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Article

Forecasting Farm Produce Inflation in Nigeria

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Abstract

Given the increasing costs of agricultural products, it is crucial to conduct a comprehensive analysis of inflation in farm produce in Nigeria. Effective policies must be developed that account for the overall price increases over time. This paper emphasizes the significance of price forecasting for agricultural products and seeks to statistically validate predictions for key crops in 2025, utilizing time series data from January 2009 to September 2024. Results were derived using univariate ARIMA modelling techniques. The study shows that the ARIMA model serves as a reliable forecasting tool, with practical models indicating price predictions for 2025. The low values of Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) further affirm the accuracy of these forecasts

Keywords: Inflation, Farm produce, ARIMA, Differencing method, Forecasting.

1. Introduction

Inflation is defined as a sustained increase in the general price level of goods and services in an economy over time. The inflation rate is considered a vital economic indicator for countries and is one of the most pressing and dynamic macroeconomic issues confronting economies worldwide [1]. Its fluctuating nature makes it an important matter to address. Numerous researchers and economists utilize a variety of time series and econometric models to forecast or analyse national inflation rates, recognizing its importance for economic growth. These models include Autoregressive Integrated Moving Average (ARIMA) models, Seasonal Autoregressive Integrated Moving Average (SARIMA) models, along with time domain models, error correction models, VAR, and other econometric techniques.

Farm produce are the Crops and other agricultural products sold by farmers [2]. Srivastava [3] carried out an Investigation on food inflation and found that the food inflation was found to be more volatile as compared to non-food inflation and followed a cyclical trend. Further, trend in food inflation was not uniform across different food commodities. Primary food articles were found to be the driving force for the overall food inflation. The improvement in marketing and processing infrastructure will help in reducing the food inflation. Although Nigeria relies heavily on the oil sector for its budgetary revenue, it remains primarily an agricultural country. As the main stay of the economy, agriculture remains the major source of food for most of the Nigerian population, providing the means of livelihood for over 70% of the population and a major source of raw materials for the agro-allied industries [4]. Badmus and Ariyo [5] focused on forecasting the cultivated area and production of maize in Nigeria using ARIMA and obtained result which shows maize production forecast for the year 2020 to be about 9952.72 thousand tons with lower and upper limits 6479.8 and 13425.64 thousand tons respectively and concluded from the study that, total cropped area can be increased in future, if land reclamation and conservation measures are adopted. Iqbal et al. [6] predicted the area and production of wheat in Pakistan up to the year 2022. The ARIMA model predicts that wheat production will hit 29,774.8 thousand tons in 2022. The potential for expanding both the cultivated area and overall production relies on several factors, including access to adequate resources, educating and training farmers, soil conservation and reclamation efforts, and particularly, supportive government policies aimed at enhancing wheat production in the country. Jadhav et al. [7] demonstrate the utility of price forecasting of farm produce, validating the same for major crops and obtained result from the application of univariate ARIMA techniques to produce price forecasts for cereal and precision of the forecasts were evaluated using the standard criteria of MSE, MAPE and Theils U coefficient criteria.

1.1 Some Useful Terms

ARIMA (Autoregressive Integrated Moving Average): A time series model combining autoregressive, differencing and moving average components to analyse and forecast data.

SARIMA (Seasonal Autoregressive Integrated Moving Average): This is an enhancement of the ARIMA model that accounts for seasonal variations.

VAR (Vector Autoregression): This statistical model is used to identify linear relationships among multiple time series by treating each variable as a linear function of its own past values and the past values of other variables in the system.

KPSS (Kwiatkowski-Phillips-Schmidt-Shin Test): This is a test designed to assess the stationarity of a time series, with the null hypothesis indicating that the series is stationary.

MSE (Mean Squared Error): This statistic represents the average of the squared differences between predicted values and actual outcomes.

MAPE (Mean Absolute Percentage Error): The average percentage error between predicted and actual values.

AIC (Akaike Information Criterion): A model selection criterion balancing fit and complexity, where lower values indicate better models.

SIC (Schwarz Information Criterion): Also known as BIC (Bayesian Information Criterion), is a criterion for model selection that penalizes complexity more than AIC and prefers lower values

HQC (Hannan-Quinn Criterion): A model selection criterion that penalizes complexity less than **BIC** but more than **AIC**.

