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# Econometric Modeling and Forecasting of Arabica and Robusta Coffee Production for Sustainable Agriculture Development

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***Author's contribution***

*The sole author designed, analyzed, interpreted and prepared the manuscript.*

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## ABSTRACT

In the present study, we have used Box-Jenkins approaches an Autoregressive Integrated Moving Average model (ARIMA) for modeling and forecasting of annual amount of Arabica and Robusta coffee production and yield (ARCPY) in India. In this study used time series data was collected from the official website of the coffee board of India from 1986 to 2023 (38 observations). Augmented Dickey-Fuller (ADF) test has used for testing the stationarity of the time series, and the appropriate ARIMA model has selected based on minimum Akaike Information Criterion (AIC). The ARIMA models has compared with the other ARIMA models with respect to forecast accuracy measures, and the residuals has diagnosed for possible presence of autocorrelation, and white noise heteroscedasticity (WNH) test of the fitted models. The MAPE value of ACP and ACY has 8.94 and 9.35 percent respectively shows highly accurate forecasting percentage rate respectively. While, the MAPE value of RCP and RCY has 16.03 and 11.43 percent respectively shows good accurate forecasting percentage rate respectively. Thus, we found the ARIMA (2, 1, 4), (3, 1, 2), (0, 1, 3) and

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(2, 0, 1) models for Arabica and Robusta coffee; which has observed as the best suitable model for predicting the future annual amount of Arabica coffee production (ACP), Arabica coffee yield (ACY), Robusta coffee production (RCP) and Robusta coffee yield (RCY) respectively, and we have estimated that the annual amount of ACP and ACY achieved in the year 2023-24 from 97379.67 MTs, and 472.29 kg/hectare respectively to 93272.91 MTs, and 379.31 kg/hectare respectively in the year 2034-35 will decrease, and the annual amount of RCP and RCY achieved in the year 2023-24 from 268655.21 MTs, and 1110.68 kg/hectare respectively to 318614.85 MTs, and 1012.90 kg/hectare respectively in the year 2034-35 will reach.

*Keywords: Time series analysis; forecasting; ARC, ARIMA; AIC; MAPE; WNH.*

**JEL Code:** C12, C22, C51, C52, C53

## ABBREVIATIONS

| | | |
|---|---|---|
| *ARIMA* | : | *Autoregressive Integrated Moving Average Model* |
| *ARCPY* | : | *Arabica and Robusta Coffee Production and Yield* |
| *ADF* | : | *Augmented Dickey-Fuller* |
| *WNH* | : | *White Noise Heteroscedasticity* |
| *AIC* | : | *kaike Information Criterion* |
| *SIC/BIC* | : | *Schwarz (Bayesian) Information Criterion* |
| *MAPE* | : | *Mean Absolute Percentage Error* |
| *MAE* | : | *Mean absolute error* |
| *RMPE* | : | *Root Mean Square Error* |
| *ARC* | : | *Arabica and Robusta Coffee* |
| *ACP* | : | *Arabica Coffee Production* |
| *ACY* | : | *Arabica Coffee Yield* |
| *RCP* | : | *Robusta Coffee Production* |
| *RCY* | : | *Robusta Coffee Yield* |
| *ACPY* | : | *Arabica Coffee Production and Yield* |
| *RCPY* | : | *Robusta Coffee Production and Yield* |
| *MTs* | : | *Metric Tonne* |
| *FY* | : | *Financial Year* |
| *ANN* | : | *Automatic Natural Network* |
| *ELM* | : | *Extreme Learning Machine* |
| *VAR* | : | *Victor Autoregressive* |
| *BJM* | : | *Box-Jenkins Methodology* |
| *BLUE* | : | *Best Linear Unbiased Estimator* |
| *AR* | : | *Autoregressive* |
| *MA* | : | *Moving Average* |
| *ACF* | : | *Autocorrelation Function* |
| *PACF* | : | *Partial Autocorrelation Function* |
| *JB* | : | *Jarque - Bera* |
| *SER* | : | *Standard Error of Regression* |
| *GAP* | : | *Good Agricultural Practices* |
| *GMP* | : | *Good Management Practices* |

## 1. INTRODUCTION

Since the journey of Indian coffee production is a long one dating back almost 400 years, it holds a very special place in historical taste. This unique journey has started from the hands of Yaman, who handed over seven magical beans to Bababudan, who planted it in the Chandragiri hills of Karnataka. This magical beginning paved the way for coffee with the aroma, taste, flavour and acidity we experience today [1,2]. Coffee is one of the most popular beverages in the world [3,2]. Coffee from India is the best shade-grown light coffee in the world. Among plantation crops, coffee has contributed significantly to the Indian economy during the last 50 years [4,5,6]. Coffee plays vital role in Indian economy. A normal consumption of coffee, which means that two to three cups a daily, and it's connected with a range of physiological belongings, and can be fit inside healthy, impartial diet and dynamic way of life. Coffee production is conquered in the South Indian states. i.e., in Karnataka with 70.46%, afterward Kerala with 20.58%, Tamil Nadu with 5.31% and other state like Andhra Pradesh, Orissa and North Eastern Region with 3.65% of on the whole production with 352000 MTs in FY2022-23. Indian coffee is specifically identified for its hand-picked coffee grown in darkness rather than direct sunlight everywhere else in this world.

In India, traditional coffee growing States are Karnataka, Kerala and Tamil Nadu. Some of the non-traditional areas are Andhra Pradesh, Odisha and North Eastern Region including Assam, Meghalaya, Manipur, Arunachal Pradesh and Tripura. The three traditional areas together accounted for 79.7 per cent of area and 96.2 per cent of coffee production. The major coffee growing areas in India are Hassan, Chikmagalur and Coorg in Karnataka, Wayanad, Idukki and Nelliyampathy in Kerala, Shevaroys, Palani, Pulneys and Nilgiri hills in Tamil Nadu [7,2]. Both the varieties of coffee has been more or less equal in its area, production and productivity under traditional areas except Tamil Nadu. Tamil Nadu is the one of the State which has more production of Arabica coffee comparing with Robusta Coffee [6]. Since every Indian coffee grower spends his entire time in coffee production, it is no miracle or wonder that India produces extraordinary variety of coffee and exports it to different parts of the world over 150$^{th}$ years. In all around India 250,000 coffee growers are working in the country, and moreover 98% of people are small coffee producers [1,2]. Coffee production and productivity are incessant rising in India respectively 3195 lakh tonnes and 767 kg/hectare in FY 2018-19. In FY 2020-21 3340 lakh tonnes and 790 kg/hectare which is increase to respectively 3420 lakh tonnes and 797 kg/hectare in FY 2021-22. In the present study, researcher's main purpose of the study to forecast the annual amount of Arabica and Robusta coffee production and yield in India, and used of time series data from 1986 to 2023 for the study.

## 2. LITERATURE REVIEW

Gopinath et al. [1] researchers' used monthly time series data from the period 2010 to 2015, and attempted to forecast coffee production in India between the years 2015 to 2025 using ARIMA model. In the study, they found that ARIMA (2, 1, 1) were the most appropriate model among ten studied ARIMA models. With the help of which the coffee production amounts for the next eleventh years were forecasted. Naveena et al. [4] developed a hybrid model for the Price of Robusta Coffee in India with Hybrid ARIMA-ANN methods; and suggested that hybrid model of ARIMA and ANN is the best model for Robusta coffee price projection. Yashavanth et al. [8] researchers' used Vector auto-regression (VAR) model for forecast the monthly wholesale prices of Arabica coffee in three different coffee consuming centres in India, viz. Bengaluru, Chennai and Hyderabad; and used of monthly data series period of January, 2001 to March, 2014. Finally, in this study, VAR (2) was found to be the most appropriate model among other models in forecasting the coffee price for the next 10 month. Prabha et al. [6] studied the coffee trend in area, production and yield in India from 1985-2000, and he was found that the best fitted ARIMA (1, 1, 1) and (1, 1, 0) models for forecasting of coffee production. Chandra and Brahme, [9] researchers' studied the groundnut trend in production and productivity in India. He was used annual time series data from the period 1970-71 to 2021-22, and he was found that the best fitted ARIMA (0, 1, 2) and (0, 1, 2) models for forecasting of groundnut production and productivity. Deina et al. [10] the researchers used extreme learning machine (ELM) neural networks to forecast Arabica and Robusta coffee prices, based on autoregressive and autoregressive integrated and moving average (ARIMA) linear models, the most commonly used method for coffee price forecasting. Krishnan and Brahme, [11] researchers' studied the food grains production and productivity in India. He was used yearly time series data from the period 1951 to 2023, and he was found that the best fitted ARIMA (0, 1, 1) and (0, 1, 1) models for forecasting of food grains production and productivity. Chandra, [12] researcher's used yearly time series data from the period 1971 to 2022, and attempted to forecast tea production in India between the years 2023 to 2041 using ARIMA model. In the study, they found that ARIMA (1, 1, 1) were the most appropriate model among twenty studied ARIMA models. With the help of which the tea production quantity for the next nineteen years were forecasted. Ahalya et al. [13] researcher's used yearly time series data from 2000 to 2022 for coconut production and productivity, and for price of coconut from 2012 to 2023 was collected, and attempted to forecast coconut price in India between the months August to December 2023 using ARIMA (1, 1, 1) model. Esther and Wangui, [14] used ARIMA model (1, 1, 2) to forecast pulses production in Kenya and find out that pulses production was decreasing in forecasting period.

