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Modelling and forecasting of land use land cover statistics in India

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Abstract
Modelling land use land cover (LULC) change is critical to understand its spatiotemporal trends to protect the land resources sustainably. India has the total geographical area of 3,28,726 thousand hectares out of which, only 1,18,746 thousand hectares area was under cultivation in 1950-51with 111.1% cropping intensity. It has been increased to about 1,40,000 thousand hectares with 151.1% cropping intensity in the year 2019-20. The growth rates in the total cropped area and cropping intensity may not support to the growing population in the country, as per capita availability of land is decreasing day to day. The *ARIMA* models with different *p, d* and *q* values were tested to the land use, land cover statistics data of total cropped area, area sown more than once, area under non-agricultural uses, percentage forest area and barren land area and found the best fitted model based on the highest R^2 value, lowest *RMSE*, *MAPE* and *Normalized BIC* values. The total cropped are, area sown more than once, area under non-agricultural uses and percentage forest area have shown increasing trend in the study period, whereas the barren land area has shown negative trend. The total cropped area and the area sown more than once were best fitted with the $ARIMA(0, 1, 1)$ model. The area under non-agricultural uses and the percentage forest area were best fitted with the $ARIMA(0, 1, 0)$ model. Whereas the barren land area was best fitted with the $ARIMA(1, 1, 6)$. Forecasts of land use, land cover statistics data were made for five years from 2020 to 2024 using the best fitted model.

Keywords: ACF, PACF, ARIMA, RMSE, MAPE, Forecasting, stationarity, modelling, correlogram

Introduction
Land use/land cover change (LULC) analyses are crucial for a well-informed decision-making regarding proper land uses planning policy. Human population growth, movement, and demand have a substantial impact on land use and land cover dynamics. The phrase "land cover" refers to the habitat or kind of vegetation present, such as a forest or an agricultural area (Mishra *et al*., 2014) [12] which may be natural and anthropogenic features that can be observed on the Earth's surface, *i.e*., forests, tidal wetlands, developed/built areas, grasslands, and water (Semegnew *et al.* 2021) [14] whereas "land use" refers to the manner in which humans use the land and its resources. Land use planning (LUP) plays a key role in natural resource management. Land-use and land-cover change (LUCC) also referred to as "land change" is used to describe how humans have altered the surface of the Earth. It is commonly acknowledged that LULC have a significant impact on the majority of ecosystems as well as the operation of the Earth's systems as a whole. This change is based on the purposes of need *i.e*., change in land cover, change in intensity and management (Mishra *et al*., 2014) [12]. Land serves as the foundation for all types of economic activity and is a crucial natural resource for agriculture. Therefore, it is necessary to analyze how it is used in various activities in order to develop appropriate policies that would ensure its best usage (Manjunatha *et al.*, 2021) [10]. One of the main study projects in global change studies is examining how changes in land use and land cover affect the environment on regional and global scales. These changes are also emerging as a major environmental concern. Climate change, biodiversity loss, and water, soil, and air pollution are among the biggest environmental worries facing modern human populations. Therefore, it has become a top priority for academics and policymakers worldwide to monitor and mitigate the harmful effects of LULC while maintaining the production of necessary resources (Mishra *et al*., 2014) [12].

Dynamics of land use and land cover are significantly impacted by human population expansion, mobility, and demand. It is simpler to create plans that strike a balance between preservation, competing uses, and growth compressions by using thematic maps of land use and land cover (LULC) as a reference for examining, source administration, and forecasting. Prediction of land use or land cover by using time serious data is most important for the future management plan of LULC, and it is regularly used for a varied suitability measure as a proxy of human influence on land change processes

Understanding current and future LULC changes and patterns is a significant topic that calls for timely investigation as the pressure of the LULC change is increasing in many places. The future management plan for LULC must consider the prediction of LU/LC utilizing time serious data, and it is frequently used for a variety of suitability measures as a stand-in for human influence on land change processes. A Markov model is one in which the system's future state can be predicted solely from its recently passed state. By building a transition probability matrix of LULC change from period one to period two, it is possible to predict future change. Researcher (Hyandye *et al*. 2017) [5] employed the CA-Markov chain model and multispectral satellite photos to forecast the LULC change in various places. Additionally, it calculated the states between various land uses and calculated the transition rate between them. Thus, future scenarios can be estimated using a combination of the elements that influence LULC change (Leta *et al*., 2021) [8].

Distinct locations have distinct motivating causes for LULC modifications. LULC change analysis aids in identifying the factors that cause changes in various regions. For instance, research from the Afar region identified more than 15 LULC change driving factors, including migration brought on by drought, changes in land tenure, and changes in governmental policy. According to a study from the central rift valley, the main causes of LULC changes in the study area are population expansion, a loss in agricultural output, a change in land ownership, and irregular rainfall. Therefore, based on the agroecology and socioeconomic situation of the area, it is important to address and explore the local driving causes of LULC changes of specific ecosystems or locations (Leta *et al*., 2021) [8]. The understanding of earth-atmosphere interaction, forest fragmentation, biodiversity loss, and future management plans are all significantly impacted by the analysis and prediction of LULC changes. Additionally, the inspection and analysis of LULC have significantly improved, offering the most precise assessment of the health and spread state of the world's forest, grassland, and agricultural resources (Tadese *et al*., 2021) [17].

Dynamics of land use and land cover are significantly impacted by human population expansion, mobility, and demand. It is simpler to create plans that strike a balance between preservation, competing uses, and growth compressions by using thematic maps of land use and land cover (LULC) as a reference for examining, source administration, and forecasting. It is important to understand land use pattern across the different regions which helps in development of future research strategy on land use planning and land use policies (Thanuja *et al*., 2021) [18].

The *ARIMA* model is the most comprehensive form of the time series forecasting model. Various series arises in the forecasting process in modelling includes the Auto-Regressive. Appearance of lags of forecast errors in the model refers Moving average. For forecasting variables, Box and Jenkins proposed the *ARIMA* model (Box and Jenkins 1976) [2]. Several fields like economics, business have widely used these methods for forecasting (Brown 1959) [3]. For forecasting economic data, the uni-variate time series have been used (Ljung and Box 1978) [9] and (Pindyck and Rubinfeld 1981) [13]. For forecasting the maize cultivation and production in Nigeria, the *ARIMA* models were used (Badmus and Ariyo 2011) [1]. The *ARIMA* (1, 1, 1) was best fitted for the cultivated area, production was best fitted with the *ARIMA* (2, 1, 2). The future values of Pakistan's wheat production potential were derived using *ARIMA* (Falak and Eatzaz 2008) [4]. The *ARIMA* model was used to anticipate wholesale paddy prices in 5 major Indian states for the coming crop year (Kathayat and Dixit 2021) [7]. Numerous academics have widely used the *ARIMA* method to forecast demand in terms of domestic consumption, imports and exports in order to implement acceptable solutions (Shabur and Haque 1993) [15]. Reports are on the *ARIMA* method to investigate the trend in total pulse production in India (Mishra *et al.*, 2021) [11]. The Box and Jenkins *ARIMA* model was applied to South Indian paddy production forecasts (Kannan and Karuppasamy 2020) [6]. An attempt has been made in the present study to find the Box-Jenkins *ARIMA* model for the land use land cove data in India. The specific objective of the study is to forecast the land use and land cove data in India.

Materials and Methods

The present study was based on the secondary data for 70 years from 1950-51 to 2019-20 pertaining to the land use statistics of agriculture sector, forests, non-agricultural uses and barren land in India. The data was collected from the Ministry of Agriculture & Farmers Welfare, Government of India in *indiastat.com* website. The data was analyzed using the software SPSS 20.0.

Time series is a historical record of a certain activity, with measurements taken at regular intervals using a consistent method of measurement and activity. Box and Jenkins popularized the *ARIMA* stochastic model, which was used to model the data (Box and Jenkins 1976) [2]. The *ARIMA* (*p*, *d*, *q*) model combines the Autoregressive (*AR*) model, which illustrates a link between the present and previous values, with a random value and a Moving Average. Moving average model that demonstrates the present value is related to the previous residuals. This model is chosen among others for forecasting future values because it considers the differences between values in a series rather than evaluating the actual values.

Moving Average (*MA*) process

The moving average models were introduced and first used by (Slutsky 1927) and (Wold 1938). The moving average can be expressed as follows:

$$Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \text{------------------- } \mathbf{(1)}$$

Where Y_t represents the original series and e_t represents the error series.

A series of this type is known as a moving average of order *q* and it is abbreviated as *MA* (*q*).

Autoregressive (*AR*) Progress

Autoregressive processes were first studied (18). Autoregressive processes are regressions on one self, as their name implies. In particular, the equation is satisfied by a p^{th}-order autoregressive process Y_t.

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + e_t \text{ ------------------ } \mathbf{(2)}$$

The series' most recent value Y_t is a linear combination of it self's p most recent past values plus a "innovation" term that includes anything new in the series at time t that is not explained by the past values. Consequently, for each t, we assume that e_t is independent of $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$.

Autoregressive Integrated Moving Average (*ARIMA*) model

Box and Jenkins's method is the cornerstone of the contemporary approach to time series analysis. The Box and Jenkins approach is used to create an *ARIMA* model from an observed time series. The technique focuses on stationary processes, passing through appropriate preliminary data modifications. The Box-Jenkin's *ARIMA* model is used to fit in this study. This is the generalized version of the non-stationary *ARMA* model represented by $ARIMA(p,q)$.

