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Arima Model for Forecasting Rainfall Pattern in Yola Nigeria

BONGI VEINO LESLIE[1], RAFIYATU HAFISU[2], FADIMATU BAWURO MOHAMMED[3]
[1, 2, 3]*Department of Statistics, Adamawa State Polytechnic, Yola*

Abstract- This study focuses on the use of Autoregressive Integrated Moving Average (ARIMA) to forecast rainfall pattern in Yola Nigeria. It is aimed at estimating the trend of the monthly rainfall data in Yola for a period of 26years (2000-2025) to determine the pattern of rainfall, find the best ARIMA model that fits the data to make forecast. Data for this study was collected through extraction from the records in the Nigeria Meteorological Agency, Yola International Airport Adamawa State. The data covered a period of 26years (2000-2025) giving a total of 312 monthly rainfall readings. The data was analysed using Autoregressive Integrated Moving Average (ARIMA). Of all the ARIMA models considered, ARIMA (3,1,2) gave the least Akaike Information Criterion value of 3180.448187. Hence, it was chosen as the best model to fit the data and make rainfall forecast for the twelve months in 2026. The result shows that rainfall commenced in April, 2026 and ended in October, 2026. The highest rainfall of 207.3589mm was recorded in August, 2026. The identified model is appropriate for short term forecast which will help both the government and farmers to make decisions that will enhance agricultural production and rain water management.

Keywords: Monthly Rainfall, Rainfall Forecasting, Autoregressive Integrated Moving Average (ARIMA), Box –Jenkins Methodology, Akaike Information Criterion (AIC), Nigeria.

I. INTRODUCTION

Rainfall is a fundamental comp
onent of the hydrological cycle and plays a critical role in agricultural productivity, water resource management, ecosystem sustainability, and socioeconomic development. The spatial and temporal distribution of rainfall influences crop production, groundwater recharge, reservoir operations, hydropower generation, and environmental stability. In many developing countries, particularly in Sub-Saharan Africa, agriculture remains predominantly rain-fed, making food production and rural livelihoods highly vulnerable to rainfall variability and climate-related hazards. Consequently, accurate rainfall forecasting has become indispensable for agricultural planning, water resource allocation, disaster risk reduction, and climate-resilient development (Food and Agriculture Organization [FAO], 2023; Intergovernmental Panel on Climate Change [IPCC], 2023; World Meteorological Organization [WMO], 2023).

Climate change has substantially altered global precipitation patterns, resulting in increased rainfall variability, more frequent extreme weather events, and greater uncertainty in seasonal rainfall distribution. The IPCC (2023) reported that anthropogenic climate change has intensified the global hydrological cycle, leading to significant changes in the frequency, intensity, and duration of precipitation events worldwide. Similarly, the WMO (2024) observed an increasing occurrence of floods, droughts, and irregular rainfall patterns across Africa, with serious implications for agricultural productivity, water security, and sustainable development. In Nigeria, these climatic changes have manifested through delayed rainfall onset, shortened growing seasons, prolonged dry spells, and recurrent flooding, thereby threatening agricultural production, water availability, and rural livelihoods (World Bank, 2023; WMO, 2025). These developments have reinforced the need for reliable rainfall forecasting systems capable of supporting evidence-based planning and climate adaptation.

Rainfall distribution in Nigeria is primarily controlled by the seasonal interaction between the moist southwesterly maritime air mass from the Atlantic Ocean and the dry northeasterly continental air mass from the Sahara Desert. These air masses converge along the Inter-Tropical Discontinuity (ITD), whose seasonal migration determines the onset, duration, and cessation of the rainy season and explains much of the

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observed spatial and temporal variability in rainfall across the country (Odekunle, 1997). Northern Nigeria, including Adamawa State, is particularly sensitive to fluctuations in seasonal rainfall because agricultural production depends largely on natural precipitation. Consequently, changes in rainfall characteristics have profound implications for crop production, livestock management, water resources, and household food security.

