Forecasting Southern Nigeria's Monthly Rainfall Using Seasonal Arima (Sarima) Models For Environmental and Agricultural Planning

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Abstract: - In Nigeria, rainfall has a significant impact on land use patterns, agricultural output, and ecological systems. For agriculture, water resource management, and other climate-sensitive industries to make wise decisions, reliable rainfall forecasting is essential. The Nigerian Meteorological Agency (NiMet) provided monthly rainfall data (measured in millimeters) for southern Nigeria from Jan. 2009 to Dec. 2024. This study uses time series techniques to evaluate the data. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) and Augmented Dickey–Fuller (ADF) tests were used to evaluate the series' stationarity. The SARIMA(5,0,5)(0,0,1)[12] model offered the greatest fit, according to model identification and selection based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Diagnostic analyses confirmed the adequacy of the model, as the residuals were approximately normally distributed and exhibited no significant autocorrelation. The selected model was subsequently used to forecast for the monthly rainfall from Jan. 2025 to Dec. 2026, with 80% and 90% confidence intervals. The results suggest a relatively stable rainfall pattern characterized by pronounced seasonal variations, highlighting the reliability of the model's predictive performance. These findings offer valuable insights for agricultural stakeholders, supporting informed crop scheduling, irrigation planning, and disaster risk management. Overall, the study demonstrates the effectiveness of SARIMA-based forecasting as a tool for climate-responsive planning and resilience enhancement in southern Nigeria."

Key-Words: - Rainfall Forecasting, Time Series Analysis, SARIMA Model, Southern Nigeria, Agricultural Planning

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1 Introduction

According to [21], rain is defined as liquid water in the form of droplets that have condensed from atmospheric water vapor and precipitated, becoming heavy enough to fall under gravity. The majority of the fresh water on Earth is deposited by rainfall, an essential part of the water cycle. In addition to providing water for agricultural irrigation and hydroelectric power facilities, it also creates ideal circumstances for a variety of habitats. Many natural events are impacted by rainfall (Mirzaei et al., 2024). According to [2], precise rainfall forecasts are crucial for sustainable development because of the region's reliance on rain-fed agriculture and its susceptibility to flooding. The region's climate variability, which is influenced by elements including the Inter-Tropical Convergence Zone (ITCZ), ocean currents, El Niño-Southern Oscillation (ENSO), and local topography, makes rainfall forecast challenging. In order to improve spatial rainfall forecasting, studies have highlighted the value of combining remote sensing data with ground-based observations [11]. According to [6], rising trends in rainfall variability have made drainage and water delivery system planning more challenging. The necessity for localized rainfall forecast models that take into account the particular climatological and topographical circumstances of this region was emphasized by [15].

The distribution of rainfall in Enugu State, Nigeria, from January 2002 to December 2016 was studied by [1]. They evaluated several time-series models using the Box–Jenkins method and found that SARIMA(0,0,0)(1,0,1)[12] was the best model for forecasting monthly rainfall, exhibiting a tendency for rising rainfall values in successive forecasts. [10] observed an increasing early retreat of rainfall and a notable decrease in rainfall frequency in September and October, indicating that Nigeria's geography and closeness to the Atlantic Ocean have a significant influence on variations in rainfall features. The livelihoods of people residing in Nigeria's frontline states are seriously threatened by desertification and environmental degradation, according to [23]. According to [19], the main source of rain is moisture traveling along weather fronts, which are three-dimensional zones of temperature and moisture differences. When there is sufficient moisture and upward motion, convective clouds like cumulonimbus produce precipitation, which can form narrow rain bands. The wet and dry seasons moved from south to north and, to a lesser extent, from east to west between the 1960s and 1980s, according to [18], examination of Nigeria's rainfall patterns. In a national research, [7] determined that SARIMA (2,0,1)(2,1,1)[12] was the best model after applying SARIMA to monthly rainfall data for Nigeria from 1980 to 2015 (from the World Bank Climate Portal). They predicted rainfall from 2018 to 2042, noting that November is the retreat month and April is the onset month. Similarly, in Kogi State, [13] used monthly data from NiMet (2010–2022) to test SARIMA and SARIMAX models (with temperature and relative humidity as exogenous variables) and discovered that SARIMAX performed better than SARIMA. In southern Nigeria, where many meteorological stations have irregular data collection, inadequate maintenance, or missing records, the absence of trustworthy, long-term rainfall data is a recurring issue in rainfall forecasting. The training and validation of statistical and machine-learning models are impacted by these data constraints. To increase forecast accuracy, studies like [5] highlighted the necessity of data homogeneity and the development of strong data gathering frameworks. The objective of this study is to develop an effective time series model for forecasting monthly rainfall in southern Nigeria. This is because erratic rainfall causes poor agricultural planning, raises the risk of flooding, and impedes efficient management of water resources. The novelty of this study lies in its regional focus on Southern Nigeria, a climatically strategic zone characterized by strong seasonal rainfall dependence and high agricultural vulnerability. While previous studies by the authors and other scholars have examined rainfall forecasting at state or national levels, this study employs a distinct and updated regional dataset spanning January 2009 to December 2024. The study further contributes by linking SARIMA-based rainfall forecasting directly to environmental planning, agricultural scheduling, flood preparedness, and climate resilience strategies in Southern Nigeria. This broader spatial scope and applied policy relevance clearly differentiate the present work from earlier publications.