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \text{ ---(3)}$$

Where, Y_t is the original series for every t, we assume that e_t is independent of $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-p}$.

If the d^{th} difference $W_t = \nabla dY_t$ is a stationary *ARMA* process, a time series Y_t is an integrated autoregressive moving average (*ARIMA*) model. We call Y_t, an $ARIMA(p, d, q)$ process if W_t follows an $ARIMA(p,q)$ model. Fortunately, we can usually use d = 1 or 2 for practical purposes. Take a look at $ARIMA(p,1,q)$ process with $W_t = Y_t - Y_{t-1}$, we have

$$W_t = \phi_1 W_{t-1} + \phi_2 W_{t-2} + \ldots + \phi_p W_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \text{ --(4)}$$

The model is estimated in 4 steps: identification stage, parameter estimation, diagnostic verification and forecasting.

Identification stage

In the identification phase, the values of p, d and q are determined using the Box-Jenkins approach. These values are estimated using the autocorrelation function (*ACF*) and partial autocorrelation function (*PACF*).Theoretical PACF has non zero partial autocorrelation at lags and zero partial autocorrelation at all other delays for each process, whereas theoretical ACF has zero autocorrelation at all lags. The nonzero delays of the sample *PACF* and *ACF* are provisionally accepted as the parameters p and q. The non-stationary time series data will be differenced to make it stationary. The number of differences performed to make the series stationary will be the order of d for the $ARIMA(p,d,q)$ model. The difference order $d = 0$ for the stationary time series data, $ARIMA(p,q)$ will be the model in this case.

Parameter Estimation

Diagnostic Checking

The $ARIMA(p,d,q)$ will be analyzed with different p, d, and q values and identified best fitted model based on highest R^2 value, lowest Root Mean Square Error (*RMSE*), Mean Absolute Percentage Error (*MAPE*) and Normalized Bayesian Information Criterion (*BIC*) values. The diagnostic checks will be made on the residuals, to determine whether they are randomly and regularly distributed.

The Ljung-Box Testwill be used to check for residual autocorrelation. The residuals should be low for best fitted model. Consequently, the null hypothesis is

$$H_0 : \rho_1(e) = \rho_2(e) = \rho_3(e) = \ldots = \rho_k(e) = 0,$$

tested with the Box-Ljung statistic

$$\sum (N-k)\rho^2 k^{(e)} \qquad (5)$$

$$Q^* = N(N+1) \qquad (6)$$

Where, N is the number of data points used to estimate the model.

This statistic Q^* closely resembles the chi square distribution with (k-q) df, where q is the number of parameters in the model that should be evaluated. If Q^* is large, it is suggested that the residuals' group autocorrelation is significantly different. Random and zero shocks in the derived model are most likely auto-correlated. The model should be reformulated accordingly.

Forecasting

The future values of area under the agriculture sector, forests, non-agricultural uses and barren land will be forecasted by using the best fitted $ARIMA(p,d,q)$ model derived in process explained above.

Results & Discussion

The total cropped area has shown an increasing trend in the study period, and it is evident from Fig. 1(a) that the data is not stationary with constant variance. Further the *ACF* and *PACF* charts shown in Fig. 1(b) and Fig. 1(c) are indicating that the data is not stationary. The first difference data as shown in Fig. 2(a) has removed the trend component and showing constant variance and there are no significant spikes in the *ACF* and *PACF* charts shown in Fig. 2(b) and Fig. 2(c) of the first difference data, confirming the stationarity of the data. It is evident from the correlogram given in Fig. 2 that, the autocorrelation and partial autocorrelation decays rapidly after the initial lag indicating that the series might be of moving average time series of order 1.

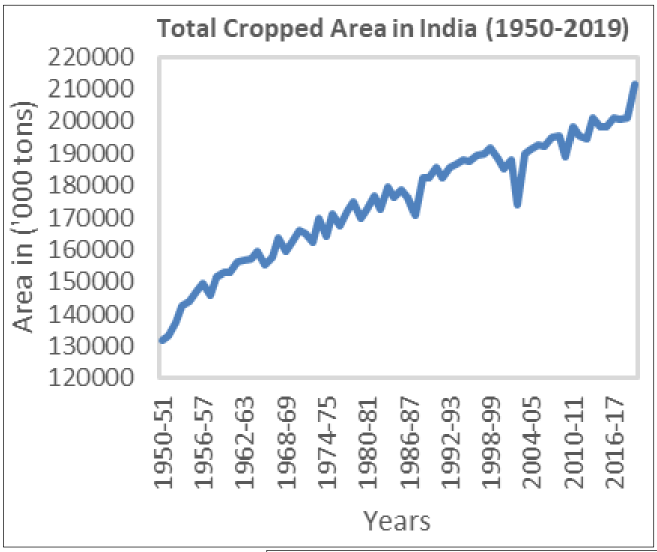
The Dickey-Fuller unit root test was used to test the stationarity of first differenced data and the results show that

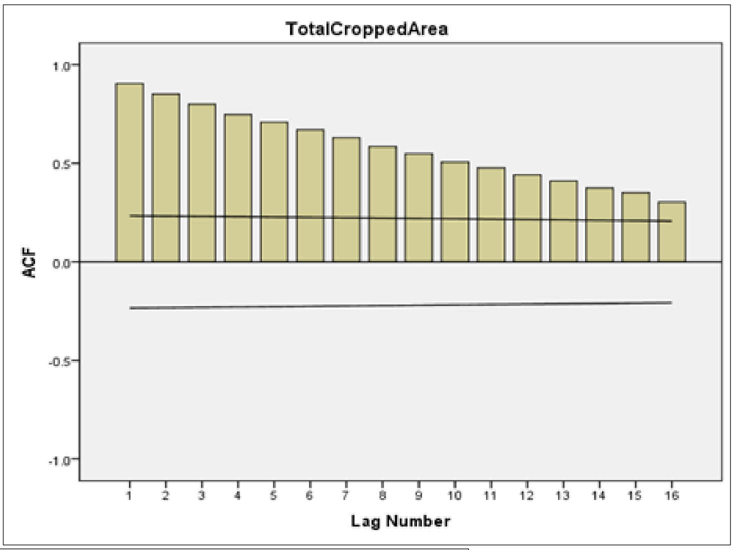
$$\Pr\left(|t| > 5.863 \right) < 0.01$$

indicating theoretically that the first differenced data is stationary and significant at 1% level.

The total cropped area data was subjected to different *ARIMA* models with difference of order 1. The $ARIMA(0, 1, 1)$ was best fitted with highest R^2 value (0.955), lowest *RMSE*

(3890.34), *MAPE* (1.65) and *Normalize BIC* (16.66) values. Hence $ARIMA(0, 1, 1)$ was used for making forecast for next five years of total cropped area in India. The forecasts with lower confidence limits and upper confidence limits were displayed in Fig. 3 and the forecasted values are given in the table 3.





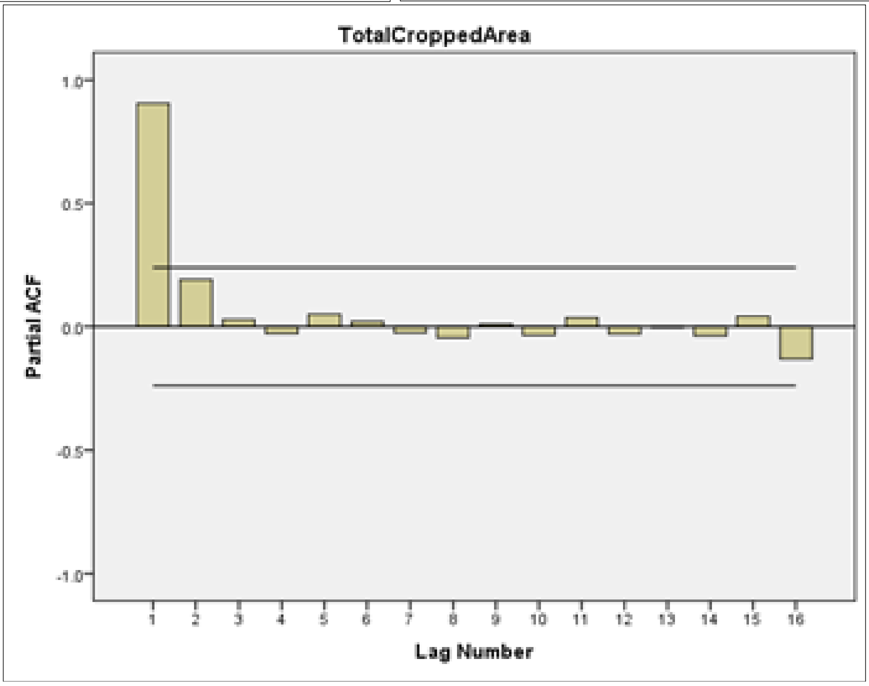
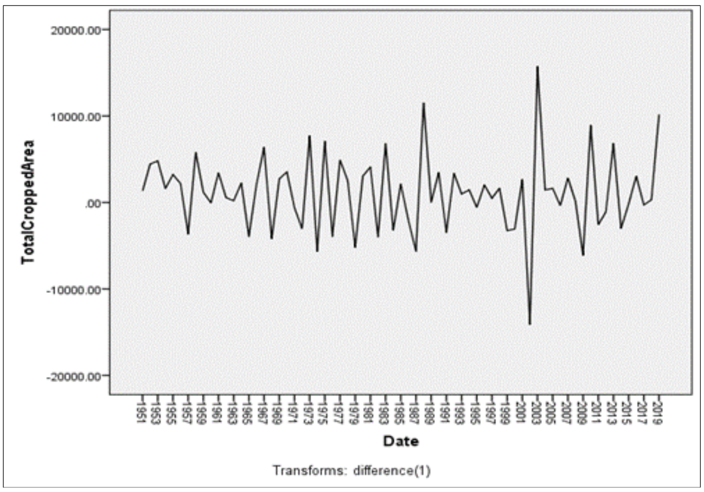
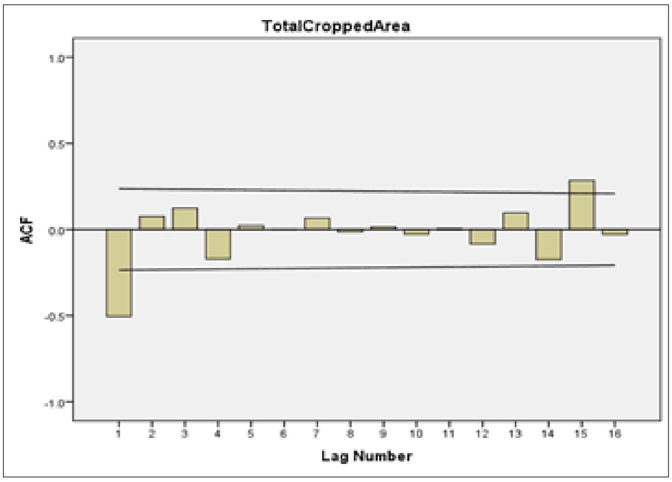


