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Application of an STL–ARIMA Hybrid Framework for Monthly Rainfall Forecasting in Maiduguri, Nigeria

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ABSTRACT

The problems of climate variability in Sahel regions with severe rainfall anomalies bring serious challenges to the water resource management and mitigation of the flood disasters. This paper analyzes the effectiveness of a hybrid STL-ARIMA model to predict monthly rainfall in Maiduguri, Nigeria, which is a town that was affected by the 2024 floods. The article compares the hybrid, traditional Seasonal ARIMA (SARIMA) and Exponential Smoothing by Holt-Winter to assess previous rainfall data of 1981-2023. The suggested method employs Seasonal-Trend Decomposition by Loess (STL) to single out non-linear and seasonal trends that are too complicated then subjecting the time series to ARIMA modeling. With regards to performance, it can be seen that the STL-ARIMA model is far ahead of the conventional approach with a Root mean square error of 29.54mm, as opposed to 43.94mm and 43.01mm using the SARIMA and Holt-Winter models respectively. The hybrid model minimized the Mean Squared Error (MSE) by nearly 55% and it was more effective in terms of capturing the sharp variance variation and extreme wet-season peaks, which are characteristic of the area. These results provide a strong scientific foundation in enhancing flood early warning systems directly related to SDG 13 (Climate Action) goals in Northeastern Nigeria.

INTRODUCTION

Climate change has a transpiring path as a long-term, continual change in the average weather conditions that differ greatly in both the time and the space (Karabulut et al., 2008). This is a primary risk to all natural systems, which threatens the development and survival of human beings in both the economic, social, and political levels (Oluwafemi et al., 2010). Furthermore, it is widely acknowledged that developing nations in tropical areas, like Nigeria, are significant affected by the climate than their developed counterparts. Rainfall is one of the climate parameters that affect the pattern and behavior in which humans live. It impacts all elements of the ecosystem, including plants and animals. Therefore, the examination of rainfall cannot be overemphasized (Obot and Onyeukwu, 2010). In addition to its positive effects, rainfall can also have negative effects, such as producing natural disasters like floods, which can then lead to drought (Ratnayake & Herath, 2005).

The Sahel Zone, running along West to East Africa, is renowned for the very high variability in its climate and the resultant environmental stressors (Epule et al., 2018). Mitigating climate variability and change in the Sahel, as elsewhere in Africa, is challenged by among other factors a dearth of suitable expertise, lack of preparedness, and inadequate resources to deal with climate-related issues (Washington et al., 2006). Sahel rainfall patterns have also shown significant variability in the remote past (Zhang et al., 2021; Nicholson et al., 2018), with forecasts indicating that similar significant alterations are likely to occur in near future (Chadwick et al., 2016). Though both drought and flood are associated phenomena of the hydrological cycle, studies have been biased towards drought since the 1970s when there were drastic dry periods (Nicholson et al., 2018). The floods in the Sahel have therefore been relatively ignored. By 2018, scientific studies on drought put floods research 44 percent behind, which has exposed populations to immense risk (Epule et al., 2018). This disparity aggravated the susceptibility of both humans and the environment to the effects of flood (Canton 2021). In addition, historical records of floods are usually not standardized and are not rigorous (Elagib, 2021; Umuakpero et al 2025).

The Intergovernmental Panel on Climate Change (IPCC, 2023) states that there is an increase in rainfall in the world, there are indications that it is rising on the African continent through warming conditions (Biasutti et al., 2019). The similarities in local data complications are reflected in the variables in Nigeria, with earlier analyses of meteorological stations indicating falling rainfall conditions (Adefolalu, 1986), It is commonly observed behavior of rainfall to increase or decrease depending on the location and period of time of data analyzed (Jayawardene et al., 2005). This can be particularly felt in Maiduguri in northeast Nigeria whereby temperature dynamics dominate the monsoon system. In 2024, Maiduguri was hit by its highest precipitation of more than 300 mm in August after about 200mm in July. This rush took over drainage systems causing severe flooding (Umar et al., 2025). Without intervention, experts note that such events will become the order of the day rather than being the exception.