2 Methodology

Monthly rainfall data (in millimeters) covering January 2009 to December 2024 were obtained from the Nigerian Meteorological Agency (NiMet) for Southern Nigeria. The data were first screened for completeness, consistency, and temporal ordering. Missing observations, where present, were cross-validated with adjacent monthly records and NiMet summaries before aggregation into a continuous monthly time series. Exploratory decomposition was then performed to separate trend, seasonal, and irregular components. The Box–Jenkins framework was subsequently employed, involving identification, estimation, diagnostic checking, and forecasting stages. All analyses were implemented using R statistical software.

2.1 Stationarity

Stationary and non-stationary time series are both possible. According to [25] stationary series are defined by a constant dispersion around a constant mean level and a sort of statistical equilibrium around that mean level. To build an efficient time series model for future prediction, stationarity is a prerequisite. If a series' mean is fixed and its variance is constant, it is considered weakly or second-order stationary.

2.2 The SARIMA Models

SARIMA models, which successfully model seasonal time series data, are created by adapting ARIMA models. According to [8], seasonality in time series is described as a regular pattern of repeating variations over a specified period of time. In an ARIMA prediction □□, seasonal AR and MA factors rely on prior data employing residual errors and lag multiples of s (the period of the series' seasonality). Conversely, the seasonal ARIMA model, represented as ARIMA (p,d,q) (P, D, Q)s, integrates both seasonal and non-seasonal elements which is usually written as;
$\mathrm{SARIMA}\ (p, d, q)(P, D, Q)s$
Let □□ represent the operator then we have,

$\Phi_p(B^s)\phi_p(B)(1-B)^d(1-B^s)^D X_t = \theta_q(B)\Theta_q(B^s)\alpha_t$(2)

Where X_t is the time series at time t, $\phi_p(B)$ and $\theta_q(B)$ are the regular AR and MA factors (polynomials) and $\Phi_p(B^s)$ and $\Theta_q(B^s)$ are the seasonal autoregressive and moving average factors, respectively. α_t is the zero mean white noise process and the seasonal period, s = 12 for monthly data while B is the backward shift operator.

2.3 Theoretical Conditions for Model Adequacy

For a SARIMA(p,d,q)(P,D,Q)s process to be valid, the autoregressive polynomials must satisfy stationarity conditions such that all roots lie outside the unit circle, while the moving-average polynomials must satisfy invertibility conditions under the same requirement. Given that the rainfall series was found stationary at level through ADF and KPSS tests, the differencing orders were set to d=0 and D=0. The selected seasonal period s=12 reflects the annual rainfall cycle in monthly observations and captures recurring wet and dry season dynamics. Although the selected model SARIMA(5,0,5)(0,0,1)12 is relatively high-order, model adequacy was ensured through minimum AIC/BIC, residual whiteness, and parameter stability checks.