We have documented a detailed literature on predicting the various data series from 1950-51 to 2022-23. The academicians carried study on forecasting of coffee prices, coffee production and seeds, groundnut production, pluses production, coconut production and productivity, price of coconut and food grains production; and there is do not any study available of Arabica and Robusta coffee production forecasting in India, and as well as do not any study available for period 2023-24 to 2034-35. Thus, it's a gap, and motivated us to undertake study on forecasting the Arabica and Robusta coffee production in India. This paper is structured as followed: In Section 1 introduction is given about to the coffee production and area of coffee production. Section 2 Literature review, Section 3 provides research methodology (objectives of the study, research design, data collection and econometric models), Section 4 Result and discussion and Section 5 provides respectively conclusion and references.

## 3. METHODOLOGY

### 3.1 Objective of the Study

The main objectives of this research are as follows:

1. To test the stationarity of the time series data compiled for the study, i.e., Arabica coffee production (ACP), Arabica coffee yield (ACY), Robusta coffee production (RCP) and Robusta coffee yield (RCY).
2. To identify the order of difference at which the time series would become stationary.
3. To perform the model estimation, i.e., ARIMA (p, d, q) and diagnostic checking.
4. To forecast the future values of ACP, ACY, RCP and RCY using the estimate ARIMA model.

### 3.2 Research Design

In order to fulfil the above objectives of the study, exploratory research design and stochastic trend model have been adopted. Exploratory research interprets the already available information and emphasizes on the analysis and interpretation of the available secondary data. Akaike information criterion (AIC), Schwarz (Bayesian) information criterion (SIC/BIC), Root mean square error (RMSE), Mean absolute percentage error (MAPE), Mean absolute error (MAE) and Sigma Square has used for selecting the best ARIMA model and forecasting the time series.

### 3.3 Data Collection

The time series data of Arabica and Robusta coffee production and yield in India has collected from the official website of the https://coffeeboard.gov.in/database-coffee.html for the period of 1986 to 2023 (38 observations). At this range of data, the researcher's has tried to forecast the future values for the period of 2023-24 to 2034-35 (12 Observations).

### 3.4 The Box-Jenkins Methodology (BJM)

**Step I**- In the first phase of the study, the time series data selected for the study is collected from a reliable source, after which a graphical presentation of the series is seen, which shows whether the series is showing a trend or not. After this, stationarity of the series is checked at the level, and if there is no stationarity at the category level, then stationarity is checked at the first difference, and if there is no stationarity of the series at the first difference, then this process continues till this continues until the series becomes stationary. By the way, most of the series becomes stationary at the first difference. After the series is stationary, the correlogram is seen, with the help of which the model is selected (Gujarati et al. [15]; Chandra et al. [2]).

**Step II-** In the second step of the study, the equation of the model (*p*, *d*, *q*) selected in the first phase is derived, and then the equation is formed by writing the parameters of the selected model with their given values (Gujarati et al. [15]; Chandra et al. [2]).

**Step III-** In the third phase of the study, a diagnostic check of the residuals of the selected model (*p*, *d*, *q*) is carried out in the second step, in which the autocorrelation (ACF and PACF), white noise, JB and Ljung-Box test is done of the selected model. If all the tests after diagnostic testing of the residuals of the selected model (*p*, *d*, *q*) are found to be significant, then the forecasting process of the selected model is done, and if all the tests after diagnostic test of the residuals of are not found to be significant, then all the process is started again from the first phase of the study (Gujarati et al. [15]; Chandra et al. [2]; Ashoka et al. [16]).

**Step IV-** In the fourth stage of the study, after diagnostic testing residuals of the model selected in the third stage, all the tests are found significant, and follow the Gauss-Markov theorem [17]. Thus, the model constructed is terms are the best linear unbiased estimator “BLUE”. Thereafter the forecasting process of the selected model is completed, and then reporting of the model is done (Gujarati et al. [15]; Chandra et al. [2]). Fig. 1 shows the Box-Jenkins methodology consist of following four steps (Gujarati et al. [15]; Chandra, [12]).

### 3.5 Econometric Models

To selecting the best fitted ARIMA model, many statistical tools are being applied, viz., AIC, BIC/SIC, MAPE, MAE, RMSE and Ljung-Box test, and thus, models are formulation as bellow:

The RMSE has been used as a standard metric to measure the model performance in time series forecasting. While applying the RMSE, the underlying assumption is that the errors are unbiased and follow a normal distribution. It provides a complete picture of the error distribution, and its value should be relatively low (Draxler, [18]; Gnana et al. [19]; Borkar, [20]; Prakash et al., [3]; Chandra, [12]; Chandra and Brahme [9]; Chandra et al. [2]). The RMSE can be calculated by using the following formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(X_i - \overline{X}_i\right)^2}{n}} \qquad \text{Eq. (1)}$$

The MAPE is a measure of prediction accuracy of a forecasting method. It usually expresses the forecasting accuracy of a model in percentage terms (Armstrong and Collopy, [21]; Goodwin and Lawton, [22]; Ren and Glasure, [23]; Tofallis, [24]; Reddy, [25]; Borkar, [20]; Prakash et al., [3]; Chandra, [12]; Chandra and Brahme [9]; Chandra et al. [2]). If, MAPE values less than 10 (<10) indicate highly accurate forecasting, 10 to 20 (10 - 20) indicate good predicting accuracy, while MAPE values between 20 and 50 indicate reasonable predicting accuracy, and MAPE values greater than 50 indicate inaccurate predictions (Lewis, [26] ; Moreno et al. [27]). The MAPE can be calculated by using the following formula:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{X_i - \overline{X}_i}{X_i}\right| \qquad \text{Eq. (2)}$$

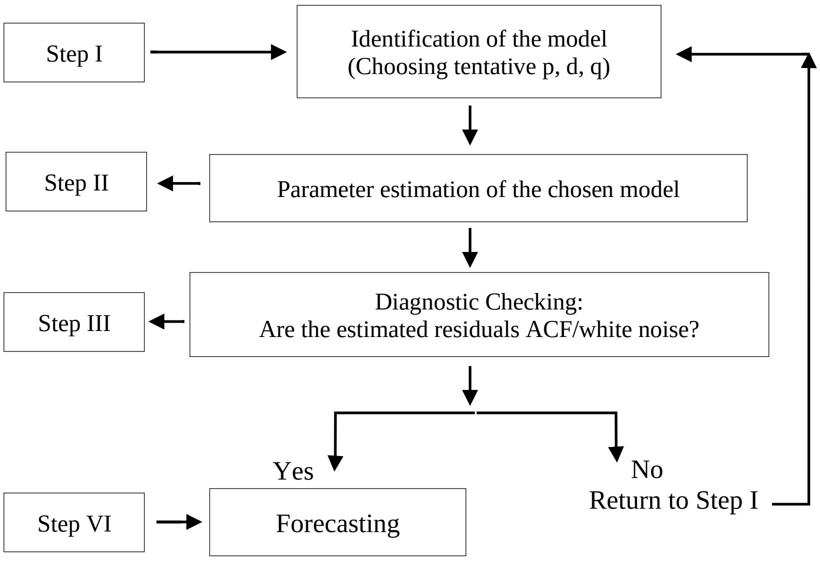



**Fig. 1. The Box-Jenkins methodology**
*(Source: Gujarati et al. [15]; Chandra, [12])*

The MAE measures how much the series varies from its Model-predicted level (Reddy, [25]; Chandra, [12]). MAE can be calculated by using the following formula:

$$MAE = \sum_{i=1}^{n} \left| \frac{X_i - \overline{X}_i}{X_i} \right| \qquad \text{Eq. (3)}$$

AIC is a criterion for model selection among a finite set of models. It is based on the likelihood function (Akaike, [28]; Priya et al., [29]; Chandra, [12]; Chandra and Brahme [9]; Chandra et al. [2]).