Advances in meteorological observations and computational techniques have led to the development of numerous approaches for rainfall modelling and forecasting. These approaches include statistical time-series models, machine learning algorithms, deep learning methods, and hybrid forecasting techniques. Although machine learning models have demonstrated considerable predictive capability, conventional statistical methods continue to be widely applied because of their interpretability, computational efficiency, and relatively modest data requirements. Among these methods, the Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) model remains one of the most widely used approaches for modelling univariate climatic time series because of its ability to capture temporal dependence and generate reliable short-term forecasts (Abdulrahman et al., 2022; Wang et al., 2022).

Recent studies have reaffirmed the usefulness of ARIMA-based approaches for rainfall forecasting under different climatic conditions. Obot et al. (2025) demonstrated that statistical time-series models produced reliable monthly rainfall forecasts across selected Nigerian locations when appropriate model identification and validation procedures were employed. Similarly, Ibrahim et al. (2026) reported that ARIMA and Seasonal ARIMA models accurately predicted rainfall and temperature patterns in selected Nigerian cities, thereby providing valuable information for climate adaptation and urban planning. Maina and Grema (2026) further showed that hybrid STL–ARIMA models improved forecasting accuracy for monthly rainfall in northeastern Nigeria by effectively accounting for seasonal variability. Beyond Nigeria, Satheesh et al. (2024) demonstrated the effectiveness of combining atmospheric predictors with statistical learning techniques for rainfall prediction across tropical Africa, while Wang et al. (2022) emphasized the importance of rigorous model validation for improving precipitation forecasting over the African continent. Collectively, these studies demonstrated that statistical time-series models remain robust and practical tools for operational rainfall forecasting, particularly where long-term meteorological observations are available.

Despite these advances, important research gaps remain. Many previous studies conducted in Nigeria have focused on specific ecological zones, relatively short observation periods, or historical datasets that may not adequately reflect recent climatic variability. Furthermore, relatively few studies have investigated long-term monthly rainfall forecasting for Yola, Adamawa State, using updated observations extending to 2025. As one of Nigeria's major agricultural regions, Adamawa State depends heavily on seasonal rainfall for crop production and water availability. Developing an accurate forecasting model based on recent long-term rainfall records is therefore essential for improving agricultural planning, water resource management, and climate adaptation strategies. Addressing this gap will provide location-specific evidence capable of supporting informed decision-making under increasing climate uncertainty.

Against this background, the present study applied the Box–Jenkins ARIMA methodology to monthly rainfall data obtained from the Nigerian Meteorological Agency (NiMet) for Yola, Adamawa State, covering the period from 2000 to 2025. Specifically, the study examined the temporal characteristics of the rainfall series, identified the most appropriate ARIMA model, evaluated its forecasting performance, and generated monthly rainfall forecasts to support agricultural planning, water resource management, and climate-resilient decision-making in north-eastern Nigeria.

I. MATERIALS AND METHODS

2.1 Study Area

The study was conducted in Yola, the capital of Adamawa State, located in north-eastern Nigeria. The area lies within the Sudan Savannah ecological zone and experiences two distinct seasons: a rainy season, which generally extends from April to October, and a dry season from November to March. Agriculture is

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the dominant economic activity in the region and is largely dependent on seasonal rainfall. Consequently, accurate rainfall forecasting is essential for agricultural production, water-resource management, and climate-risk mitigation.

2.2 Data Source

Monthly rainfall data used in this study were obtained from the Nigerian Meteorological Agency (NiMet), Yola International Airport, Adamawa State, Nigeria. The dataset consists of 312 monthly rainfall observations recorded over a period of 26 years, spanning January 2000 to December 2025. Rainfall amounts, measured in millimetres (mm), constituted the response variable used for time-series modelling and forecasting. Prior to analysis, the dataset was examined for completeness and arranged chronologically to preserve the temporal sequence required for time-series modelling.