3 Data analysis

3.1 Test stationary

The rainfall time series exhibits a generally stable trend pattern, as shown in Figure 1, with observations fluctuating around a relatively constant mean level over time. This behavior suggests the absence of a pronounced long-term upward or downward trend in the original series. The decomposed time series plot for the period spanning January 2009 to December 2024, presented in Figure 2, provides further insight into the underlying components of the series, clearly separating the trend, seasonal, and irregular variations. The presence of recurring seasonal fluctuations indicates that the rainfall data possess a seasonal structure, thereby justifying the application of a Seasonal Autoregressive Integrated Moving Average (SARIMA) model.

Furthermore, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots displayed in Figure 3 serve as preliminary tools for model identification. The PACF shows a sharp cut-off after lag 4, whereas the ACF decays gradually, exhibiting a tailing-off pattern. This behavior is characteristic of a possible non-seasonal autoregressive process of order four, AR(4). When considered alongside the evident seasonal pattern in the decomposition plot, these results provide an empirical basis for specifying an appropriate SARIMA (p,d,q)(P,D,Q)s structure for subsequent estimation and diagnostic checking.

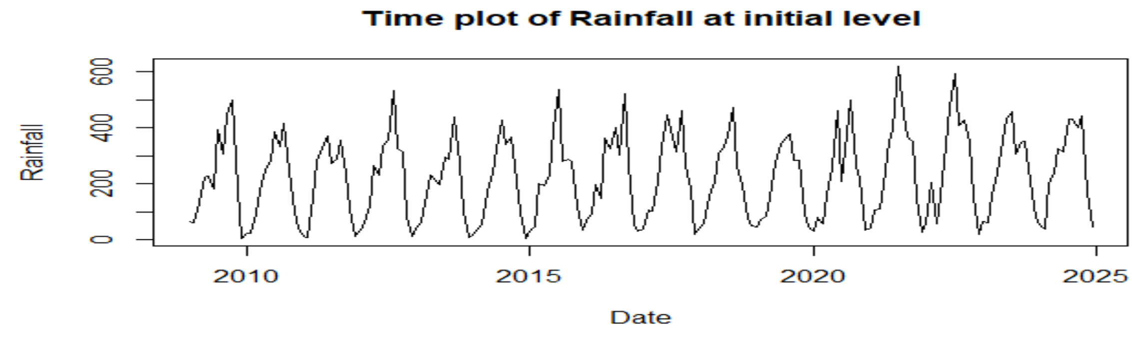

Fig. 1: Time plot of monthly rainfall in Southern Nigeria (January 2009–December 2024)