ACF (Autocorrelation Function): A measure of the correlation between a time series and its lagged values.

PACF (Partial Autocorrelation Function): A measure of the correlation between a time series and its lagged values, excluding intermediate lags.

2 Methodology

2.1 Autoregressive Process {AR (p)}

An autoregressive process of order p denoted by AR (p) (an AR (p) model), is a time series (X_t) which satisfies the equation

$$X_t = m^1 + e_t + \phi_1 X_{n-1} + \phi_2 X_{n-2} + \ ...\ + \phi_p X_{n-p} \qquad (1.1.1)$$

$$\text{i.e. } X_t = m^1 + e_t + \sum_{k=1}^{p} \phi_k X_{n-k}$$

For t $\geq$ 0, where { e_t }$_n \geq 0$ is a series of independent, identically distributed (***i.i.d***) random variable and m^1 is some constant.

2.2 Moving Average Process {MA (q)}

The moving average technique is often used for linear fitting and as defined by Box and Jekins [8], a moving average process of order q denoted by MA(q) is a stationary time series { X_t } if it has the representation:

$$X_t = m^1 + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \ ...\ + \theta_q e_{t-q} \qquad (2.2.1)$$

$$\text{i.e. } X_t = m^1 + e_t + \sum_{k=1}^{q} \theta_k e_{t-k}$$

For t≥1 where { e_t } is a white noise process, E { e_t } = 0, Var{ e_t } = $\sigma^2 < \infty$, m^1 is the mean, also called constant and $\theta_1, \theta_2, \theta_3, \theta_4 ..., \theta_q$ are the parameters to be estimated in the given data. X_t is represented on the current value of the white noise process and the immediate passed value of the white noise process.

2.3 Autoregressive Moving Average Process {ARMA (p, q)}

According to Box and Jekins [8], an ARMA (p,q) process is the combination of pth-order autoregressive and qth-order moving average process. A time series { X_t } is considered an ARMA (p,q) process if it can be represented as follows:

$$X_t - \sum_{k=1}^{q} \theta_k e_{t-k} = m^1 + e_t + \sum_{j=1}^{q} \theta_j e_{t-j} \qquad (2.3.1)$$

It can also be represented as:

$$X_t = m^1 + e_t + \sum_{k=1}^{p} \phi_k x_{t-k} + \sum_{j=1}^{q} \theta_j e_{t-j} \geq 0$$

Where { X_t }≥1, m^1 is some constant and the ϕ_k and θ_i are defined as parameters for AR and MA models respectively.

An ARMA process is classified as stationary when its autoregressive (AR) component exhibits stationarity. Additionally, it is labelled invertible if the moving average (MA) component meets the criteria for invertibility.

2.4 Autoregressive Integrated Moving Average Process {ARIMA (p, d, q)}

Box and Jekins [8] defined the procedure for de-trending and unveiling hidden systematic patterns in non-stationary data since ARMA process only fits stationary data (i.e. shows no trend and seasonal variation).

The ARIMA process first takes a non-stationary time series and transforms it by differencing times, then, fits an ARIMA (p, d, q) model to the time series formed after the transformation. As explained earlier, sometimes non-stationary time series can be transformed into stationary ones through a process of differencing. This representation allows for the differencing of a non-stationary time series several times which can be considered as a single difference series (the trend part has been removed).

A time series (X_t) is classified as integrated of order d(I(d)), (d = 1, 2, 3, …, ∞). It is essential to recognize that all stationary time series are also integrated of order d(I(d)). When we perform differencing on the series and it can be represented as ARIMA (p,d,q), the time series can be expressed in the following manner:

$$\phi(L)\Delta^d X_t = \theta(L)e_t \tag{2.4.1}$$

If $(1-L)^{d-1} X_t$ is not stationary, then $(1-L)^d X_t$ is stationary and has the representation of the form: $$\phi(L)\Delta^d X_t = \theta(L)e_t \tag{2.4.2}$$

Where $\Delta^d (1-L)^d$ is a stationary series and $(1-L)^d$ represents regular difference number, and e_t is the white noise.

