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Statistical Modeling for Forecasting Fertilizer Consumption in India

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Abstract

Fertilizers have contributed significantly to increased agricultural yields, particularly for cereal crops and they will still be an important part of the science-based farming that is needed to feed the world's growing population. Fertilizers replenish the soil nutrients lost by the harvested crops, promote the use of high-yielding cultivars and boost biomass in tropical soils that are deficient in nutrients. In this study, data on fertilizer consumption in India was gathered from Agricultural Statistics at a Glance from 1950-51 to 2020-21 and utilized to fit the ARIMA model and forecast future usage. Forecasting has been done using the Box-Jenkins ARIMA approach. The ARIMA model is the most popular and widely applied forecasting model for time series data. The data was calculated using autocorrelation and partial autocorrelation functions. R programming software was used to estimate model parameters. The performance of the fitted model was evaluated using various goodness of fit criteria, such as AIC, BIC and MAPE. Empirical results revealed that the ARIMA model was best suited to forecasting India's future total fertilizer use. Similarly, the ARIMA model was fitted for nitrogen, phosphorus, and potassium consumption in India independently. Forecasts from 2021-22 to 2030-31 are calculated using the chosen model. By 2030-31, total fertilizer use is predicted to reach 32058.55 thousand tonnes. Policymakers should preferably base their judgments on reliable forecasts in order to tighten policies and achieve outcomes. Predicting future events using an appropriate time series model will assist policymakers, marketing strategies in making decisions related to export/ import and developing appropriate fertilizer consumption strategies.

Keywords

ACF, ARIMA, fertilizer consumption, forecasting, model selection criteria, PACF, residual analysis.

Introduction

Agriculture continues to be the primary source of income for rural people. Fertilizers are regarded as a crucial element in Indian agriculture for meeting the demand for food grains caused by the nation's expanding population. Chemical fertilizer has a direct association with food grain production, along with other factors such as High Yielding Varieties (HYVs), irrigation, credit, increased total elements of productivity, tenure circumstances, product market size and the pricing they confront for both inputs and outputs and so on.

One-third of the growth in cereal production around the world and half of the growth in grain production in India between the 1970s and 1980s can be attributed to more fertilizer use (1). Smil estimated that nitrogen fertilizer has contributed 40 % to increases in per-capita food production over the past 50 years (2). The role of chemical fertilizers in enhancing agricultural productivity is widely recognized, particularly in developing nations such as India. Some argue that fertilizer contributed up to 50 % of the yield rise in Asia during the Green Revolution, making it as essential as seed (3-5). The FAO predicts that fertilizer use would rise from the current level of 166 million tonnes per year in 2005-2007 to 263 million tonnes in 2050 (1). Developing countries currently account for about 70 % of global fertilizer usage, a figure that might rise to more than 3-quarters by 2050 (1). China and India contribute about 2/3 of emerging countries' fertilizer usage, but this might fall to approximately half by 2050 as other regions catch up. Others have discovered that the use of fertilizer and other related production factors accounts for 1/3 of the world's cereal production (6).

Organic farming is thought of as a safer substitute. It is becoming popular in India. Land under organic cultivation in India has increased from 5.2 lakh ha in 2007 to 59 lakh ha in 2022 (www.pib.gov.in). According to one assessment, India also has the most producers of organic food. However, this only accounts for about 2.5% of the nation's overall cropland. According to the studies, while organic farming is less polluting than conventional farming, it only accounts for 1% of global agricultural land. Yields are lower (a recent study estimated that they are 25% lower on average), as is productivity (the amount of money produced per unit of land is up to 44% lower than in conventional agriculture). More land would need to be brought under agricultural use if more farmers switched to organic practices. Due to habitat conversion and loss, this would put additional strain on existing natural habitats. The research discovered that as more land is used for organic produce, production costs will rise and food will become less affordable for low-income customers in developing nations. Organic food is currently only available to high-income groups, in fact. This is due to the fact that organic farming results in less intense agriculture, which lowers crop output. This could put India at a disadvantage in terms of food security; scientists have noted that farmers are already suffering significant losses as a result of changing rainfall patterns brought on by climate change.

The ARIMA model is the most comprehensive form of the time series forecasting model. The "Auto-Regressive" process refers to the various series that arise in forecasting equations. "Moving average" refers to the appearance of lags of forecast errors in the model. Box and Jenkins proposed the ARIMA model for forecasting variables in 1976 (7). These methods have been widely used to forecast economic time series, inventory and sales models (8). Univariate time series have been used in forecasting (9, 10). Reports are on the forecast on the area of maize cultivation and production in Nigeria using the ARIMA model (11). For the cultivation area, they estimated ARIMA (1, 1, 1), and for the production, ARIMA (2, 1, 2). Reports are on Pakistan's future wheat production potential (12). The Cobb-Douglas production function for wheat was used to derive the parameters of their forecasting model, while the future values of other inputs were derived using separate ARIMA estimations for each input and each province. 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 (13-15). The ARIMA model was used to anticipate wholesale paddy prices in 5 major Indian states for the coming crop year (19). Reports are on the ARIMA method to investigate the trend in total pulse production in India (20). In the special context of COVID-19, reports are on the variables that affect vegetable price variations in both vertical and horizontal dimensions an ARIMA model of short-term price production was used and its performance was assessed (21). The Box and Jenkins ARIMA model was applied to South Indian paddy production forecasts (22).

