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Evaluation of SARIMA Model for Rainfall Forecast in Ogbaru in Anambra State, Nigeria

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***Abstract*: Ogbaru community is blessed with arable land suitable for crop production. However, this region cannot be fully harnessed without proper understanding of the rainfall pattern. Modelling and forecasting rainfall in this region is crucial considering the climate change that has brought a new narrative into the rainfall pattern nationwide. This study applied Seasonal Integrated Moving Average (SARIMA) models in modelling and forecasting rainfall in Ogbaru. The yearly rainfall data for this locality between 1995 and 2025 (30 years) was obtained from the NIMET. To assess the stationarity of the time series, initial exploratory analysis was conducted through graphical visualization. Formal stationarity was carried out using the Augmented Dickey–Fuller (ADF) test. Adopting a 5% significance level, a p-value below 0.05 ($p < 0.05$) was considered as been stationary. Following the establishment of stationarity, tentative Seasonal ARIMA (SARIMA) models were identified. The identification of this structure was guided by the inspection of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. This manual method of model identification was cross-validated using the auto-arima procedure in Python, which optimizes parameters based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). Model parameters were estimated with 95% confidence intervals, and goodness-of-fit was evaluated using the Ljung–Box test and a p-value greater than 0.05 ($p > 0.05$). Based on the result of out-of-sample forecast performance, SARIMA (1,0,2) $(1,0,1)_{12}$ was found to be suitable for rainfall forecast. Finally, ten years foecast for Ogbaru was obtained using the optimal model. The findings show that the seasonal terms were statistically significant in the model which justified the use of SARIMA models in modelling rainfall in Ogbaru. Findings also revealed that SARIMA model is good for long-term forecasting of rainfall in this location.**

***Keywords*: Akaike Information Criterion, Bayesian Information Criterion, Augmented Dickey Fuller, long term forecast, Modelling, Ogbaru community, Python software, Rainfall data, SARIMA, Validation.**

1. Introduction

Rainfall forecast simply means the application of different analytical methods to evaluate future rainfall event during a certain period at a specific area [1]. Due to the irregularity and complex nature of rainfall data, this process involves simulation and modeling of rainfall data [2]. Though technological advancement and innovation in data processing have substantially enhanced the accuracy of rainfall forecast over the last decade, yet no forecast model can be perfect [1].

The analysis of rainfall trend is crucial due to the occurrence and magnitude of extreme events which has constantly influence the ecosystems, social and economic activities of the society [3], [4]. Many studies on historical rainfall data have shown that heavy rainfall and consequent landslides and flooding threaten watershed management, urban and rural development [5]-[9]. Moreover, fluctuation in timing of the rainfall has affected agriculture significantly as research has revealed that approximately 95% of agricultural production in low-income countries is rain-fed [10], [11]. Hence, forewarning of inception and cessation of rainfall is vital to farmers for proper planning of their farming activity [12].

Ogbaru community is notable for its involvement in agricultural activities and live in the coastal area of the state. These farmers rely highly on rainfall for their agricultural activities [13] to achieve high crop yield [14]. According to Onyegbula and Oladeji [15], Ogbaru have been experiencing heavy rainfall caused by fluctuation in timing and amount of rainfall due to climate change. Furthermore, flooding is a serious environmental issue that threatens this region [16]. According to Nnadi et al. [17], this community suffered greatly during a severe flooding in 2012; which destroy lives and properties. Hence, the ability to forecast extreme hydrological events is crucial for urban development and mitigation strategies [18].

Currently, stochastic model is an interesting topic in hydrology, and widely used in more complex climatic forecast for better understanding of the rainfall process. It provides clarity to doubtful outcome associated climate research [19]. This model simulates rainfall data that have similar properties to the actual ones measured from rain gauge stations [18]. Lately, stochastic models like SARIMA (Seasonal Autoregressive Integrated Moving Average) and ARIMA (Autoregressive integrated moving average) are being used in forecasting of hydrological processes. These models are better than other statistical models due to its unique techniques in forecasting time series [20]. The SARIMA model is another version of ARMA where alteration are made in time-series to remove its seasonality and non-stationary behaviour through trend and seasonal differencing [21]. In the work, SARIMA models were developed for future forecasts of the rainfall in in Ogbaru community.