3.0 Data Collection and Analysis

3.1 Source of Data

The data used in this research work, "Analyses On Farm Produce Inflation in Nigeria", is from Nigeria National Bureau of Statistics (NBS), recorded (monthly) on inflation in All items index minus the All items less farm produce, from 2009 to 2024. The data is a secondary one extracted from the CPI_REPORT_SEPT_2024 [9]. Hence, the documentary method of collecting data is used for this research work as the observation was not directly done by the investigators; and the documentary data serve as a reliable source of information for this research.

3.2 Data Analysis

Steps involved in the Box-Jenkins Methodology

Stage1: Model identification and Selection

Stage2: Model Estimation

Stage3: Model Checking

Stage4: Forecasting

3.2.1 ARIMA Model Identification and Selection

Table 1: ARIMA model selection for the Farm Produce

Model	AIC	SIC	HQC
ARIMA(1,1,1)	583.8181	596.7211	589.0468
ARIMA(1,1,2)	569.1622	585.2909	575.6982
ARIMA(1,1,3)	564.4104	583.7649	572.2536
ARIMA(2,1,1)	584.3118	600.4405	590.8478
ARIMA(2,1,2)	557.8620	577.2164	565.7051
ARIMA(2,1,3)	554.8544	577.4346	564.0048
ARIMA(3,1,1)	575.4515	594.8059	583.2946
ARIMA(3,1,2)	554.7674	577.3476	563.9177
ARIMA(3,1,3)	556.6508	582.4567	567.1083

Table 1 was used to select nine models with low information criteria. The minimum AIC (Akaike Information Criterion) and HQC (Hannan-Quinn Criterion) was suitable for ARIMA (3, 1, 2) model, thus it was selected.

3.2.2 ARIMA Model Evaluation

Table 2: Result of ARIMA model evaluation for the Farm Produce

	Mean Squared Error	Root Mean Squared Error	Mean Absolute Error
ARIMA(3,1,2)	-0.015292	1.0073	0.72132

Table 2 above found the best model with the minimum MSE which was found to be ARIMA (3, 1, 2).

3.2.3 ARIMA (3, 1, 2) Model Estimation

Once the optimal model has been selected, the next step involves estimating its parameters. The outcomes of this estimation, along with a residual normality test, are presented in the table below:

Table 3: Result of ARIMA model identification for the Farm Produce

Parameters	Coefficient	Std. Error	Z	P-value
Constant	0.00234939	0.00261297	0.8991	0.3686
Phi_1	0.114654	0.0727652	1.576	0.1151***
Theta_1	−1.96156	0.0181551	−108.0	0.0000 ***
Theta_2	0.989252	0.0187383	52.79	0.0000 ***

3.2.4 Model Checking

One simple diagnostic test to check if the model selected above is a reasonable fit to the data is to obtain residuals of the estimated model (ARIMA (3,1,2) and obtain the following tests.

Table 4: Result of ARIMA (3,1,2) model checking

Test	Level of Significance	Test Statistics	P-Value
Chi-Square	5%	36.0486	1.48646e-08
ARCH	5%	9.88587	0.999983