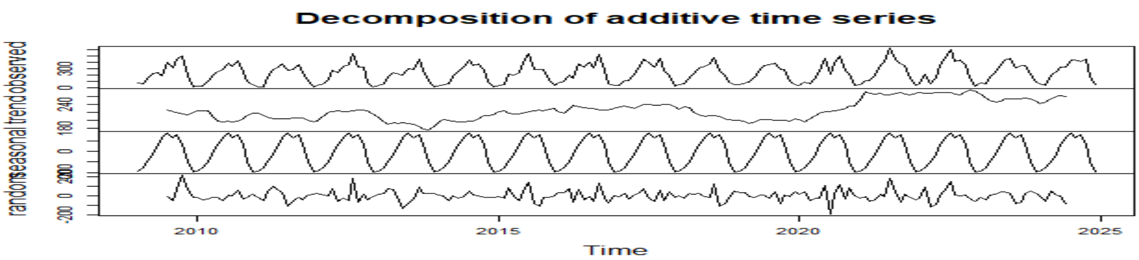

Fig. 2: Seasonal decomposition of monthly rainfall series at the original level

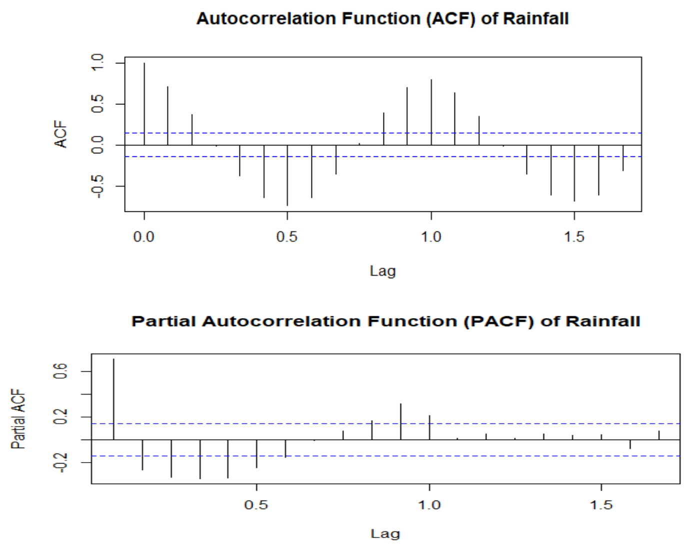

Fig. 3: ACF and PACF plots of the monthly rainfall series at level

The stationarity tests reported in Table 1 confirm that the rainfall series is stationary at its original level. Specifically, the ADF test rejects the null hypothesis of a unit root ($p < 0.05$), indicating stationarity, while the KPSS test fails to reject the null hypothesis of stationarity ($p > 0.05$). The agreement between these complementary tests provides strong evidence that both non-seasonal and seasonal differencing orders are unnecessary, hence the selection of d = 0 and D = 0.

Table 1. Result of ADF and KPSS at at the original level of rainfall (millimeter) from January 2009 to December 2024

Var. status		Stat.	No const.	lag-order
ADF	Rainfall	Value	12.432	5
Original level		Pv	0.01	
KPSS	Rainfall	Value	0.14657	4
Original level		pv	0.1	

Note: Pv= P-value

3.2 Model selection for Rainfall (millimeter)

Using the chosen criteria, the Akaike Criterion and the Bayesian Criterion, Table 2 displays the results of testing different SARIMA models to see which one is best for the data. As can be observed, SARIMA (5, 0, 5) (0, 0, 1) [12] has the lowest result for both the Bayesian and Akaike criteria. Since SARIMA (5, 0, 5) (0, 0, 1) [12] meets two of the three criteria taken into consideration and indicates that rainfall (millimeters) shows seasonal patterns, it is the acceptable model (Table 3).

Table 2. Result of the Model Identification SARIMA (p, d, q)

Model	**Akaike Criterion**	**Bayesian Criterion**	**sigma^2**	**Log-likehood**
SARIMA (5,0,5) (0,0,1) [12]	2180.97	2223.31	4308	-1077.48

Table 3. Result of the estimated parameter of SARIMA (5, 0, 5) (0, 0, 1) [12]

	Coefficient	Std. Error
ar1	0.1091	0.1689
ar2	0.2691	0.17
ar3	0.2334	0.1234
ar4	-0.1292	0.1656
ar5	-0.8126	0.1638
ma1	-0.0212	0.1431
ma2	-0.3439	0.1472
ma3	-0.4235	0.1329
ma4	0.0818	0.1422
ma5	0.9473	0.1637
sma1	0.3251	0.0764
mean (μ)	225.9019	5.5858

Beyond global information criteria, parameter-level diagnostics suggest that the dominant autoregressive coefficients AR, MA5, and the seasonal moving-average coefficient are substantively large relative to their standard errors, indicating that the higher-order structure is not purely an overfitting artifact. This supports the retention of the selected specification despite its relatively large order.

3.3 Model estimation

The selected SARIMA model equation is given thus:

$$Y_t = \mu + \sum_{i=1}^{5} \emptyset_i Y_{t-i} + \sum_{i=1}^{5} \theta_j \varepsilon_{t-j} + \theta_1 \varepsilon_{t-12} + \varepsilon_t (3)$$

$$Y_t = 225.9019 + 0.1091Y_{t-1} + 0.2691Y_{t-2} + 0.2334Y_{t-3} - 0.1292Y_{t-4} - 0.8126Y_{t-5} - 0.0212\varepsilon_{t-1} - 0.3439\varepsilon_{t-2} - 0.4235\varepsilon_{t-3} + 0.0818\varepsilon_{t-4} + 0.9473\varepsilon_{t-5} + 0.3251\varepsilon_{t-12} + \varepsilon_t (4)$$

3.4 Checking the model's diagnostics

An autocorrelation test was used to further analyze the residuals and evaluate the model's suitability. The absence of significant autocorrelation in the residuals was indicated by p-values larger than 0.05 obtained using the Ljung Box Q-statistic. This suggests that the residuals resemble white noise, indicating that the fitted model is adequate and sufficient. [17].