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2. Materials and Method

A. Study Area

Ogbaru is one of the Local Government Areas (L.G.A) in Anambra State, Nigeria. It comprises of a wide wetland zone, situated in the southwest region of the State. It is located at latitudes 5°42' and 6°08'N and Longitudes 6°,42' and 6°50E and shares boundaries with the following towns such as Onitsha, Idemili, Ekwusigo and Ihiala. It is also surrounded by three States namely; Imo States. Delta State and Rivers State. The area is made up of swampy lowland (less than 120m above sea level) with network of creeks, lakes, ponds and terrain plunges towards water bodies [22]. Its geology is dominated by alluvium and located close to River Niger and Ulasi River. The vegetation is made up of grassland, rainforest and guinea savannah. It has an average temperature range of 24°C - 30°C and experience two seasons namely: dry and wet season. Normally, the wet season starts from March and ends in October, while the dry season last from November till February. The inhabitants of this community are mostly farmers. They are the major producers of rice in Southeast Nigeria.

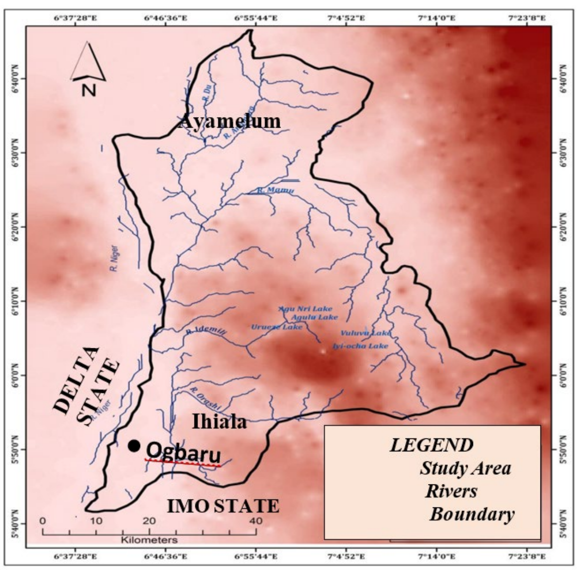

Fig. 1. Anambra state map depicting the study area

B. Software used in the Study

All the SARIMA modelling were implemented in Python 3.11.3 software. The predictive analysis was conducted using open-source libraries (like statsmodels and sklearn). The data manipulation was performed with pandas, mathematical operation was carried out with numpy, while data visualization and exploratory analysis were done with Matplotlib.

C. Data Collection

Monthly and annual rainfall data spanning from January 1995 to December 2025 (30 years), were collected from the Nigerian Meteorological Agency (NIMET), Enugu-Agidi, Anambra. State. The choice of the rainfall sample size was based on the sampling theorem proposed by [23]; which states that the sample size of hydrologic process for statistical analysis lies in the range of 25 - 27.5 year. Hence thirty (30) year sample size was considered appropriate for this study.

D. Data Analysis

To evaluate the stationarity of the rainfall data, initial exploratory analysis was conducted through graphical visualization. Time series plots were generated to identify trends, and seasonality. Given that rainfall data is typically characterized by positive skewness, non-constant variance, and multiplicative seasonal effects, a natural logarithmic transformation was applied. This transformation stabilizes the variance, reduces skewness, and converts multiplicative relationships into additive ones, rendering the series more suitable for linear modelling. All analyses were implemented in Python 3.11.3 software.

E. Augmented Dickey Fuller (ADF) test for stationarity

Augmented Dickey-Fuller test are performed to ascertain the stationarity claim of the visual displays of the rainfall data. The ADF test is conducted with hypothesis;

H_O: The rainfall data is unit root non stationary

H_1: The rainfall data is stationary

Decision: A p-value below 0.05 ($p < 0.05$) was considered as being stationary. Hence, the null hypothesis is rejected. For this test adfuller function was imported from 'statsmodels.tsa.stattools' library in python 3.11.3 software and adopting a 5% significance level.

F. Model identification

SARIMA models were employed in to incorporate seasonality in the rainfall; which includes additional parameters for seasonal autoregressive (SAR) and seasonal moving average (SMA) parameters. The SARIMA model for rainfall was SARIMA (p, d, q) (P, D, Q)$_S$.