In this present study, an attempt has been made to develop a Box-Jenkins ARIMA model for the fertilizer consumption data in India. The specific objective of the study is to forecast the consumption of fertilizers in India. These forecasts would help to preserve a substantial amount of our nation's valuable resources that would have otherwise been wasted.

Materials and Methods

From the website of the Fertilizer Association of India, the data on fertilizer consumption in India for the period 1950-51 to 2020-21 was collected. The data was further classified into training and test dataset in the ratio of 80:20.The training dataset was utilized for model fitting and test dataset for validation purpose. The analysis was done by using the R programming software.

A time series is a collection of numbers that show the progress of an activity through time. It 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 (1976). An 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

Slutsky and Wold investigated moving average models for the first time (16, 17). The moving average can be expressed as follows:

$$Yt = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \_\_\_\_\_ \theta_q e_{t-q} \quad \textbf{(Eqn. 1)}$$

A series of this type is known as a moving average of order q and it is abbreviated as MA (q). Where Yt represents the original series and et represents the error series.

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.

$$Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + --- + \phi_p Y_{t-p} + e_t$$

(Eqn.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 isn't explained by the past values. Consequently, for each t, we assume that e_t is independent of $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-q}$.

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 ARMA(p,q), which can be expressed as:

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

(Eqn. 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 $W_t = \nabla^d Y_t$ 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 ARMA (p,q) model. Fortunately, we can usually use d = 1 or 2 for practical purposes. Take a look at an ARIMA (p,1,q) process with $W_t = Y_t - Y_{t-1}$, we have

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

(Eqn. 4)

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

Identification stage

The identification stage determines the values of p, d, and q using the Box-Jenkins approaches. The values are estimated by using the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). The theoretical PACF has nonzero partial autocorrelations at lags 1, 2,..., p and zero partial autocorrelations at all lags for every ARIMA (p, d, q) process, whereas the 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. For a series that is not stationary, the data are differentiated to make it stationary. The order of d is determined by the number of differences performed on the series. For stationary data, d = 0 and ARIMA (p, d, q) can be expressed as ARMA (p, q).

Parameter Estimation

Parameter estimate is the next step, which involves estimating the model parameters for the preliminary models that have been chosen.

Diagnostic Checking

To ensure that the estimated model accurately represents the series, it must be validated. The best model was chosen based on the lowest Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Normalized Bayesian Information Criterion (BIC), Akaike Information Criterion (AIC), and the highest R-square values. On the residuals, diagnostic checks are calculated to determine if they are randomly and regularly distributed.

To check for residual autocorrelation, utilize the Lj ung-Box Test. The residuals should be low if a model is well-fitted. Consequently, the null hypothesis is H0: $\rho1 (e) = \rho2(e)=\ldots\ldots= \rho\, k(e)=0$ is tested with the Box-Ljung statistic

$$Q^* = N(N+1) \sum_{i=1}^{k} (N-k) \rho^2 k^{(e)}$$

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 (significantly different from zero). Random and zero shocks in the derived model are most likely auto-correlated. As a result, the model should be reformulated.

Forecasting

In forecasting stage, the time series' future values are projected. For time series analysis, building ARIMA models, and forecasting fertilizer consumption, R programming language was used. Additionally, these methods have proven effective in a number of scenarios requiring the development of models for discrete time series and dynamic systems.

Results & Discussion

The time series data on fertilizer consumption is plotted in Fig. 1. For the purpose of modelling, the consumption of fertilizers viz., Nitrogen, phosphorus, potassium and total (N+P+K) in India for the past 71 years were utilized. Fig. 1 shows an increasing trend in nitrogen, phosphorus, potassium and total fertilizer consumption in India. The largest fertilizer use was 32535.6 thousand tons in the year 2020-2021, while the lowest was 69.8 thousand tons in the year 1950-51.

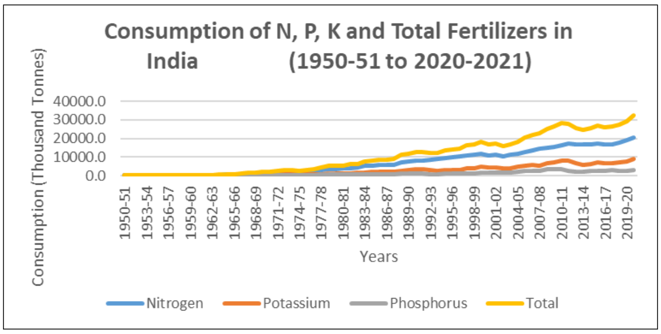


Fig. 1. Consumption of Nitrogen, Phosphorus, Potassium and Total Fertilizers in India.

Initially, it is crucial to determine which order of difference in the time series nitrogen consumption data meets the stationarity criterion. Fig. 2 illustrates that the original nitrogen consumption series exhibits a rising trend and does not have a constant variance, but by removing the trend impacts on nitrogen consumption, the second order differenced series has stable variance. Again, the presence of moving average impacts on the initial nitrogen consumption series is indicated by large spikes in the ACF plot, indicating that the series is not stationary, as evidenced by the ACF and PACF plots.