2.3 Research Design

The study adopted a quantitative longitudinal time-series research design. Historical monthly rainfall observations were analysed using the Box–Jenkins Autoregressive Integrated Moving Average (ARIMA) modelling framework to identify an appropriate stochastic model capable of describing the temporal behaviour of rainfall and generating reliable short-term forecasts.

The Box–Jenkins methodology was selected because it provides a systematic procedure for modelling univariate time-series data through the processes of model identification, parameter estimation, diagnostic evaluation, and forecasting.

2.4 Method of Data Analysis

Time series method will be used for the analysis of data.

Time series is defined as an ordered sequence of data or values of a variable at an equally time intervals. It is a stochastic process. Forecasting is the process of estimation in an unknown situation from the historical or past data. Time series methods use past or historical data as the basis for estimating future outcomes i.e ., given called time series, time series analysis predicts

In statistics, and in particular in times series analysis, the use of appropriate statistical procedure such as normality test using Kolmogorov-Smirnov test, Anderson-Darling test, etc. stationary test and unit root test that allows the application of Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) test of stationarity.

In this research work, the statistical tool used for the analysis is JMulTi to find a suitable time series model for forecasting of rainfall in Yola. The data for the analysis is the monthly rainfall data in millimetres (mm) obtained from the Nigerian Meteorological Agency (NIMET) Yola, Adamawa State for the period of 2000 to 2025.

2.5 Autoregressive Integrated Moving Average (ARIMA) Models

In statistics, and in particular in time series analysis, autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average(ARMA) model.

Also, in statistics, ARIMA models, sometimes called Box-Jenkins models after the iterative Box-Jenkins methodology usually used to estimate them, are typically applied to time series data for forecasting.

Given a time series of data Yt-1, Yt-2…Y2, Y1, the ARIMA model is a tool for understanding and, perhaps, predicting future values in the series. The model consists of three parts: an Autoregressive (AR) part, a moving average (MA) part and the differencing part. The model is usually referred to as the ARlMA (p, d, q) model, where p is the order of the autoregressive part, d is the order of the differencing part and q is the order of the moving average part. For example, a model as ARIMA (1,1,1) means that the model contains 1 autoregressive parameter and moving average parameter for the time series data after it was differenced once to attain stationarity.

If $d = 0$, the model become ARMA, which is a linear stationary model. ARIMA ($d > 0$) is a linear non-stationary model, taking the difference of the series with itself d times makes it stationary, and then ARMA is applied on to the differenced part (Ette et al, 2013).

2.6 Forecasting Using ARIMA Models

Forecasting Yt for Yt_1,Yt_2, …, Y2, Y1, using ARIMA model consists of the following steps. The main stages in setting up a forecasting ARIMA model includes model identification, model parameter estimation and diagnostic checking for the identified model appropriateness for modelling and forecasting.

Model identification is the first step of this process. The data would be examined to check, the most appropriate class of ARIMA process through selecting the order of the consecutive and seasonal differencing required in making the series stationary, as well as specifying the order of the regular and seasonal autoregressive and moving average polynomials necessary to adequately represent the time series model.

The autocorrelation function (ACF) and the partial autocorrelation function (PACF) are the most important elements of the time series analysis and forecasting. The ACF measures the amount of linear dependence between observations in a time series that are separated by a lag k. The PACF plots help to determine how many autoregressive terms are necessary to reveal one or more of the following characteristics: time lags where high correlations appear, seasonality of the series, trend either in the mean level or in the variance of the series.

In addition to the non-seasonal ARIMA (p, d, q) model introduced above, we could identify seasonal ARIMA (P, D, Q) parameters for our data. These parameters are: seasonal autoregressive (P), seasonal differencing (D) and seasonal moving average (Q).
The Akaike information criterion (AIC) is a measure of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection.

The Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC) is a criterion for model selection among a finite set of models; the model with the lowest BIC is preferred. It is based, in part, on the likelihood function and it is closely related to the Akaike information criterion (AIC).