Where; p is non-seasonal Auto-Regressive (AR)order, d is non-seasonal differencing, q is non-seasonal Moving Average (MA) order, P is seasonal Auto-Regressive (AR) order, D is seasonal differencing, Q is seasonal Moving Average (MA) order, and S is time span of recurring seasonal pattern (e.g. 12 for monthly data with annual cycle)

The non-seasonal ARIMA model for a set of equidistant measurements $Z = [Z_1, Z_2 \ldots Zn]$ can be written as,

$$\phi_p(B)\nabla^d Z_t = \theta_q(B)\varepsilon_t \quad (1)$$

where ϕ_p and $\theta_q$are polynomials of order p and q, respectively.

∇^d is the difference operator
d is the number of differences;
t is discrete time;
ε_t is the white noise.

SARIMA model is obtained from equation (1) through integration of seasonal component as seen in equation (2)

$$\varphi_p(B^s)\phi_p(B)\nabla_s^D\nabla^d Z_t = \Theta_Q(B^s)\,\theta_q(B)\varepsilon_t \quad (2)$$

where,
∇_s^D is seasonal difference
∇^d is the regular difference
$\Theta_Q\ (B^s)$ is seasonal autoregressive operator of order q
$\theta_q(B)$is regular autoregressive operator of order q
$\varphi_p(B^s)$ is seasonal moving average operator of order of p
$\phi_p(B)$ is seasonal moving average operator of order of p
ε_t is the white noise

G. *Model parameter estimation*

This is a computational analysis of all the parameters of the tentative models using neither maximum likelihood nor least-square method. In this study, the auto_ARIMA function was used to automatically obtain the optimum order for all tentative models. In Python, the auto_ARIMA function produced the best order for the model's parameters by applying a maximum likelihood technique. Then, the best fitted model from all the tentative ones are chosen based on the least Akaike Information Criteria (AIC) and Bayesian Information Criterion (BIC). The equation is written as:

$$\text{AIC} = -2\ln L + 2k \tag{3}$$

where
L is the value of the likelihood,
n is the number of recorded measurements
k is the number of estimated parameters.

$$\text{BIC} = -2\ln L + k\ln(n) \tag{4}$$

where
L is the value of the likelihood,
n is the number of recorded measurements
k is the number of estimated parameters.

H. *Residual diagnostic check*

This phase checks whether a final selected model among the tentative models conforms with the demands of a stationary univariate process by obtaining a flat correlogram of the residue; with the lag fallen within the standard error bound or 95% confidence interval. To confirm the goodness of fit, a Ljung–Box test was performed with hypothesis;
H_O: Residuals are not white noise
H_1: Residuals are white noise
Decision: A high p-value ($p > 0.05$) implies that the residuals were white noise, suggesting an adequate fit. Therefore, the null hypothesis is rejected. The equation is written as:

$$\text{Ljung-Box test (Q)} = n(n+2)\sum_{k=1}^{h}\frac{p_k^2}{n-k} \tag{5}$$

where
n is sample size
p_k^2 is sample autocorrelation at lag k
h is the number of lags being tested
k is time lag (number of intervals between data point)

I. *Model Evaluation Metrics*

Model performance is evaluated using the mean absolute error (MAE) and Root mean squared error (RMSE). They provide a detailed analysis of the reliability and accuracy for rainfall forecasting. The formulas for these metrics are shown in equations (6) - (7).

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{7}$$

where n is the total number of data points, y_i is true value and $\hat{y}_i$ is forecasted value.

J. *Model training and out-of-sample validation*

The rainfall data was partitioned into training and testing subsets; with 80% (from 1995 to 2023) of the data used to train the various SARIMA models and the remaining 20% (2024 to 2026) reserved for out-of-sample testing. The plot of the actual values and predicted values were used for model validation. Finally, forecasting of future rainfall data was based on the final selected SARIMA model.

3. Results and Discussion

Figure 2 depicts the longitudinal analysis of average annual rainfall across Ogbaru between 1995 and 2025. In the graph, there was a convergence in rainfall in all the locations except in Awka. The trends also show a wide fluctuation in the inter-annual rainfall in all the study areas for the period of 2015 – 2020. This result agrees with [17]; who researched on the effects of rainfall variation on gender of farmers in Anambra, and his findings revealed a rise and fall in the rainfall trend in Ogbaru. The maximum mean annual rainfall was recorded in 2019, while the minimum was recorded in 2021 across the stations, suggesting that this is the driest year between the periods of study.