Mitigating such risks is in accordance with the global sustainability models. Sustainable Development Goal 13 (climate action) requires urgent actions to boost resilience and adaptive capacity towards climate related hazards (United Nations, 2024). This is critical to the Sahel and Nigeria that have a disproportionate load of climate aberrations (WMO, 2024). In spite of mitigation activities in the world, there is a growing disparity in developing countries (UNEP, 2024; IPCC, 2023). Thus, the operationalization of SDG 13 will require the use of an advanced hydrological forecasting model, including the hybrid methods put forward in this research. These models would also promote the climate intelligence that policymakers require to reposition disaster risk governance away from reactive intervention models toward proactive resilience strategies (Biermann et al., 2025).

In order to accomplish this predictive accuracy, in this study time series forecasting methods of great strength have been utilized. Autoregressive Integrated Moving Average (ARIMA) is a popular statistical tool that employs the past observations and lag error to predict future values (Lem, 2024). Also, Seasonal- Trend Decomposition with Loess (STL) is used to separate the time series data into trend, seasonality and residual. This isolation improves the performance of ARIMA in decisional action of seasonal change by isolating the factors (Lem, 2024). Exponential Smoothing State Space (ETS) models are also considered in the study to emphasize recent data over the old data (Hyndman et al., 2018). Considering STL before ETS or Seasonal ARIMA (SARIMA), it eliminates the seasonality factor, making the modeling process easier and improvements in the forecasting business more frequent (Ouyang et al., 2021; Hyndman et al., 2018).

Although such sophisticated statistical techniques are available, there is a huge deficit in using the techniques to Maiduguri, the micro-climate. The available literature on the Sahel largely concentrates on drought indices or uses individual forecasting models which might not be in a position to represent the complex and non-linear volatility of the recent years. The literature on the hybrids (STL-ARIMA and STL-ETS) and their effectiveness in particular in the context of the historic rain patterns witnessed in 2024 is lacking. Moreover, there is a lack of studies on the connection between high-precision local predicting and operationalization of SDG 13 targets in northeastern Nigeria. This study aims to fill this gap through the evaluation of comparative precision of hybrid ARIMA, SARIMA and exponential smoothing in order to offer an effective paradigm on the prediction of rainfalls in the area in future.

Significant of Study

Research data on rainfall variability in northeast Nigeria especially the Maiduguri is insufficient when compared to other areas of the country. The proposed study will help to address this gap, since it will produce localized information and model methods, which can be utilized in the event of a future climate-oriented research and development.

MATERIALS AND METHODS

Study Area

Maiduguri is the state capital of Borno State, North Eastern Nigeria. The state lies within latitude and longitude of the state is 11°51’N and 13°40’E respectively with an Altitude of 300m above mean sea level and borders with Chad, Cameroun and Niger (Olofin, 1997). The land has an area of 543km^2 and has a population of about 357,104 people. It is within the semi-arid climatic zone referred to as the SAHEL zone. The city practically experiences two distinct climatic seasons yearly. These are; a short rainy season usually from the month of June to September and a long dry season from October to May. The hottest months in the year are March, April and May having temperatures ranging between 30°C-43°C (Alkali et al., 2017).

