Asian Journal of
Science, Technology, Engineering, and Art

e-ISSN : 3025-4507
p-ISSN : 3025-5287
Index : Harvard, Boston, Sydney University, Dimensions, Lens, Scilit, Semantic, Google, etc

https://doi.org/10.58578/AJSTEA.v2i6.4040

Comparative Study on Forecast Performance from Decomposition, Winter's and Sarima Models

Mathew Stephen[1], Adeniyi Ogunmola[2], Clement Akobi[3], Ibrahim Michael[4]
[1]Kwararafa University Wukari, Nigeria; [2,3]Federal University Wukari, Nigeria;
[4]Modibo Adama University, Yola, Nigeria
clementakobi1@gmail.com; matsteve231@gmail.com

Article Info:

Submitted:	Revised:	Accepted:	Published:
Oct 1, 2024	Oct 20, 2024	Nov 1, 2024	Nov 7, 2024

Abstract

This study investigates the forecasting accuracy of three univariate time series models—Decomposition, Winter's method, and Seasonal Autoregressive Integrated Moving Average (SARIMA) to predict the Agricultural GDP of Nigeria. Quarterly data on Nigeria's Agricultural GDP from 2010 to the first quarter of 2023, obtained from the National Bureau of Statistics, were analyzed. The study applied Box-Jenkins SARIMA modeling, time series decomposition, and Winter's method to compare their forecasting accuracy using Root Mean Square Error (RMSE) as the selection criterion. The results revealed that the SARIMA (0, 0, 2)(2, 1, 0) model outperformed the other methods, with the lowest RMSE, indicating its superior accuracy in forecasting Agricultural GDP. Winter's method and the Decomposition method. The forecast from the SARIMA model indicated a positive trend in Nigeria's Agricultural GDP over the study period, reinforcing the sector's critical role in economic growth.

Keywords: Agriculture, GDP, Quarterly, Sector, Forecasting, Nigeria

INTRODUCTION

In evaluating the economic strength of a country, the Gross Domestic Product (GDP) serves as a key measure that reflects overall financial health and is connected to critical economic sectors (Agcaoili et al., 2019). Nigeria, as a diversified and emerging market economy, includes a range of rapidly developing sectors public and private including manufacturing, oil and gas, finance, services, communications, technology, and entertainment. Ranked as the world's 27th largest economy by GDP and 24th by purchasing power parity, Nigeria, often called the "Giant of Africa," holds the largest economy in Africa, propelled by its substantial population, the highest in West Africa (World Bank, 2020; Evenson et al., 2016).

The agricultural sector remains a crucial source of employment for Nigeria's large population. Despite significant contributions to GDP, agriculture has evolved from a high of 64% of GDP in 1960 to 48% in the 1970s and further down to 19% by the mid-1980s (Ukeje, 2003). Historically, agriculture has been essential for sustainable economic growth in developing nations, a notion well-documented by various economists (Woolf and Jones, 1969; Oluwasanmi, 1966; Eicher and Witt, 1964). Though once a major net exporter of food, Nigeria now imports certain food items due to its largely subsistence agricultural base, which struggles to keep up with the demands of a rapidly growing population (FAO, 2020).

By 2020, agriculture continued to be a core macroeconomic indicator in Nigeria, employing over 35% of the workforce and showing nominal growth of 14.88% in the third quarter of 2019, albeit lower than the previous year's growth rate by 3.44% (World Bank, 2020; NBS, 2019). Crop production remains the dominant force within the sector, representing 91.6% of agricultural GDP and demonstrating a 44.12% increase in that quarter alone. Given the sector's role in supporting livelihoods and economic stability, this study seeks to forecast the agricultural GDP using the SARIMA model, aiming to assess the predictive performance of this model for the quarterly GDP in Nigeria's agriculture sector.