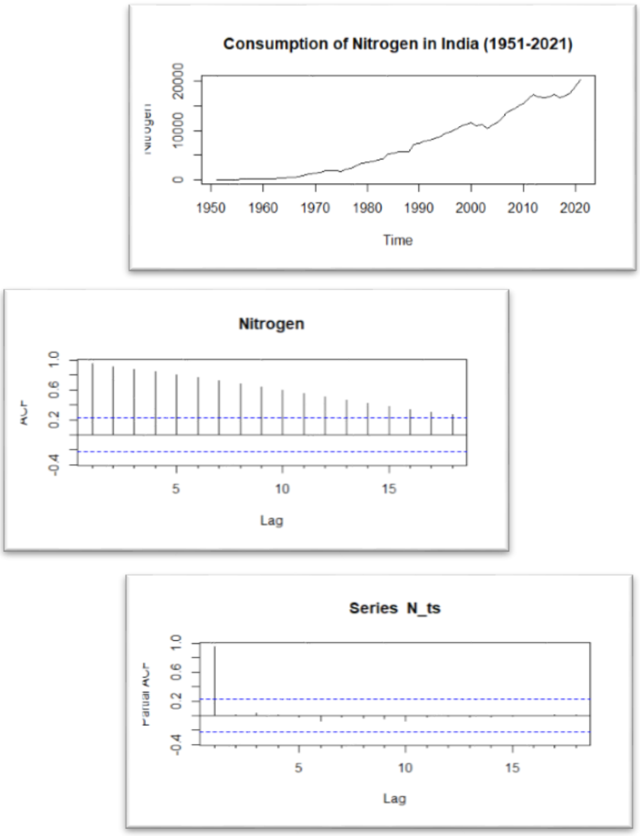


Fig. 2. Correlogram for the original series of Nitrogen consumption in India.

Fig. 2 and Fig. 3 also indicate the ACF and PACF graphs for nitrogen consumption in the model specification. The autocorrelation function revealed the order of the autoregressive components "q" of the model, whereas the partial correlation function indicated the parameter "p", i.e. the moving average order. The ACF and PACF plots of the nitrogen consumption time series (Fig. 2) demonstrated that the series was not stationary. To make the data consistent, they were differentiated. The initial modification was not adequate to stop the flow of data. Therefore, second differentiation was taken. The autocorrelation function and partial autocorrelation function for the consumption second differenced series in Fig. 3 decreased rapidly, showing that the series was stationary. At the same time, there is no significant spike in the ACF and PACF of second order differenced series, indicating that the series is stationary with second-order difference (Fig. 3); and implies that for second order difference series, there are no significant effects of Autoregressive and Moving Average order, showing stable variance. It is evident from the correlogram that both series are moving average series, as the partial autocorrelation decays rapidly after the initial lag, whilst the autocorrelation decays gradually, and one notable spike of autocorrelation has been identified for both cases. Therefore, both series initially appear to be moving average time series of order 1.

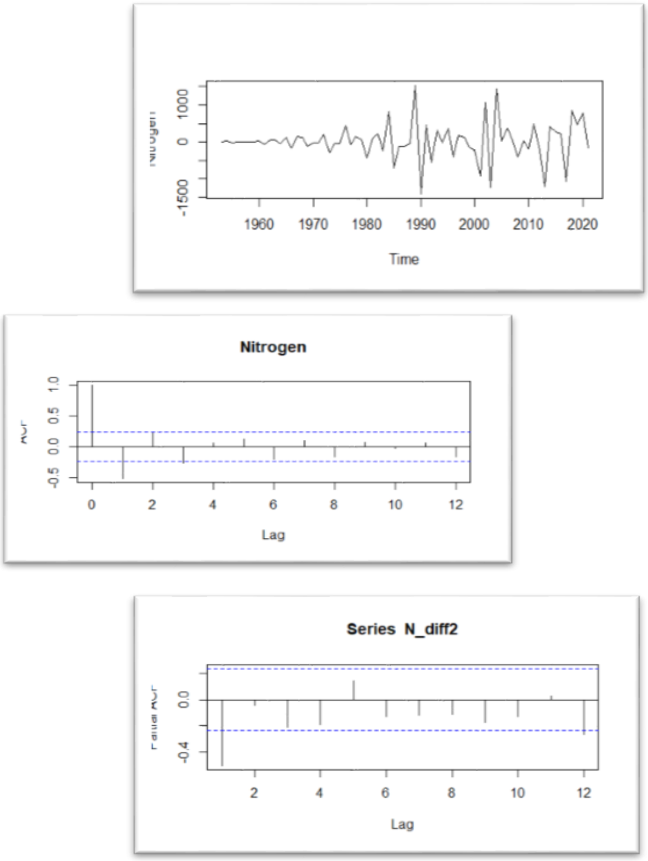


Fig. 3. Correlogram for the second differenced series of Nitrogen consumption in India.

Using the Dickey-Fuller unit root test and charting time series of nitrogen consumption, it may be theoretically and visually verified. The Pr(|t| > -5.864) < 0.01, which strongly suggests that there is no unit root at the second order difference of nitrogen consumption at the 5% significance level, satisfies the stationarity requirement at the second order difference according to the results of the Dickey-Fuller unit root test.

Based on the analysis, ARIMA (1,2,1) with AIC = 1035.49 and BIC = 1042.2 is the best ARIMA model for forecasting nitrogen consumption in India. Table 1 shows the parameter estimations for the fitted ARIMA (1,2,1).