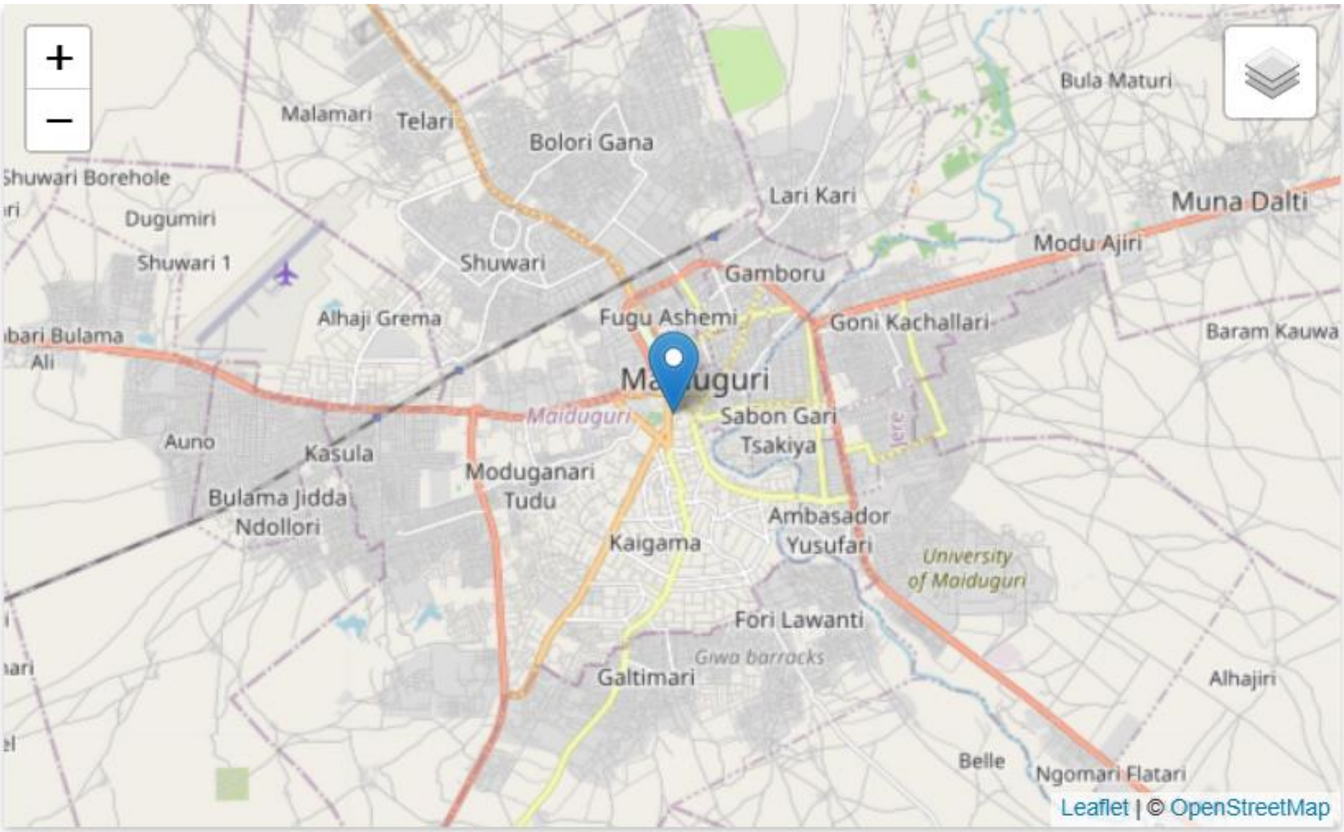

Figure 1: Location Map of Maiduguri, Borno State

Study Dataset and Temporal Coverage

The data of 42 years of monthly rainfall (mm) was gathered by the Nigerian Meteorological Agency (NiMet) at its ground-based stations covering the period between 1981 and 2023. Being the official meteorology authority in Nigeria, NiMet is the main provider of climate data, with the information not being completely stored in the open-access, open-global depositories, yet the data can be obtained by formal data requests and working partnerships, which both grants the data credibility and traceability.

Model Training and Validation Strategy (Data Splitting)

The dataset of monthly rainfall that spans the years January 1981 to December 2023 was split into the training set and testing set to obtain unbiased estimation of the model. Since the climatic data is time dependent, a chronological (non-random) division was made since it ensured that temporal structure is maintained and information leakage is not exhibited.

In particular, the data between January 1981 and December 2015 (35 years; 420 months) served as a model training and parameters estimation and January 2016-December 2023 (8 years; 96 months) as an out of sample control and out of sample forecast validation. The division offers an adequate time scale in which to learn the dynamics of learning season and trends, whereas the timing of the test covers the years of the past and the present that are marked by high increases in rainfall variation and extreme weather patterns.

All the models SARIMA, Holt-Winters, and the hybrid of STL-ARIMA were only fitted using the training data. Multi-step ahead forecasting technique was then used to generate the forecasts on the period of testing and the predicted values were compared to the actual data on rainfall.

Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) were measured in the test set only. This out-of-sample validation model guarantees just and standardized comparisons of predictive accuracy of rival models.