Fig 1: Correlogram of the total cropped area data from 1950-51 to 2019-20 in India





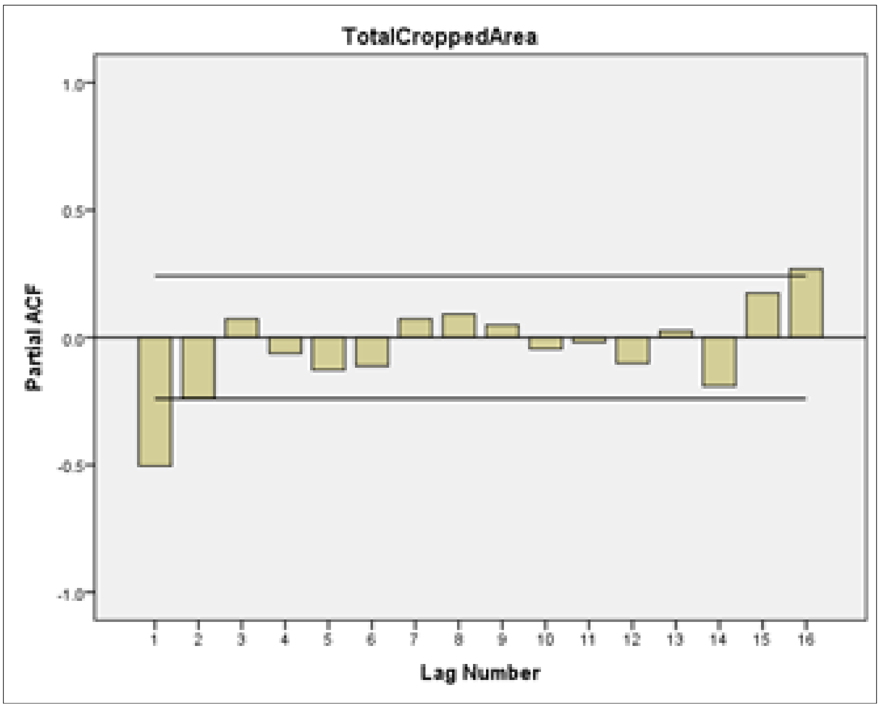


Fig 2: Correlogram of the first differenced data of total cropped area from 1950-51 to 2019-20 in India

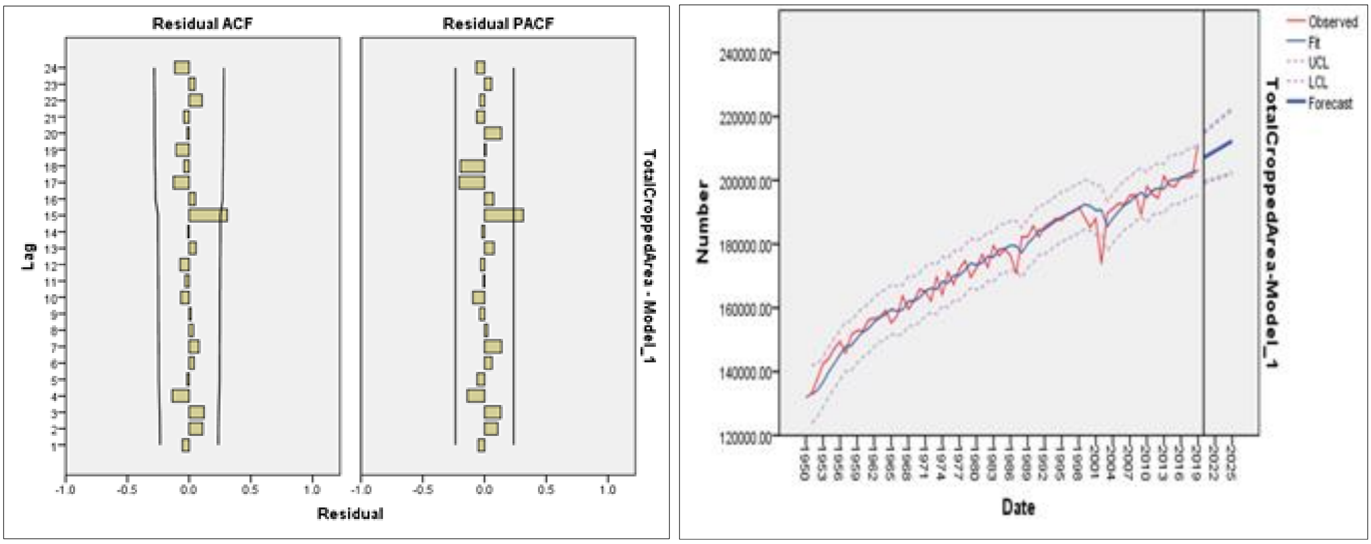


Fig 3: Forecast of total cropped area through *ARIMA* (0, 1, 1)

The graph of the data pertaining to the area sown more than once during the study period is given in Fig. 4(a) it has shown an increasing trend and not stationary with constant variance. Further the *ACF* and *PACF* charts given in Fig. 4(b) and Fig. 4(c) are indicating that the data is not stationary. The first difference data given in Fig. 5(a) indicating that there is no trend component and showing constant variance and there are no significant spikes in the *ACF* and *PACF* charts shown in Fig. 5(b) and Fig. 5(c), confirming the stationarity of the data. It is evident from the correlogram given in Fig. 4 and Fig. 5 that, the autocorrelation and partial autocorrelation decays rapidly after the initial lag indicating that the series might be of moving average time series of order 1.

For testing the stationarity of first differenced data, the Dickey-Fuller unit root test was used and the result shows $\Pr\left(|t| > 5.138 \right) < 0.01$, indicating theoretically that, the first differenced data is stationary and significant at 1% level.

Different *ARIMA* models were tested with difference of order 1 to find the best fitted model for the area sown more than once. Highest R^2 value (0.981), lowest *RMSE* (2075.36), *MAPE* (4.12) and *Normalize BIC* (15.40) values were found to the $ARIMA(0, 1, 1)$ model. Hence $ARIMA(0, 1, 1)$ was found to be the best fitted and used for making forecast for next five years of area sown more than once. The forecasts with lower and upper confidence limits were displayed in Fig. 6 and the forecasted values are given in the table 3.

