

Article

Comparative evaluation of ARFIMA and SARIMA models for forecasting rice production in Nigeria

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Abstract: Accurate forecasting of agricultural output is critical in ensuring effective planning for food security in Nigeria. This study compares and evaluates the forecasting efficiency of the Autoregressive Fractionally Integrated Moving Average (ARFIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models in forecasting rice production in Nigeria. Annual rice production data from 1960 to 2024 were collected from the Central Bank of Nigeria Statistical Bulletin and subjected to time series econometric analysis. The data series was checked for stationarity using the Augmented Dickey-Fuller test before estimating both ARFIMA and SARIMA models. The performance of both models was evaluated using forecast accuracy measures such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). The study found that the SARIMA (1,1,1) model provided a better fit and forecasting efficiency compared to the ARFIMA model in forecasting rice production in Nigeria. The SARIMA model provided lower forecast error values (RMSE = 0.04476; MAE = 0.03842) and a lower MAPE of 1.047%, indicating a forecasting accuracy of 98.95%. The study concluded that rice production in Nigeria is better forecasted using short-memory seasonal structures of the SARIMA (1,1,1) model than using fractional long-memory processes of the ARFIMA model. The study recommends the use of the SARIMA (1,1,1) model for effective forecasting of rice production to support agricultural planning and policy formulation.

Keywords: rice production; forecasting; SARIMA; ARFIMA; agricultural forecasting.

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1. Introduction

Rice serves as a crucial staple in Nigeria, eaten by various socioeconomic classes and playing a vital role in food security, job creation, and economic growth. In the last twenty years, the demand for rice has surged significantly because of population increase, urban expansion, and evolving consumption habits [1], [2]. In spite

of several government measures designed to enhance local production, including initiatives like the Anchor Borrowers' Programme and the Presidential Fertilizer Initiative, Nigeria still relies significantly on rice imports to satisfy domestic needs. This discrepancy emphasizes the pressing requirement for precise predictions of rice output to inform policy development, resource distribution, and farming strategies [3], [4], [5]. Predicting agricultural output, especially for rice, allows stakeholders to foresee future shortages or excesses, enhance input efficiency, and formulate data-driven strategies. Time series modeling has been extensively utilized in this context, with conventional models like the Autoregressive Integrated Moving Average (ARIMA) and its seasonal variant, SARIMA, ranking as some of the most frequently employed methods. The SARIMA model is recognized for its efficiency in modeling time series data featuring seasonal patterns and has demonstrated strong results in agricultural forecasting endeavors [6], [7], [8], [9], [10]. Although these studies confirmed the effectiveness of SARIMA models in capturing seasonal variations and short-term fluctuations in agricultural output data, some researchers argued that SARIMA models may produce suboptimal forecasts when the underlying series exhibits persistent long-range dependence and strong autocorrelation structures. This limitation becomes particularly important in agricultural production systems where shocks and trends may persist over long periods. A significant drawback of SARIMA is its assumption of short-memory processes, limiting its capability to capture long-term dependencies in data. In several agricultural situations, such as rice cultivation, shocks or trends might have lasting impacts that persist over extended durations, making it essential to utilize models that can incorporate long-memory characteristics [11], [12], [13]. The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model overcomes this constraint by permitting fractional differencing, which allows the model to encapsulate both short- and long-memory behaviors within one framework [14], [15], [16]. Recent developments in time series econometrics have underscored ARFIMA's ability to exceed traditional integer-differenced models when addressing persistent and autocorrelated data structures [17], [18], [19], [20].

The growing application of ARFIMA models in Nigerian time series studies further supports their relevance in modeling persistent data structures. [21] utilized the ARFIMA framework to model malaria morbidity data and emphasized the suitability of fractional integration for capturing long-memory behavior in temporal datasets. [17] as well as [19] demonstrated that ARFIMA models generally outperform conventional ARIMA and SARIMA models in datasets characterized by strong long-memory persistence. Similarly, [18] observed that fractional integration techniques enhanced forecasting accuracy in economic and agricultural time series affected by persistent shocks. These findings suggest that while SARIMA models are effective for modeling seasonal behavior, ARFIMA models may provide greater flexibility and improved forecasting performance where long-term dependence exists. However, even with its strong theoretical foundation, ARFIMA is still not widely used in agricultural forecasting research in Nigeria. The lack of empirical studies contrasting ARFIMA and SARIMA in relation to rice production forecasting indicates a notable deficiency in the literature. Many current studies have mainly used SARIMA or ARIMA models, potentially missing the enhanced predictive accuracy that ARFIMA could provide in long-memory situations. While SARIMA models have demonstrated efficiency in short-term, seasonal predictions, they might not completely utilize the memory characteristics present in agricultural time series. The lack of empirical research evaluating the relative effectiveness of SARIMA and ARFIMA in modeling rice production data from Nigeria indicates a methodological and practical deficiency. Closing this gap is crucial for increasing forecasting accuracy and refining agricultural policy formulation. Despite the widespread use of SARIMA models in agricultural forecasting, their assumption of short-memory processes may limit forecasting accuracy when agricultural production data exhibit persistent long-term dependence. Although ARFIMA models provide a flexible framework for capturing both short- and long-memory dynamics, empirical studies comparing the forecasting

performance of SARIMA and ARFIMA models for rice production in Nigeria remain limited. Consequently, the most suitable model for accurately forecasting Nigerian rice production has not been sufficiently established, thereby creating a methodological gap in agricultural forecasting literature and policy planning. Due to the strategic significance of rice in Nigeria's food economy and the long-memory characteristics seen in its production patterns, it is crucial to recognize and utilize models that reflect both seasonal and enduring trends. The SARIMA model, although strong for seasonal patterns, might struggle to accurately model data with considerable autocorrelations that extend beyond the seasonal lag components. On the other hand, the ARFIMA model offers the ability to incorporate fractional differencing, enhancing its flexibility in detecting fundamental long-term dependencies [22], [16]. Consequently, a comparative assessment of these two models is required to determine the more appropriate tool for predicting rice production in Nigeria. This research utilizes empirical data to evaluate the forecasting accuracy of ARFIMA and SARIMA models through common assessment metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Akaike Information Criterion (AIC). The results are anticipated to assist agricultural stakeholders in choosing the most suitable model for planning and executing policies. The study aims to examine the presence of long-memory characteristics in Nigeria's rice production data, develop and compare the forecasting performance of ARFIMA and SARIMA models using standard evaluation metrics, and determine the most suitable model for improving agricultural forecasting and policy planning in Nigeria.