AIC = (-2log L + 2m); where: m= p + q, L = Likelihood function and -2log L = approximately equal to {n (1+ log 2π) + n log $\sigma^2$}, where: $\sigma^2$ = the model MSE.

AIC written as follow:

$$AIC = \{n\,(1+\log 2\pi) + n \log \sigma^2 + 2m\} \qquad \text{Eq. (4)}$$

SIC is also known as a Bayesian Information Criterion (BIC) (Reddy, [25]; Chandra, [12]). The BIC can be calculated by using the following formula:

$$BIC = \log\left(\frac{rss}{n}\right) + \frac{k}{n}\log n \qquad \text{Eq. (5)}$$

Where, "*rss*" = the residual sum of squares; *k* = the number of coefficients estimated, i.e., *1* + *p* + *q* + P + Q; and *n* = the number of observations, and Ljung-Box test has been applied to the residuals after a forecast model has been fit to the data. This test says whether the errors in the forecast model are serially correlated. The small p-values ($p<0.05$) indicate that there is significant serial autocorrelation, and if, p-values ($p>0.05$) more than significant value indicate that there is no serial autocorrelation (Box and Jenkins, [30]; Gujarati et al. [15]; Khandelwal and Mohanty, [31]; Chandra, [12]; Chandra and Brahme [9]; Chandra et al. [2]). The Ljung-Box Q-statistic can be calculated by using the following formula:

$$Q = n(n+2)\sum_{i=1}^{k} \frac{r_i^2}{n-i} \qquad \text{Eq. (6)}$$

Where, *n* = the number of observations, $r^2$ = value of $i^{th}$ the number of observations.

## 3.6 Modelling of Time Series Data

To introduce several ideas, some old and some new (Gujarati et al. [15]), let us work with the ACP, ACY, RCP and RCY time series data for the India. A plot of this time series has given in Fig. 2 represent quantiles graphs, and Fig. 3 represent the original series of the data. Fig. 4 represent the stationary series; recall that series Arabica coffee production (ACP), Arabica coffee yield (ACY) and Robusta coffee production (RCP) are nonstationary from the level but in the (first) differenced from it is stationary, and the series Robusta coffee yield (RCY) is stationary in the level. If, a time series is stationary, we can model it in a variety of ways (Chandra, [12]).

### 3.6.1 An Autoregressive (AR) Process

Let $Y_t$ represent the at time *t*. If we model $Y_t$ as,

$$(Y_t - \delta) = \alpha_1\,(Y_t - \delta) + u_t \qquad \text{Eq. (7)}$$

Where: δ = the mean of Y and $u_t$ = an uncorrelated random error term with zero mean and constant variance $\sigma^2$ (i.e., it is white noise), then we say that $Y_t$ follows a first-order autoregressive (AR1) process. We consider this model,

$$(Y_t - \delta) = \alpha_1\,(Y_{t-1} - \delta) + \alpha_2\,(Y_{t-2} - \delta) + u_t \qquad \text{Eq. (8)}$$

Then we say that $Y_t$ follows a second order autoregressive (AR 2) process. That is, the value of *Y* at time *t* depends on its value in the previous two times depends, the Y values being expressed around their mean value δ. In general we can have,

$$(Y_t - \delta) = \alpha_1\,(Y_{t-1} - \delta) + \alpha_2\,(Y_{t-2} - \delta) + \ldots\ldots + \alpha_p\,(Y_{t-p} - \delta) + u_t \qquad \text{Eq. (9)}$$

Where, $Y_t$ = $p^{th}$ - order autoregressive process.

### 3.6.2 A Moving Average (MA) Process

The AR process is not only mechanism that may have generated *Y*. suppose we model *Y* as follows:

$$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} \qquad \text{Eq. (10)}$$

Where: *μ* = constant, *u* = white noise stochastic error term. Thus, we say that *Y* follows a first-order moving average (MA 1) process. But *Y* follows the expression,

$$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} \quad \text{Eq. (11)}$$

Then it is an MA (2) process. More generally, is an MA ($q$) process. In short, a moving average process is simply a linear combination of white noise error terms.

$$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \dots\dots\dots + \beta_q u_{t-q} \quad \text{Eq. (12)}$$

### 3.6.3 An Autoregressive and Moving Average (ARMA) Process

Of course, is it quite likely that $Y$ has characteristics of both AR and MA and is therefore ARMA. Thus, $Y$ follows an ARMA (3, 4) process if it can be written as:

$$Y_t = \theta + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \alpha_3 Y_{t-3} + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \beta_3 u_{t-3} + \beta_4 u_{t-4} + u_t \quad \text{Eq. (13)}$$

### 3.6.4 An Autoregressive Integrated Moving Average (ARIMA) Process

ARIMA is a linear regression model for time series forecasting, and it uses its own lags as predictors. Any 'non-seasonal' time series that exhibits patterns and is not a random white noise can be modelled with ARIMA models. An ARIMA model is characterised by 3 terms: $p, d, q$ (Box and Jenkins, [30]; Gujarati et al. [15]; Binuomote et al. [32]; Chandra, [12]; Chandra and Brahme [9]; Chandra et al. [2]).

Where: $p$ = the order of the AR term

$q$ = the order of the MA term
$d$ = order of differencing required to make the series stationary ($I$).

## 3.7 ARIMA Model Identification for Arabica and Robusta Coffee

In generally, a non-stationary series is made stationary after differentiating '*d times*', and is said to be integrated of order '*d*', denoted by *I (d)*. If, the original series is stationary $d=0$, and then the ARIMA model transform into an ARMA model. The time series data used for the present study, i.e., ACP, ACY, RCP and RCY. The series ACP, ACY, and RCP has become stationary after the 1st order differencing. Since, there is no need for further differencing the series, and it is necessary to adopt $d=1$ (first difference) for ARIMA ($p, d, q$) model. But the series RCY has stationary in the level, and there is no need