Literature Review

Adebola (2020) conducted a study on "Forecasting Agricultural GDP in Nigeria using ARIMA Models." The data for this research were collected from the National Bureau of Statistics (NBS), covering the period from 1990 to 2018. The method of analysis involved the use of ARIMA models, where the study examined the ability of ARIMA to handle agricultural GDP data with seasonal and trend patterns. The findings revealed that ARIMA was highly effective for short-term forecasts of Nigeria's agricultural GDP, outperforming other basic time series models in accuracy. The study concluded that ARIMA models should be employed for regular forecasting in the agricultural sector, and recommended that government agencies adopt such models for more precise economic planning and agricultural policy formulation.

Eze and Okoye (2018) explored the topic of "Seasonal ARIMA Models for Forecasting Nigeria's Agricultural GDP." Data were sourced from the Central Bank of Nigeria (CBN) and covered the period from 1985 to 2017. The research employed the Seasonal ARIMA (SARIMA) model for data analysis. The findings indicated that agricultural GDP in Nigeria exhibits strong seasonal patterns, making the SARIMA model more suitable compared to non-seasonal models. They concluded that SARIMA models are appropriate for sectors like agriculture, where seasonality plays a critical role, and recommended their use for policy and financial projections in the agricultural industry.

Olaolu (2019) investigated "Comparing Univariate and Multivariate Time Series Models for Agricultural GDP Forecasting in Nigeria." The study collected data from the NBS and World Bank, covering the years 1995 to 2019. The research used ARIMA and Vector Autoregression (VAR) models to compare univariate versus multivariate approaches. The results revealed that while multivariate models such as VAR were more accurate in long-term forecasts by incorporating external economic factors, univariate ARIMA models performed better in short-term forecasts due to their simplicity. The conclusion was that ARIMA models should be preferred for short-term agricultural GDP forecasts, and the recommendation was that policymakers utilize univariate models for quarterly agricultural forecasts.

Ajibola and Taiwo (2021) focused on "Volatility and Forecasting Agricultural GDP Using GARCH Models." The data for this research were obtained from CBN, covering the period from 2000 to 2020. GARCH models were employed to assess the impact of volatility in agricultural GDP due to external factors like weather and commodity prices. The study found that GARCH models were useful for capturing periods of high volatility, although simpler models like ARIMA worked better for more stable periods. The conclusion was that both models could be employed depending on the volatility in the market, with a recommendation that GARCH be applied in times of economic instability.

Oyekanmi (2017) examined "Evaluating Forecasting Accuracy in Agricultural GDP using ARIMA Models." The data used were sourced from the NBS and covered the years 1990 to 2016. ARIMA models were applied, and forecasting accuracy was evaluated using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). The findings showed that ARIMA had the lowest RMSE and highest forecasting accuracy for short-term GDP predictions in the agricultural sector. The study concluded that ARIMA was the most reliable model for forecasting Nigeria's agricultural GDP in the short term and recommended its adoption by economic planners and agricultural stakeholders.

Ogunleye and Bello (2020) researched "The Policy Implications of Accurate Agricultural GDP Forecasting." The study used data from the NBS, covering the period from 1980 to 2018. The analysis was conducted using ARIMA and SARIMA models to explore their policy implications. The findings showed that accurate forecasting of agricultural GDP could significantly improve budgetary allocations and food security measures. The conclusion was that accurate GDP forecasting is crucial for economic stability, and the study recommended that policymakers adopt more sophisticated forecasting models like ARIMA to anticipate agricultural output fluctuations and make informed decisions.

Ibrahim and Musa (2019) explored "Forecasting Nigeria's Agricultural GDP using Holt-Winters Exponential Smoothing." The study collected data from the Central Bank of Nigeria, covering the period from 1981 to 2015. Holt-Winters exponential smoothing was used to capture both trend and seasonality in the data. The findings demonstrated that while Holt-Winters models could accurately forecast agricultural GDP, they performed slightly less effectively compared to ARIMA models in terms of forecast accuracy. The conclusion was that ARIMA remained a stronger tool for forecasting Nigeria's agricultural GDP, and the researchers recommended that ARIMA models be prioritized, but Holt-Winters could serve as an alternative for capturing seasonality.