Models

This research uses the ARIMA (Auto-Regressive Integrated Moving Average) model in examining and predicting rainfall patterns in Maiduguri, Nigeria. The ARIMA model is a popular time series forecasting approach which incorporates autoregressive (AR) and moving average (MA) components, as well as differencing to ensure that the data becomes stationary. Under this model, the ordering is done using the shape of the autocorrelation function plot (ACF) and partial autocorrelation function plot (PACF) in order to come up with appropriate orders for the AR and MA components. Model performance is also tested using statistical indices such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) that are compared to determine how accurate the forecast is. Through the use of the ARIMA model, the study will serve a solid base to the interpretation and forecasting of the rainfall patterns of Maiduguri thereby supporting flood risk prediction, early warning systems, and proactive flood mitigation planning within Maiduguri.

The Autoregressive (AR) Model

An autoregressive model of order, p, that is AR(p) an autoregressive model assumes that the current value, x t, is expressed as a linear combination of its past values in the series of length p, plus an element of error. In general, it is expressed as follows:

$$x_t = \mathrm{c} + \sum_{i=1}^{p} \phi_{\mathrm{i}}\, \mathrm{x}_{\mathrm{t-i}} + \varepsilon_{\mathrm{t}} \tag{1}$$

Where, $\mathrm{x_t}$ is the dependent factor (monthly rainfall) at time t, $\mathrm{x_{t-i}}$ are independent factors at time lag $t-1, t-2, \ldots t-I$, $\phi_{\mathrm{i}}(\phi_1, \phi_2, \ldots, \phi_{\mathrm{p}})$ are the autoregressive coefficient to be estimated, c is a constant (intercept) and ε_{t} is the white noise term at time t, assumed to be independently distributed with mean zero and constant variance.

The Moving Average (MA) model

The Moving Average model of order q is generally represented as MA(q), and uses past forecast errors in a regression-like model:

$$\mathrm{x_t} = \mu + \varepsilon_{\mathrm{t}} + \sum_{j=1}^{q} \theta_{\mathrm{j}} \varepsilon_{\mathrm{t-j}} \tag{2}$$

Where $\varepsilon_{\mathrm{t-j}}$ is the error term predicted at time lags and $t-1, t-2, \ldots, t-q$, $\theta_j(\theta_1, \theta_2, .., \theta_q)$ are the moving average coefficients

The ARIMA Model

The ARIMA model is a generalization of the AR and MA models in the sense that it adds differencing in order to manage non-stationarity. An $ARIMA(p,d,q)$ Model can be represented as B, marking backward shift operator, where by $\mathrm{B}X_t = X_{t-1}$.

The model can be explained by the following equation:

$$\phi_p(\mathrm{B})(1-\mathrm{B})^d X_t = c + \theta_q(\mathrm{B})\varepsilon_t \tag{3}$$

Where, $(1-\mathrm{B})^d$ is the differencing operator of order d, which makes the non-stationary series X_t stationary, $\emptyset_p(\mathrm{B})$ is the autoregressive polynomial of order p:

$$\phi_p(\mathrm{B}) = 1 - \phi_1\mathrm{B} - \phi_2\mathrm{B}^2 - \phi_3\mathrm{B}^3 - \phi_4\mathrm{B}^4 - \ldots - \phi_p\mathrm{B}^p \tag{4}$$

$\theta_q(\mathrm{B})$ is the moving average polynomial of order q:

$$\theta_q(\mathrm{B}) = 1 + \theta_1\mathrm{B} + \theta_2\mathrm{B}^2 + \theta_3\mathrm{B}^3 + \theta_4\mathrm{B}^4 + \ldots + \theta_q\mathrm{B}^q \tag{5}$$

C is the constant

ε_t is the white noise error term

Seasonal ARIMA (SARIMA)

When a time series display a recurring seasonal pattern after every s observation, it is said to have a seasonal component. For instance, in monthly data $s = 12$, while for quarterly data $s = 4$. To effectively capture and model seasonality, the ARIMA framework is extended into the seasonal ARIMA (SARIMA) model.

The SARIMA model is denoted as $ARIMA(p,d,q) \times (P,D,Q)_s$, where (p,d,q) represents the non-seasonal part and $(P,D,Q)_s$ represents the seasonal part.