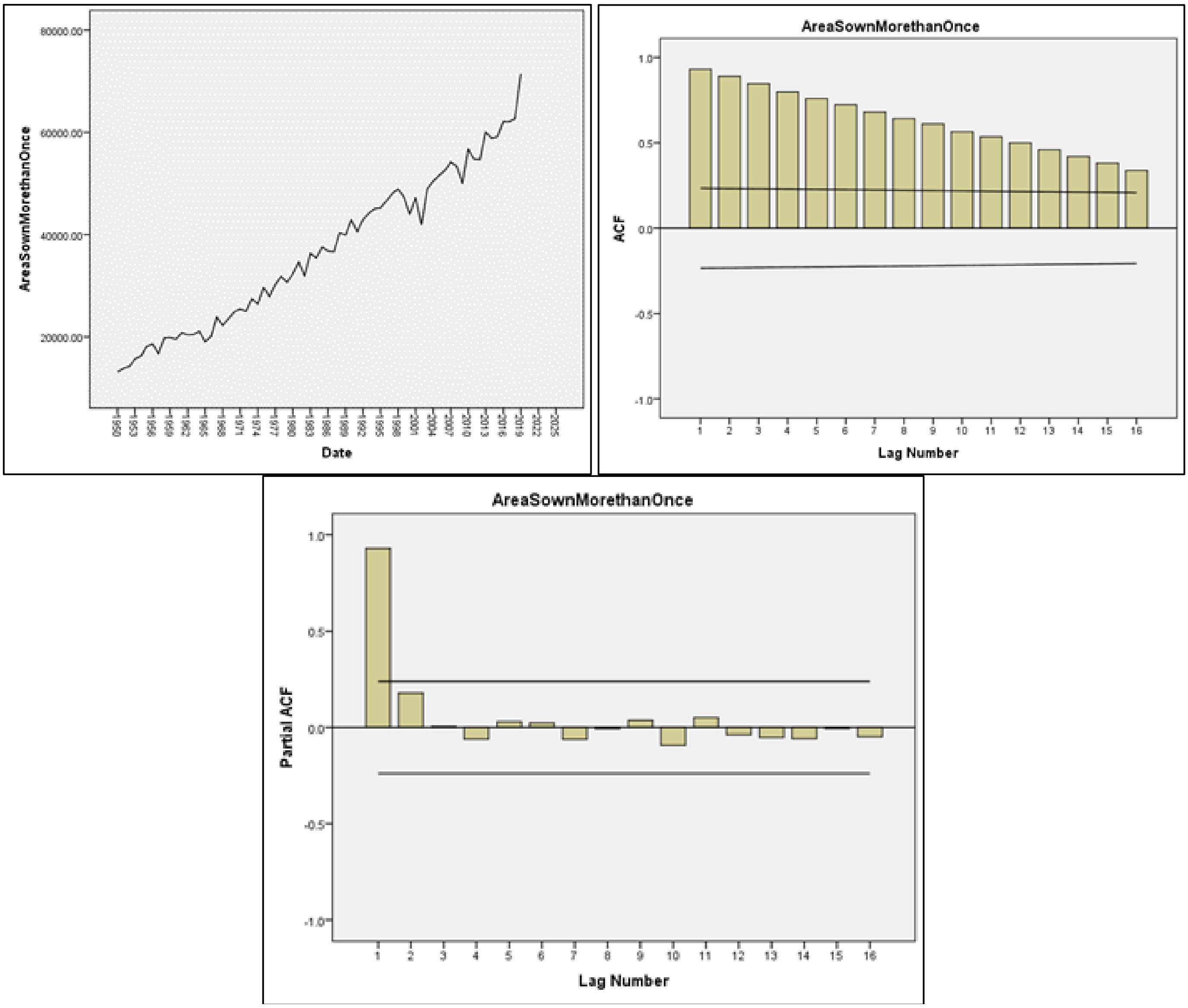
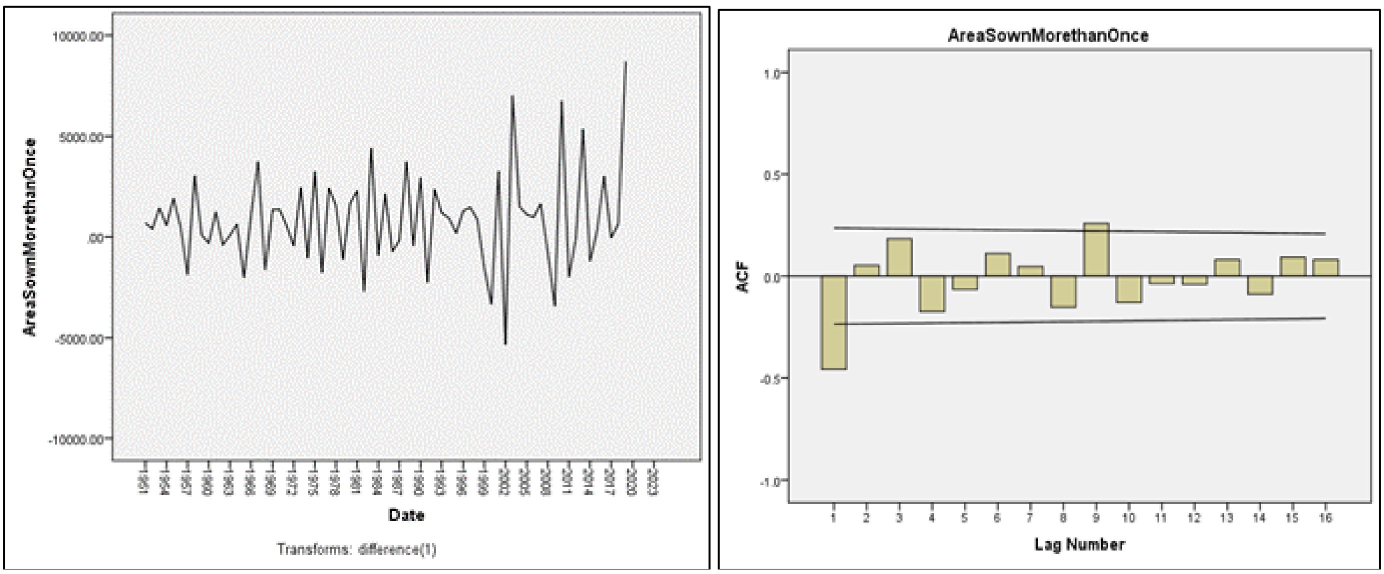


Fig 4: Correlogram of the area sown more than once data from 1950-51 to 2019-20 in India



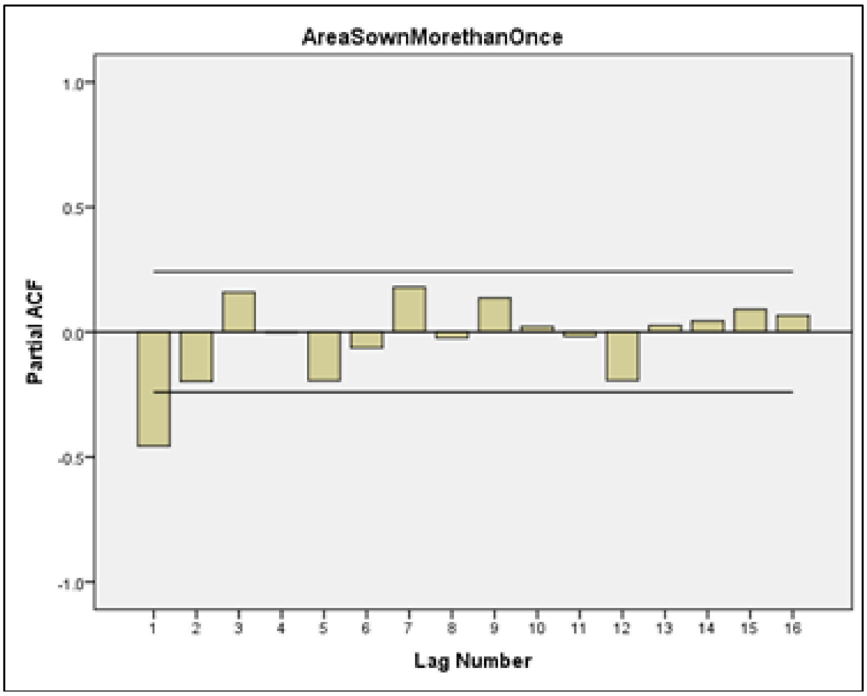


Fig 5: Correlogram of the first differenced data of area sown more than once from 1950-51 to 2019-20 in India

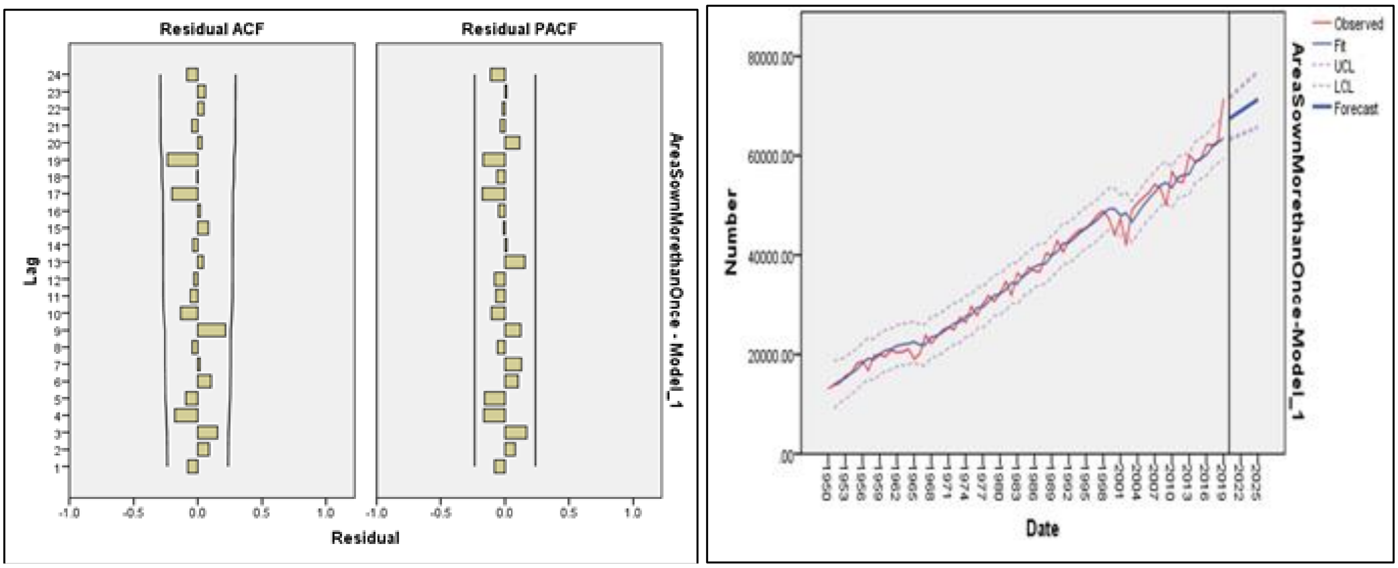


Fig 6: Forecast of the area sown more than once through *ARIMA* (0, 1, 1)

An increasing trend was noticed in the area under non-agricultural uses during the study period (Fig. 7(a)). The *ACF* and *PACF* charts shown in Fig. 7(b) and Fig. 7(c) of area under non-agricultural uses are explaining that the data is not stationary. The chart given in Fig. 7(d) of first difference data has removed the trend component and showing constant variance, confirming that the data is stationarity. The autocorrelation and partial autocorrelation of the original data decays rapidly after the initial lag, indicating that the series might be of differencing time series of order one.