Fig. 4 depicts the graphical phosphorus consumption series that does not have constant variance, but the first-order differenced series (Fig. 5) has a more stable variance than the original series. Again, strong spikes in the ACF plot indicate the presence of moving average effects on the original phosphorus consumption series, showing that the series is not stationary, as evidenced by the ACF and PACF plots. At the same time, there is no significant spike in the ACF and PACF of first order differenced series (Fig. 5), indicating that the series is stationary with first-order difference; and it implies that there are no significant effects of Autoregressive and Moving Average order at the first order differenced series, indicating stable variance.

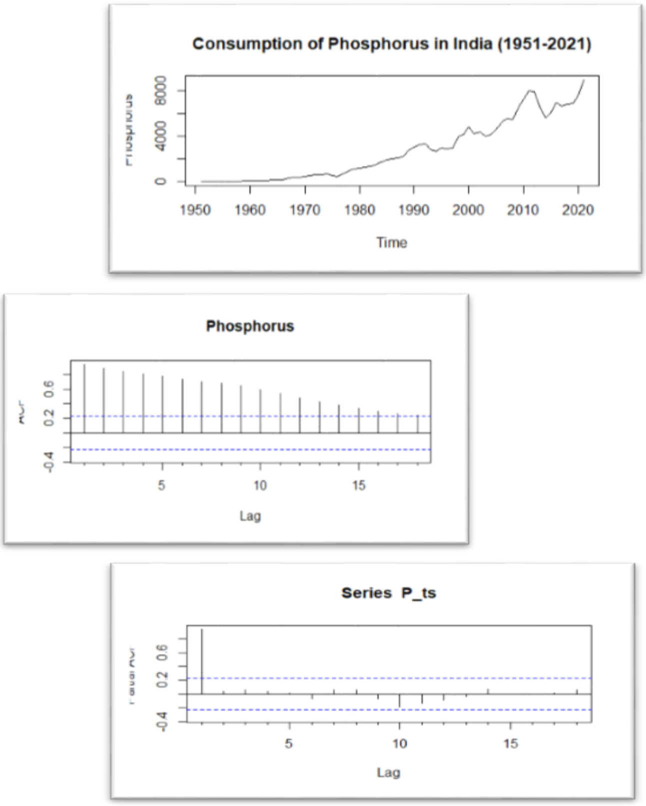


Fig. 4. Correlogram for the original series of Phosphorus consumption in India

The Dickey-Fuller unit root test indicates that, at the first order difference of phosphorus consumption at the 5% level of significance, stationarity is satisfied with the Pr (|t| > -7.0736) < 0.01, strongly indicating that there is no unit root.

The best ARIMA model for forecasting phosphorus consumption in India is ARIMA (2,1,2) with AIC = 1032.72 and BIC = 1039.46. Table 1 shows the parameter estimates for phosphorus consumption for the fitted ARIMA (2, 1, 2) model.

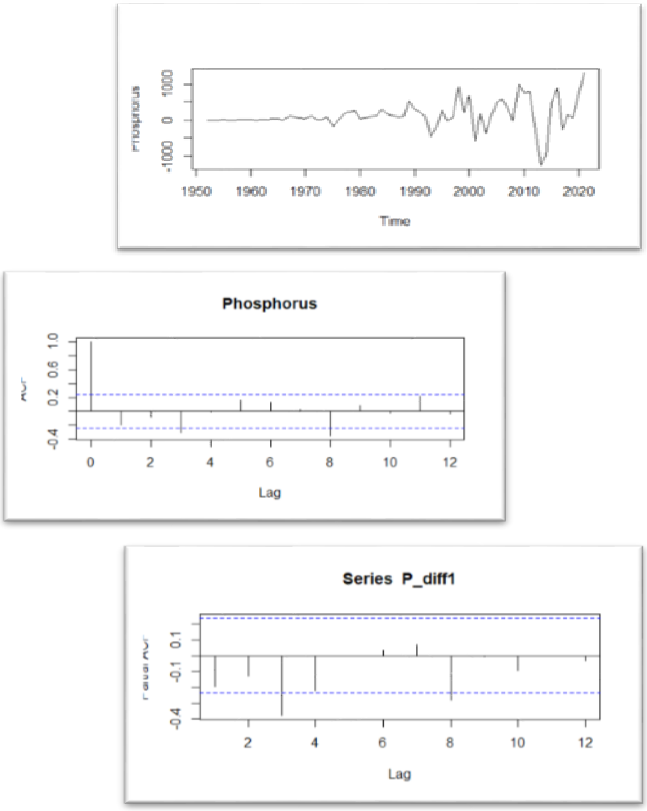


Fig. 5. Correlogram for the first differenced series of Phosphorus consumption in India

Table 1. Paramerters estimate of Nitrogen, Phosphorus, Potassium and Total Fertilizer Consumption

Nitrogen Consumption ARIMA (1,2,1)				
Coeffi-	**Estimates**	**Std. Error**	**t-value**	**p-value**
ar1	0.2195	0.1295	1.6954	0.0899
ma1	-0.9288	0.0467	-19.8938	<2e-16***
Phosphorus Consumption ARIMA (2,1,2)				
Constant	132.2839	59.0609	2.2398	0.0251
ma1	0.3396	0.1011	3.3588	0.0007***
Potassium Consumption ARIMA (0,1,1)				
ma1	0.3745	0.1063	3.5234	0.0004***
Total Fertilizer Consumption ARIMA (1,2,1)				
ar1	0.3549	0.1277	2.7789	0.0054**
ma1	-0.951319	0.0427	-22.2418	<2.2e-16***