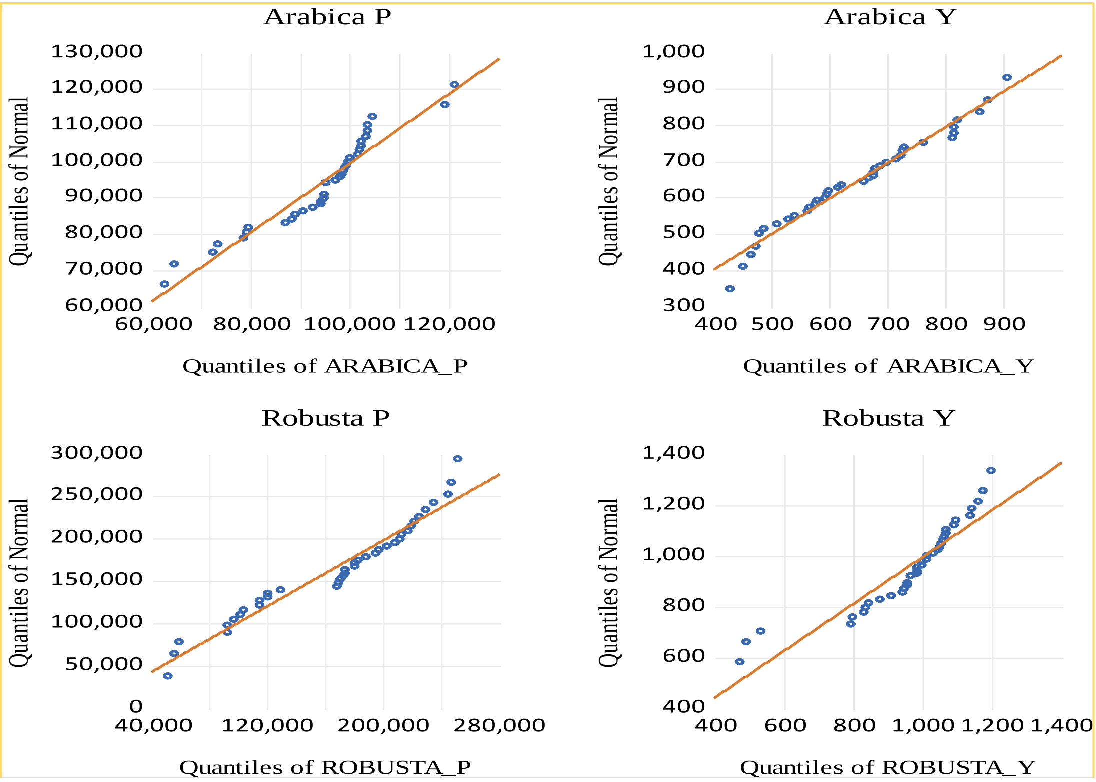



**Fig. 2. Represent of Quantiles graphs of Arabica and Robusta coffee**

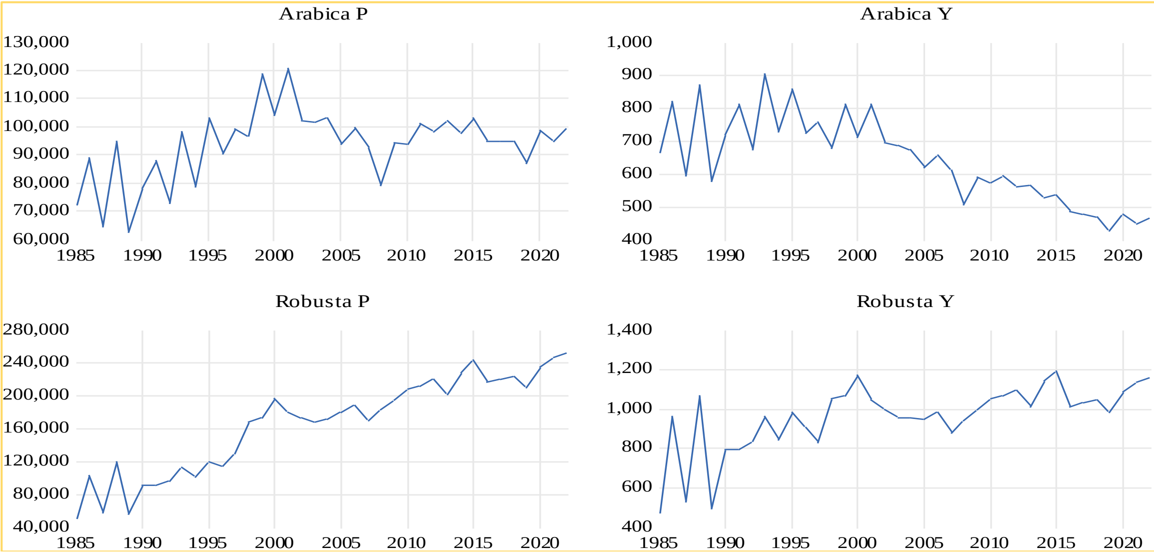



**Fig. 3. Graphical representation of Original series of Arabica and Robusta Coffee**

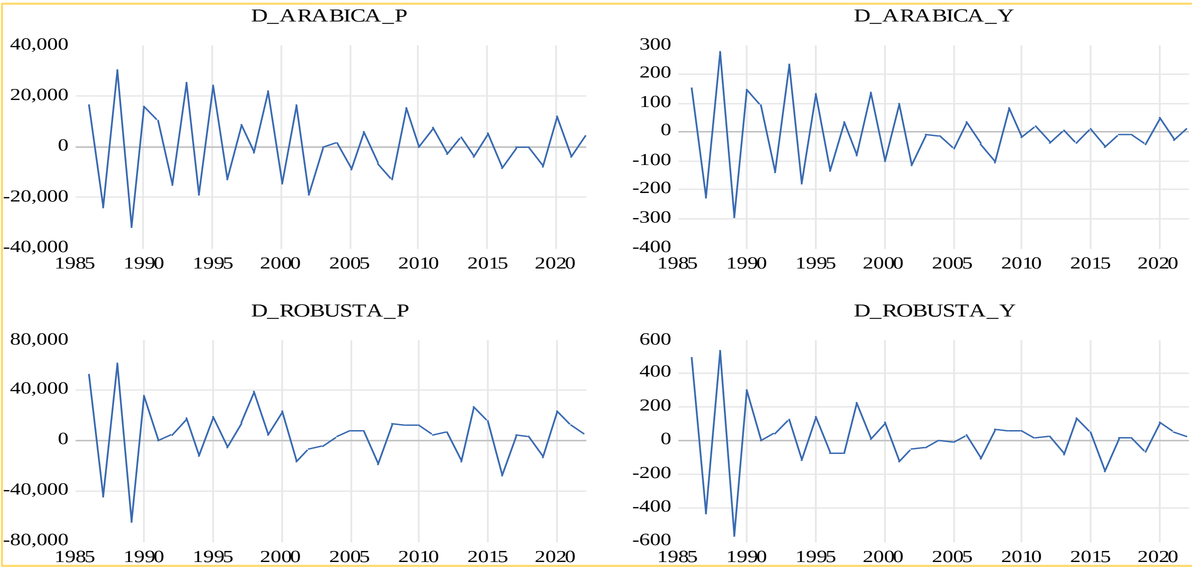



**Fig. 4. Representation of zero mean stationary series graph of Arabica and Robusta Coffee**

for further differencing the series. We have checked the Correlogram after first difference, and the level in time series (given Fig. 5). Since, there are no significant spikes of ACF and PACF residuals of the selected ARIMA and ARMA models. To get the appropriate numbers for '*p*' (in AR) and '*q*' (in MA) in the models, and thereafter we have checked white noise in the Correlogram after first difference and the level in time series (given Fig. 6). Since, there are no significant spikes of ACF and PACF residuals of the selected ARIMA and ARMA models, and therefore there is no need for further consideration of any more AR (*p*) and MA (*q*). The models convinces all the norms (comparatively lowest value of AIC, comparatively low values of BIC, and MAPE, MAE and RMSE). Therefore, these models have been considered to be the best predictive model, which have been used to forecast the future values of the time series, viz., DACP, DACY, DRCP and RCY. Table 4 shows that selected best fitted ARIMA model with parameters, and Table 5 provides the estimation results of various parameters of AR (*p*) and MA (*q*) of the ARIMA and ARMA models for production and yield. Using these values, the best fit ARIMA (*p, d, q*), and ARMA models for predicting the time series

DACP, DACY, DRCP and RCY has been identified. The prediction equation for models can be written as below:

The equation for ACP (Eq. 14) and ACY (Eq. 15) respectively -

$Y_t = \theta + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \beta_1 u_{t-1} + \beta_2 u_{t-2} + \beta_3 u_{t-3} + \beta_4 u_{t-4} + u_t$ Eq. (14), and

$Y_t = \theta + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \alpha_3 Y_{t-3} + \beta_0 u_t + \beta_1 u_{t-1} + \beta_2 u_{t-2} + u_t$ Eq. (15)

The equation for RCP (Eq. 16) and RCY (Eq. 17) respectively-

$Y_t = \mu + \beta_0 u_t + \beta_1 u_{t-1} + \beta_1 u_{t-2} + \beta_1 u_{t-3} + u_t$ Eq. (16), and

$Y_t = \theta + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \beta_0 u_t + \beta_1 u_{t-1} + u_t$ Eq. (17)

Based on the estimation results of ARIMA (2, 1, 4), (3, 1, 2), (0, 1, 3), and (2, 0, 1) models (Intercept and regression coefficients given in Table 5) respectively, and the functional form of the time series forecasting models may be presented as follows (Eq. 18, 19, 20 and, 21):

Model for Arabia Coffee Production (ACP)-

$Y_t = 11.441 + 0.7476Y_{t-1} - 0.0870Y_{t-2} - 0.7849u_{t-1} + 1.1557u_{t-2} - 0.7849u_{t-3} + 0.9999u_{t-4} + u_t$
Eq. (18), and