The first difference data was subjected to the Dickey-Fuller unit root test to test for the stationarity. The result shows that $\Pr\left(\ |t| > 4.670\right) < 0.01$, indicating that the first differenced data is stationary and is significant at 1% level.

The data on area under non-agricultural uses was subjected to different *ARIMA* models to find the best fitted model. The *ARIMA* with first difference, autoregressive order zero (0) and moving average order zero (0) is found to be the best fitted with highest R^2 value (0.990), lowest *RMSE* (474.82), *MAPE* (1.41) and *Normalize BIC*(12.39) values. Hence for forecasting the area under non-agricultural uses for next five years, $ARIMA(0, 1, 0)$ was used. The forecasted values are given in the table 3 and the forecasts with lower and upper confidence limits were displayed in Fig. 8 and the.

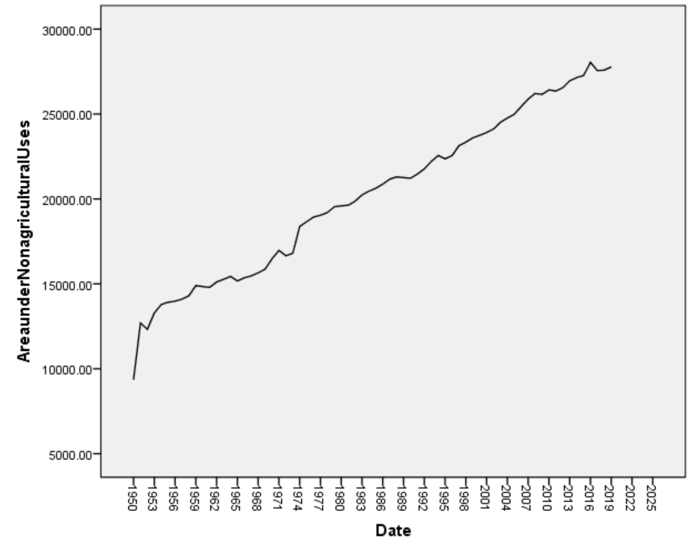


Fig. 7(a)

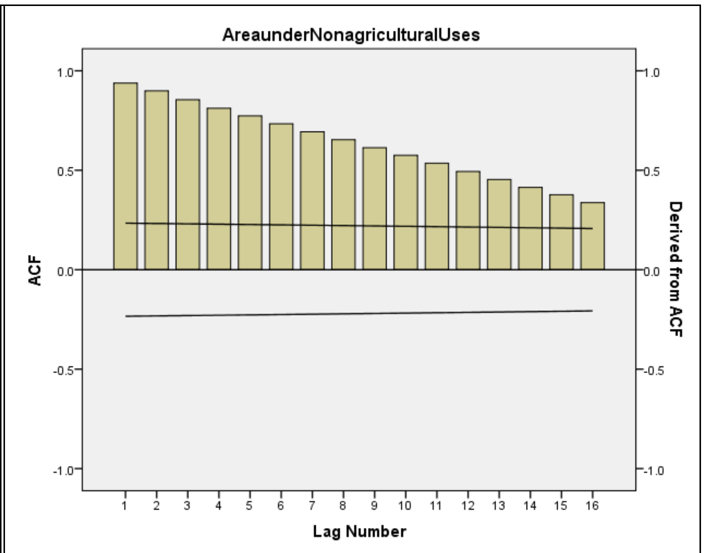


Fig. 7(b)

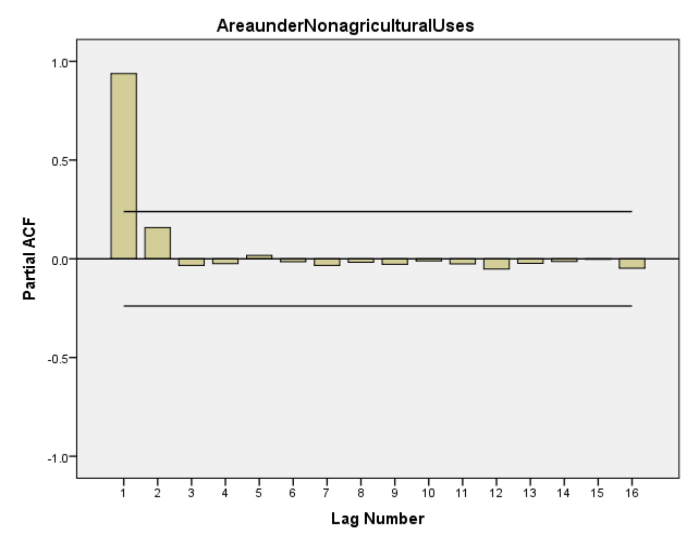


Fig. 7(c)

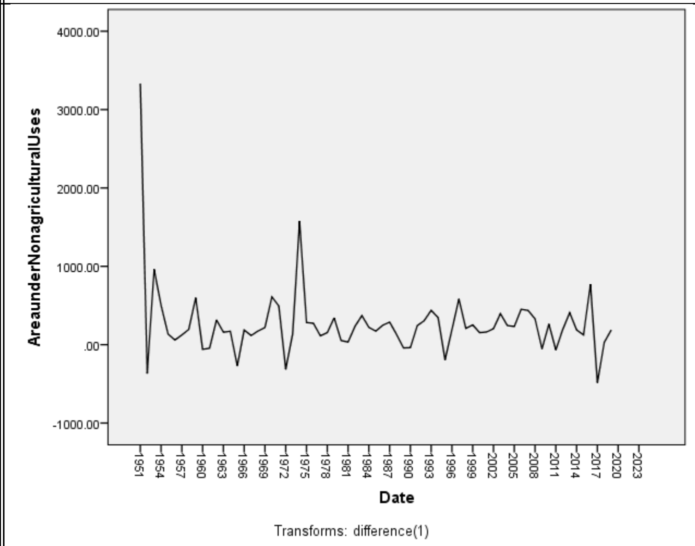


Fig. 7(d)

Fig 7: Correlogram of the area under non-agricultural uses from 1950-51 to 2019-20 in India

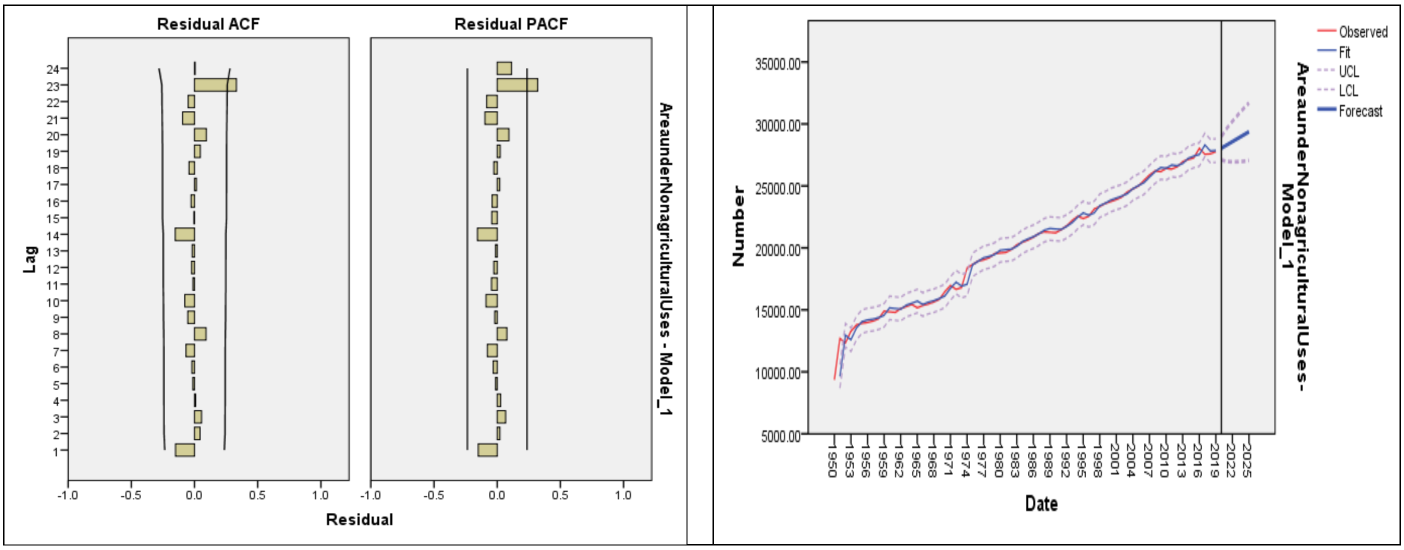


Fig 8: Forecast of area under non-agricultural uses through *ARIMA* (0, 1, 0)