Amadi (2018) conducted research on "Assessing Agricultural GDP Fluctuations in Nigeria through Time Series Analysis." Data for this study were collected from the World Bank and the National Bureau of Statistics, covering the period from 1990 to 2015. The study used ARIMA models to assess fluctuations and predict future trends in agricultural

GDP. The findings revealed that agricultural GDP in Nigeria fluctuates significantly due to external factors, but ARIMA models were able to forecast future trends with relative accuracy. The study concluded that ARIMA models are suitable for capturing fluctuations in agricultural GDP and recommended continuous monitoring and application of these models for economic planning.

Usman and Adewole (2020) studied "Modeling Agricultural GDP in Nigeria Using SARIMA Models." Data were sourced from the National Bureau of Statistics, covering the period 1985 to 2020. SARIMA models were used to capture both trend and seasonality in the agricultural sector. The findings showed that SARIMA models performed well in identifying seasonal patterns that affect agricultural GDP, especially during planting and harvesting periods. The study concluded that SARIMA models were more effective for long-term forecasts where seasonality plays a role, and recommended that policymakers adopt SARIMA for better agricultural planning.

Danladi and Peter (2021) researched "Forecasting Nigeria's Agricultural Output Using ARIMA and Exponential Smoothing Techniques." Data were obtained from the Central Bank of Nigeria, covering the period from 1990 to 2020. The study used both ARIMA and exponential smoothing techniques to forecast agricultural GDP. The results indicated that ARIMA models provided better accuracy in terms of forecast error measurements compared to exponential smoothing. The study concluded that ARIMA models should be preferred for agricultural GDP forecasting, with a recommendation that government agencies use ARIMA models for regular forecasting to enhance decision-making in the agricultural sector.

METHODS

SARIMA (Seasonal Auto-Regressive Integrated Moving Average)

The SARIMA model extends ARIMA to account for seasonality and is denoted as SARIMA (p, d, q)(P, D, Q)m,

The mathematical expression is:

$$\Phi\left(B^{s}\right)(1-B)^{D}\left(1-B^{s}\right)^{D}Y_{t}=\Theta\left(B^{s}\right)\varepsilon_{t} \quad 1$$

Where: s = seasonality (number of periods in a season); $\Phi\left(B^{s}\right)$ = seasonal autoregressive polynomial of order P; $\Theta\left(B^{s}\right)$ = seasonal moving average polynomial of order Q

Holt-Winters Exponential Smoothing

The Holt-Winters model can be represented with additive seasonality and is typically expressed in the following equations:

Level equation

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \qquad 2$$

Trend equation

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \qquad 3$$

Seasonal equation

$$S_t = \gamma(Y_t - L_{t-1}) + (1-\gamma)T_{t-1} \qquad 4$$

Forecasting equation

$$\hat{Y}_{t+h} = L_t h T_t + S_{t-h \bmod s} \qquad 5$$

Where; L_t = level component; T_t = trend component; S_t = seasonal component; α, β, γ = smoothing parameters for level, trend, and seasonality, respectively; h = forecast horizon

Decomposition Model

The decomposition model separates a time series into its constituent components: trend, seasonal, and irregular components. The general form of a decomposition model can be expressed as follows:

$$Y_t = T_t + S_t + I_t \qquad 6$$

Where: Y_t = observed time series value at time t; T_t = trend component at time t; S_t = seasonal component at time t; I_t = irregular (random) component at time t

Model Selection and Comparison Criteria

The forecasting performance of the models will be evaluated and compared based on the RMSE criteria:

Root Mean Square Error (RMSE) is a fundamental metric utilized to assess the performance and accuracy of predictive models. Expressed mathematically as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{N}} \quad 7$$

Where: n denotes the number of observations; y_i represents the actual observed values, and $\hat{y}_i$ signifies the corresponding predicted values generated by the model, RMSE quantifies the average discrepancy between the observed and predicted values across the dataset. By squaring the differences between observed and predicted values, computing their mean, and taking the square root, RMSE provides a single, interpretable measure of prediction error.