Model for Arabica Coffee Yield (ACY)-

$Y_t = -6.6702 - 2.0182Y_{t-1} - 1.7848Y_{t-2} - 0.5698Y_{t-3} + 1.1954u_{t-1} + 0.9999u_{t-2} + u_t$ Eq. (19)

Model for Robusta Coffee Production (RCP)-

$Y_t = 5004.42 + 0.8242u_{t-1} + 0.5090u_{t-2} - 0.6848u_{t-3} + u_t$ Eq. (20), and

Model for Robusta Coffee Yield (RCY)-

$Y_t = 950.31 + 0.0653Y_{t-1} + 0.7644Y_{t-2} + 0.0266u_{t-1} + u_t$ Eq. (21)

## 4. RESULTS AND DISCUSSION

### 4.1 Descriptive Statistic

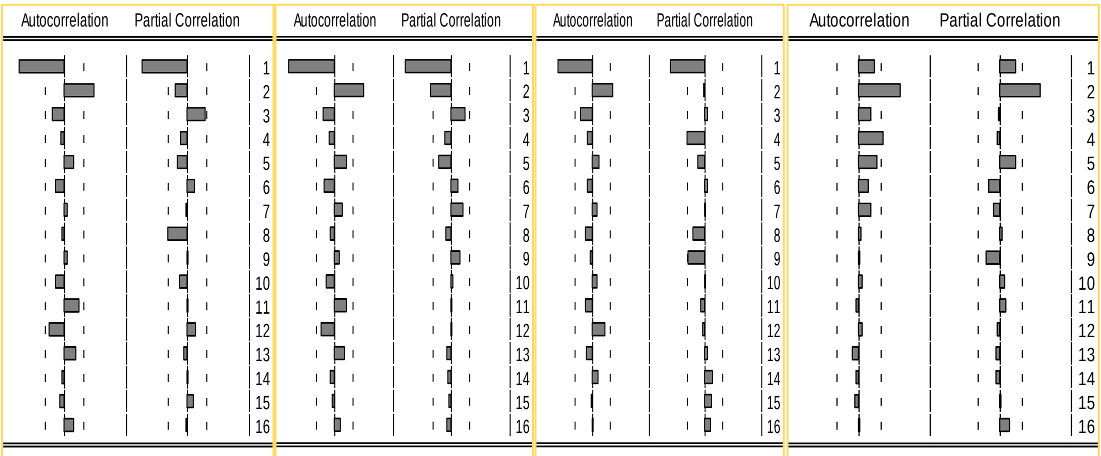
In Table 1 shows that descriptive statistics of original series of Arabica coffee production & yield (ACPY), which mean are respectively 93852.92 and 642.0, standard deviation are 12450.9 and 130.9, skewness are -0.601 and 0.224, and kurtosis are 3.758 and 2.095, and JB test p-value are 0.202 and 0.445 respectively. The JB test of both of the original series has statically insignificant. So it is clear that the original series of ACPY is followed normal distribution. Table 1 also presents that descriptive statistics of original series of Robusta coffee production & yield (RCPY), which mean are respectively 166166.1 and 960.8, median are 176350.0 and 990.5, standard deviation are 57781.1 and 170.4, skewness are -0.499 and -1.433, and kurtosis are 2.082 and 4.977, and JB test p-value are 0.271 and 0.000 respectively. The JB test of the original series of RCP has statically insignificant but series RCY has statically significant. So it is clear that RCP has normally distributed. Fig. 2 represent of quantiles graphs of Arabica and Robusta coffee, and Fig. 3 represent original series trend of Arabica and Robusta coffee.

In Table 2 shows that descriptive statistics of stationary series of Arabica coffee production & yield (ACPY), and which mean are respectively 748.35 and -5.486, standard deviation are 14505.23 and 118.61, skewness are -0.027 and 0.054, and kurtosis are 2.568 and 3.369, and JB test p-value are 0.864 and 0.891 respectively. The JB test of ACPY series has statically insignificant. So it is clear that the stationary series of ACPY is followed normal distribution, and stationary series of ACPY are more stable. Table 2 also presents descriptive statistics of RCPY, and which mean are respectively 5455.70 and 18.594, median are 5000.0 and 19.0, standard deviation are 23893.83 and 195.29, skewness are -0.37 and -0.15, and kurtosis are 4.422 and 5.829, and JB test p-value are 0.138 and 0.001 respectively. The JB test of the stationary series of RCP has statically insignificant but series RCY has statically significant, and thus it is clear that RCP has normally distributed. Thus stationary series of RCPY are more stable, and after that we go out for stationary test (ADF test) all of the series (ACP, ACY, RCP and RCY). Fig. 4 represent graphs of zero mean stationary series.

### 4.2 Stationary test- Argument Dickey-Fuller (ADF test)

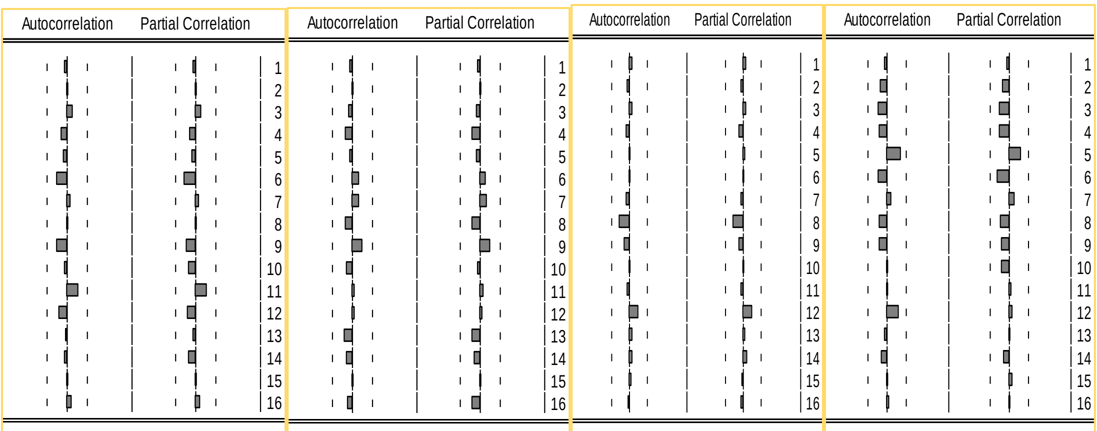
The results of Argument Dickey-Fuller (Dickey-Fuller, [33]) unit root test at level and 1st order difference given in Table 3. Table 3 presents that the calculated t–statistics value of ACP and ACY at level are respectively = -1.681899 and -2.291403 and p-value are respectively = 0.7386 and 0.4277, thus ACP and ACY series has statically not significant, so it's not stationary. Than after we go through 1st differenced, and 1st order difference series DACP and DACY calculated t–statistics value are respectively = -16.76781 and -19.04494 and p-value are respectively = 0.0000 and 0.0000, and which are smaller than critical values at 1%, 5% and 10% levels of significance. Hence, we fail to accept the null hypothesis for unit root. It means the series DACP and DACY is not containing the unit root and thus it is stationary.

Table 3 shows the results of Argument Dickey-Fuller (ADF) unit root test at level and 1st order difference of series RCP and RCY, and the calculated t–statistics value of RCP and RCY at level are respectively = -4.903121 and -8.105773 and p-value are respectively = 0.0017 and 0.000, thus RCP and RCY series has statically significant at level, and thus series RCY has stationary at the level. But series RCP has diagrammatically shows autocorrelation, so it's not stationary. Than after we have go through 1st differenced, and 1st order difference series DRCP calculated t–statistics value = -13.21163, and p-value = 0.0000, and which is smaller than critical values at 1%, 5% and 10% levels of significance. Hence, we fail to accept the null hypothesis for unit root. It means the series DRCP is not containing the unit root, and thus it is stationary. Figure 5 part (a), part (b), part (c) and part (d) represent the plot of Correlogram (ACF and PACF) of the stationary series DACP, DACY, DRCP and RCY for lags 1 to 16 at the 1st order difference and level respectively.