Table 1: Model parameters of the Land use and land cover data in India

Model	No of Predictors	Model Statistics: Model Fit statistics: Stationary R^2	R^2	RMSE	MAPE	MAE	Max. APE	Max. AE	Normalized BIC	Ljung-Box Q (18): Statistics	DF	Sig.	Number of Outliers
Total Cropped Area													
ARIMA (0, 1, 1)	0	.307	.955	3890.34	1.65	2856.49	9.65	16784.06	16.66	16.08	17	.518	0
Area Sown More than Once													
ARIMA (0, 1, 1)	0	.272	.981	2075.36	4.12	1438.87	18.03	7998.60	15.40	17.22	17	.439	0
Area under Nonagricultural Uses													
ARIMA (0, 1, 0)	0	0.000	.990	474.82	1.41	240.12	24.16	3066.04	12.39	6.22	18	.995	0
Percentage Forest Area													
ARIMA (0, 1, 0)	0	0.000	.958	.42	1.18	.21	16.26	2.42	-1.69	19.28	18	.375	0
Barren Land													
ARIMA (1, 1, 6)	0	.186	.992	648.83	1.69	433.05	6.95	2113.06	13.13	23.43	15	.076	0

The percentage forest area during the period under study shown graphically in Fig. 9(a) is indicating that it has positive growth rate. Further from the graph, it is evident that the data is not stationary with constant variance. The first difference data as shown in Fig. 9(d) has removed the trend component and showing constant variance and there are no significant spikes in the *ACF* and *PACF* charts of the original data shown in Fig. 9(b) and Fig. 9(c), confirming the stationarity of the data. It is evident from the correlogram given in Fig. 9 that, the series might be of difference time series.

It was used the Dickey-Fuller unit root test to test the stationarity of first differenced data and the results reveal that $\Pr\left(|t| > 2.755\right) < 0.01$, indicating the stationarity of the first differenced data and is significant at 1% level.

The *ARIMA* models with different *p*, *d* and *q* values were tested for the percentage forest area in India during period under the study. The $ARIMA(0, 1, 0)$ was best fitted with highest R^2 value (0.958), lowest *RMSE* (0.42), *MAPE* (1.18) and *Normalize BIC* (-1.69) values. Hence $ARIMA(0, 1, 0)$ was used for making forecast for next five years of percentage forest area in India. The forecasts with lower and upper confidence limits were shown in Fig. 10 and the forecasted values are given in the table 3.

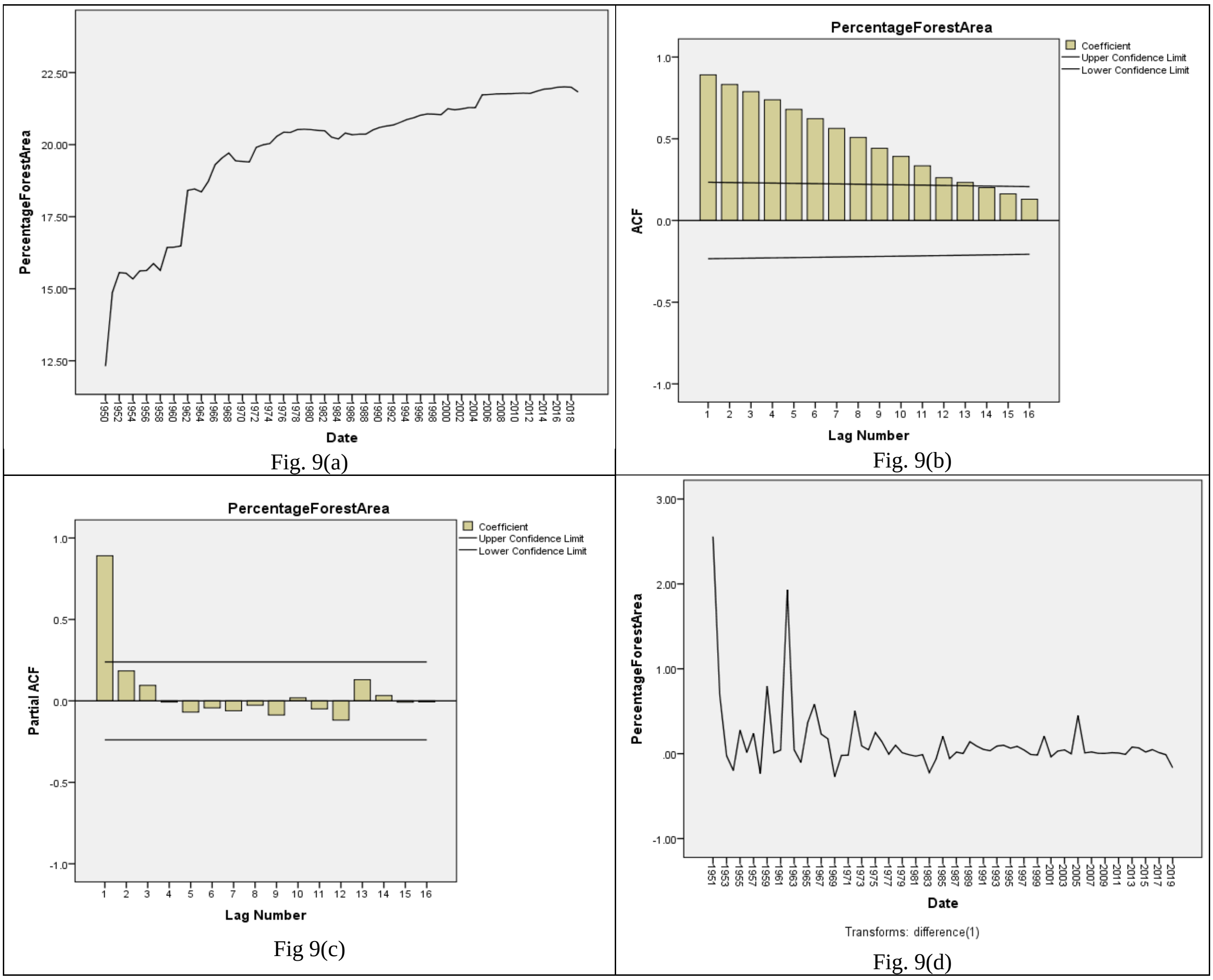


Fig. 9(a) Fig. 9(b) Fig 9(c) Fig. 9(d)

Fig 9: Correlogram of percentage forest area from 1950-51 to 2019-20 in India

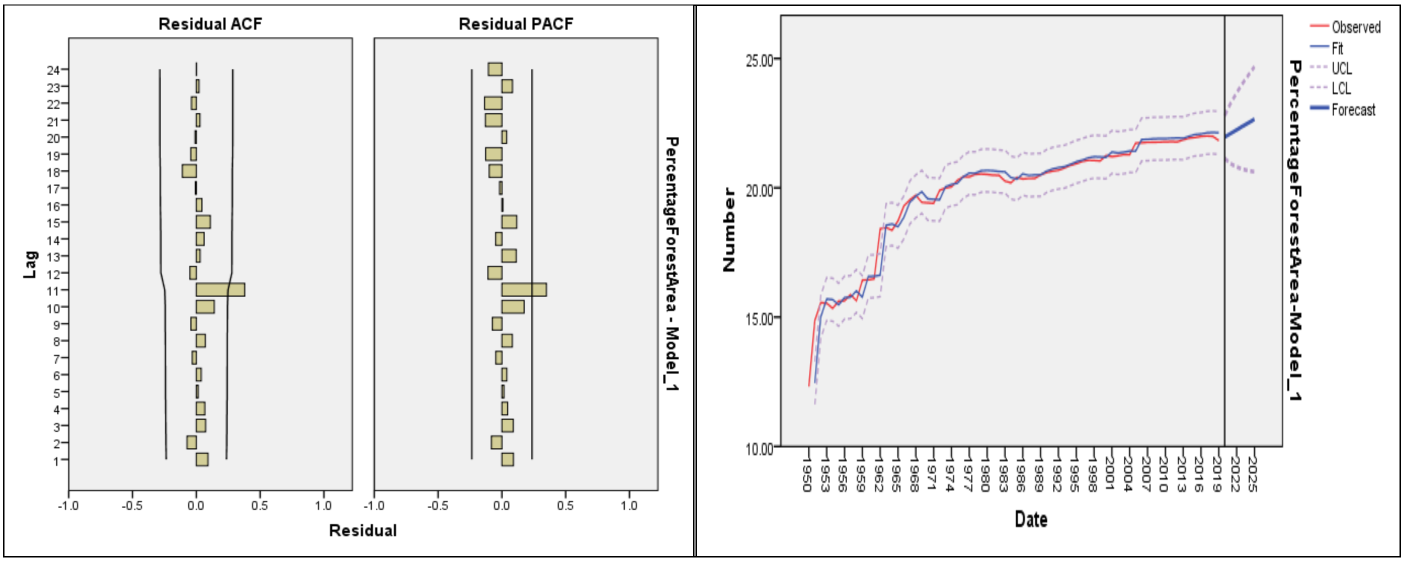


Fig 10: Forecast of percentage forest area through *ARIMA* (0, 1, 0)