ACF and PACF of these residuals

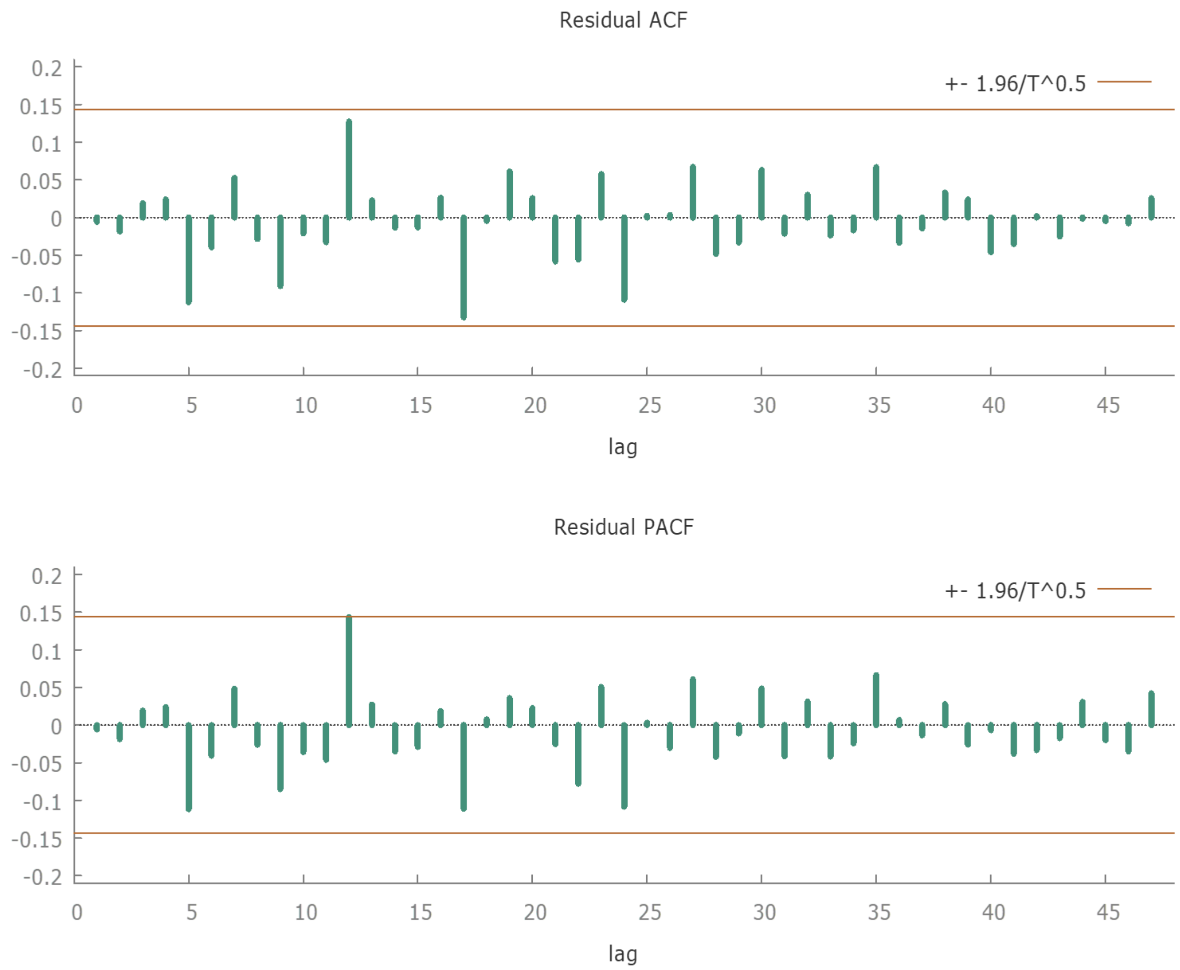

Figure 1: Farm Produce Residual Correlogram

3.2.5 Forecasting

This is one of the factors contributing to the popularity of ARIMA modeling. Often, the forecasts produced using this approach are more precise than those derived from conventional econometric models.