When fitting models, it is possible to increase the likelihood by adding parameters, but doing so may result in overfitting. Both BIC and AIC attempt to resolve this problem by introducing a penalty term for the number of parameters in the model; the penalty term is larger in BIC than in AIC.

2.7 Test for Stationarity
Suppose that a variable Y_t is generated by the following first order autoregressive (AR) process

$$Y_t = pY_{t-1} + u_t$$

If p = 1, then Y_t will be non-stationary and it is possible to re-arrange and accumulate Y_t for different periods, starting with an initial value of Y_{t_n},, to obtain

$$Y_t = Y_{t-1} + \sum_{j=1}^{n} ut - j$$

That is, the current value of Y_t depends on its initial value and all disturbances accruing between t — n +1 and t, while the variance of Y_t is $t\sigma^2$ and this increases to .become infinitely large as t $\rightarrow\infty$.

However, if p <1, then Y_t will be stationary and it is possible to rearrange and accumulate Y_t for Efferent periods, starting with an initial value of Y_t-$_n$t° obtain

$$Yt = Yt-1 + \sum_{j=1}^{n} ut - j$$

Since p < 1, as n $\rightarrow\infty$, equation above reduces to Y_t being determined solely by a finite moving average (MA) process order n with most weight being placed on the first elements of the disturbance term (i.e. u_t+ pu_t -14- p^2u-t-2 + …). Thus, when Y_t is stationary, it has a constant lean and variance (and indeed covariance) that are independent of time. Analytically, the unit jot method mostly used to check if a time series is stationary or not.

2.8 Normality Test of Residuals
Many data analysis methods depend on the assumption that the data are sampled from a normal distribution or at least from a distribution which is sufficiently close to the normal distribution. For example, one often test

normality of residuals after fitting a linear model to the data in order to ensure the normality assumption of the model is satisfied.

There are several tests available to determine if a sample comes from a normally distributed population. These theory-driven tests include Kolmogorov-Smirnov test, Anderson-Darling test, Cramer von Mises test, Shapiro-Wilk's test, Shapiro-Francia test, etc. To complement the results of formal tests, graphical methods (such as Box-plots and Q-Q plots) have also been used and increasingly so in recent years.

2.9 Augmented Dickey-Fuller (ADF) Test

If a simple AR (1) DF model is used when in fact it follows an AR (p) process, then the error term will be auto correlated to compensate for the misspecification of the dynamic structure of Y_t. Auto correlated errors will invalidate the use of DF distributions, which are based on the assumption that u_t is "white noise'. Thus, assuming that Y_t follows an p^{th} order AR process,

$$Yt=\psi 1\,Yt-1\,\psi 2\,Yt-2+\ldots\psi p+ut \;\vee ¿$$
$$\Delta Yt=\psi * Y+\Delta Yt-1+\psi 2\,\Delta Yt-2+\ldots\psi p\,\Delta Yt-p+ut$$

$ut \sim II\left(O,\sigma^2\right)$, where $\psi * = (\psi 1+\psi 2+\ldots\psi P)-1$ if $\psi * = 0$, against the alternative $\psi* < 0$, then Y_t contains a unit root. To test the null hypothesis, we again calculate the DF t — statistic $\frac{\psi *}{se\,\psi *)}$, which can be compared against the critical values.