2. Methodology

2.1. Material Selection

The data utilized in this study consists of annual rice production figures from Nigeria for a duration of sixty-five years, spanning from 1960 to 2024. The information has been obtained from the Central Bank of Nigeria Statistical Bulletin, a reliable source of agricultural and economic data in Nigeria. Every figure represents the complete Nigerian rice output in metric tons for the given year. The dataset's time series nature indicates that the data is both sequential and continuous. Preliminary analysis indicates consistent non-stationarity and long-memory features, characteristics commonly found in agricultural time series [9], [23], [24]. These characteristics necessitate the use of advanced statistical techniques capable of identifying both short-term variations and long-term relationships within the data. These characteristics make the dataset highly appropriate for fractional time series modeling techniques, while also supporting long-range dependence and improving predictive precision. This validated the selection of the ARFIMA model. Similarly, because of its yearly periodic nature and possible seasonal or cyclical variations, the SARIMA model is regarded as a suitable standard for comparison [10], [8]. This research employs two rival time series models: the Seasonal Autoregressive Integrated Moving Average (SARIMA) model and the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model. These models are selected for their distinct advantages in capturing seasonal and long-memory traits that are inherent in agricultural production data [17], [19].

3. Theoretical Results

3.1. The ARFIMA Model

The Autoregressive Fractionally Integrated Moving Average (ARFIMA) model extends the conventional ARIMA model by enabling fractional differencing, which makes it ideal for time series data that show long memory or persistence. This frequently occurs with agricultural time series such as rice production, where shocks (like policy shifts or climatic events) can lead to long-lasting effects.

To grasp ARFIMA, we start with the conventional ARIMA (p, d, q) framework. ARIMA, representing

Autoregressive Integrated Moving Average, integrates three elements: autoregression (AR), differencing (I) to achieve stationarity, and moving average (MA). The ARIMA(p, d, q) model is expressed as:

$$Y_t = c + \sum_{i=1}^p \phi_i Y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t, \quad (1)$$

where Y_t is the value of the time series at time t , c denotes a constant term, ε_t is the white noise, and ϕ_i and θ_j are the parameters of the autoregressive and moving average part, respectively.

In this standard ARIMA model, d is an integer representing the count of differences required to reach stationarity. The ARIMA model incorporates short memory characteristics via integer differencing. By permitting d to assume fractional values ($0 < d < 0.5$), we derive the ARFIMA(p, d, q) model. If we allow d to take on fractional values ($0 < d < 0.5$), we obtain the ARFIMA(p, d, q) model.

Hence, the ARFIMA model is written as:

$$\phi(B)(1-B)^d Y_t = \theta(B)\varepsilon_t, \quad (2)$$

where $d \in \mathbb{R}$ and typically $0 < d < 0.5$, $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$ is the autoregressive (AR) polynomial of order p , $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$ is the moving average (MA) polynomial of order q , $(1-B)^d$ is the fractional differencing operator with d being a real number such that $0 < d < 0.5$ and ε_t is a white noise error term.

In this model, the fractional differencing operator $(1-B)^d$ is defined using a binomial expansion:

$$(1-B)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)}{\Gamma(-d)\Gamma(k+1)} B^k. \quad (3)$$

This extension enables the adaptable representation of long-range dependence by utilizing a diminishing weight framework for previous observations. The primary unique element of ARFIMA is the fractional differencing term $(1-B)^d$, permitting the model to capture long-term dependence in the data while avoiding excessive differencing. When d is a fraction, the series is considered long memory; specifically, past values exert a diminishing yet significant impact on future values as time progresses.

3.2. The SARIMA Model

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model enhances the standard ARIMA model by including both seasonal and non-seasonal elements. SARIMA is especially useful for time series data showing seasonal trends, typical in agricultural production patterns like rice farming.

To achieve stationarity in the series, ARIMA incorporates differencing of order d , and the model is represented in operator notation as shown in (2).

To account for seasonality, SARIMA adds seasonal components. SARIMA model is typically denoted as SARIMA(p, d, q)(P, D, Q) $_s$, where p , d , and q represent the order of the non-seasonal autoregressive, differencing, and moving average terms respectively, and P , D , and Q are the corresponding seasonal components. The parameter s denotes the length of the seasonal period.

The general SARIMA model equation is given by:

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t, \quad (4)$$

where Y_t is the value of the time series at time t , B is the backshift operator such that $B^k Y_t = Y_{t-k}$, $\phi_p(B)$ and $\theta_q(B)$ are the non-seasonal autoregressive (AR) and moving average (MA) polynomials, $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ are the seasonal AR and MA polynomials, $(1-B)^d$ and $(1-B^s)^D$ are the non-seasonal and seasonal differencing components, respectively, ε_t is a white noise error term.

The model structure allows SARIMA to capture recurring seasonal trends and cycles observed in agricultural time series [20]. In the context of rice production in Nigeria, SARIMA can account for regular seasonal patterns such as rainfall cycles, planting, and harvesting seasons that repeat annually.

The selection of SARIMA and ARFIMA for this study is informed by the underlying characteristics of the rice production data. SARIMA is well-suited for modeling seasonality and short-term dynamics, which are often present in agricultural cycles such as rainfall, planting, and harvesting. On the other hand, ARFIMA is chosen for its ability to capture long-range dependencies and persistent shocks, which are evident from the time series' slow-decaying autocorrelations and structural influences spanning multiple decades.

By employing both models, this study offers a robust comparative framework for evaluating the performance of short-memory seasonal models versus long-memory fractional models in forecasting Nigeria's rice production. This approach enhances the reliability of forecasts and supports better agricultural policy and planning decisions.

3.3. Evaluation, Comparison of Models and Selection Criteria

To evaluate and compare the forecasting performance of the SARIMA and ARFIMA models, standard forecast accuracy measures and model selection criteria were employed. Forecast evaluation is essential in time series analysis because it helps determine the model that provides the most accurate and reliable predictions for future observations [7],[6]. In this study, the performance of the competing models was assessed using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Akaike Information Criterion (AIC).

