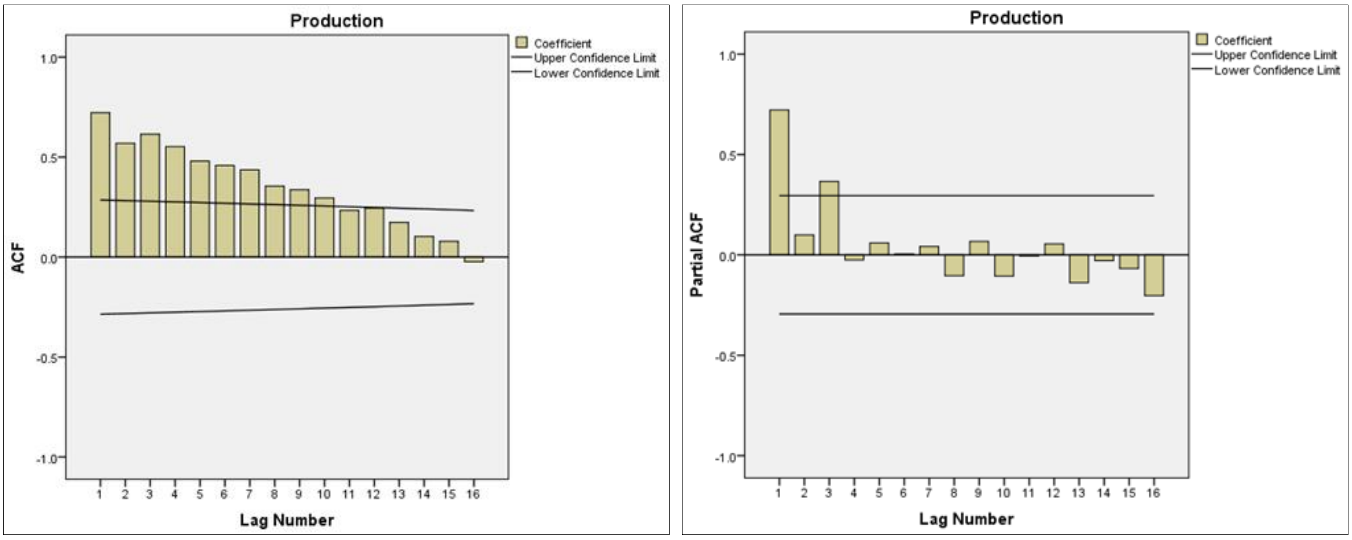

Fig 10: ACF AND PACF of Cotton in Raichur district

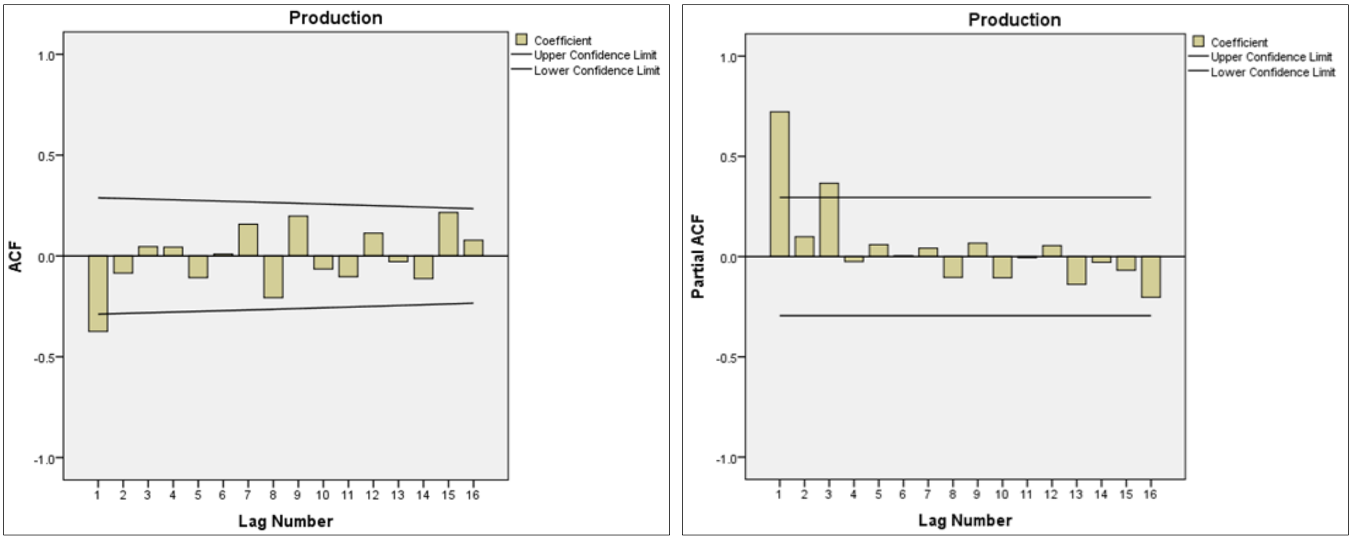

Fig 11: Autocorrelations and Partial autocorrelations at different lags of 1st differenced time series for production of cotton in Raichur district

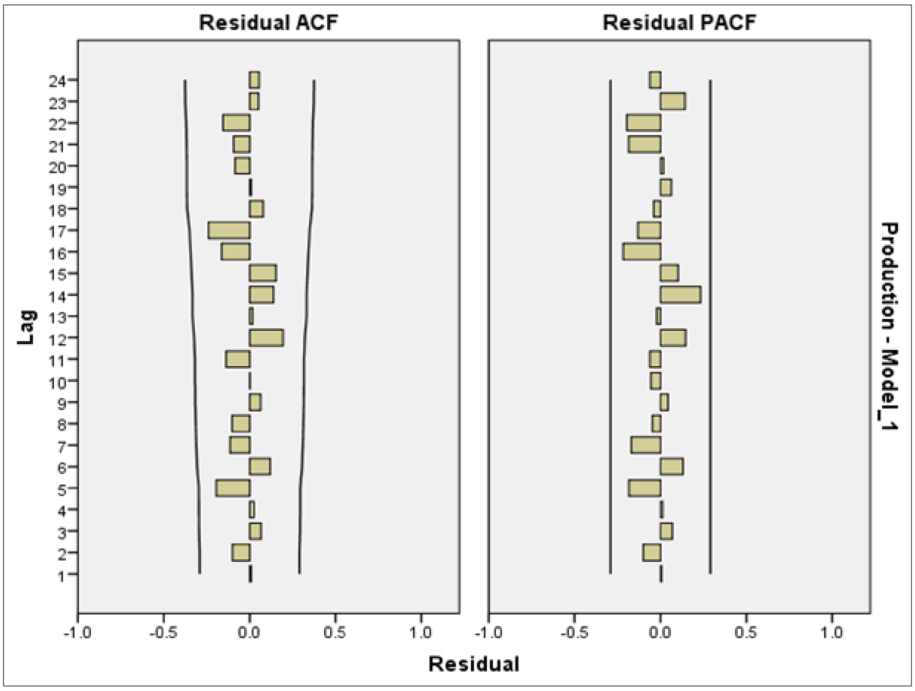

Fig 12: Residual autocorrelation and partial autocorrelations for production of cotton in Raichur district

Time series models for forecasting the production of cotton crop in Ballari district

ARIMA model

SPSS 20.0 statistical package was used to fit ARIMA model. The first step in the analysis was to plot the given data. Fig.5shows the plot of production of cotton crop from 1970-71 to 2015-16 for Ballari district. An examination of Fig. 5 revealed a positive trend over time which indicates the non-stationary nature of the series. This was confirmed, through the Auto Correlation Function (ACF) Partial Autocorrelation Function (PACF).

ACF of the time series in Fig.6 shows a slow linear decay of the autocorrelation coefficients. Fig.7 represents the PACF plot which showed significance at lags 1. This indicates the non-stationarity of the series. To make the series stationary, it was first differenced after which the data attained stationarity as shown in Fig. 8.

Identification of the model

ARIMA (2, 1, 2) model was fitted best based on the Autocorrelation function and Partial autocorrelation function of the differenced series as shown in Fig. 7 and Fig. 8 as all the lagged values remained within the limit for both ACF and PACF plots. The outliers were detected and removed to get a significant model. Based on R^2, RMSE and MAPE values, it was observed that ARIMA (2, 1, 2) was found to be the best fit after eliminating three significant outliers. Three significant outliers were detected and removed as depicted in Table 1. The estimates of the parameters are given in Table 2. The adequacy of the model was also appraised based on the values of Ljung-Box Q statistics as shown in Table 3 which are found to be non-significant. The R^2, RMSE and MAPE values for ARIMA (2, 1, 2) model are given in Table 3.Residual analysis was carried out to check the adequacy of the model. The residuals of ACF and PACF were obtained from the tentatively identified model. All the lags were found to be non-significant as shown in Fig. 8. Hence, it was inferred that ARIMA (2, 1, 2) model was adequate for forecasting production in Ballari district.