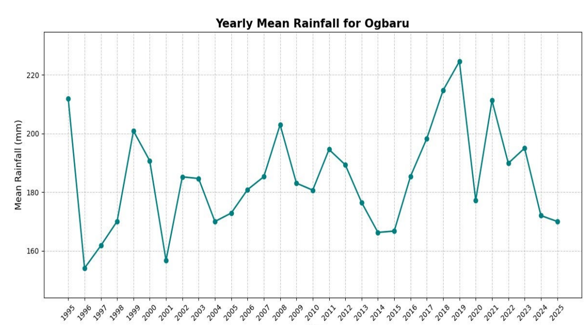

Fig. 2. Distribution of yearly mean rainfall

A. *Correlogram of rainfall time series*

One technique used for model identification is the examination of the correlogram (graph) of autocorrelation function (ACF) and the partial autocorrelation function (PACF). In this study, the correlogram presents the graphs of autocorrelation function as well as partial autocorrelation function (PACF) for Ogbaru is presented in Figure 3. Seasionality is evident is evident in the data from the ACF graph, which shows upward and downward movement over the lags. It proves that there is autocorrelation in the rainfall series. SARIMA is a perfect model for the rainfall data because it exhibits periodic events. The data has a yearly seasonal component, as indicated by the ACF with a significant peak at a lag 12.

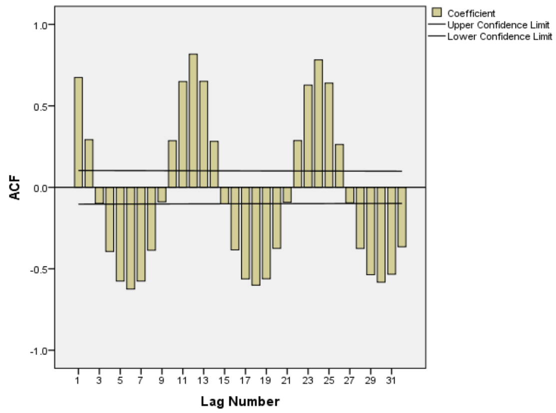

Fig. 3. A chart of ACF verses Lag

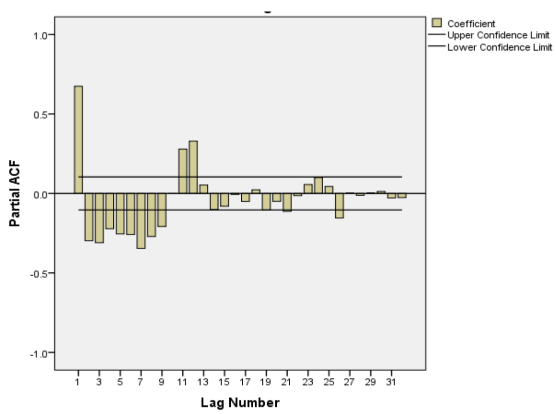

Fig. 4. A chart of Partial ACF verses Lag

B. Stationarity of the Rainfall Data

The actual rainfall data collected from NIMET was subjected to ADF test after transformation and the result is displayed in Table 4.2 with p-values of 0.0011 for Ogbaru, Since the p-value is less than the 0.05 significance level. Hence, Ho (null hypothesis) is rejected.

This implies stationarity in the data, and therefore, no need for differencing. It is assumed that stationarity determines the accuracy of a model and this assertion is in line with agreement with the reports of [24], [25]; who studied the effect of non-stationarity on model.

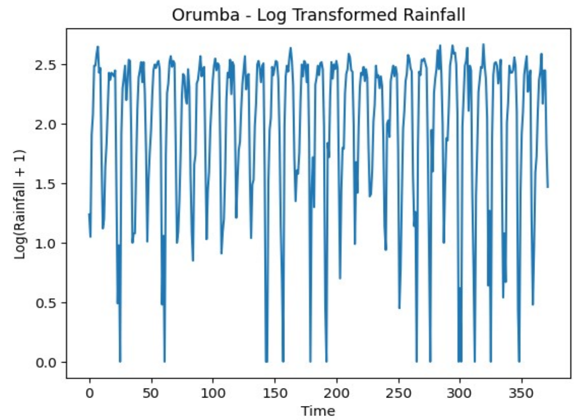

Fig. 5. Plot of log transformed rainfall

Table 1
Summary result of the test of a stationarity using ADF test

Type of test	Test statistics	P-value
ADFS	-4.0608	0.0011

The outcome of Table 1 agrees with [26]; who studied rainfall forecast in some African stations using SARIMA. His result shows that the test stationarity of rainfall in most African cities was stationary at levels, as the order of differencing were found to be zero as seen in Table 2.