3.3.1. Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^T (\hat{y}_t - y_t)^2}, \quad (5)$$

where $\hat{y}_t$ represents the forecasted rice production value at time t , y_t denotes the actual observed rice production value, and T is the total number of observations used in the analysis.

3.3.2. Mean Absolute Error (MAE)

The MAE is computed as:

$$MAE = \frac{1}{T} \sum_{t=1}^T [\hat{y}_t - y_t]. \quad (6)$$

3.3.3. Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error (MAPE) is a scale-independent measure that expresses forecast error as a percentage of the observed values, thereby facilitating comparison across different forecasting models. It is given by:

$$MAPE = \frac{100}{T} \sum_{t=1}^T \left[\frac{\hat{y}_t - y_t}{y_t} \right]. \quad (7)$$

Lower values of RMSE, MAE, and MAPE indicate better forecasting performance and higher predictive accuracy of the fitted model.

3.3.4. Akaike Information Criterion (AIC)

In addition to forecast error measures, the Akaike Information Criterion (AIC) was employed for model selection. The AIC, introduced by [25], is a widely used information-theoretic criterion for comparing competing statistical models (i.e., the suitability of the SARIMA and ARFIMA models in forecasting rice production in Nigeria). The criterion balances model goodness-of-fit with model complexity by penalizing excessive parameters, thereby reducing the risk of overfitting [6]. The model with the lowest AIC value is

generally considered the most appropriate model among competing alternatives.

The AIC is mathematically expressed as:

$$AIC = -2 \ln(L) + 2k, \quad (8)$$

where L represents the maximum likelihood of the fitted model, which reflects how well the model explains the rice production data, while k denotes the number of estimated parameters in the model.

Accordingly, the SARIMA and ARFIMA models were compared based on their respective RMSE, MAE, MAPE, and AIC values, and the model with the lowest forecast errors and minimum AIC value was selected as the most suitable model for forecasting rice production in Nigeria.

4. Application

This section presents the practical application of the SARIMA and ARFIMA models to the annual rice production data in Nigeria. The analysis begins with a graphical examination of the original time series in order to understand the underlying pattern, trend behavior, and possible fluctuations present in the data before model estimation and forecasting procedures are carried out.

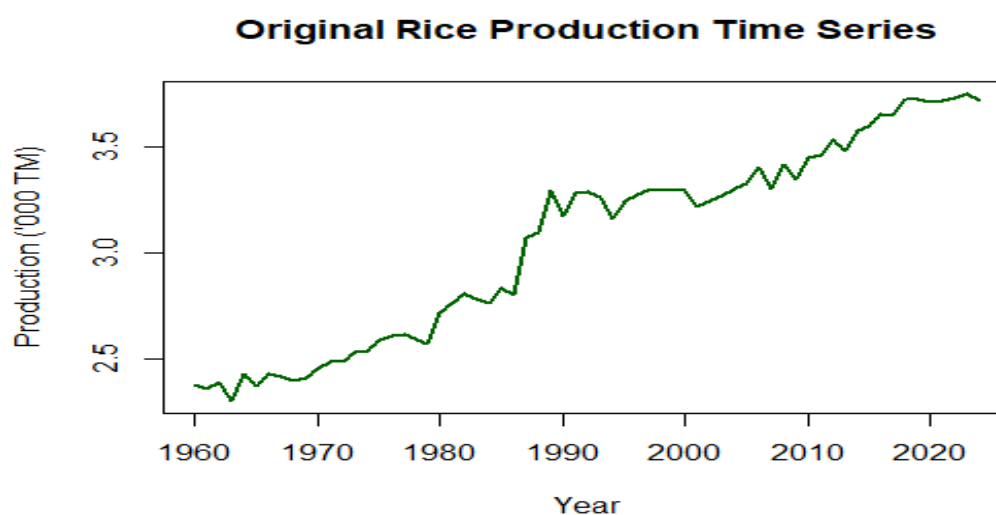


Figure 1. Original rice production time series.

The time series plot in Figure 1 demonstrates how the production of rice has evolved. The visual analysis indicates a potential trend component, which implies that there were some gradual changes in the production levels during the given period. There are also certain fluctuations, which demonstrate the cyclic rises and falls in production as a result of seasonal shifts, policy interventions, or environmental factors. The overall trend of the series indicates that there is a possible growth process, but the fluctuations between the periods imply that the series cannot be rigidly stationary. Therefore, to make reliable statistical inferences and forecasting behavior, a stationarity transformation is required before the use of ARIMA-type models.

4.1. Stationary Test

To determine whether the rice production series is stationary, the Augmented Dickey–Fuller (ADF) test was applied. The results of the unit root test are presented in Table 1.

Table 1. Augmented Dickey-Fuller test result (first difference).

Test	Value
Dickey-Fuller Statistic	-4.152
Lag Order	3.000
p-value	< 0.010

The null hypothesis of the ADF test states that the time series possesses a unit root, implying that the series is non-stationary. The alternative hypothesis states that the series is stationary. The test statistic of -4.152 with a p-value less than 0.01 indicates strong statistical evidence against the null hypothesis. This means that the differenced rice production series is stationary at the 1% significance level. The rejection of the unit root hypothesis confirms that the first differencing transformation successfully removed the non-stationary characteristics of the original series. Consequently, the differenced series can be used for model identification and estimation in the ARIMA framework.

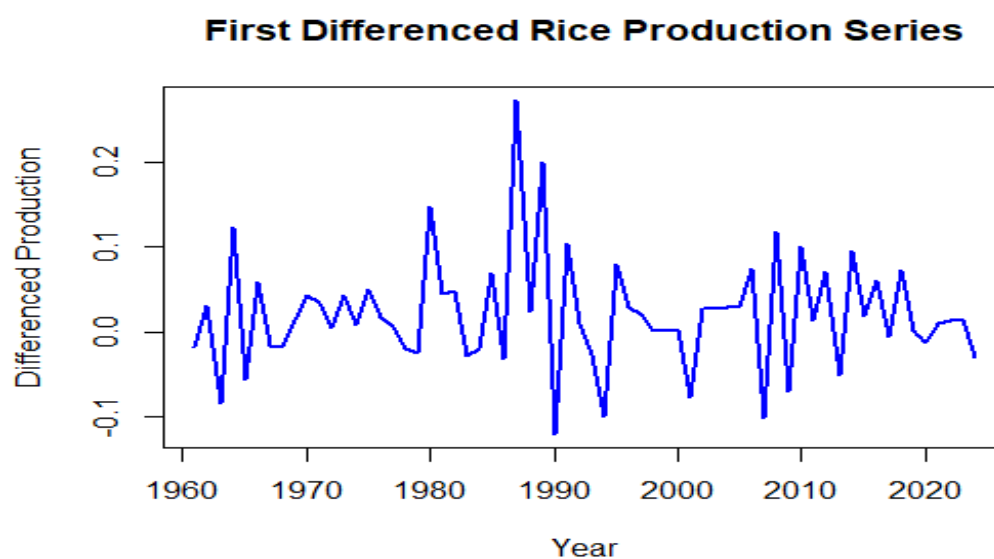


Figure 2. First-differenced rice production series.