II. RESULTS

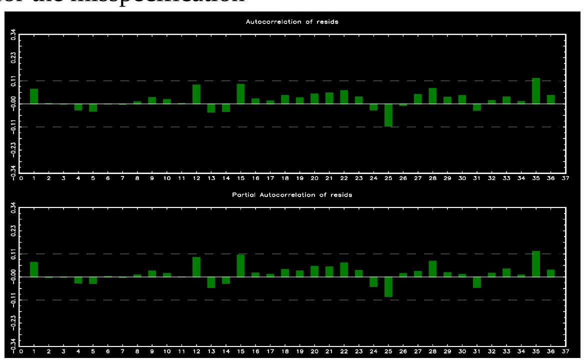
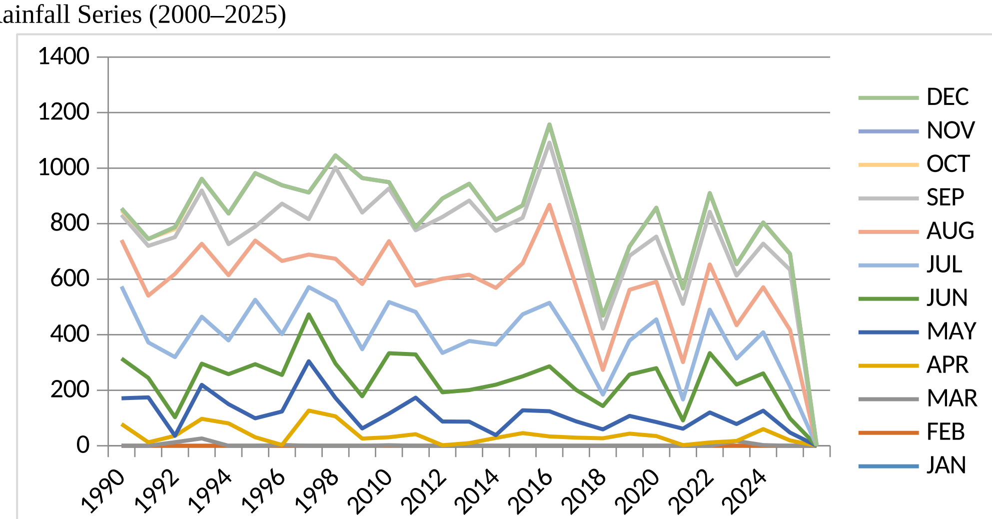


Figure 1 Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the Original Monthly Rainfall Series (2000–2025)



Time

Figure 2: Time Series Plot of Monthly Rainfall in Yola, Adamawa State (2000–2025)

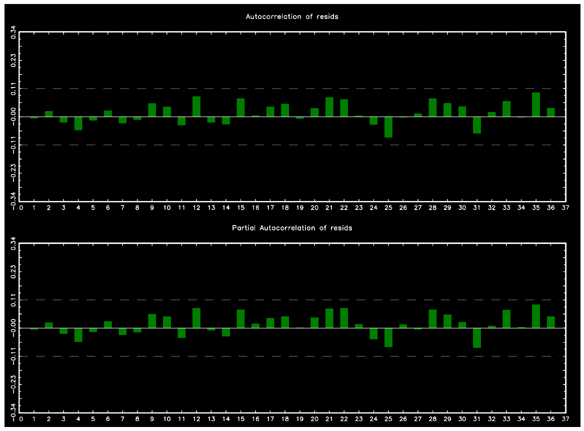
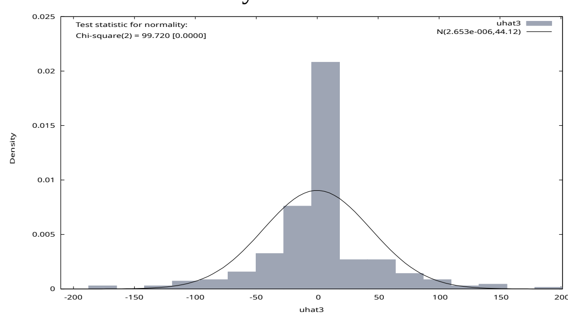


Figure 3 Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the First-Differenced Monthly Rainfall Series



Test for null hypothesis of normal distribution:

Chi-square (2) = 99.720 with p-value 0.00000

Figure 4 Normality Assessment of the Residual Series of the Selected ARIMA (3,1,2) Model

Table 1: Augmented Dickey–Fuller (ADF) Unit Root Test Results for Monthly Rainfall Series

Series	Number of Lags	Sample Size	Test Statistic (τ)	p-value	Decision
Original rainfall series	18	293	-1.17872	0.686	Non-stationary
First-differenced rainfall series	2	308	-17.26010	<0.001	Stationary