**(a) ACP** **(b) ACY** **(c) RCP** **(d) RCY**

**Fig. 5. Correlogram of Stationary Series Arabica and Robusta Coffee**




**(a) ACP** **(b) ACY** **(c) RCP** **(d) RCY**

**Fig. 6. Autocorrelation test (ACF and PACF) of Arabica and Robusta Coffee**

**Table 1. Descriptive statistics of original series of coffee**

| Statistics | Arabica | | Robusta | |
|---|---|---|---|---|
| | Production | Yield | Production | Yield |
| Mean | 93852.92 | 642.0 | 166166.1 | 960.8 |
| Median | 95000.0 | 638.5 | 176350.0 | 990.5 |
| Std. Dev. | 12450.9 | 130.9 | 57781.1 | 170.4 |
| Skewness | -0.601 | 0.224 | -0.449 | -1.433 |
| Kurtosis | 3.758 | 2.095 | 2.082 | 4.977 |
| Jaurqe-Bera | 3.198 | 1.615 | 2.609 | 19.21 |
| Prob. | 0.202 | 0.445 | 0.271 | 0.000 |

*Source: Author's calculation*

**Table 2. Descriptive statistics of stationary series of coffee**

| Statistics | Arabica | | Robusta | |
|---|---|---|---|---|
| | Production | Yield | Production | Yield |
| Mean | 748.35 | -5.486 | 5455.70 | 18.594 |
| Median | - | -9.000 | 5000.00 | 19.000 |
| Std. Dev. | 14505.23 | 118.61 | 23893.83 | 195.29 |
| Skewness | -0.027 | 0.054 | -0.37 | -0.15 |
| Kurtosis | 2.568 | 3.369 | 4.422 | 5.829 |
| Jaurqe-Bera | 0.291 | 0.228 | 3.958 | 12.473 |
| Prob. | 0.864 | 0.891 | 0.138 | 0.001 |

*Source: Author's calculation*

**Table 3. Results of Argument Ducky Fuller (ADF) test (Level and Difference)**

| Variable | | Level | | 1st Difference | | Result |
|---|---|---|---|---|---|---|
| | | t-Statistics | Prob. | t-Statistics | Prob. | |
| Arabica | Production | -1.681899 | 0.7386 | -16.76781 | 0.0000* | Series Stationary |
| | Yield | -2.291403 | 0.4277 | -19.04494 | 0.0000* | Series Stationary |
| Robusta | Production | -4.903121 | 0.0017 | -13.21163 | 0.0000* | Series Stationary |
| | Yield | -8.105773 | 0.0000* | - | - | Series Stationary |

*Note: (*) Shows there is No need for further difference and ADF test Statistically Significant.*
*Source: Author's calculation*

**Table 4. Appropriate model selection for arabica and robusta coffee production and yield**

| Variables | | ARIMA | $\sigma^2$ | Adj.$R^2$ | SER | AIC | BIC | RMSE | MAPE | MAE |
|---|---|---|---|---|---|---|---|---|---|---|
| Arabica | (P) | (2,1, 4) | 0.005510 | 0.6539 | 0.0834 | -1.6696 | -1.3249 | 10525.82 | 8.9399 | 8170.18 |
| | (Y) | (3,1, 2) | 2676.612 | 0.7653 | 57.455 | 11.2841 | 11.5889 | 74.4532 | 9.3483 | 58.5101 |
| Robusta | (P) | (0,1, 3) | 2.39E+08 | 0.5161 | 16620.2 | 22.5001 | 22.7178 | 30375.63 | 16.0311 | 25481.88 |
| | (Y) | (2,0, 1) | 13535.10 | 0.4632 | 124.84 | 12.6624 | 12.8779 | 131.13 | 11.43 | 111.76 |

*Source: Author's calculation Using EView*

## Table 5. Estimation Parameters of Arabica and Robusta Coffee Production and Yield

| Variable | | Parameters | Intercept | AR (1) | AR (2) | AR (3) | MA (1) | MA (2) | MA (3) | MA (4) | Log Likelihood |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Arabica | | C | 11.441 | 0.7476 | -0.0870 | - | -0.7849 | 1.1557 | -0.7849 | 0.9999 | |
| | (P) | Std. Error | 0.0540 | 0.3209 | 0.2686 | - | 998.17 | 1807.1 | 1475.5 | 3126.9 | 39.723 |
| | | Prob. | 0.0000 | 0.0267 | 0.7481 | - | 0.9994 | 0.9995 | 0.9996 | 0.9997 | |
| | | C | -6.6702 | -2.0182 | -1.7848 | -0.5698 | 1.1954 | 0.9999 | - | - | |
| | (Y) | Std. Error | 6.3895 | 0.2287 | 0.3549 | 0.2140 | 797.71 | 1334.6 | - | - | -201.756 |
| | | Prob. | 0.3049 | 0.0000 | 0.0000 | 0.0124 | 0.9988 | 0.9994 | - | - | |
| Robusta | | C | 5004.42 | - | - | - | 0.8242 | 0.5090 | -0.6848 | - | |
| | (P) | Std. Error | 625.51 | - | - | - | 716.18 | 405.78 | 1171.83 | - | -411.25 |
| | | Prob. | 0.0000 | - | - | - | 0.9991 | 0.9990 | 0.9995 | - | |
| | | C | 950.31 | 0.0653 | 0.7644 | - | 0.0266 | - | - | - | |
| | (Y) | Std. Error | 109.41 | 0.1354 | 0.0948 | - | 0.2506 | - | - | - | -235.58 |
| | | Prob. | 0.0000 | 0.6327 | 0.0000 | - | 0.9160 | - | - | - | |

*Source: Author's calculation Using EViews*

## Table 6. Results of the Ljung-Box test

| Variable | | Models | leg | Q- Stat. | Prob. | Result |
|---|---|---|---|---|---|---|
| Arabica | (P) | (2, 1, 4) | 16 | 7.1090 | 0.715 | Insignificant |
| | (Y) | (3, 1, 2) | 16 | 6.4371 | 0.843 | Insignificant |
| Robusta | (P) | (0, 1, 3) | 16 | 4.5819 | 0.983 | Insignificant |
| | (Y) | (2, 0, 1) | 16 | 10.923 | 0.617 | Insignificant |

*Source: Author's calculation Using EViews*

**Table 7. Forecast Value of Arabica and Robusta Coffee Production and Yield (with Upper and Lower limit)**

| Year | Arabica Coffee | | | | | | Robusta Coffee | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Production (MTs) Forecast Value | Upper limit (95%) | Lower limit (95%) | Yield (Kg/hectare) Forecast Value | Upper limit (95%) | Lower limit (95%) | Production (MTs) Forecast Value | Upper limit (95%) | Lower limit (95%) | Yield (Kg/hectare) Forecast Value | Upper limit (95%) | Lower limit (95%) |
| 2023-24 | 97379.67 | 115968.1 | 78791.21 | 472.29 | 590.37 | 354.21 | 268655.2 | 424240.6 | 113069.9 | 1110.68 | 1360.36 | 861.00 |
| 2024-25 | 97983.75 | 115985.0 | 79982.47 | 428.54 | 550.88 | 306.20 | 270271.2 | 425094.7 | 115447.6 | 1121.86 | 1372.60 | 871.12 |
| 2025-26 | 104019.1 | 134487.5 | 73550.70 | 457.08 | 631.42 | 282.74 | 273575.0 | 427643.3 | 119506.8 | 1084.12 | 1400.14 | 768.10 |
| 2026-27 | 100794.2 | 126642.9 | 74945.52 | 437.00 | 616.64 | 257.36 | 278579.5 | 431898.9 | 125260.0 | 1090.20 | 1407.66 | 772.74 |
| 2027-28 | 97858.63 | 127532.9 | 68184.39 | 415.68 | 622.38 | 208.98 | 283583.9 | 436161.1 | 131006.6 | 1061.75 | 1412.45 | 711.05 |
| 2028-29 | 95982.60 | 127494.2 | 64471.02 | 442.45 | 663.69 | 221.21 | 288588.3 | 440430.0 | 136746.6 | 1061.53 | 1413.77 | 709.29 |
| 2029-30 | 94847.27 | 126821.2 | 62873.35 | 402.08 | 634.94 | 169.22 | 293592.7 | 444705.7 | 142479.8 | 1042.93 | 1413.79 | 672.07 |
| 2030-31 | 94165.77 | 126116.6 | 62214.95 | 412.09 | 665.99 | 158.19 | 298597.2 | 448988.3 | 148206.0 | 1043.69 | 1415.99 | 671.39 |
| 2031-32 | 93756.53 | 125570.5 | 61942.53 | 412.85 | 679.27 | 146.43 | 303601.6 | 453277.8 | 153925.4 | 1027.25 | 1410.49 | 644.01 |
| 2032-33 | 93510.41 | 125194.2 | 61826.63 | 380.61 | 660.09 | 101.13 | 308606.0 | 457574.4 | 159637.6 | 1026.72 | 1411.20 | 642.24 |
| 2033-34 | 93362.21 | 124949.0 | 61775.47 | 402.77 | 700.43 | 105.11 | 313610.4 | 461878.2 | 165342.7 | 1014.12 | 1405.18 | 623.06 |
| 2034-35 | 93272.91 | 124793.4 | 61752.39 | 379.31 | 689.13 | 69.49 | 318614.9 | 466189.3 | 171040.5 | 1012.90 | 1404.98 | 620.82 |