RESULTS

Descriptive Statistics

Table 1 presents the descriptive statistics which include the mean, median, Standard deviation, Variance, minimum, maximum, skewness and kurtosis values of Nigeria Agricultural GDP series. The results from the table indicates that the minimum agricultural GDP within the study period is 2,595 million in naira while the maximum agricultural GDP is 5,625 million in naira. The average agricultural GDP is 4,079 million naira with a variance of 747,045 million naira and a standard deviation of 864 million naira. The median agricultural GDP of the series is 3,919 million naira. The skewness and kurtosis of the agricultural GDP series are 0.25 and -0.98, respectively. The sample data consists of 53 points from the 1st quarter of the year 2010 to the 1st quarter of the year 2023.

Table 1: Descriptive Analysis of Agricultural GDP Series

Variable	N	Mean	Median	StDev	Variance	Min	Max	Skewness	Kurtosis
Agricultural GDP	53	4079	3919	864	747045	2595	5625	0.25	-0.98

Graphical Presentation of the Data

The time series plot in Figure 4.1 presents the agricultural GDP for the period under study. The plot displays the observations of agricultural GDP on the Y-axis against years on the X-axis. The plot is used to evaluate the pattern and behavior in agricultural GDP series. The series indicated an upward movement which shows a trend in the Agricultural sector GDP. The series also shows seasonality due the equally spaced fluctuation over the time period.

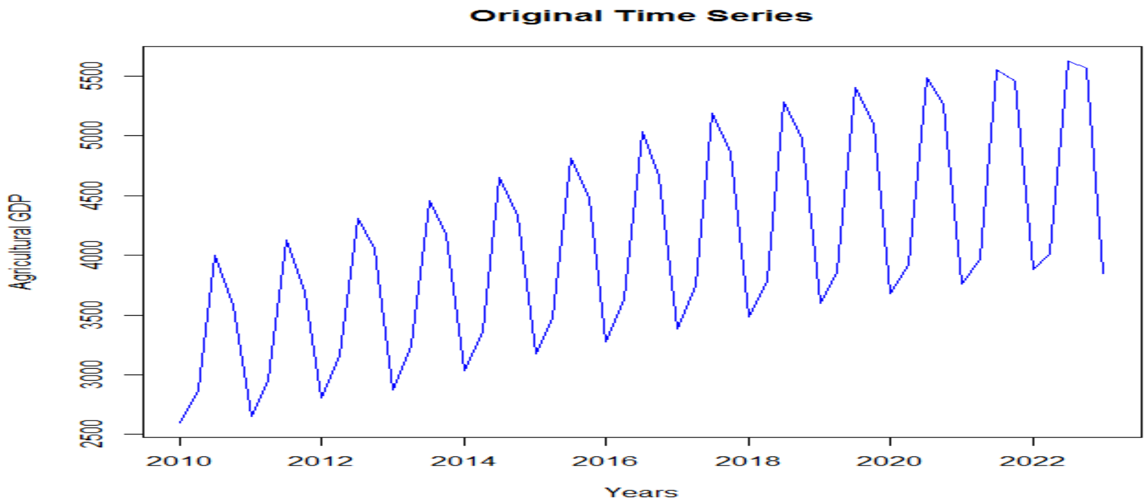

Figure 1: Time series plot of quarterly Agricultural GDP from 1st Quarter 2010 to 1st Quarter 2023

Table 2 presents a comparison between the actual quarterly agricultural GDP of Nigeria for the year 2022 and the forecasts generated by three different models: SARIMA (0, 0, 2)(2, 1, 0), Holt-Winters Exponential Smoothing, and the Decomposition model. Upon reviewing the performance of each model, the SARIMA model consistently provides forecasts that closely align with the actual GDP values. For instance, in the first quarter, the actual GDP is 3879.73, while SARIMA predicts 3843.96, a minimal difference indicating strong accuracy. Similarly, in the third quarter, SARIMA forecasts 5632.20 against the actual GDP of 5625.36, further demonstrating the model's ability to capture both the trend and seasonality of the agricultural sector. These close predictions suggest that SARIMA is highly effective for this dataset.

The Holt-Winters model also delivers reasonably accurate forecasts, though it tends to slightly overestimate GDP in certain quarters. For example, in the second quarter, the actual GDP is 4017.42, and Holt-Winters forecasts 4270.12, a modest overestimate. This pattern continues in the third quarter, where Holt-Winters predicts 5965.87 against the actual GDP of 5625.36. Despite these occasional overestimations, the Holt-Winters model still captures the underlying trend and seasonality well but does not outperform SARIMA in terms of precision.