Table 2: Model fit statistics of the Land use and land cover data in India

ARIMA Model Parameters							
				Estimate	SE	t	Sig.
Total Cropped Area							
ARIMA (0,1,1)	No Transformation	Constant		1034.443	176.449	5.863	.000
		Difference		1			
		MA	Lag 1	.633	.100	6.346	.000
Area Sown More than Once							
ARIMA (0,1,1)	No Transformation	Constant		776.270	103.400	7.507	.000
		Difference		1			
		MA	Lag 1	.600	.117	5.138	.000
Area under Non-agricultural Uses							
ARIMA (0,1,0)	No Transformation	Constant		266.957	57.161	4.670	.000
		Difference		1			
Percentage Forest Area							
ARIMA (0,1,0)	No Transformation	Constant		.138	.050	2.755	.008
		Difference		1			
Barren Land							
ARIMA (1,1,6)	No Transformation	AR	Lag 1	1.000	.005	181.856	.000
		Difference		1			
		MA	Lag 1	.703	.085	8.288	.000
			Lag 6	.292	.103	2.819	.006

Table 3: Forecast of the of the Land use and land cover in India from 2020-21 to 2024-25

Model		**2020-21**	**2021-22**	**2022-23**	**2023-24**	**2024-25**
Total Cropped Area						
ARIMA (0,1,1)	Forecast	207133.92	208168.36	209202.81	210237.25	211271.69
Area Sown More than Once						
ARIMA (0,1,1)	Forecast	67435.14	68211.41	68987.68	69763.95	70540.22
Area under Non-agricultural Uses						
ARIMA (0,1,0)	Forecast	28043.96	28310.91	28577.87	28844.83	29111.78
Percentage Forest Area						
ARIMA (0,1,0)	Forecast	21.96	22.10	22.24	22.38	22.52
Barren Land						
ARIMA (1,1,6)	Forecast	16440.32	16386.03	16278.69	16130.02	15906.04

The graph of the barren land area in the study period is given in Fig. 11(a) and has shown increasing trend and not stationary with constant variance. Further the *ACF* and *PACF* charts given in Fig. 11(b) and Fig. 11(c) are indicating that the data is not stationary. The first difference data as shown in Fig. 12(a) has removed the trend component and showing constant variance and there are no significant spikes in the *ACF* and *PACF* charts shown in Fig. 12(b) and Fig. 12(c), confirming the stationarity of the data. It is evident from the correlogram given in Fig. 12 and Fig. 13 that, the autocorrelation and partial autocorrelation decays rapidly after the initial lag.

The Dickey-Fuller unit root test was used to test the stationarity of the first differenced data, and the result reveal that the $\Pr\left(|t|>2.819\right)<0.01$, indicating that the first differenced data is stationary and is significant at 1% level.

The data under the barren land was subjected to different *ARIMA* models to find the best fitted model. The $ARIMA(1, 1, 6)$ model was used for forecasting the area under the barren land as it was found to be the best fitted model with highest R^2 value (0.992), lowest *RMSE* (648.83), *MAPE* (1.69) and *Normalize BIC* (13.13) values. The forecasted values are given in the table 3.

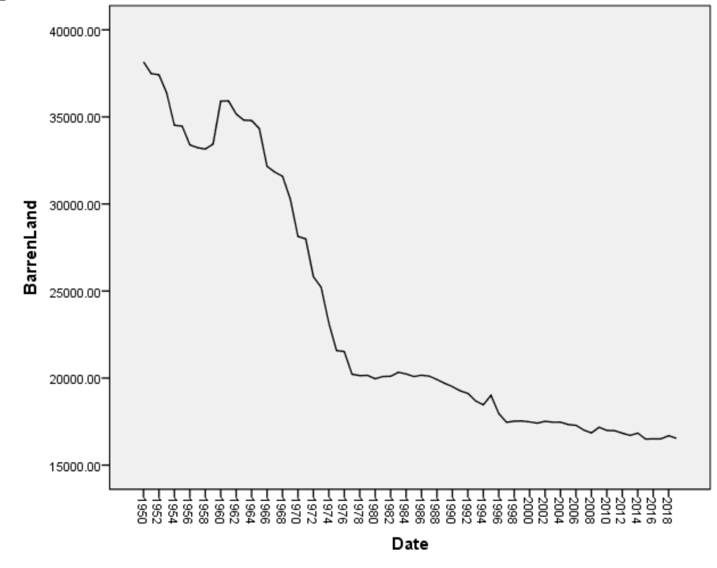


Fig. 11(a)

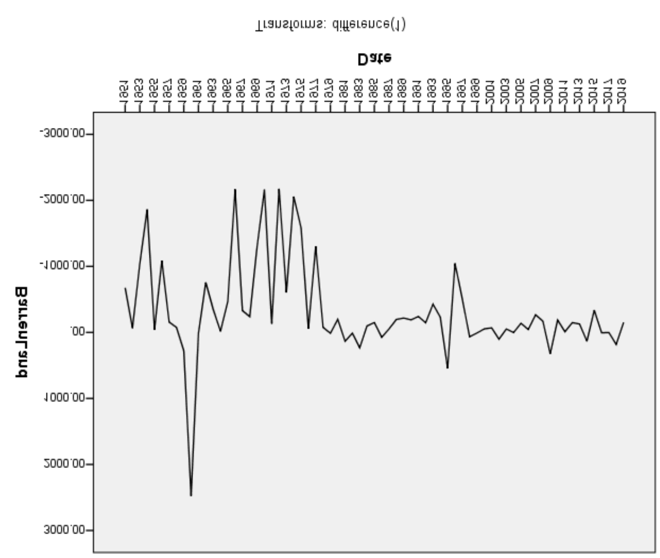


Fig. 12(a)

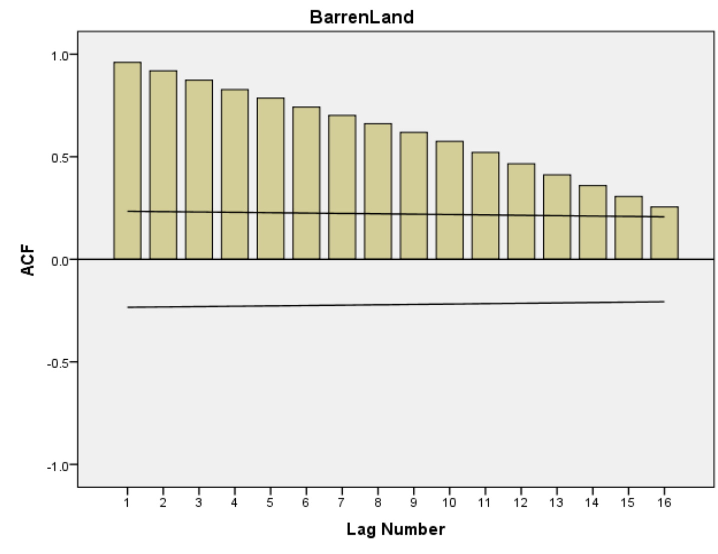


Fig. 11(b)

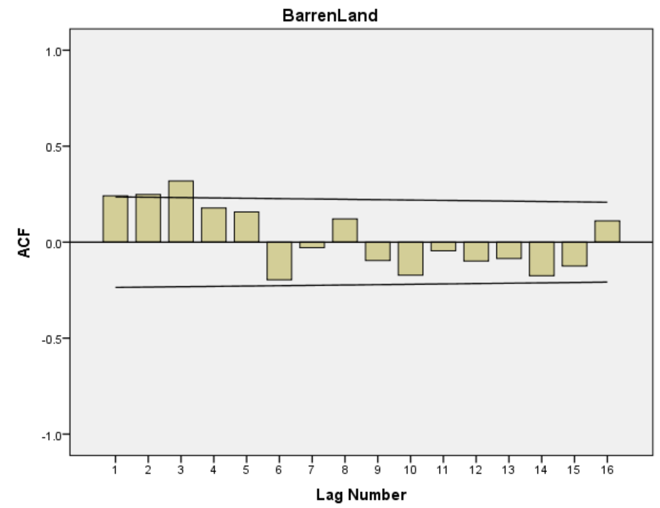


Fig. 12(b)

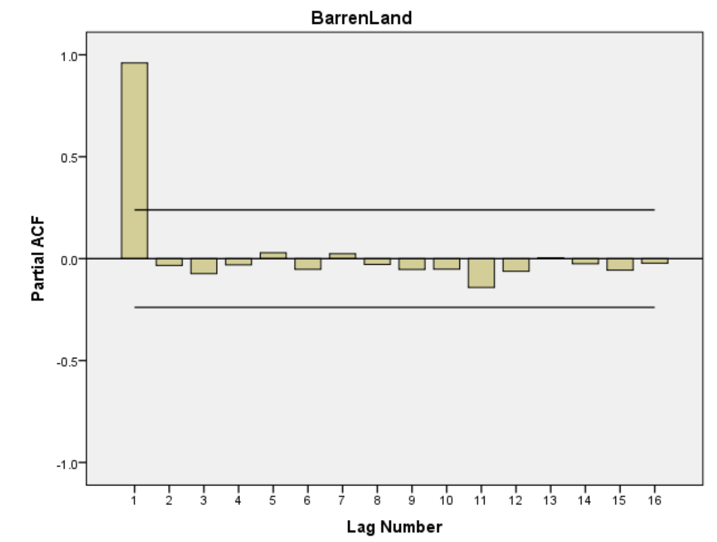


Fig. 11(c)