Figure 2 shows the first-differenced rice production series. it can be seen that the differenced series seems to have a relatively fixed mean, thus suggesting that the overall direction that the original data are taking is eliminated. Besides, the deviation of the observations seems more solid, which can indicate that the variance has been fixed. These features affirm that the series is now appropriate for autoregressive and moving average modelling.

4.2. Model Identification and Estimation

Following the achievement of stationarity through first differencing, the stationary rice production series was subjected to model identification and estimation. The ACF and PACF plots were examined to determine the appropriate autoregressive and moving average structures suitable for the data.

The ACF plot in Figure 3 demonstrates the gradual erosion trend, which indicates the appearance of a moving average component. These plots, in combination, do not rule out the hypothesis that the model that should be specified is ARIMA (1,1,1), i.e., it has one autoregressive, one differencing, and one moving average term. This specification is the basis of SARIMA model estimation. Figure 4 shows the PACF plot has a large spike at lag one, as would be due to an autoregressive process of order one (AR (1)).

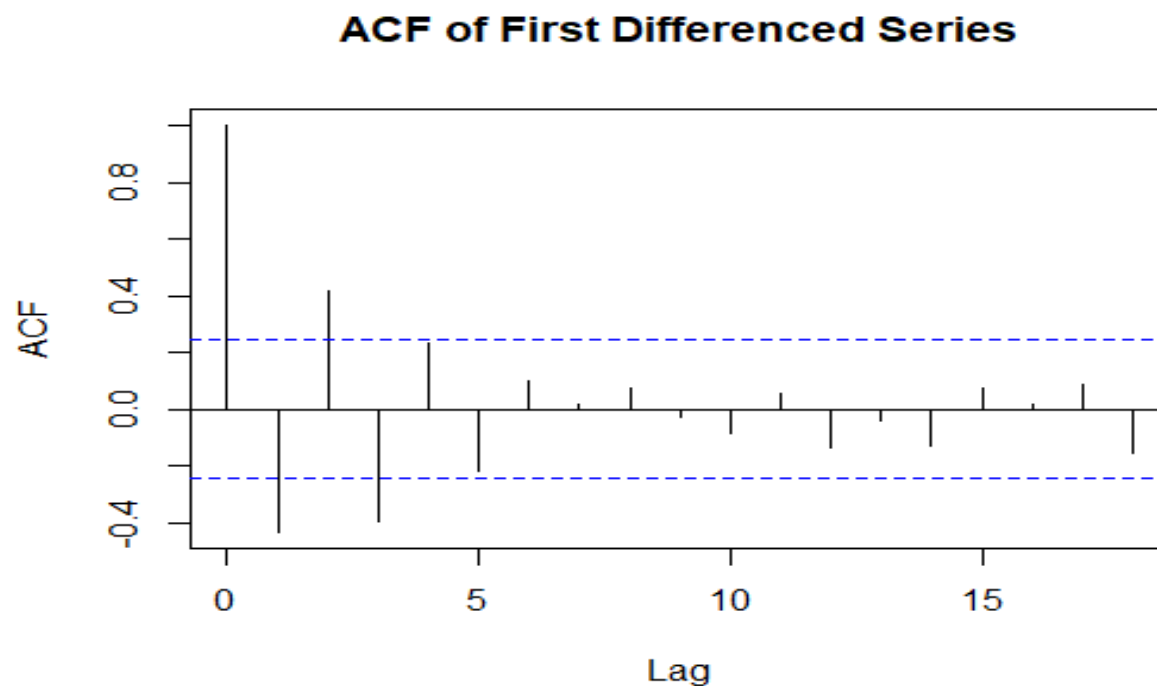


Figure 3. ACF of first differenced series.

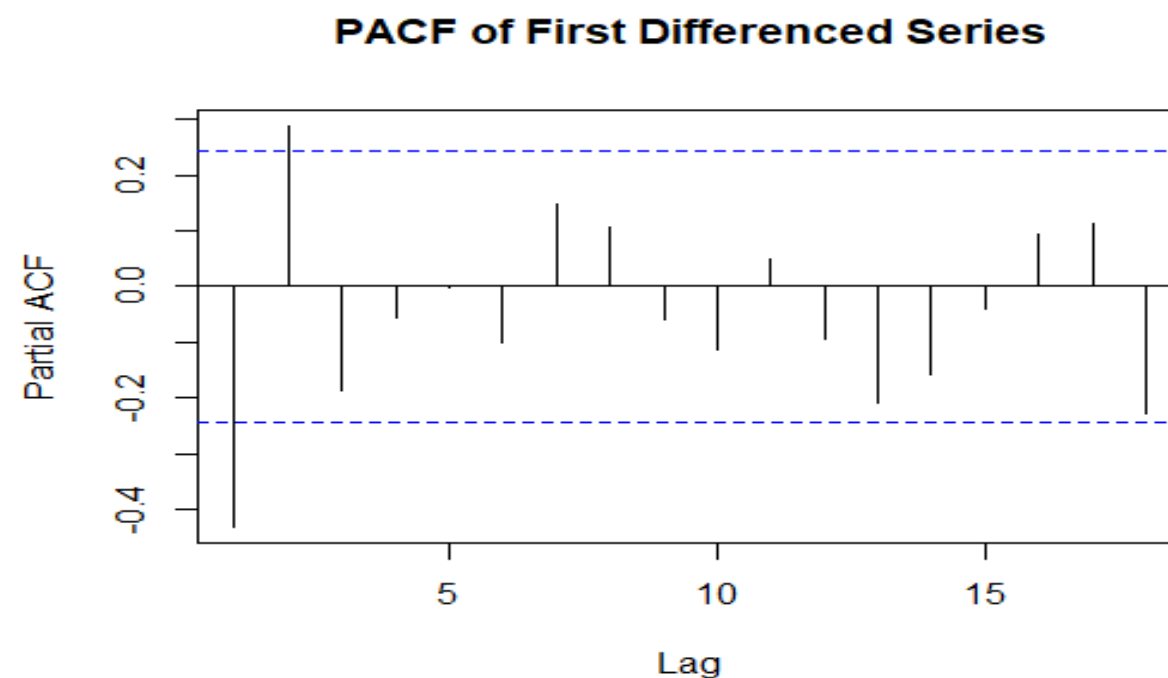


Figure 4. PACF of first differenced series.