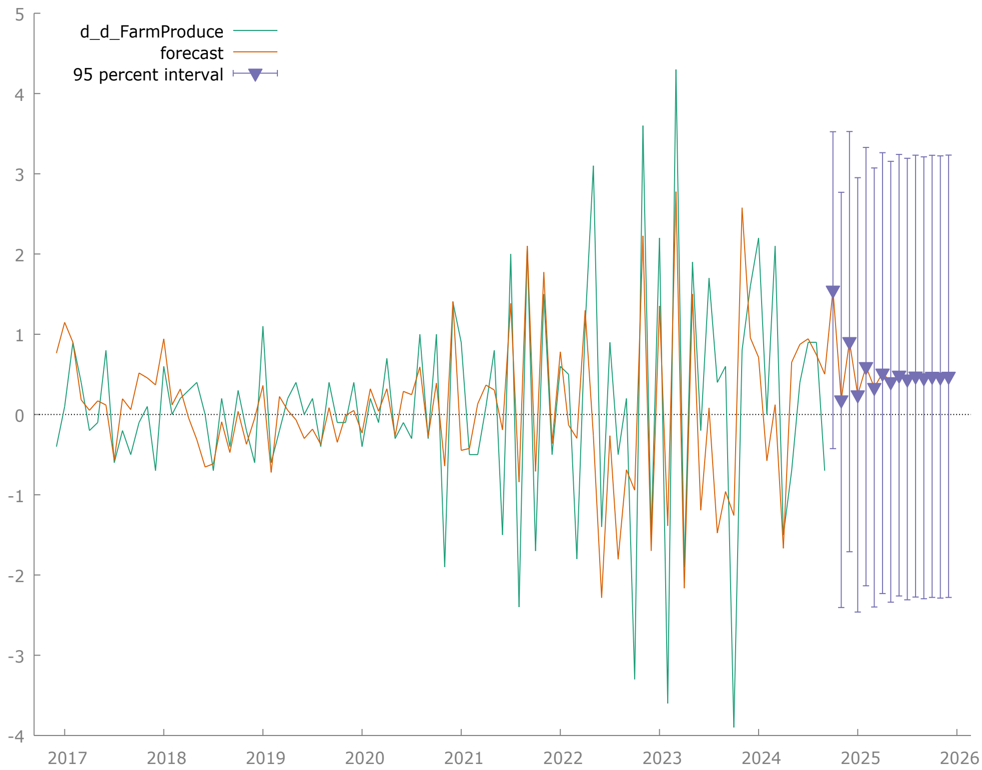

Figure 2: The forecast result given by ARIMA(3,1,2) Model of the first difference of the log Farm Produce.

Figure 2 plots the actual and the predicted one year three months' future values of Farm Produce given by ARIMA (3,1,2) showing the behaviour of the future values. It can be asserted that the model was adequate for the data.

4.0 Results and Discussion

4.1 Stationarity Tests: Graphical Analysis

4.1.1 Graph of Series before Differencing

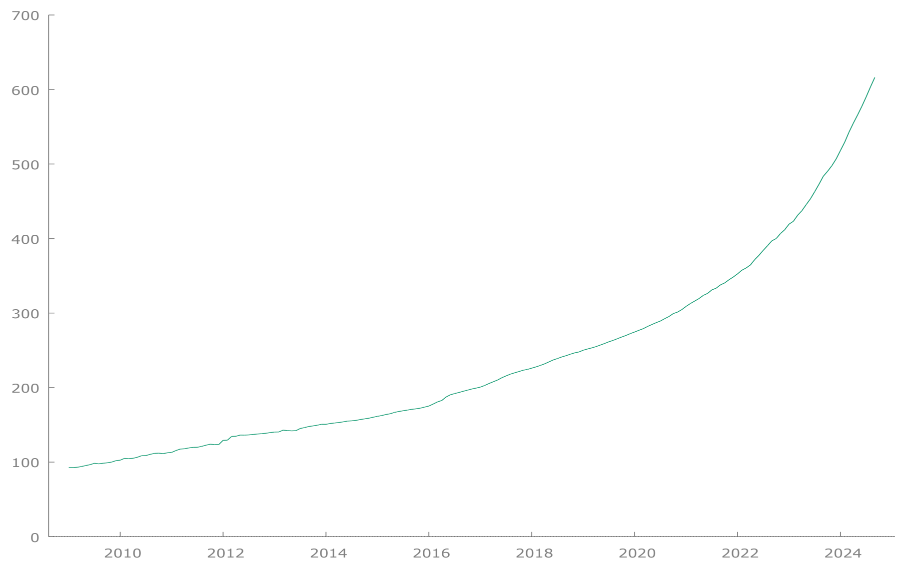

Figure 3: Before differencing

Figure 3 which is a time plot of the series under analysis provides the initial basis for the likely features of the time series of Farm Produce. The time period for this study shows that the log of the Farm Produce has a tendency to increase with time. This is a sign of positive trend and we can hypothesize that there has been some fluctuation in the average amount of Farm Produce logged within Nigeria on the basis of time or chronology. Thus, the series is said to be non-stationary