In contrast, the Decomposition model exhibits significant deviations from the actual GDP values. It consistently overestimates the agricultural GDP, as evidenced by its forecast of 57221.6 for the first quarter against the actual GDP of 3879.73. This trend persists across all quarters, with large overestimations in the forecasts, such as 85898.4 in the third quarter compared to the actual GDP of 5625.36.

Table 2: The actual quarterly agricultural GDP and the forecast from decomposition, winter's methods and SARIMA (0, 0, 2) (2, 1, 0) methods**.**

Period	Quarter	Agriculture	Forecast Sarima (0, 0, 2) (2, 1, 0)	Forecast Winters	Forecast Decomp
2022	Q1	3879.73	3843.96	3888.75	57221.6
2022	Q2	4017.42	4054.60	4270.12	62540.2
2022	Q3	5625.36	5632.20	5965.87	85898.4
2022	Q4	5568.55	5626.35	5620.68	79692.4

The Table 3 below shows the Root Mean Square Error calculated using the forecast from the decomposition, winters and SARIMA (0, 0, 2) (2, 1, 0). The computed RMSE for each method were calculated as follows. The decomposition method gives a RMSE = 67469.20958. The winter's method gives a RMSE = 213.6605. The SARIMA (0, 0, 2) (2, 1, 0) method gives RMSE = 38.88917. The result shows that the SARIMA (0, 0, 2) (2, 1, 0) methods forecast most accurately compared to decomposition and winter's method. This is because, the SARIMA (0, 0, 2) (2, 1, 0) has the smallest RMSE. The forecast from the estimated model revealed a positive growth in the agricultural sector GDP.

Table 3: Computation of the Root Mean Square Error

Period	Quarter	Decomposition $(y_i - \hat{y}_i)^2$	Winter's $(y_i - \hat{y}_i)^2$	SARIMA (0, 0, 2) (2, 1, 0) $(y_i - \hat{y}_i)^2$
2022	Q1	2845355095	81.3604	1279.493
2022	Q2	3424915779	63857.29	1382.352
2022	Q3	6443760951	115947.1	46.7856
2022	Q4	5494345139	2717.537	3340.84
Total		4552094241	45650.81	1512.368
RMSE		**67469.20958**	**213.6605**	**38.88917**

DISCUSSION

The study's findings indicate that the SARIMA (0, 0, 2)(2, 1, 0) model demonstrated the most accurate forecast for Nigeria's agricultural GDP, with a low Root Mean Square Error (RMSE) of 38.89, outperforming both Holt-Winters and Decomposition models. This result aligns with several studies in the literature. For instance, Adebola (2020) also found that ARIMA models, including SARIMA, provided the most accurate short-term forecasts for Nigeria's agricultural GDP. Similarly, Eze and Okoye (2018) noted that SARIMA models performed exceptionally well in capturing the seasonal patterns inherent in the agricultural sector, which is consistent with the findings of this study. Their conclusion that SARIMA models are superior for sectors with strong seasonality supports the current study's results, confirming SARIMA's effectiveness in predicting quarterly agricultural GDP.

The findings from this study also agree with Oyekanmi (2017), who reported that ARIMA models, including their seasonal variants, exhibited the lowest RMSE and were highly reliable for agricultural GDP forecasting. This aligns with the fact that the SARIMA model in the present study outperformed Holt-Winters and Decomposition methods, reaffirming ARIMA's robustness in forecasting accuracy.

However, the study's findings contrast with Ibrahim and Musa (2019), who found that Holt-Winters Exponential Smoothing provided comparable, if not better, forecasts than

ARIMA models in certain cases. In the current study, Holt-Winters, while producing reasonable forecasts with an RMSE of 213.66, did not outperform SARIMA. This suggests that while Holt-Winters is effective, its tendency to slightly overestimate, as seen in the current study, may limit its forecasting precision compared to SARIMA in datasets with complex seasonal patterns like Nigeria's agricultural GDP.