From Table 2, the AR(1) parameter coefficient is negative, which indicates that there is an inverse relationship between the present and the past values in the differenced series, thus indicating the existence of a corrective adjustment mechanism in the dynamics of rice production. The positive MA(1) coefficient implies that previous forecast errors have a positive implication on the current value of the series. The drift term is also

rather small, but this is the average change in rice production over time. The error variance (0.0035) is low, which indicates that there is a relatively low amount of unexplained variability in the model. Moreover, the value of AIC is negative, which indicates a good fit to the model, as the lower the AIC, the better the model.

The ARFIMA model estimation results in Table 3 show that the AR(1) coefficient near unity (0.9830) indicates that the persistence of the rice production series is so high that past values have a significant impact on the value of the current observation. The negative MA(1) is a sign of a reverse form of correction mechanism of the past shocks. ARFIMA framework permits the use of fractional differencing and is therefore apt in modelling long-memory in processes. Nonetheless, the ARFIMA model has a larger error variance (0.0073) and a poorer AIC value than the SARIMA model, which is not as compelling evidence to support the model performance in this dataset.

Table 2. SARIMA (1,1,1) model estimation results.

Component	Estimate	Std. Error
AR(1)	-0.8369	0.1005
MA(1)	0.5165	0.1447
Drift	0.0213	0.0060
Sigma ²	0.0035	
Log-Likelihood	91.6500	
AIC	-175.3100	

Table 3: ARFIMA model estimation results.

Component	Estimate	Std. Error
AR(1)	0.9830	0.0209
MA(1)	-0.4214	0.1169
Intercept	-0.1181	0.2272
Sigma ²	0.0073	
Log-Likelihood	66.4900	
AIC	-124.9700	

The diagnostic results of the residual of both models suggest the fitted models were sufficient to track the underlying structure of the series of rice production. Based on the SARIMA residual plot in Figure 5, the residuals vary around the line at zero randomly and do not follow any obvious pattern, which implies that the model has managed to eliminate the systematic aspects in the data. This can also be confirmed by the ACF plot of the SARIMA residuals in Figure 6, where the majority of the autocorrelation values are within the 95% confidence limits, meaning that there is no big correlation between serial values. On the same note, the ARFIMA residual diagnostics in Figure 7 indicate that the residuals are more or less normally distributed and mostly independent over the lags, which means that the time-series dependence is also being well explained. Nevertheless, the SARIMA residual looks more stable and well-behaved as well, which supports previous forecasting outcomes that SARIMA is the more accurate model to predict rice production in Nigeria.

The SARIMA forecast plot in Figure 8 indicates a predictable projection of the rice production level with moderate forecast intervals. The model presents the inherent trend of the historic data and makes smooth predictions. Conversely, Figure 9 shows that the deviations of the ARFIMA forecasts are higher than those of the observed values, which implies that the predictive power is low. The comparison identifies a difference in

the way that each of these models addresses the issue of temporal dependence and predicts the uncertainty.

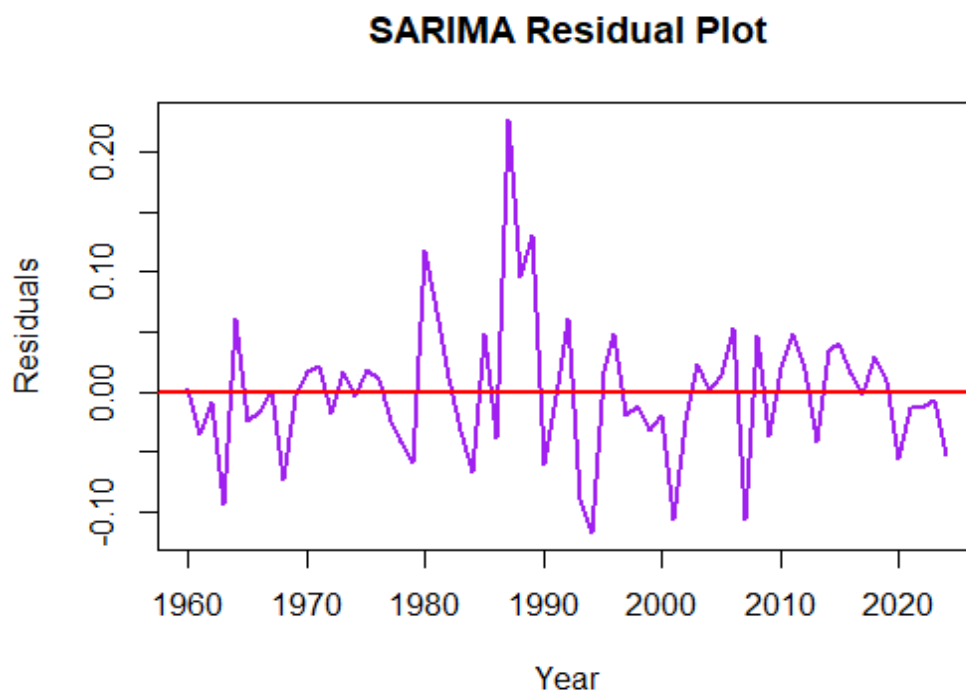


Figure 5. SARIMA residual plot.