3.5 Predicting

After subjecting the equations to SARIMA model diagnostic tests, an out-of-sample forecast was generated for the subsequent two years.

Table 4. Result for residual autocorrelation rainfall (millimeter)

LAG	ACF	Q-stat	df	P-value
Rainfall 24	0.0474	19.046	13	0.1217

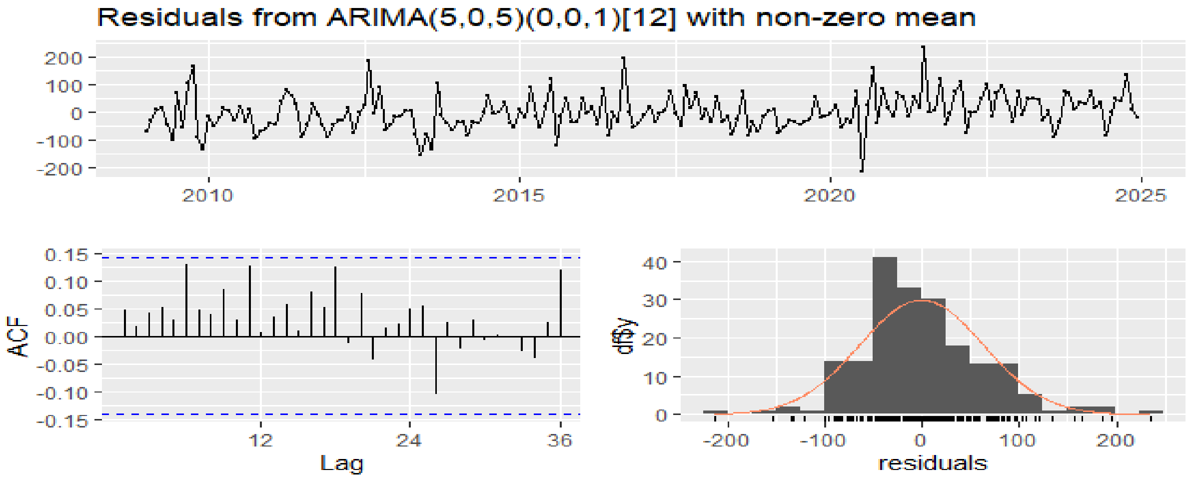

Fig. 4:Residual ACF plot of the fitted SARIMA(5,0,5)(0,0,1)[12] model

The comparative evaluation of the fitted SARIMA models based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) is presented in Table 3. Among the candidate models considered, the SARIMA (5,0,5)(0,0,1)12(5,0,5)(0,0,1)_{12}(5,0,5)(0,0,1)12 model emerged as the most suitable specification, having the lowest AIC and BIC values, which indicates superior goodness-of-fit relative to the competing models while maintaining model parsimony.

The adequacy of the selected model was further assessed through residual diagnostic checks. As reported in Table 4, the Ljung–Box Q-statistics and their corresponding p-values at the examined lags were all greater than the 5% significance level (p>0.05p > 0.05p>0.05), implying that the residuals are free from serial autocorrelation. This confirms that the model successfully captured the temporal dependence structure inherent in the rainfall series.

In addition, Figure 4 provides further evidence of model validity, showing that the residuals are approximately normally distributed and randomly fluctuate around the zero mean line, with no obvious systematic pattern. These diagnostic outcomes collectively support the adequacy and sufficiency of the selected SARIMA model for forecasting purposes.

Finally, the forecast results presented in Table 5 and Figure 5 suggest that the rainfall amount is expected to remain relatively stable over the forecast horizon, with no substantial upward or downward movement, indicating a largely constant rainfall pattern throughout the projected period.