Table 2: Comparison of Candidate ARIMA Models

MODELS	AIC	SBC	DF
1,1,2	3181.789700	3237.934748	297
1,1,3	3183.697230	3243.567181	296
2,1,1	3181.785720	3237.930768	297
2,1,3	3184.661782	3248.292836	295
3,1,1	3183.629456	3243.517507	296
3,1,2	3180.448187	3244.079241	295
3,1,3	3180.756096	3248.130154	294

Table 3. Parameter Estimates for the Selected ARIMA(3,1,2) Model

Parameter	Estimate	Standard Error	t-Ratio	p-value
AR(1)	0.016034	0.061018	0.263	0.79291
AR(2)	-0.988292	0.015526	-63.652	<0.001
AR(3)	0.097315	0.059489	1.636	0.10293

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MA(1)	-0.062417	0.077896	-15.203	0.38749
MA(2)	-0.999999	0.055158	0.875	0.58813
Constant	0.583600	7.305659	0.080	0.93638

Table 4: Seasonal Effects

Season	Estimate	Standard Error	t-Ratio	p-value
S1	-0.142599	9.857307	-0.014	0.98847
S2	-1.377637	9.973734	-0.138	0.89023
S3	1.405516	10.252278	0.137	0.89105
S4	37.501572	10.603630	3.537	<0.001
S5	83.400839	10.307916	8.091	<0.001
S6	128.230395	10.031547	12.783	<0.001
S7	157.175965	10.321576	15.228	<0.001
S8	195.421288	10.598268	18.439	<0.001
S9	173.987213	10.246700	16.980	<0.001
S10	59.817816	10.013687	5.974	<0.001
S11	-0.524720	9.837494	-0.053	0.95750

Table 5: Model Summary

Statistic	Value
Selected Model	ARIMA(3,1,2)
Number of Observations	312
Log-Likelihood	-1573.224093
AIC	3180.448187
SBC	3244.079241
Error Variance	1463.697007
Standard Error	38.258293
Degrees of Freedom	295

Table 6: Forecasted Monthly Rainfall for 2026

Month	Forecast Rainfall (mm)
January	0.0000
February	0.0000
March	0.0000
April	49.0862
May	87.1114
June	117.5977
July	155.5600
August	207.3589
September	175.8352
October	48.9866
November	0.0000
December	0.0000

Source: Monthly rainfall forecasts generated using the selected ARIMA(3,1,2) model.

III. DISCUSSION

The Box–Jenkins methodology was employed to develop an appropriate ARIMA model for forecasting monthly rainfall in Yola, Adamawa State. The exploratory analysis began with the examination of the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the original rainfall series. As shown in Figure 1, the ACF exhibited a gradual decay with several autocorrelation coefficients extending beyond the 95% confidence limits, indicating the presence of serial correlation and suggesting that the original rainfall series was non-stationary. The PACF also displayed significant spikes at the initial lags, providing evidence of temporal dependence in the rainfall observations and supporting the need for differencing before model estimation.

The temporal characteristics of the rainfall data are illustrated in Figure 2, which presents the monthly rainfall observations for the period 2000–2025. The figure demonstrates a clear seasonal rainfall pattern, with rainfall concentrated during the wet season and little or no rainfall during the dry season. The series also exhibits noticeable fluctuations in rainfall intensity across the study period, with relatively higher rainfall amounts observed around 2016 and 2019. These variations highlight the dynamic nature of rainfall in Yola and justify the application of time-series modelling techniques capable of capturing both seasonal behaviour and temporal dependence.

Following first-order differencing, the ACF and PACF plots shown in Figure 3 indicate that the autocorrelation structure of the rainfall series was substantially reduced. Most of the autocorrelation coefficients fell within the 95% confidence limits, suggesting that the differenced series had achieved stationarity. This graphical evidence is consistent with the statistical results presented in Table 1, where the Augmented Dickey–Fuller (ADF) test indicated that the original rainfall series was non-stationary ($\tau = -1.17872$, $p = 0.686$), whereas the first-differenced series became stationary ($\tau = -17.26010$, $p < 0.001$). These findings confirm that one level of differencing was sufficient to satisfy the stationarity assumption required for ARIMA modelling.