Fig. 6 demonstrates that the original potassium consumption series has an ascending trend and does not have a constant variance; however, by removing the trend effects, the first-order differenced potassium consumption series (Fig. 7) exhibits a constant variance. Again, the ACF and PACF plots indicate that the ACF plot contains large spikes, indicating the presence of moving average impacts on the original potassium consumption series, indicating that the series is not stationary. Similarly, Fig. 7 shows that there is no significant spike except one, suggesting that the series is stationary with a first-order difference; and the autoregressive and moving average orders have no significant influence on first-order differenced series, demonstrating stable variance.

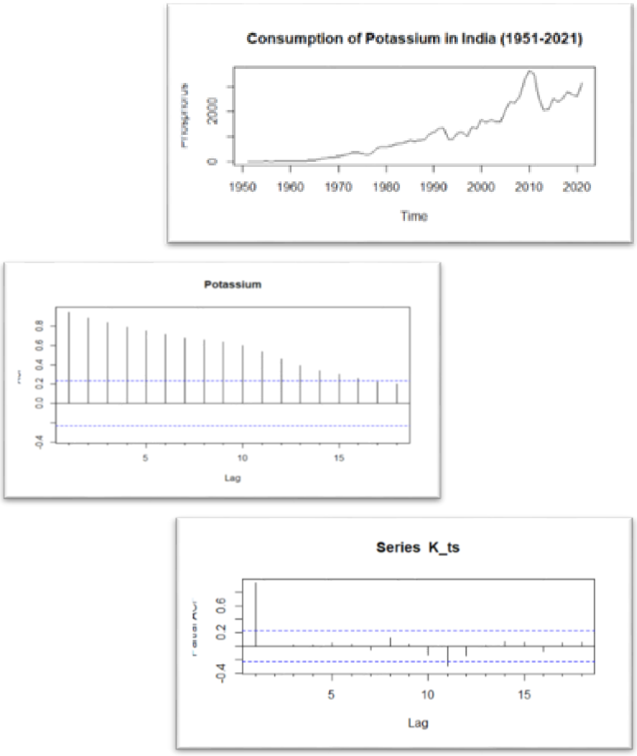


Fig. 6. Correlogram for the original series of Potassium consumption in India

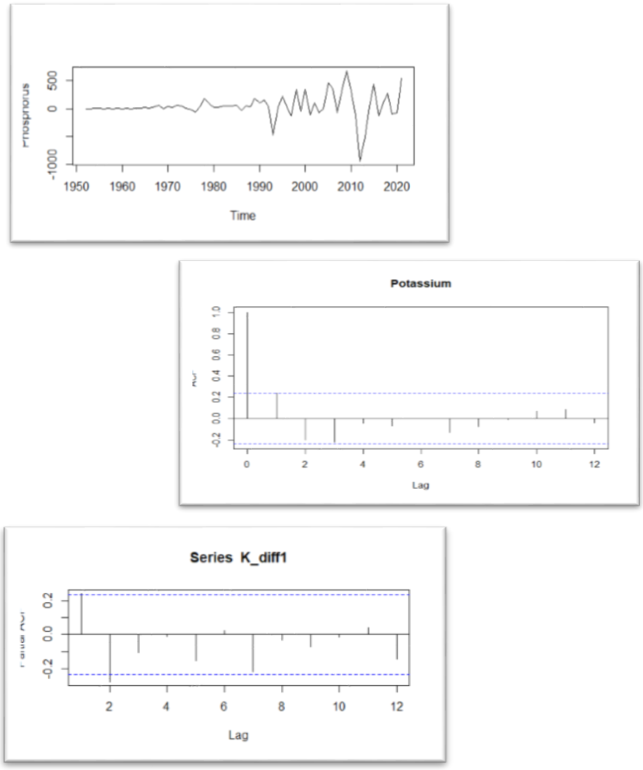


Fig. 7. Correlogram for the first differenced series of Potassium consumption in India.

The Dickey-Fuller unit root test for potassium consumption series finds stationarity at difference order one with the Pr(|t| > -4.3449) < 0.01, clearly indicating that there is no unit root at the first order difference of phosphorus consumption at the 5% level of significance. Based on the analysis, the best-fitted ARIMA model to forecast potassium consumption in India is ARIMA (0,1,1), with AIC = 951.23 and BIC = 955.73. Table 1 shows the parameter estimates of the fitted ARIMA (0, 1, 1) for potassium consumption.

The time sequence of the total fertilizer consumption series was checked both conceptually and graphically by utilizing the Dickey-Fuller unit root test and fertilizer consumption time series plot in India. The Dickey-Fuller unit root test reveals that stationarity is satisfied at difference order two, and at the 5% level of significance, the Pr(|t| > -6.1651) < 0.01 indicates that there is no unit root at the first order difference in fertilizer consumption.

Fig. 8 and 9 depict the graphical stationarity test of the original and second differenced series of fertilizer using ACF and PACF. To determine if the forecast errors are normally distributed with a mean zero and constant variance, we can produce a time plot and histogram (with a normal curve superimposed).