C. Model Identification, Diagnostic Check and Validation for Ogbaru

Table 2 shows that two tentative SARIMA models were identified as being suitable for predicting rainfall dynamics in Ogbaru. These models were SARIMA$(2,0,1)(1,0,1)_{12}$ and ARIMA$(2,0,1)(1,0,1)_{12}$, with each showing no evidence of autocorrelation of the errors as reveals by the p-values of 0.061435 and 0.0672 ($p>0.05$). This implies that these candidates' ARIMA models are adequate in forecasting rainfall in Ogbaru (Table 4.5). Among the two competing models, SARIMA $(2,0,1)(1,0,1)_{12}$ provided the least AIC (654.030) and BIC (677.143) as well as the least RMSE (35.5350) and MAE (25.6798). This therefore makes SARIMA $(1,0,2)(1,0,1)_{12}$ appropriate for forecast of rainfall in Ogbaru. In Figure 4.9, the chart of the actual and predicted values display a close relationship; which reveals that the proposed SARIMA $(1,0,2)(1,0,1)_{12}$ adequately capture the dynamics in rainfall in

Table 2
Comparative performance of SARIMA models for modelling rainfall in Ogbaru

	Fitness performance		Forecasting performance		Diagnostic checking	
SARIMA models	AIC	BIC	RMSE	MAE	Lj.Box	p-value
$(2,0,1)(1,0,1)_{12}$	654.6	677.6	35.6	25.7	28.0	0.06
$(1,0,2)(1,0,1)_{12}$	654.0	677.1	35.5	25.7	27.7	0.07

Table 3
Parameter estimate of the best SARIMA model for rainfall forecast in Ogbaru [ARIMA $(1,0,2)(1,0,1)_{12}$]

Parameters	Coefficient	SE	Z-value	P-value	LCL	UCL
AR1	0.9984	0.017	58.420	0.000	0.965	1.032
MA 1	-0.8937	0.032	-28.154	0.000	-0.956	-0.831
MA 2	-0.0912	0.019	-4.897	0.000	-0.128	-0.055s
SAR1	0.9989	0.001	732.796	0.000	0.996	1.002
SMA1	-0.9128	0.053	-17.075	0.000	-1.018	-0.808

Table 4
Mean of Monthly and Annual Rainfall (mm) in Ogbaru (2026–2035)

Month	2026	2027	2028	2029	2030	2031	2032	2033	2034	2035
January	15.9	13.1	13.0	13.0	13.0	12.9	12.9	12.9	12.8	12.8
February	19.3	17.9	17.9	17.8	17.8	17.7	17.7	17.6	17.5	17.5
March	69.3	69.0	68.6	68.2	67.9	67.5	67.1	66.7	66.3	65.9
April	140.3	140.0	139.1	138.2	137.3	136.3	135.4	134.4	133.4	132.5
May	239.9	238.1	236.4	234.6	232.7	230.9	229.1	227.2	225.4	223.5
June	297.6	295.3	292.9	290.6	288.2	285.9	283.5	281.1	278.7	276.3
July	373.0	370.0	366.9	363.8	360.7	357.6	354.4	351.3	348.1	345.0
August	254.4	252.5	250.6	248.7	246.7	244.7	242.8	240.8	238.8	236.8
September	337.3	334.6	331.9	329.1	326.4	323.6	320.8	318.0	315.2	312.4
October	275.5	273.4	271.3	269.1	266.9	264.8	262.6	260.4	258.2	256.0
November	53.8	53.6	53.3	53.1	52.8	52.5	52.2	51.9	51.7	51.4
December	8.8	8.8	8.8	8.8	8.8	8.7	8.7	8.7	8.7	8.6

Ogbaru. The comparative performance of tentative models for forecasting of rainfall in Ogbaru is presented in Table 2, while the model parameter analysis is presented in Table 3.