4.1.2 Graph of ACF and PACF for Farm Produce before differencing

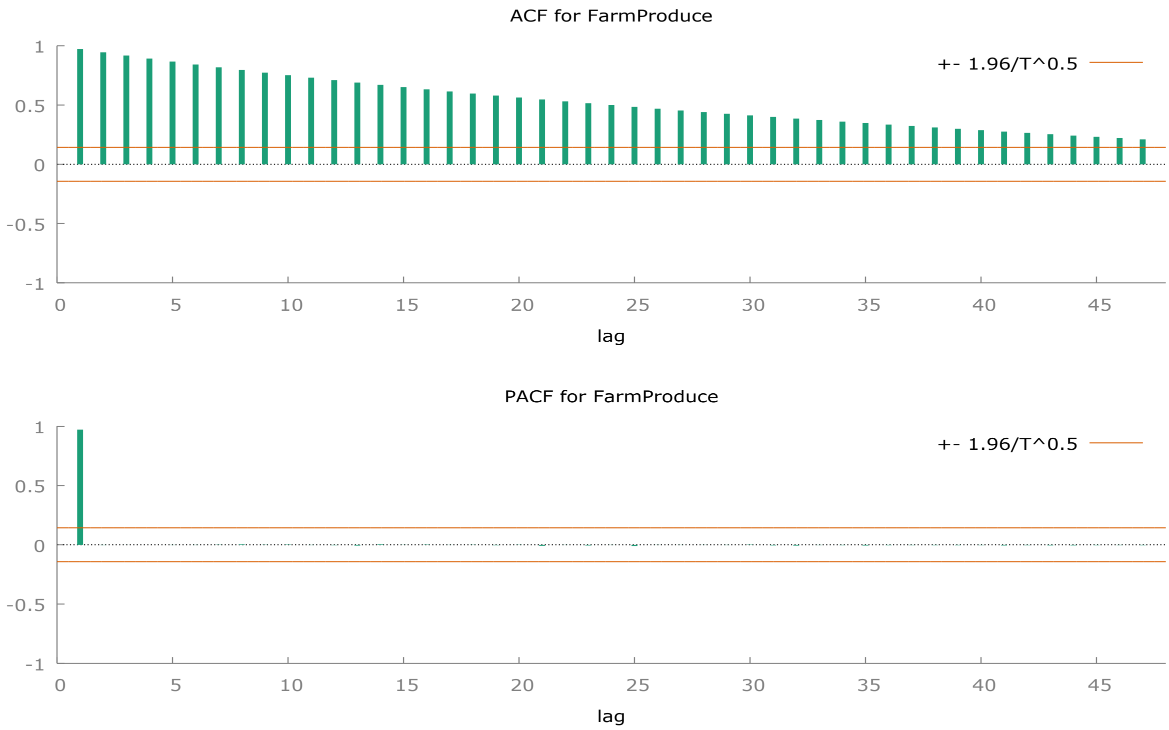

Figure 4: The ACF and PACF of Farm Produce before differencing

The correlogram (ACF and PACF) for the Farm Produce data series prior to differencing is illustrated in Figure 4 above. A notable aspect of this correlogram is the presence of high autocorrelation coefficients at various lags, beginning with lag 1 at 0.9719*** and extending to lag 47 months, with lag 34 at 0.2104***. All these values are statistically significant, as they exceed the 95% confidence limits. This pattern suggests that the time series is non-stationary. The autocorrelation begins at a very high level and gradually decreases towards zero as the lags increase. In contrast, the PACF displays a sharp drop after the first lag, with most PACF values beyond lag 1 being statistically insignificant.

4.1.3 Unit Root Tests before Differencing

Table 5: ADF tests before Differencing

Test	Test Statistics	P-Value
Without constant	-1.46262	0.1344
With constant	0.792473	0.994
With constant and Trend	5.35829	1.0000

Stationary Test before Differencing

KPSS TEST H_0: The series is stationary.

Table 6 KPSS tests for Farm Produce

Test	Test Statistics	Critical Value
With Trend	0.156257	5% (0.148)
Without trend	0.514924	5%(0.462)

Table 6 shows the results of the Augmented Dickey-Fuller and KPSS unit root tests, which indicate that the Farm Produce series is non-stationary, as the test statistics surpass the critical values at specific levels.

Given that the Farm Produce time series is non-stationary, it must be converted into a stationary series prior to implementing the Box-Jenkins methodology. This conversion is achieved by calculating the first difference of the series; if it continues to exhibit non-stationarity, the second difference is taken.