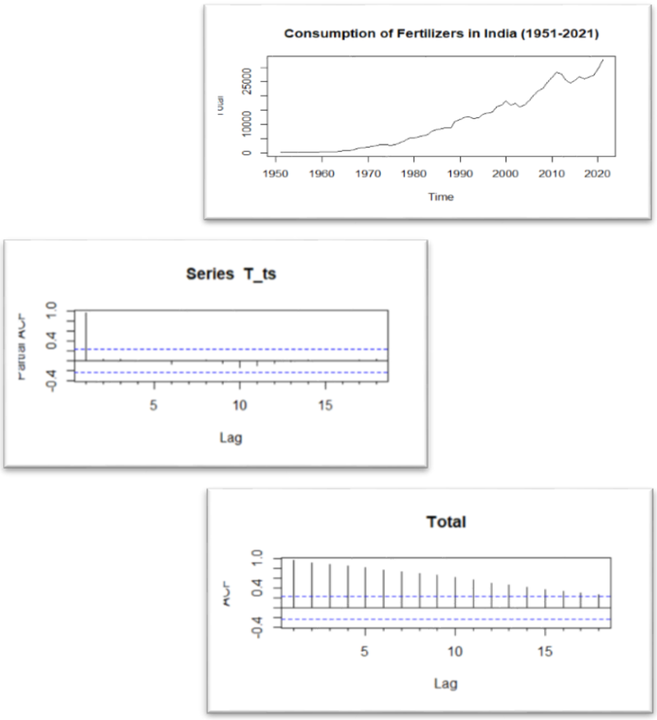


Fig. 8. Correlogram for the original series of Fertilizer consumption in India.

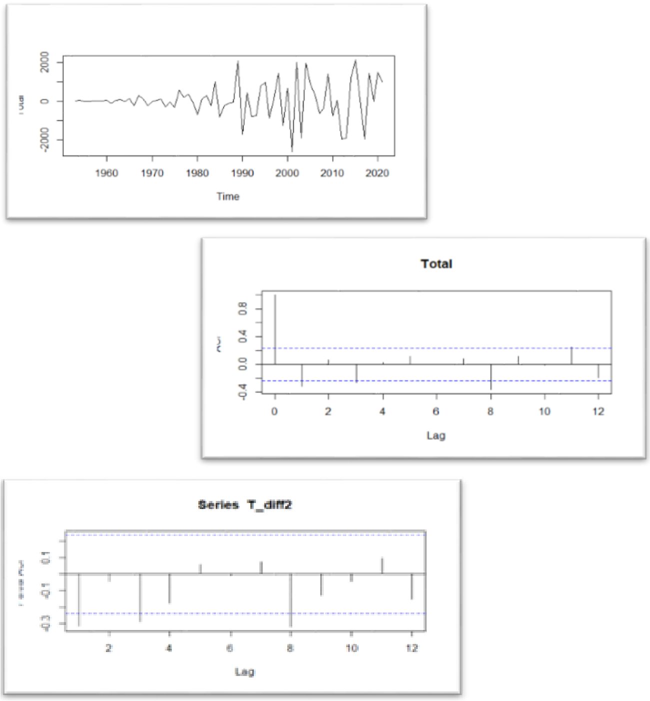


Fig. 9. Correlogram for the second differenced series of Fertilizer consumption in India.

Fig. 10 plots demonstrates the histogram of forecast errors of residuals of nitrogen, phosphorus, potassium and total nitrogen consumption in India. The variation of the in -sample forecast errors appears to be approximately consistent throughout time based on the forecasting error time plot. The histogram of the time series indicates that the forecast errors have a normal distribution with a mean close to zero. Therefore, it is possible for the forecast errors to have a normal distribution with a zero-mean and a constant variance. Due to the apparent lack of a connection between subsequent forecast errors and the forecast errors appears to be normally distributed with mean zero and constant variance, the ARIMA model (1,2,1), (2,1,2), (0,1,1) and (1,2,1) appears to be appropriate for predicting the nitrogen, phosphorus, potassium and total fertilizers.

Fig. 11 shows the actual and forecasted plots of fertilizer consumption in India. Ten year ahead forecast was done for nitrogen, phosphorus, potassium and total fertilizer consumption in India using the fitted ARIMA models i.e., ARIMA (1,2,1), (2,1,2), (0,1,1) and (1,2,1) at the 95 % confidence interval. From the above figure, it is observed that the nitrogen consumption is showing an increasing trend. The forecasted values for nitrogen consumption in 2030-31 was found to be 21,107.88 thousand tonnes. Similarly, it is also observed that the phosphorus consumption is showing a slightly increasing trend. The forecasted values of phosphorus consumption were found to increase from 7,546 thousand tonnes in 2020-21 to 7,626 thousand tonnes in 2030-31. From this study, it is also observed that the potassium consumption will remain constant throughout the study period i.e.,