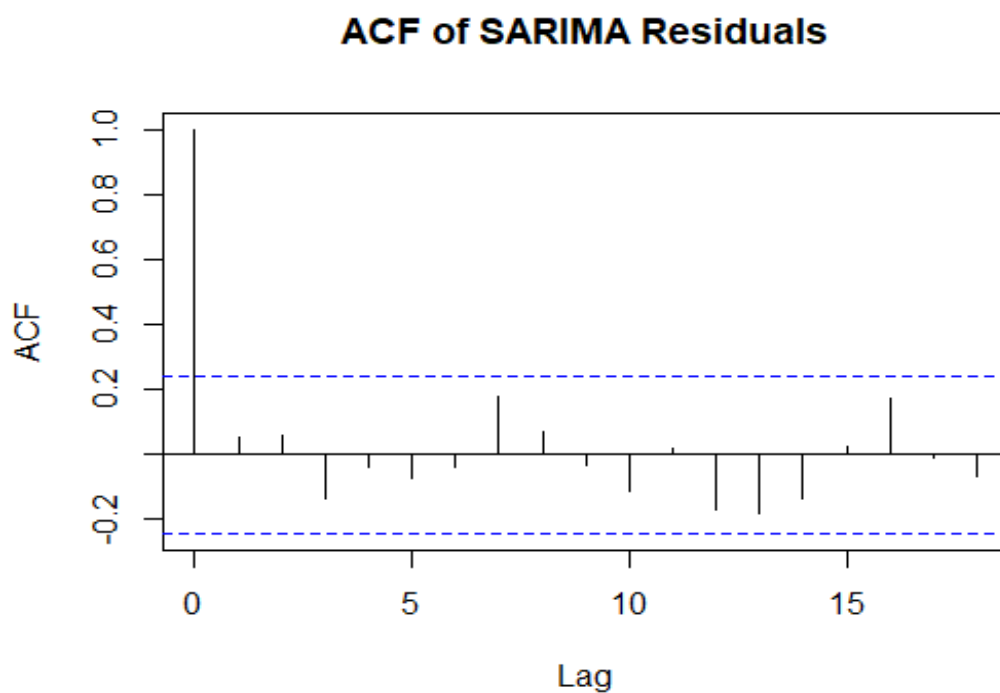


Figure 6: ACF of SARIMA residuals.

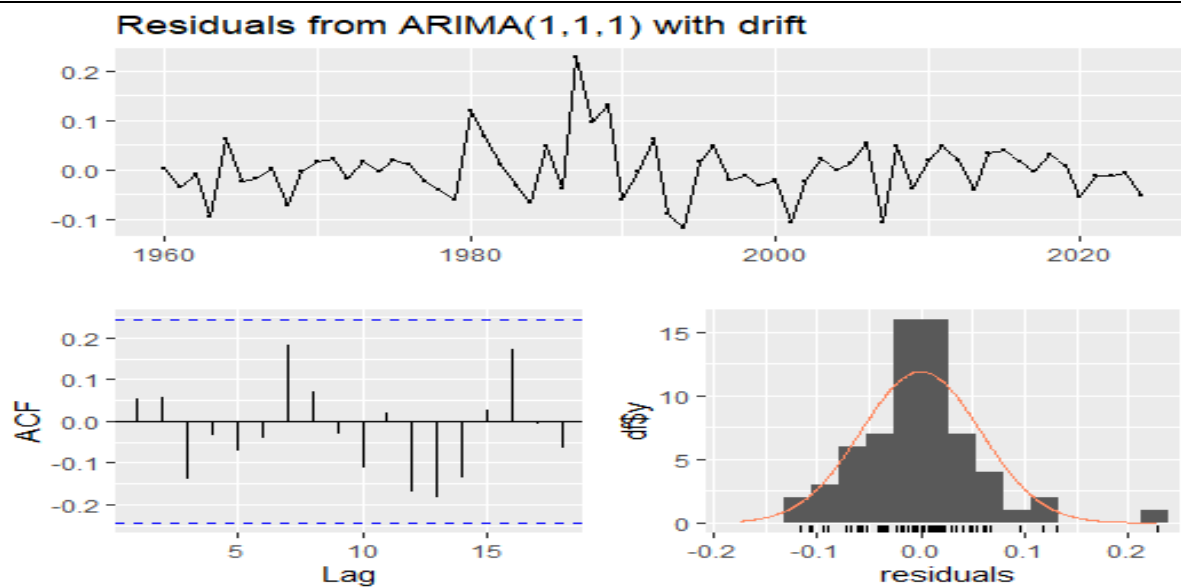


Figure 7. ACF Residuals of ARFIMA model.

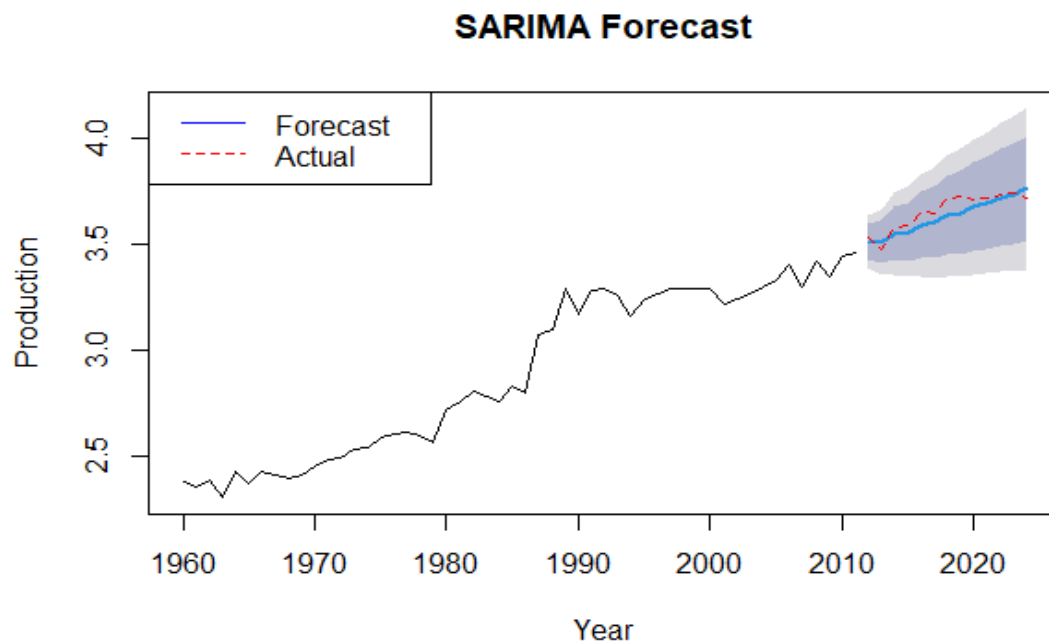


Figure 8. SARIMA forecast of rice production.