4.1.4 Time plot of the series after second differencing

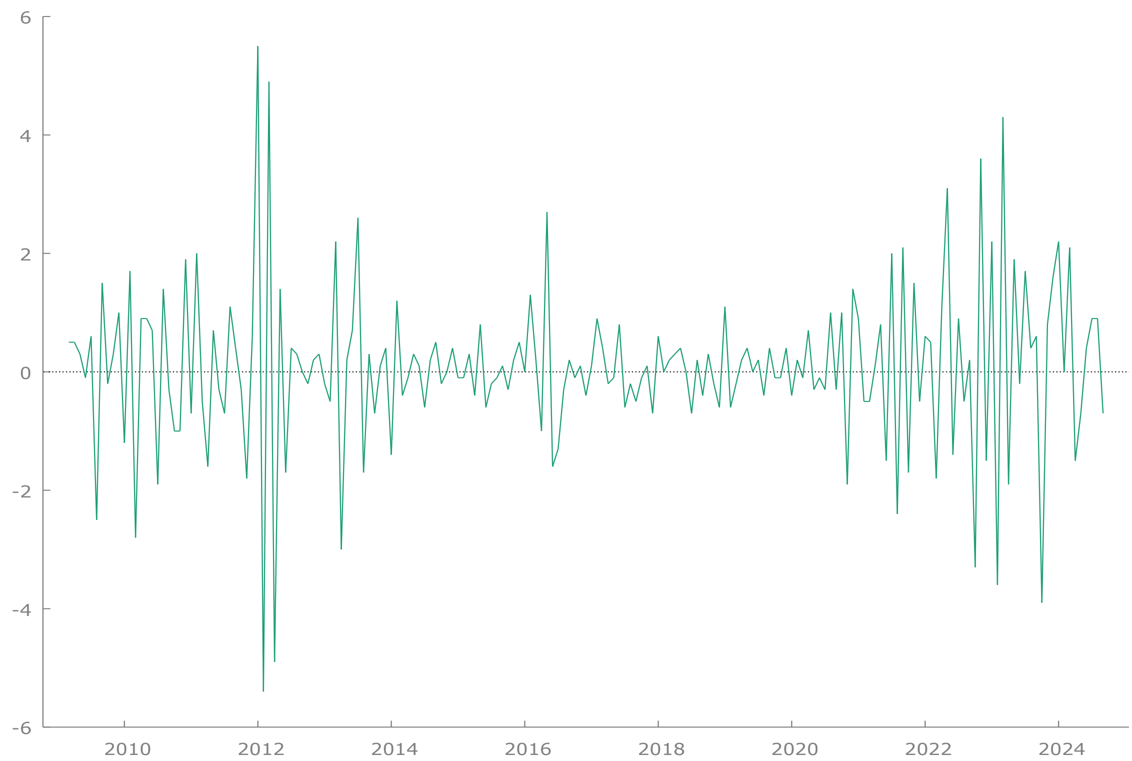

Figure 5: After first differencing

The first differences of the Farm Produce series are shown in figure 5 above. Unlike the plot in Figure 3, this plot does not exhibit any trend, suggesting that the first differences of the Farm Produce series are stationary. This observation is further supported by the ACF and PACF correlogram displayed below.

4.1.5 ACF and PACF after Second Difference of the Log FARM PRODUCE

Figure 4.4 below displays the ACF and PACF correlogram, showing a similar pattern. The ACF values at lags 1, 2, 3, 4, 5, 12, and 17 appear to be statistically significant at the 95% confidence level, indicating they are asymptotic and can be regarded as approximations, while values at other lags do not show statistical significance. Therefore, we can infer that the data series has become stationary.

4.1.6 Unit Root Tests after first Differencing

Table 7: ADF Tests after first Differencing

Test	Test Statistics	P-Value
Without constant	1.51288	0.9684
With constant	-8.98526	5.306e-16
With constant and trend	-9.10794	2.44e-16

Stationary Test after first Differencing

KPSS Tests: H_0: The series is stationary

Table 8: KPSS Tests after first Differencing

Test	Test Statistics	Critical Value
With trend	0.146637	5% (0.148)
Without trend	0.335035	5% (0.462)

Interpretation

As all the test statistics from the ADF tests fall below the critical thresholds, we reject the null hypothesis. This suggests that there is no unit root present, indicating that the time series is stationary and likely fluctuates around a deterministic trend rather than exhibiting a stochastic trend. In the KPSS tests, the test statistics are consistently lower than the p-values, leading us to accept the null hypothesis. This further confirms that the data series is stationary around a deterministic trend