*Source: Author's calculation Using EView*

## 4.3 Diagnostic Checking

### 4.3.1 Autocorrelation and residual diagnostic

We have used automatic ARIMA forecasting for model identification and parameters estimation. After that we have go out for diagnostic checking of the selected best fitted models, and which has presented in Table 4 & Table 5. ARIMA (2, 1, 4) model for Arabica coffee production (ACP) with AR (1) = 0.7476, AR (2) = -0.0870, MA (1) = -0.7849, MA (2) = 1.1557, MA (3) = -0.7849, MA (4) = 0.9999, Intercept (θ) = 11.441, $\sigma^2$ = 0.0055, Adjusted $R^2$ = 0.6539, SER = 0.0834, AIC = -1.6696, SIC = -1.3249, RMSE = 10525.82, MAPE = 8.9399, MAE = 8170.18 and log likelihood = 39.723 has been identified as the best model for forecasting (given in Table 4 & table 5). ARIMA (3, 1, 2) model for Arabica coffee yield (ACY) with AR (1) = -2.0182, AR (2) = -1.7848, AR (3) = -0.5698, MA (1) = 1.1954, MA (2) = 0.9999, Intercept ($\mu$) = -6.6702, $\sigma^2$ = 2676.612, Adjusted $R^2$= 0.7653, Standard Error of Regression = 57.455, AIC = 11.2841, SIC = 11.5889, RMSE = 74.4532, MAPE = 9.3483, MAE = 58.5101 and log likelihood = -201.756 has been identified as the best model for forecasting (given in Table 4 & Table 5). ARIMA (0, 1, 3) model for Robusta coffee production (RCP) with MA (1) = 0.8242, MA (2) = 0.5090, MA (3) = -0.6848, Intercept (θ) = 5004.42, $\sigma^2$ = 2.39E+08, Adjusted $R^2$ = 0.5161, Standard Error of Regression (SER) = 16620.2, AIC = 22.5001, SIC = 22.7178, RMSE = 30375.63, MAPE = 16.0311, MAE = 25481.88 and log likelihood = -411.25 has been identified as the best model for forecasting (given in Table 4 & Table 5). ARMA (2, 0, 1) model for Robusta coffee yield (RCY) with AR (1) = 0.0653, AR (2) = 0.7644, MA (1) = 0.0266, Intercept (θ) = 950.31, $\sigma^2$ = 13535.10, Adjusted $R^2$ = 0.4632, Standard Error of Regression (SER) = 124.84, AIC = 12.6624, SIC = 12.8779, RMSE = 131.13, MAPE = 11.43, MAE = 111.76 and log likelihood = -235.58 has been identified as the best model for forecasting (given in Table 4 & Table 5). But, we have perform diagnostic checking before forecasting the above selected tentative models, because it is essential to perform diagnostic checking to avoid over fitting the ARIMA models. The steps of diagnostic checking as are follow:

- The lowest values of the AIC criterions is chosen as the best fitted model for the above selected models (given in table 4).
- The lowest values of the SIC/BIC criterions is chosen as the best fitted model for the above selected models (given in Table 4).
- ARIMA model parameters, viz., MAPE, RMSE, MAE, lowest value of Sigma square ($\sigma^2$ Volatility), Standard error of regression (SER), highest values of Adjusted R-square criterions is chosen as the best fitted model for the above selected models (given in Table 4).
- The Ljung-Box test result for Arabica coffee production (ACP) and Arabica coffee yield (ACY) respectively ARIMA (2, 1, 4) and (3, 1, 2), and Robusta coffee production (RCP) and Robusta coffee yield (RCY) respectively ARIMA (0, 1, 3), and (2, 0, 1) are shows insignificant at 5% level of significance (given in Table 6).
- After fitting the appropriate ARIMA models, the goodness of fit can be estimated by plotting the ACF of residuals of the fitted models. If most of the sample autocorrelation coefficients of the residuals lie within the limits ($\pm 1.96/\sqrt{N}$), where N = the number of observations, then the residuals are white noise indicating that the models fit are appropriate [25,12].
- The null hypothesis of this test is, there is no autocorrelation in residuals, and we have found that p-values shows insignificant of all the models, which is indicated that there is no autocorrelation. Therefore, we can be summarised that the residuals are not correlated with each other or in other words, it can be said that the residuals obtained from the models are independent from each other. The following Fig. 6 (a), Fig, 6 (b), Fig, 6 (c) and fig. 6 (d) represents the ACF of the residual, for models (2, 1, 4), (3, 1, 2), (0, 1, 3) and (2, 0, 1) respectively.
- Here, the goodness of fit of the ARIMA (2, 1, 4), (3, 1, 2), (0, 1, 3) and (2, 0, 1) models can be checked through Correlogram of residuals. Normally, a flat Correlogram with insignificant spikes is most ideal (represents in Fig. 6). So, we have go out for forecasting the above models (Forecasting result given in Table 7).

## 4.4 Forecasting of Selected ARIMA Models

### 4.4.1 Forecasting Results analysis of ARIMA models

This research study is based on annual amount of the Arabica and Robusta coffee production, and covering the period of 1986 to 2035 (50 observations); of which 38 observations ranging from 1986 to 2023 were historical data and 12 observations ranging the period of 2024 to 2035 is forecasted amount of Arabica and Robusta coffee production and yield. In table 7 exhibits the forecasting results of ARIMA (2, 1, 4), (3, 1, 2), (0, 1, 3) and (2, 0, 1) for Arabica and Robusta coffee production, and the ARIMA (2, 1, 4), (3, 1, 2), (0, 1, 3) and (2, 0, 1) models for Arabica and Robusta coffee which is observed as the best suitable model for predicting the future amount of Arabica coffee production, Arabica coffee yield, Robusta coffee production and Robusta coffee yield respectively; and we have estimated that the yearly amount of ACP and ACY achieved in the year 2023-24 from 97379.67 MTs, and 472.29 kg/hectare respectively to 93272.91 MTs, and 379.31 kg/hectare respectively in the year 2034-35 will decrease. The forecasting data series line of ARC and ACY continuous decreasing throughout the forecast period of 2023-24 to 2034-35 (given in table 7). Hence, we summarise that Arabica coffee production amount will decrease in the future, but Arabica coffee yield amount will stochastic increase in the future. Table 7 also presents upper and lower limit of ACP and ACY. We have also estimated that the yearly amount of RCP and RCY achieved in the year 2023-24 from 268655.21 MTs, and 1110.68 kg/hectare respectively to 318614.85 MTs, and 1012.90 kg/hectare respectively in the year 2034-35 will reach. The forecasting data series line of RCP continuous increasing throughout the forecasted period of 2023-24 to 2034-35, but RCY continuous decreasing throughout the forecast period of 2023-24 to 2034-35 (given in table 7). Hence, we summarise that Robusta coffee production amount will increase in the future, but Arabica coffee yield amount will decrease in the future. Table 7 also presents upper and lower limit of RCP and RCY.