4.3. Forecast Accuracy Comparison of SARIMA and ARFIMA Models

To further evaluate the predictive performance of the fitted models, forecast accuracy measures were computed for both the SARIMA and ARFIMA models. The comparison was based on Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and forecasting accuracy. Lower values of RMSE, MAE, and MAPE indicate better forecasting performance and higher predictive reliability of the model.

From Table 4, it is shown that the SARIMA model produced substantially lower RMSE (0.0448) and MAE (0.0384) values compared to the ARFIMA model, indicating smaller forecast errors and superior predictive performance. The forecasting accuracy of 98.9530% further demonstrates the strong predictive capability of the

SARIMA model in modeling rice production in Nigeria. The comparatively lower forecasting error obtained from SARIMA suggests that the rice production series is more strongly characterized by seasonal and short-term stochastic fluctuations than by persistent long-memory dependence. Although the ARFIMA model is theoretically advantageous for datasets exhibiting long-range dependence due to its fractional differencing mechanism, its weaker performance in this study implies that the long-memory properties in the rice production data may not be sufficiently dominant to provide substantial forecasting improvement over the seasonal structure captured by SARIMA.

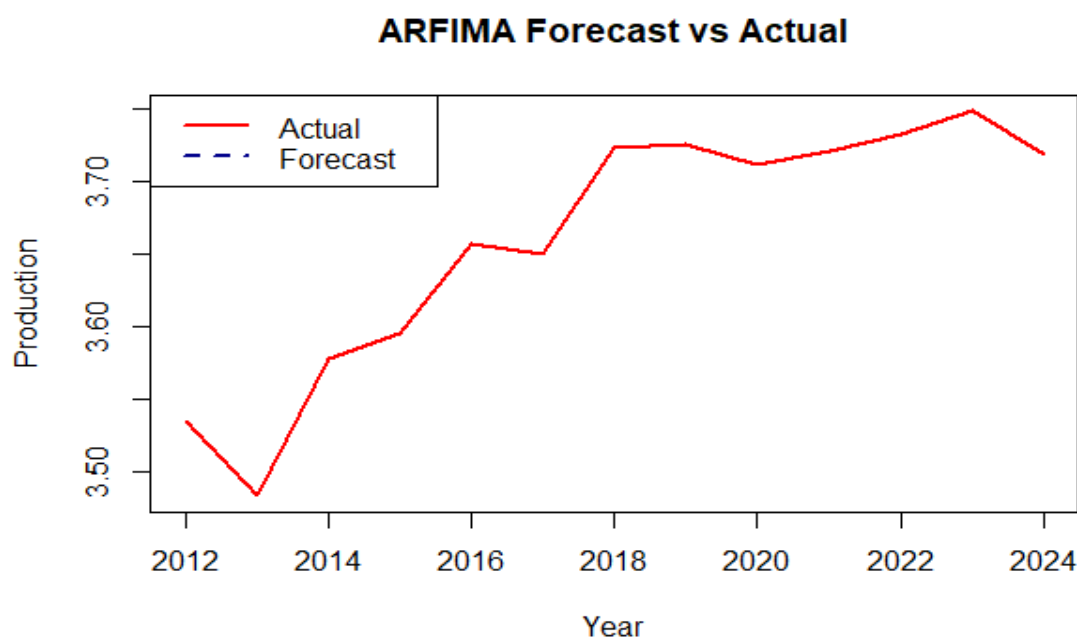


Figure 9. ARFIMA forecast vs actual values.

Table 4. Forecast accuracy of SARIMA and ARFIMA models.

Model	RMSE	MAE	MAPE (%)	Accuracy (%)
SARIMA	0.0448	0.0384	1.0470	98.9530
ARFIMA	3.5618	3.5605	97.2730	2.7270

5. Results and Discussion

The findings of this study revealed that the SARIMA model provided a superior statistical fit compared to the ARFIMA model, as indicated by its lower error variance and more favorable Akaike Information Criterion (AIC) value. Although the ARFIMA model effectively captured persistence within the time series data, its overall forecasting performance was comparatively weaker. The SARIMA model further demonstrated better predictive accuracy by producing lower forecast error measures, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), with an overall forecasting accuracy of approximately 98.95%.

The results suggest that rice production dynamics in Nigeria are more strongly influenced by short-memory seasonal structures than by fractional long-memory processes. This implies that seasonal fluctuations, climatic conditions, planting cycles, harvesting periods, and policy interventions exert greater influence on rice production behavior than persistent long-term dependencies. Consequently, the SARIMA framework proved

more effective in capturing the underlying temporal structure of the rice production series.

The superior performance of the SARIMA model further confirms the suitability of seasonal time series approaches for agricultural forecasting in Nigeria. These findings provide important methodological implications for researchers and practical insights for policymakers and agricultural stakeholders interested in improving production planning, food supply management, and agricultural forecasting accuracy.

6. Conclusions

This study comparatively evaluated the forecasting performance of SARIMA and ARFIMA models using annual rice production data in Nigeria. The study established that the SARIMA model outperformed the ARFIMA model based on forecast accuracy measures and model selection criteria. Specifically, the SARIMA framework produced lower RMSE, MAE, MAPE, and AIC values, indicating superior predictive performance and better model adequacy.

The study concluded that rice production in Nigeria is better characterized by seasonal short-memory dynamics than by long-memory fractional processes. Therefore, the SARIMA model represents a more suitable and reliable approach for forecasting rice production in Nigeria. The application of this model can support evidence-based agricultural planning, policy formulation, and strategic interventions aimed at improving domestic rice production and strengthening national food security.

This study also contributes to the existing literature by providing empirical evidence on the comparative performance of SARIMA and ARFIMA models in agricultural forecasting within the Nigerian context.

Author contributions

This work was carried out in collaboration among all authors. All authors contributed equally.

Funding Statement

This research received no external funding.

Data Availability

The data that support the findings are available from the corresponding author upon request.

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Conflict of Interest

The authors declare no conflict of interest.