The distribution of the residual series was examined using the normality test presented in Figure 4. The figure reports a Chi-square statistic of 99.720 with an associated p-value of 0.00000. This result forms part of the model diagnostic assessment and should be interpreted alongside other diagnostic measures when evaluating the adequacy of the fitted model.

Several competing ARIMA models were estimated and compared to determine the most suitable forecasting model for the rainfall series. As presented in Table 2, seven candidate ARIMA models were evaluated using the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). Among these models, ARIMA(3,1,2) produced the lowest AIC value (3180.448187) and SBC value (3244.079241), indicating that it provided the most parsimonious representation of the rainfall series among the models considered. The use of these information criteria ensured that the selected model achieved a balance between model fit and complexity.

The parameter estimates of the selected ARIMA (3,1,2) model are presented in Table 3, while the corresponding seasonal effects are reported in Table 4. The model incorporates three autoregressive terms and two moving-average terms, reflecting the temporal dependence structure present in the rainfall series. The seasonal parameter estimates further demonstrate substantial variation across the months of the year, with positive and statistically significant seasonal effects observed during the core rainy season. These seasonal coefficients are consistent with the climatological characteristics of Yola, where rainfall increases progressively from April, reaches its maximum during August, and declines thereafter.

The overall performance of the selected forecasting model is summarized in Table 5. The ARIMA (3,1,2) model was estimated using all 312 monthly rainfall observations and produced a log-likelihood value of −1573.224093, an AIC of 3180.448187, and an SBC of 3244.079241. These model fit statistics indicate that the selected model adequately captured the underlying temporal behaviour of the rainfall series and was therefore considered appropriate for forecasting monthly rainfall in the study area.

The monthly rainfall forecasts generated by the selected ARIMA model are presented in Table 6. The forecast indicates that rainfall is expected to commence in April, increase steadily throughout the rainy season, and attain its maximum value of approximately 207.36 mm in August before declining during September and October. No rainfall was forecast for January, February, March, November, and December. These predictions closely reflect the established seasonal rainfall regime of Yola and demonstrate that the selected ARIMA model successfully reproduced the historical rainfall pattern observed over the study period. The forecasts provide useful information for agricultural planning, irrigation scheduling, water-resource management, and climate adaptation initiatives within the study area.

The results obtained from the graphical analyses (Figures 1–4) and the statistical summaries (Tables 1–6) consistently indicate that the ARIMA (3,1,2) model provides an adequate representation of the monthly rainfall series and is suitable for short-term rainfall forecasting in Yola, Adamawa State. The findings demonstrate the usefulness of the Box–Jenkins modelling framework as a practical tool for analysing seasonal rainfall behaviour and supporting evidence-based planning in climate-sensitive sectors.

IV. CONCLUSION

This study developed an Autoregressive Integrated Moving Average (ARIMA) model to forecast monthly rainfall in Yola, Adamawa State, Nigeria, using monthly rainfall records spanning 2000–2025. The findings demonstrated that the original rainfall series was non-stationary but became stationary after first-order differencing. Among the candidate models evaluated, ARIMA (3,1,2) provided the best fit according to the Akaike Information Criterion and Schwarz Bayesian Criterion.

The selected model successfully reproduced the seasonal rainfall characteristics of the study area, forecasting the onset of rainfall in April, peak rainfall in August, and the cessation of rainfall toward the end of October. These forecasts provide valuable information for agricultural production, irrigation planning, water-resource management, and climate adaptation.

Although the ARIMA (3,1,2) model performed well for short-term forecasting, future research should investigate seasonal and hybrid forecasting models and evaluate their predictive performance using additional accuracy measures. Such studies would further strengthen rainfall forecasting and support evidence-based environmental planning in north-eastern Nigeria.

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