## 5. CONCLUSION

Coffee is very popular in present time on the all over world. Among all the coffee producing regions, India is the only country where coffee is grown under shade. Indian coffee holds this great position among all the countries due to its taste, aroma, mild and less acidic nature. Forecasts of agricultural productions are useful to the farmers, policymakers and agribusiness industries. In this globalised world, there is a need for efficient and reliable production forecasting models to management of the food security in developing countries like India where agriculture is dominates. In this present study, ARIMA (2, 1, 4), (3, 1, 2), (0, 1, 3) and (2, 0, 1) models for Arabica and Robusta coffee which is observed as the best suitable model, for predicting the future amount of Arabica coffee production and yield, and Robusta coffee production and yield in India. Study result shows that the yearly amount of ACP and ACY achieved in the year 2023-24 from 97379.67 MTs, and 472.29 kg/hectare respectively to which will decrease in the year 2034-35 respectively 93272.91 MTs, and 379.31 kg/hectare. RCP and RCY achieved in the year 2023-24 from 268655.21 MTs, to which will increase 318614.85 MTs, and 1110.68 kg/hectare to which will decrease 1012.90 kg/hectare respectively in the year 2034-35. Finally, we summarises that Arabica coffee shows the negative trend in production and yield in the future, and Robusta coffee shows a positive and negative trend in production and stochastic trend on yield in the future. Thus, coffee producing farmers need to carry out production work keeping in mind the forecast of future production. If, the cost of production of coffee is increasing due to increase in labour and input costs. So, to increase the productivity of coffee, the farmers should be trained with adoption of good agricultural practices (GAP), and good management practices (GMP) for improving the yield of the planation. Moreover, the plantations should be maintained properly, and the planters may be incentivised for compensating the higher labour and input cost.

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## DATA AVAILABILITY STATEMENT

The required data used of this study has available at official website of the coffee board of India, web: https://coffeeboard.gov.in/database-coffee.html.

## COMPETING INTERESTS

Author has declared that no competing interests exist.

## REFERENCES


1. Gopinath M, Sweka S, Vishalakshi S. Forecasting of Coffee Production in India Using ARIMA Model, International Journal of Science, Engineering and Management (IJSEM). 2019;4(10).
2. Chandra RP, Brahme R, Patel SK. Stochastic models for Coffee Production and Productivity Forecasting in India, The Indian Economic Journal, (Journal of the Indian economic association). Special issue- Dec. 2023;(7):158-171.
3. Prakash KG, Ramesh D, Rao VS, Reddy G R. Statistical Modelling on India Coffee Exports - A Time Series Approach, The Andhra Agric. J. 2022;69(1):137-144.
4. Naveena K, Singh S, Rathod S, Singh A. Hybrid ARIMA-ANN Modelling for Forecasting the Price of Robusta Coffee in India, Int. J. Curr. Microbiol. App. Sci. 2017;6(7):1721-1726. Available:https://doi.org/10.20546/ijcmas.2017.607.207
5. Naveena K, Singh S, Singh A. Hybrid time series modelling for forecasting the price of washed coffee (Arabica Plantation Coffee) in India, International Journal of Agriculture Sciences. 2017; 9(10):4004–7.
6. Prabha SA, Sivakumar SD, Murugananthi D, Joel AJ. Trend in Area, Production and Yield of Coffee in India, Asian Journal of Agricultural Extension, Economics & Sociology. 2021;39(11): 310-320. Available:https://doi.org/10.9734/AJAEES/2021/v39i1130755
7. Coffee Board of India. Database on Coffee, 2023. Available:https://coffeeboard.gov.in/database-coffee.html
8. Yashavanth BS, Singh KN, Paul AK, Paul RK. Forecasting prices of coffee seeds using Vector Autoregressive Time Series Model, Indian Journal of Agricultural Sciences. 2017;87(6):754–8.
9. Chandra RP, Brahme R. Econometric modelling and forecasting of groundnut Production and Productivity in India using ARIMA model, The Indian Economic Journal, (Journal of the Indian economic association). Special issue- Dec. 2023;(7):01-14.
10. Deina C, Prates MHDA, Alves CHR, Martins MSR, Trojan F, Sergio LSJ, Siqueira HV. A methodology for coffee price forecasting based on extreme learning machines, Information Processing in Agriculture. 2022;9:556– 565. Available:https://doi.org/10.1016/j.inpa.2021.07.003
11. Krishnan P, Brahme R. Modelling and Forecasting foodgrains Production and Productivity in India using ARIMA model, The Indian Economic Journal (Journal of the Indian economic association), Special issue- Dec. 2023;(7): 642-654.
12. Chandra RP. Econometric Modeling for High Impact Sustainable Organic Tea Production: The Box-Jenkins Approach, Asian Journal of Economics, Business and Accounting. 2023;23(24): 141–154. DOI: https://doi.org/10.9734/ajeba/2023/v23i241193
13. Ahalya SP, Murugananthi D, Rohini A, Devi RP, Kalpana M. Study on Predicting the Price of Coconut in Tamil Nadu Market. Asian Journal of Agricultural Extension, Economics & Sociology. 2023;41(10):149–158. DOI: https://doi.org/10.9734/ajaees/2023/v41i102153
14. Esther NM, Wangui MN. ARIMA Modeling to Forecast Pulses Production in Kenya, Asian Journal of Economics, Business and Accounting. 2017;2(3):1–8. Available:https://doi.org/10.9734/AJEBA/2017/32414
15. Gujarati DN, Porter DC, Gunsekar S. Basic Econometrics, Revised edition, McGraw Hill Education, New Delhi; 2015.
16. Ashoka N, Naik BK, Kulkarni VS. Behavior of arabica coffee prices in international and Indian markets, Green Farming. 2014;5(6):1-5.
17. Hellin M. Gauss-Markow theorem in Statistics, Encyclopedia of Environmetrics. January 15, John Wiley & Sons Ltd; 2013. DOI:https://doi.org/10.1002/9780470057339.vnn102
18. Draxler TC. Root Mean Square Error (RMSE) or Mean Absolute Error (MAE)? – Argument against avoiding RMSE in the Literature, Geoscientific Model Development. 2014;7(3):1247-1250.
19. Gnana PK, Ramesh D, Rao VS, Reddy GR. Statistical Modelling on India Coffee Exports - A Time Series Approach, the Andhra Agric. J. 2022;69(1):137-144.

20. Borkar Prema. Time Series Analysis of Monthly Coffee (Robusta) Prices in India using Box-Jenkins Approach, Research Biotica. 2022;4(3):156-160. Available:https://doi.org/10.54083/ResBio/4.3.2022/156-160
21. Armstrong JS, Collopy F. Error measures for generalizing about forecasting methods: Empirical comparisons, International Journal of Forecasting. 1992; 8:69-80.
22. Goodwin P, Lawton R. On the asymetry of the symmetric MAPE, International Journal of Forecasting. 1999; 15:405-408.
23. Ren L, Glasure Y. Applicability of the revised mean absolute percentage errors (MAPE) approach to some popular normal and non-normal independent time series, International Advances in Economic Research. 2009;15:409-420.
24. Tofallis C. A Better Measure of Relative Prediction Accuracy for Model Selection and Model Estimation, Journal of Operations Research Society. 2015;66(8): 1352-1362.
25. Reddy CV. Modelling and Forecasting: NCDEX AGRIDEX, SCMS Journal of Indian Management. 2000;114-130.
26. Lewis CD. Industrial and business forecasting methods, London: Butterworths, p. 40. 1982.
27. Moreno JJM, Pol AP, Abad AS, Blasco BC. Using the R-MAPE index as a resistant measure of forecast accuracy, Psicothema. 2013;25(4):500-506. DOI:https://doi.org/10.7334/psicothema2013.23
28. Akaike H. A New look at the Statistical model Identification, IEEE Transactions on Automatic Countrol. 1974; 19(6):716-723. Available:https://doi.org/10.1109/TAC.1974.1100705
29. Priya SRK, Bajpai PK, Suresh KK. Stochastic models for sugarcane yield forecasting, Indian Journal of Sugarcane Technology. 2015;30(01):1-5.
30. Box G, Jenkins GM. Time Series Analysis: Forecasting and Control, Revised edition, Holden Day, San Francisco; 1978.
31. Khandelwal S, Mohanty D. Stock Price Prediction Using ARIMA Model, International Journal of Marketing & Human Resource Research, April, 2021;2(2).
32. Binuomote SO, Lukman AF, Olumide SO, Adeleke OA. Modelling Annual Yield of Coffee in Nigeria Using ARIMA Time Series Model (2018 – 2050), International Journal of Economic and Business Management. 2018;6(3):43-56.
33. Dickey DA, Fuller WA. Distribution of the Estimators for Autoregressive Time Series with a Unit Root, Journal of the American Statistical Association. 1979; 74:366a, 427-431, Taylor & Francis Online Published; 2012. Available:https://doi.org/10.1080/01621459.1979.10482531




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