Table 5. Result for the forecast of the rainfall (millimeter) using SARIMA (5, 0, 5) (0, 0, 1) [12] for the next 2 years

Time	Forecast	80% Lower C. L	80% Highest C. L	95% Lower C. L	95 Highest C. L
01-25	92.23293	-39.8227	224.2886	-109.729	294.1946
02-25	141.554	-30.2465	313.3545	-121.192	404.3003
03-25	172.1585	-12.6805	356.9976	-110.528	454.8454
04-25	191.1492	1.528701	380.7696	-98.8503	481.1486
05-25	202.9331	11.50349	394.3628	-89.8333	495.6995
06-25	210.2453	18.12357	402.367	-83.5795	504.0701
07-25	214.7826	22.39508	407.1702	-79.4487	509.014
08-25	217.5981	25.10831	410.0879	-76.7896	511.9858
09-25	219.3451	26.816	411.8743	-75.1028	513.7931
10-25	220.4292	27.88492	412.9735	-74.0419	514.9003
11-25	221.1019	28.55177	413.652	-73.3781	515.5819

12-25	221.5193	28.96694	414.0717	-72.9641	516.0028
01-26	221.7783	29.22509	414.3316	-72.7064	516.2631
02-26	221.9391	29.38548	414.4926	-72.5462	516.4243
03-26	222.0388	29.48508	414.5925	-72.4467	516.5243
04-26	222.1007	29.54691	414.6544	-72.3849	516.5862
05-26	222.1391	29.58529	414.6928	-72.3465	516.6247
06-26	222.1629	29.60911	414.7167	-72.3227	516.6485
07-26	222.1777	29.6239	414.7315	-72.3079	516.6633
08-26	222.1869	29.63307	414.7406	-72.2987	516.6725
09-26	222.1925	29.63876	414.7463	-72.2931	516.6782
10-26	222.1961	29.64229	414.7499	-72.2895	516.6817
11-26	222.1983	29.64449	414.7521	-72.2873	516.6839
12-26	222.1996	29.64585	414.7534	-72.286	516.6852

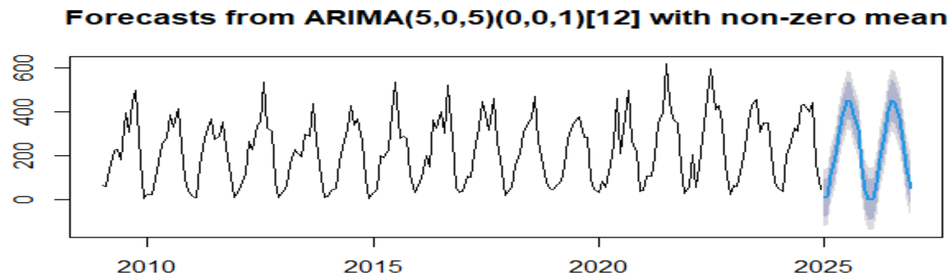

Fig. 5: Two-year forecast of monthly rainfall with prediction intervals

4 Discussions

The exploratory analysis of monthly rainfall data revealed a stable and predictable pattern over time. Rainfall (measured in millimeters) followed a normal pattern, as seen in Figure 1, and the series appeared stationary at its initial level, suggesting that the rainfall levels stayed largely constant during the research period. Figure 2 further decomposed the time series from Jan. 2009 to Dec. 2024, illustrating its observed, trend, seasonal, and residual components. This decomposition highlighted the presence of seasonal effects inherent in the rainfall pattern. The autocorrelation and partial autocorrelation plots **(**Figure 3**)** displayed a decaying ACF and a PACF cutting off at lag 4. This behavior is consistent with a stationary time series and suggests a model with significant autoregressive components. This finding was supported by the unit root tests summarized in Table 1**.** Both the ADF and the KPSS tests produced p-values less than 0.05, confirming that the series is stationary at its original level. Model selection was carried out by fitting several candidate SARIMA models and comparing them using the AIC and the BIC. As reported in Table 2, the SARIMA(5,0,5)(0,0,1)[12], [12],[12] model recorded the lowest AIC and BIC values among the competing specifications, satisfying two of the three model selection criteria. This suggests that the selected model effectively captures the seasonal dynamics of the rainfall series (see Table 3). Furthermore, diagnostic checks conducted on the residuals support the adequacy of the model. The Ljung–Box Q-statistics yielded p-values exceeding 0.05, indicating the absence of significant autocorrelation in the residuals and confirming that they behave as white noise Figure 4 supported this finding, showing residuals that are normally distributed and oscillating around the zero line. Together, these results confirm the validity and adequacy of the SARIMA (5,0,5)(0,0,1)[12] model for the data.