References

- [1] Food and Agriculture Organization of the United Nations (FAO), *FAOSTAT: Food and Agricultural Data*. Rome, Italy: FAO, 2023. [Online]. Available: <https://www.fao.org/faostat/en/>

- [2] T. Reardon and B. Minten, "The rapid transformation of the agrifood sector in developing countries," International Food Policy Research Institute (IFPRI), Washington, DC, USA, IFPRI Discussion Paper No. 01123, 2011. [Online]. Available: <https://www.ifpri.org/publication/rapid-transformation-agrifood-sector-developing-countries>
- [3] H. S. Umar, A. A. Girei, and O. A. Aliyu, "Nigeria rice output forecast: Autoregressive integrated moving average (ARIMA) approach," *J. Econ. Manage. Trade*, vol. 23, no. 5, pp. 1–6, 2019, doi: 10.9734/jemt/2019/v23i530145.
- [4] T. O. Ojo, A. A. Ogundeji, S. C. Babu, and T. Alimi, "Estimating financing gaps in rice production in Southwestern Nigeria," *J. Econ. Struct.*, vol. 9, Art. no. 12, 2020, doi: 10.1186/s40008-020-0190-y.
- [5] O. Obi-Egbedi, O. A. Akin-Olagunju, and I. B. Oluwatayo, "Rice trade policy and productivity: Empirical evidence from Nigeria's rice sub-sector," *Global J. Econ. Bus.*, vol. 11, no. 1, pp. 96–106, 2021, doi: 10.31559/GJEB2021.11.1.7.
- [6] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, 5th ed. Hoboken, NJ, USA: John Wiley & Sons, 2016.
- [7] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 3rd ed. Melbourne, Australia: OTexts, 2021. [Online]. Available: <https://otexts.com/fpp3/>
- [8] A. A. Rabi, A. S. Umar, and I. Danjuma, "Seasonal modeling of agricultural yields using SARIMA framework," *Afr. J. Econ. Sustain. Dev.*, vol. 15, no. 2, pp. 34–45, 2023.
- [9] U. H. Perez-Guerra, R. Macedo, Y. P. Manrique, E. A. Condori, H. I. González, E. Fernández, N. Luque, and M. García-Herreros, "Seasonal autoregressive integrated moving average (SARIMA) time-series model for milk production forecasting in pasture-based dairy cows in the Andean highlands," *PLoS ONE*, vol. 18, no. 11, Art. no. e0288849, 2023, doi: 10.1371/journal.pone.0288849.
- [10] U. M. Bashir and I. Yakubu, "SARIMA-based forecast of major crops in sub-Saharan Africa: An empirical review," *Afr. J. Food Agric. Stat.*, vol. 8, no. 1, pp. 11–24, 2023.
- [11] O. S. Yaya and A. I. Shittu, "Modeling long memory and persistence in Nigerian agricultural outputs," *Agric. Econ. Rev.*, vol. 13, no. 1, pp. 101–118, 2022.
- [12] A. Kumar, M. Singh, and R. Jain, "Long memory modeling in agricultural commodity prices: A case study of South Asia," *Appl. Econ. Lett.*, vol. 30, no. 8, pp. 1075–1081, 2023.
- [13] I. M. Adamu and M. Haruna, "Comparative study of seasonal and memory-sensitive models in crop yield forecasting," *Niger. J. Stat. Appl.*, vol. 9, no. 1, pp. 48–58, 2023.
- [14] C. W. J. Granger and R. Joyeux, "An introduction to long-memory time series models and fractional differencing," *J. Time Ser. Anal.*, vol. 1, no. 1, pp. 15–29, 1980, doi: 10.1111/j.1467-9892.1980.tb00297.x.
- [15] R. T. Baillie, "Long memory processes and fractional integration in econometrics," *J. Econometrics*, vol. 73, no. 1, pp. 5–59, 1996, doi: 10.1016/0304-4076(95)01732-1.
- [16] E. Bouri, A. Jain, and D. Roubaud, "Long memory and time-varying dynamics in global agricultural prices," *Agric. Econ.*, vol. 52, no. 1, pp. 23–36, 2021.
- [17] M. Falk and F. Marohn, "Forecasting persistent time series with ARFIMA: An application to climate and agriculture," *Stat. Model.*, vol. 21, no. 4, pp. 271–290, 2021.
- [18] T. I. Olayemi and I. O. Fasanya, "Fractional integration in agricultural production modeling: A comparative evaluation of ARFIMA methods," *Afr. Rev. Econ. Finance*, vol. 15, no. 1, pp. 95–110, 2023.
- [19] Y. Chen and X. Zhou, "Advances in long memory time series modeling: A review of ARFIMA-based approaches," *J. Forecast.*, vol. 41, no. 5, pp. 743–758, 2022.
- [20] H. A. Yakubu, I. Abdulaziz, and H. G. Dikko, "Efficiency of ARFIMA models in predicting agricultural outputs in northern Nigeria," *J. Appl. Econometrics Forecast.*, vol. 11, no. 1, pp. 77–90, 2024.
- [21] N. O. Okoro and F. J. Jiboku, "Fractional time series modelling of malaria morbidity among students in Federal Polytechnic Ilaro using the ARFIMA approach," *J. Multi-Discip. Res. Innov.*, vol. 1, no. 2, pp. 117–123, 2024.

- [22] F. Sowell, "Maximum likelihood estimation of stationary univariate fractionally integrated time series models," *J. Econometrics*, vol. 53, nos. 1–3, pp. 165–188, 1992, doi: 10.1016/0304-4076(92)90084-5.
- [23] P. Pandit, A. Sagar, B. Ghose, P. Dey, M. Paul, S. Alqadhi, J. Mallick, and H. G. Abdo, "Hybrid time series models with exogenous variable for improved yield forecasting of major Rabi crops in India," *Sci. Rep.*, vol. 13, Art. no. 22240, 2023, doi: 10.1038/s41598-023-49544-w.
- [24] D. Rakshit and R. K. Paul, "Modeling time series with asymmetric volatility and long memory," *Indian J. Agric. Econ.*, vol. 79, no. 2, pp. 231–244, 2024, doi: 10.63040/25827510.2024.02.004.
- [25] H. Akaike, "A new look at the statistical model identification," *IEEE Trans. Autom. Control*, vol. AC-19, no. 6, pp. 716–723, Dec. 1974, doi: 10.1109/TAC.1974.1100705.



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