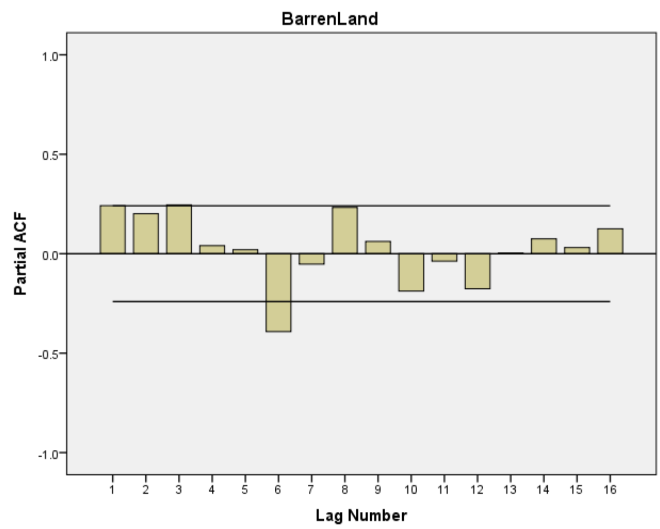


Fig. 12(c)

Fig 11: Correlogram of the barren land area from 1950-51 to 2019-20 in India

Fig 12: Correlogram of the first differenced data of barren land area from 195051 to 2019-20 in India

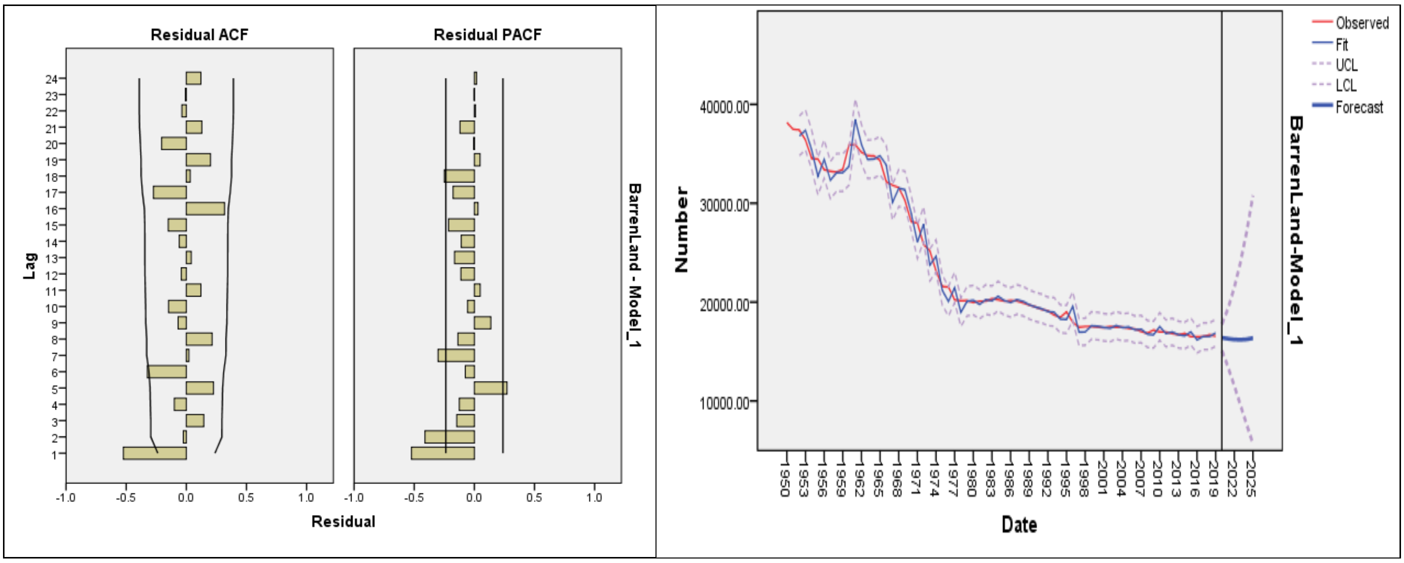


Fig 13: Forecast of barren land area through *ARIMA* (1, 1, 6)

Conclusion

The land use, land cover statistics data of total cropped are, area sown more than once, area under non-agricultural uses, percentage forest area and barren land area was subjected to different *ARIMA* models and found the best fitted model based on the highest R^2 value, lowest *RMSE*, *MAPE* and *Normalized BIC*. Forecasts of land use, land cover statistics data were made for five years from 2020 to 2024 using the best fitted model. The total cropped area and the area sown more than once have shown increasing trend during the study period and were best fitted with the $ARIMA(0, 1, 1)$ model. The area under non-agricultural uses and the percentage forest area have also shown increasing trend and were best fitted with the $ARIMA(0, 1, 0)$ model. Whereas the barren land area has shown decreasing trend in study period and was best fitted with the $ARIMA(1, 1, 6)$.

Government can take an appropriate decision for improving the facilities like to increase the area sown more than once, percentage forest area and reducing the area under the barren land to meet the food requirements of the population and have environmental sustainability.

References

1. Badmus MA. and Ariyo OS. Forecasting cultivated areas and production of maize in Nigeria using *ARIMA* model. Asian J Agric Sci. 2011;3(3):171-76.
2. Box GEP, Jenkins GM. Time series Analysis, Forecasting and Control. San Francisco, Holden Day, California, USA; c1976.
3. Brown RG. Statistical Forecasting for Inventory Control. McGraw Hill Book Co., Inc., NY, USA; c1959.
4. Falak S, Eatzaz A. Forecasting Wheat production in Pakistan. Lahore J Econ. 2008;3(1):57-85. https://doi.org/10.35536/lje.2008.v13.i1.a3
5. Hyandye C, Mandara G, Safari J. GIS and Logit Regression Model Applications in Land Use/Land Cover Change and Distribution in Usangu Catchment. American Journal of Remote Sensing. 2017;3(1):6–16. doi: 10.11648/j. ajrs.20150301.12.
6. Kannan S, Karuppasamy KM. Forecasting for agricultural production Using *ARIMA* model. PalArch’s Journal of Archaeology of Egypt/ Egyptology. 2020;17(9):5939-49.
7. Kathayat B, Dixit AK. Paddy price forecasting in India using *ARIMA* model. Journal of Crop and Weed. 2021;17(1):48-55. https://doi.org/10.22271/09746315.2021.v17.i1.1405
8. Leta MK, Demissie TA, Tränckner J. Modeling and Prediction of Land Use Land Cover Change Dynamics Based on Land Change Modeler (LCM) in Nashe Watershed, Upper Blue Nile Basin, Ethiopia. Sustainability. 2021;13:3740. https:// doi.org/10.3390/su13073740
9. Ljung GM, Box GEP. On a measure of lack of fit in time series models. Biometrika. 1978;65:67-72. https://doi.org/10.1093/biomet/65.2.297
10. Manjunatha P, Kulakarni GN, Kiresur VR, Kerur NM, Venugopal CK. An economic analysis of dynamics of land use pattern in Northern Karnataka. J Farm Sci. 2021;34(3):283-288.
11. Mishra P, Yonar A, Yonar H, Binita K, Abotaleb M. State of the art in total pulse production in major states of India using *ARIMA* techniques. Current Research in Food Science. 2021;4:800-806. https://doi.org/10.1016/j.crfs.2021.10.009
12. Mishra VN, Rai PK, Mohan K. Prediction of land use changes based on land change modeler (LCM) using remote sensing: A case study of Muzaffarpur (Bihar), India. Journal of the Geographical Institute Jovan Cvijic, SASA. 2014;64(1):111-127.
13. Pindyck RS, Rubinfeld DL. Econometric Models and Economic Forecasts. McGraw Hill Book Co. Inc., NY, USA; c1981.
14. Semegnew T, Teshome S, Tesefaye B. Analysis of the Current and Future Prediction of Land Use/Land Cover Change Using Remote Sensing and the CA-Markov Model in Majang Forest Biosphere Reserves of Gambella, Southwestern Ethiopia. □e Scientific World Journal; c2021. p. 1-18. Article ID 6685045, https://doi.org/10.1155/2021/6685045
15. Shabur SA, Haque ME. Analysis of rice in Mymensingh town market pattern and forecasting. Bang J Agric Econ. 1993;16:130-33.
16. Slutsky E. The Summation of Random Causes as a Source of Cyclic Processes. Econometrica. 1927;3(1):105-146.
17. Tadese S, Soromessa T, Bekele T. Analysis of the current and future prediction of land use/land cover change using

remote sensing and the CA-markov model in Majang forest biosphere reserves of Gambella, southwestern Ethiopia. The scientific world journal; c2021. p. 1-18.
18. Thanuja P, Meena GL, Singh H, Sharma L, Upadhyay B. Growth and Instability in the Land Use Categories of different Agro-climatic Regions of Rajasthan. Economic Affairs. 2021;66(04):599-604.
19. Wold HOA. A Study of the Analysis of Stationary Time Series. (2nd ed. 1954). Uppsala: Almqvist and Wiksells; c1938.