Finally, the out-of-sample forecast for the next two years, presented in Table 5 and Figure 5, revealed that monthly rainfall is expected to remain relatively stable during the forecast period. This suggests that the selected SARIMA model provides reliable projections and can be useful for planning purposes, such as agricultural scheduling and water resource management.

4.1 Summary

This study uses a SARIMA model to assess the monthly rainfall (in millimeters) in southern Nigeria. The time series showed a steady trend in the time plot and was discovered to be stationary at its initial level. To verify stationarity, the ADF and KPSS tests were used. Among the competing models, SARIMA(5,0,5)(0,0,1)[12] was determined to be the best match based on the AIC and BIC. Diagnostic testing demonstrated that the model residuals were normally distributed and the ACF delays fluctuated around the zero line, confirming the suitability of the selected model. Monthly rainfall was predicted at 80% and 90% confidence intervals for the January 2025–December 2026 timeframe using the fitted SARIMA model.

5 Conclusion

This study modeled and forecasted monthly rainfall in southern Nigeria using a SARIMA approach. The rainfall series was stationary at its original level, and the SARIMA (5,0,5)(0,0,1)[12] model provided the best fit, capturing both seasonality and underlying trends. Diagnostic tests confirmed the model's adequacy, with residuals approximating white noise. Forecasts for January 2025–December 2026 showed stable monthly rainfall with recurring seasonal peaks. These results indicate a predictable rainfall pattern that can inform agricultural planning, water resource management, infrastructure scheduling, and climate risk mitigation. By aligning planting, irrigation, and disaster preparedness activities with the forecasted rainfall, stakeholders can reduce weather-related losses and improve productivity. Policymakers should also leverage these findings to design climate-responsive strategies and invest in improved meteorological data systems to sustain forecast accuracy and long-term resilience in the region.

5.1 Policy Implications and Actionable Recommendations

i. **Agricultural Planning:** Farmers, cooperatives, and agribusinesses should align planting, harvesting, and irrigation schedules with forecasted rainfall patterns to minimize weather-related losses and boost productivity and food security.

ii. **Disaster Risk Management:** Emergency responders, insurance companies, and relevant agencies should incorporate rainfall forecasts into flood preparedness, drought response, and climate risk assessment plans to reduce the impact of extreme weather events.

iii. **Infrastructure & Utilities:** Construction firms and utility service providers should factor seasonal rainfall into the design and timing of drainage systems, road works, and water infrastructure to improve durability and reduce service disruptions.

iv. **Policy Development:** Governments and policymakers should use forecasted rainfall patterns to design climate-responsive policies and allocate resources more effectively across sectors.

v. **Meteorological Investment:** Increased investment in modern meteorological equipment, real-time data systems, and data quality control is essential to enhance the accuracy and reliability of future forecasts.

vi. **Public Awareness:** Launch outreach programs to educate farmers and communities on how to interpret and apply rainfall forecasts for informed decision-making, strengthening long-term climate resilience.

Future Research

To further assess predictive reliability, future revisions may incorporate holdout-sample validation using RMSE, MAE, and MAPE. These measures would complement the in-sample AIC/BIC evidence and provide a stronger empirical basis for comparing SARIMA with alternative approaches such as SARIMAX, ANN, or SVR models.

Availability of Data: The monthly rainfall data used in this study were obtained from the Nigerian Meteorological Agency (NiMet) for the period January 2009 to December 2024 and are available from the corresponding author upon reasonable request.

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Future Research

To further assess predictive reliability, future revisions may incorporate holdout-sample validation using RMSE, MAE, and MAPE. These measures would complement the in-sample AIC/BIC evidence and provide a stronger empirical basis for comparing SARIMA with alternative approaches such as SARIMAX, ANN, or SVR models.

Availability of Data: The monthly rainfall data used in this study were obtained from the Nigerian Meteorological Agency (NiMet) for the period January 2009 to December 2024 and are available from the corresponding author upon reasonable request.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.