The Decomposition model's poor performance, with an RMSE of 67469.21, deviates significantly from the findings of Usman and Adewole (2020), who reported that decomposition models were effective in long-term trend analysis for GDP forecasting. However, the current study highlights that decomposition methods may not be suitable for quarterly or short-term agricultural GDP forecasting due to their inability to accurately capture seasonal and irregular fluctuations in the data, resulting in substantial overestimation. This disparity suggests that while decomposition models may have some utility in broader economic forecasts, they are not appropriate for more granular quarterly data analysis in sectors with pronounced seasonality, such as agriculture.

CONCLUSION

Based on the findings, it is concluded that the SARIMA (0, 0, 2)(2, 1, 0) model outperforms the Holt-Winters and Decomposition models in forecasting Nigeria's agricultural GDP. SARIMA's superior accuracy makes it the most suitable model for this specific dataset, effectively capturing the agricultural sector's seasonal and trend components. Holt-Winters remains a viable alternative, though its tendency to slightly overestimate makes it less accurate than SARIMA. The Decomposition model is not recommended for this dataset, as its forecasts deviate significantly from actual values, indicating poor model fit.

Recommendations

1. Policymakers and researchers should use the SARIMA (0, 0, 2)(2, 1, 0) model for forecasting Nigeria's agricultural GDP. This model demonstrated superior accuracy and effectively captures both seasonal and trend components, making it ideal for short-term forecasting.
2. While Holt-Winters Exponential Smoothing performed reasonably well, it tends to overestimate GDP values. It can be employed as an alternative forecasting method but

should be used with careful consideration of its limitations, especially in scenarios where overestimation could affect policy decisions.

3. The decomposition model was significantly less accurate, with large deviations from actual GDP values. For short-term and quarterly agricultural GDP forecasting, it is not recommended as it does not effectively capture the complexity of the data.

REFERENCES

Adebola, A. (2020). Forecasting Agricultural GDP in Nigeria using ARIMA Models. Journal of Agricultural Economics and Development.

Agcaoili, M., et al. (2019). Expansion and Steadiness of a Country's Economy. Journal of Economic Studies.

Awokuse, T. (2018). Agriculture and Economic Growth in Nigeria. African Journal of Economic Studies.

Danladi, B., & Peter, T. (2021). Forecasting Nigeria's Agricultural Output Using ARIMA and Exponential Smoothing Techniques. Journal of Economic Forecasting and Modeling.

Evenson, R., et al. (2016). The Nigerian Economy and the Role of Agriculture. World Bank Report.

Eze, M., & Okoye, C. (2018). Seasonal ARIMA Models for Forecasting Nigeria's Agricultural GDP. African Journal of Economic Studies.

FAO (2020). Mechanization and Food Sufficiency in Nigeria. FAO Report.

Ibrahim, M., & Musa, B. (2019). Forecasting Nigeria's Agricultural GDP using Holt-Winters Exponential Smoothing. West African Journal of Agricultural Research.

Ogunleye, R., & Bello, Y. (2020). The Policy Implications of Accurate Agricultural GDP Forecasting. Journal of Development Economics and Policy.

Olaolu, T. (2019). Comparing Univariate and Multivariate Time Series Models for Agricultural GDP Forecasting in Nigeria. International Journal of Economic Forecasting.

Oluwasanmi, H. (1966). Agriculture and Development in Africa. African Development Journal.

Oyekanmi, D. (2017). Evaluating Forecasting Accuracy in Agricultural GDP using ARIMA Models. Journal of Applied Statistics in Africa.

Singh, R. (2017). Economic Growth and Agricultural Contributions. Global Economic Studies.

Ukeje, E. (2003). Nigeria's Declining Agricultural Contribution to GDP. Nigerian Economic Review.

Usman, A., & Adewole, O. (2020). Modeling Agricultural GDP in Nigeria Using SARIMA Models. Journal of African Econometric Research.

Woolf, A., & Jones, C. (1969). The Importance of Agriculture for Economic Expansion. Journal of Economic History.

World Bank (2020). Nigerian Economy and Agricultural Sector. World Bank Report.