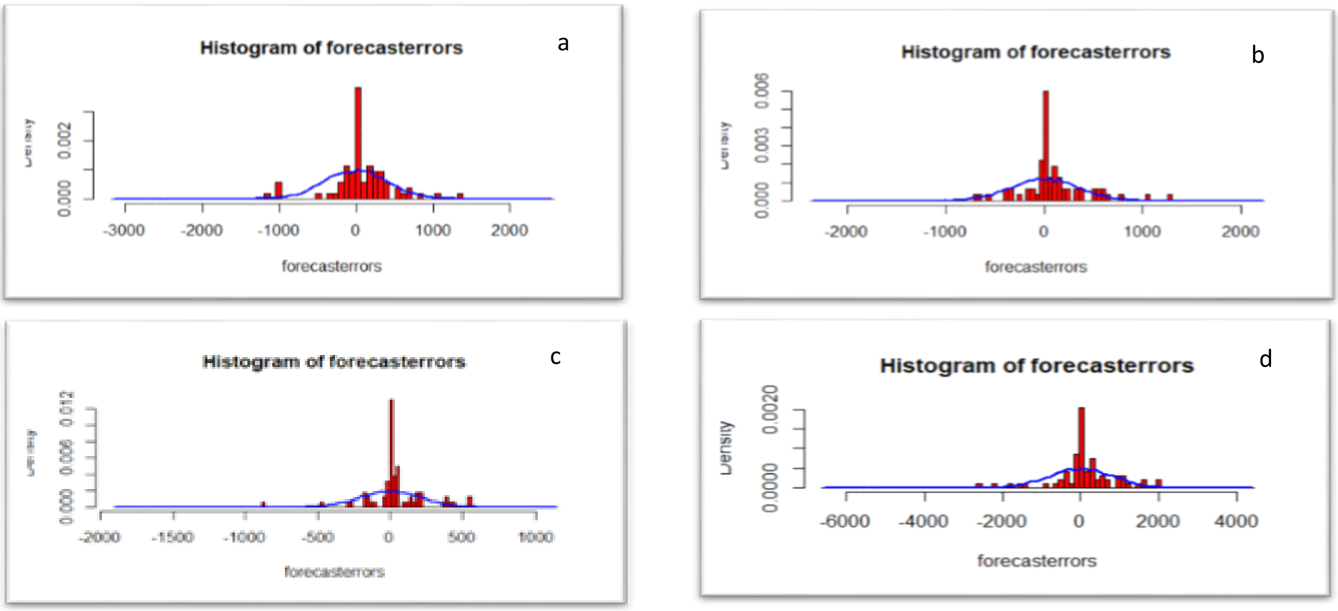
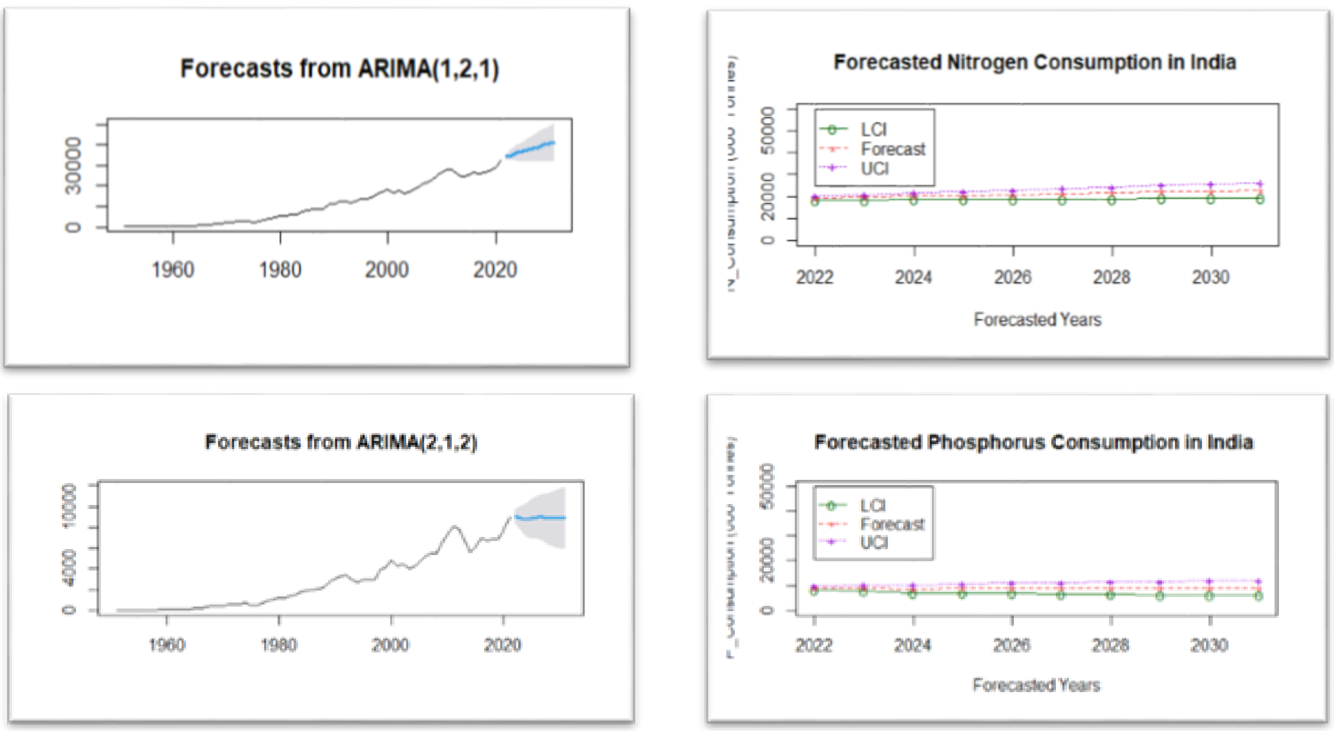


Fig. 10. (a), (b), (c), (d): Histogram of forecast errors of residuals of Nitrogen, Phosphorus, Potassium and Total Nitrogen consumption in India.