Conclusion

Through our analysis, we successfully navigated the steps of the Box-Jenkins Methodology. After applying the first difference to the Farm Produce data, we confirmed its stationarity through formal ADF and KPSS tests. We identified ARIMA (3,1,2) as the most suitable and efficient model, which we then used to forecast values for the next three years. Since all ADF test statistics fell below the critical values, we rejected the null hypothesis. This indicates the absence of a unit root, suggesting that the time series is stationary—without trends, seasonal variations, or concealed patterns—and does not exhibit a stochastic trend. Rather, it may revolve around a deterministic trend. In the KPSS tests, all test statistics were lower than the p-values, leading us to accept the null hypothesis and affirm that the data series is stationary around a deterministic trend. This outcome indicates a suitable model fit and suggests readiness for additional analysis. The findings suggest a precarious future for the Nigerian economy based on the Farm Produce forecast. There is a pressing need for the government and policymakers to implement strategies that will enhance and stabilize the macroeconomic framework of Nigeria and its agricultural sector. Future research should also explore multivariate models that incorporate additional variables, potentially including the SARIMA model.

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The author(s) hereby declare that the work presented in this article is original and that any liability for claims relating to the content of this article will be borne by them.

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APPENDIX

Farm Produce Index (2009 – 2024)

	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Jan	**92.6**	**102.6**	**113.0**	**129.2**	**140.3**	**150.7**	**161.4**	**175.2**	**200.6**	**226.1**	**250.1**	**274.6**	**309.0**	**352.7**	**419.3**	**518.2**
Feb	**92.6**	**105.0**	**115.5**	**129.4**	**140.5**	**151.8**	**162.5**	**177.9**	**202.8**	**227.8**	**251.8**	**276.9**	**312.8**	**357.5**	**423.1**	**529.5**
Mar	**93.1**	**104.6**	**117.5**	**134.5**	**142.9**	**152.5**	**163.9**	**180.8**	**205.4**	**229.7**	**253.3**	**279.1**	**316.1**	**360.5**	**431.2**	**542.9**
Apr	**94.1**	**105.1**	**117.9**	**134.7**	**142.3**	**153.1**	**164.9**	**182.7**	**207.8**	**231.9**	**255.0**	**282.0**	**319.5**	**364.6**	**437.4**	**554.8**
May	**95.4**	**106.5**	**119.0**	**136.3**	**141.9**	**154.0**	**166.7**	**187.3**	**210.1**	**234.5**	**257.1**	**284.6**	**323.7**	**371.8**	**445.5**	**566.0**
Jun	**96.6**	**108.6**	**119.8**	**136.2**	**142.2**	**155.0**	**167.9**	**190.3**	**213.2**	**237.1**	**259.2**	**287.1**	**326.4**	**377.6**	**453.4**	**577.6**
Jul	**98.4**	**108.8**	**119.9**	**136.5**	**145.1**	**155.4**	**168.9**	**192.0**	**215.7**	**239.0**	**261.5**	**289.3**	**331.1**	**384.3**	**463.0**	**590.1**
Aug	**97.7**	**110.4**	**121.1**	**137.1**	**146.3**	**156.0**	**169.8**	**193.4**	**218.0**	**241.1**	**263.4**	**292.5**	**333.4**	**390.5**	**473.0**	**603.5**
Sep	**98.5**	**111.7**	**122.7**	**137.7**	**147.8**	**157.1**	**170.8**	**195.0**	**219.8**	**242.8**	**265.7**	**295.4**	**337.8**	**396.9**	**483.6**	**616.2**
Oct	**99.1**	**112.0**	**124.0**	**138.1**	**148.6**	**158.0**	**171.5**	**196.5**	**221.5**	**244.8**	**267.9**	**299.3**	**340.5**	**400.0**	**490.3**	
Nov	**100.0**	**111.3**	**123.5**	**138.7**	**149.5**	**158.9**	**172.4**	**198.1**	**223.3**	**246.6**	**270.0**	**301.3**	**344.7**	**406.7**	**497.8**	
Dec	**101.9**	**112.5**	**123.6**	**139.6**	**150.8**	**160.2**	**173.8**	**199.3**	**224.4**	**247.8**	**272.5**	**304.7**	**348.4**	**411.9**	**506.9**	