Forecasting accuracy and forecasting

The forecasting adequacy was checked using the RMSE and MAPE values. The predicted values using ARIMA with the model fit statistics like RMSE and MAPE values are given in Table 3. ARIMA (2, 1, 2) model was the best fit with least values of RMSE (9.117) and MAPE (13.660) as given in Table 3.Forecasting was done for the next four years using the ARIMA (2, 1, 2) model. The forecasted values are shown in Table 4. ARIMA (2,1,2)was selected as a model for forecasting in ARIMA technique after analyzing the ACF and PACF plots given in Fig. 7 and Fig. 8 respectively. Thus, ARIMA (2, 1, 2) model was observed be the best fit with a R^2 value of 97.70 per cent. Hamjah (2014) [5] have also obtained ARIMA (2, 1, 2) model for rice production in Bangladesh.

Time series models for forecasting the production of cotton crop in Raichur district

ARIMA model

Fig. 9shows the plot of production of cotton crop from 1970-71 to 2015-16. An examination of Fig. 9 revealed a positive trend over time which indicates the non-stationary nature of series. This was confirmed through the Auto Correlation Function (ACF) and Partial Autocorrelation Function (PACF).

ACF of the time series presented in Fig. 10 shows a slow linear decay of the autocorrelation coefficients. Fig.11 represents the PACF plot which shows significance at lags 1 indicating the non-stationarity of time series. To make the series stationary, it was first differenced after which the data attained stationarity as shown in Fig. 12.

Identification of the model

ARIMA (1, 1, 1) model was fitted based on the Autocorrelation function and Partial autocorrelation function of the differenced series as shown in Fig.11 and Fig. 12, since all the lagged values remained within the limit both in ACF and PACF plots. Outliers were detected and removed to get a significant model. Based on R^2, RMSE and MAPE values, ARIMA (1, 1, 1) model was found to be the best fit after eliminating one significant outlier. The significant outlier detected is shown in Table 1. The estimates of the parameters are given in Table 2. The adequacy of the model was also appraised based on the values of Ljung-Box Q statistic as shown in Table 3, which was found to be non-significant. The R^2, RMSE and MAPE values for ARIMA (1, 1, 1) model are given in Table 3.Residual analysis was carried out to check the adequacy of the model. The residuals of ACF and PACF were obtained from the tentatively identified model, all the lags were found to be non-significant which is depicted in Fig. 12. Thus, from the analysis it was inferred that ARIMA (1, 1, 1) model was adequate to forecast the future production of cotton in Raichur district.

Forecasting accuracy and forecasting

The forecasting adequacy was checked using the RMSE and MAPE values. The predicted values using ARIMA with the model fit statistics like RMSE and MAPE values are given in Table 3. ARIMA (1, 1, 1) model was the best fit with lower RMSE (24.961) and lower MAPE (20.309) as given in Table 3.Forecasting was done for the next four years using the ARIMA (1, 1, 1) model as in Table 4.ARIMA (1, 1, 1)was selected as a model for forecasting in ARIMA technique after analyzing the ACF and PACF plots given in Fig. 11 and Fig. 12 respectively. The model was said to be the best fit with a R^2 value of 87.20per cent. Wali *et al.* (2017) [22] revealed that ARIMA (1, 1, 1) were the best fitted model for forecasting production of cotton crop in India.

Conclusion

A prudent attempt has been made in the present study to forecast production of cotton crop in selected districts of Karnataka. *viz*., Dharwad, Ballari and Raichur using ARIMA model The data was obtained from Directorate of Economics and Statistics, Karnataka for the period from 1970-71 to 2015-16. It was found that ARIMA (2, 1, 2) was the best model for forecasting production of cotton in Dharwad. ARIMA (2, 1, 2) was the appropriate model to predict the production of cotton in Ballari. Whereas, ARIMA (1, 1, 1) found to be suitable for forecasting production of cotton in Raichur district.

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