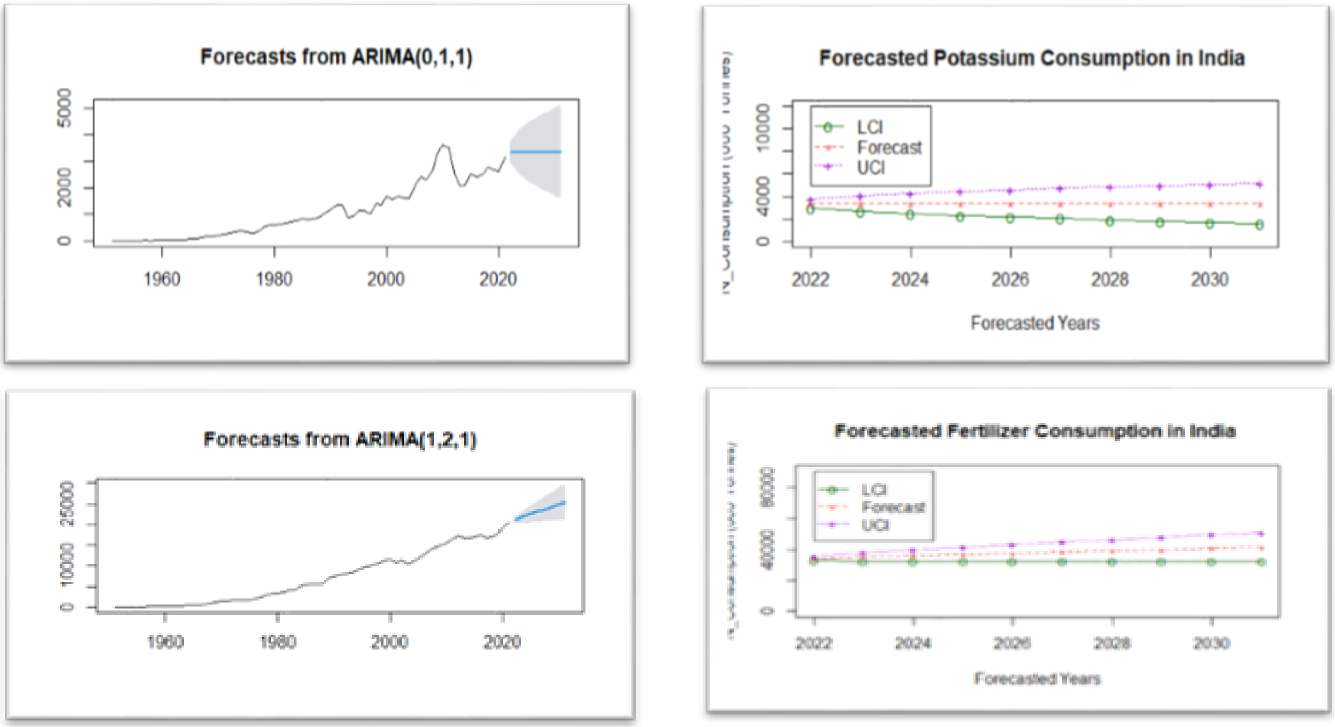


Fig. 11. Observed and Forecasted plots of Fertilizer Consumption in India.

2,649 thousand tonnes in 2030-31.

The fitted models accurately forecast 93.66 % of nitrogen consumption, 92.48 % of phosphorus consumption, 93.72 % of potassium consumption and 92.96 % of total fertilizer consumption, according to the mean absolute % error (MAPE).

Conclusion

The ARIMA model, which is based on the Box-Jenkins method, was used to predict future values based on the historical movement patterns of a variable. The ARIMA approach is a statistical strategy for assessing and developing a forecasting model that best depicts a time series by modeling the data correlations. ARIMA models, due to their purely statistical methodologies, simply require the historical data of a time series to generalize the forecast and boost prediction accuracy while keeping the model simple. In this work, a model for forecasting of nitrogen, phosphorus, potassium and total fertilizers consumption was developed. For this, yearly data of nitrogen, phosphorus, potassium and total fertilizer consumption from 1950-51 to 2020-21 were used for model fitting and forecasting future consumption. The forecasted nitrogen and total fertilizer consumption exhibited an increasing trend. Whereas phosphorus consumption exhibited a slightly increasing trend and potassium consumption exhibited no trend i.e., it will remain constant throughout the study period. The forecasted values for nitrogen, phosphorus and potassium consumption was found to be 21,107.88, 7626 and 2649 thousand tonnes respectively in 2030-31.

On the basis of the forecasting and validation findings, it is possible to conclude that the ARIMA model might be used successfully to forecast fertilizer consumption i.e., nitrogen, phosphorus, potassium and total fertilizer consumption in the coming years. These projections assist the government in formulating policies about relative price structure, production, consumption, fertilizer storage, import and/or export as well as establishing international ties.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interests to declare.

Ethical issues: None.

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