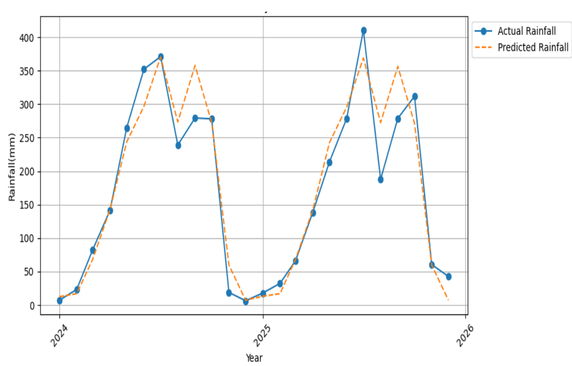

Fig. 6. Plot of the actual of rainfall and the predicted rainfall in Ogbaru with SARIMA $(1,0,2)(1,0,1)_{12}$

D. Models Parameters analysis

All the model's parameters is considered statistically significant ($p<.05$), which emphasizes the importance of these parameters in capturing the variation in rainfall in Ogbaru. The significance of the non-seasonal Autoregressive term (AR1) (Coefficient = 0.9984, $p < 0.001$), shows that prior rainfall has a significant impact on the current rainfall. The non-seasonal moving average terms are also significant, MA1 (Coefficient =-0.8937,$p < 0.001$) and MA2 (Coefficient = -0.0912, $p < 0.001$), as well as indicating that past error terms significantly play in capturing rainfall dynamics in Ogbaru. The significance of the seasonal components for both seasonal AR (coefficient = 0.9989, $p < 0.001$), and seasonal MA 2 (coefficient = -0.9128, $p < 0.001$) emphasize the significant effect of seasonal dependence as well as past seasonal errors on current rainfall.

E. Residual Analysis of the Models

The results of Ljung box test show that the SARIMA model is good fit. This is further confirmed by the chart of lag verses residual ACF and PACF (Figure 7); which lacks significant spikes that can subverting the goodness of fit of the models.

However, a decreasing trend was observed over the ten-year period in all the localities. This result aligns with [27]; who examined rainfall pattern in Nigeria from 1931–1971 and reported a 7% annual decline in 90% of the Nigerian states. Similarly, the finding was supported by [28]; who used SARIMA (2,0,1) $(2,1,1)_{12}$ to forecasts for twenty four years (2018–2042) rainfall in Nigeria. He observed a decrease from a period of 2024-2042.

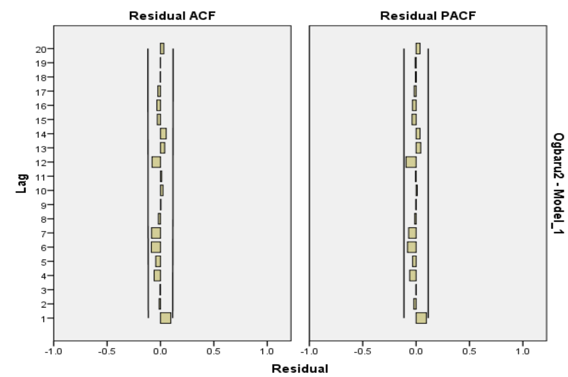

Fig. 7. Lag verses residual ACF and PACF

4. Conclusion

Based on the outcome of the result of the analysis, SARIMA $(1,0,2)(1,0,1)_{12}$ for the monthly rainfall series of Ogbaru was established as the best model having passed the diagnostics checking test and was used to forecast the monthly rainfall values for the next ten years. Moreover, the outcome of the validation were satisfactory; as predicted values were observed to be close to the actual values. This implies that the SARIMA models were able to produce fairly accurate and acceptable forecasts. In conclusion, the aim of this study has been achieved. SARIMA models were developed for making short-term (monthly) and long-term (yearly) rainfall forecasts for the selected rainfall stations. Hence, this best fitted models can help decision makers to address future events related to weather situations in the study areas. Additionally, the next ten years forecast reveals that rainfall was high in 2026 and continuously decline in the subsequent years. The deduction from this finding implies that in the next ten years, there is the possibility of lower rainfall in relation to its subsequent past years and this calls for proper strategies for rainfall harvesting, irrigation scheme and planting of drought resistant crops in response to dry spell.

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