The general mathematical formulation is expressed using the backshift operator B as follows:

$$\Phi_P(\mathrm{B}^s)\phi_p(\mathrm{B})(1-\mathrm{B}^s)^D(1-\mathrm{B})^d X_t = c + \Theta_Q(\mathrm{B}^s)\theta_q(\mathrm{B})\varepsilon_t \tag{6}$$

Where X_t is the observed time series (monthly rainfall) at time , s is the seasonal period ($s = 12$ for monthly rainfall), ε_t is the white noise error term at term t.

Non-Seasonal Operators

$\phi_p(\mathrm{B})$ is the non-seasonal Autoregressive (AR) polynomial of order p.

$$\phi_p(\mathrm{B}) = 1 - \phi_1\mathrm{B} - \phi_2\mathrm{B}^2 - \ldots - \phi_p\mathrm{B}^p \tag{7}$$

$\theta_q(\mathrm{B})$ is the non-seasonal moving average of order q.

$$\theta_{\mathrm{q}}(\mathrm{B}) = 1 + \theta_1\mathrm{B} + \theta_2\mathrm{B}^2 + \ldots + \theta_{\mathrm{q}}\mathrm{B}^{\mathrm{q}} \tag{8}$$

$(1-\mathrm{B})^d$ is the non-seasonal differencing of order d.

Seasonal Operators

$\Phi_P(\mathrm{B}^s)$ is the Seasonal Autoregressive (SAR) polynomial of order P

$$\Phi_P(\mathrm{B}^s) = 1 - \Phi_1\mathrm{B}^s - \Phi_2\mathrm{B}^{2s} - \ldots - \Phi_P\mathrm{B}^{Ps} \tag{9}$$

$\Theta_Q(\mathrm{B}^s)$ is the Seasonal Moving Average (SMA) polynomial of order Q.

$$\Theta_Q(\mathrm{B}^s) = 1 + \Theta_1\mathrm{B}^s + \Theta_2\mathrm{B}^{2s} + \cdots + \Theta_Q\mathrm{B}^{Qs} \tag{10}$$

$(1-\mathrm{B}^s)^D$ is the Seasonal Differencing of order D.

Exponential Smoothing (Holt-Winter Multiplicative)

Given that rainfall data typically exhibits seasonality where the amplitude of the seasonal variation is proportional to the level of the series, the multiplicative Holt-Winter's method is used.

The observed rainfall series X_t is modeled as the product of the level (L_t), trend (b_t), and seasonal (S_t) components:

$$X_t = (L_t + b_t)S_t + \varepsilon_t \tag{11}$$

The smoothing equations are

Level Equation

$$L_t = \alpha \frac{X_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + b_{t-1}) \tag{12}$$

Trend Equation

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \tag{13}$$

Seasonal Equation

$$S_t = \gamma \frac{X_t}{L_{t-1} + b_{t-1}} + (1-\gamma)S_{t-s} \tag{14}$$

Where X_t is the observed rainfall at time t, L_t, b_t, S_t are the level, trend, and seasonal components respectively, α, β, γ are the smoothing parameters $(0 \leq \alpha, \beta, \gamma \leq 1)$, s is seasonal period $(s = 12)$.
The h-step ahead prediction equation is:

$$\hat{X}_{t+h/t} = (L_t + hb_t)s_{t+h} - m(h+1) \quad (15)$$

Decomposition and Deseasonalization

The STL algorithm, first, is used to break down the original time series Y_t into seasonal (S_t), trend (T_t) and remainder (R_t) parts. The series, denoted as Y_t^{SA}, is derived when subtracting the seasonal series in the original series:

$$Y_t^{SA} = Y_t - S_t = T_t + R_t \quad (16)$$

Forecasting (The Components are Forecasted Separately and then Recombined)

Seasonal Component (S_t): Seasonal component is mostly determined by seasonal naive approach as it is expected that the latest pattern in the season will be repeated.
Seasonally Adjusted Component (Y_t^{SA}): The non-seasonal time series (trend and irregularity) is estimated when using an ARIMA(p, d, q) model.
The next $h-$step forecast, $\hat{Y}_{t+h}$ is a result of any summation of the forecasts of seasonal component and ARIMA forecast of seasonally adjusted series:

$$\hat{Y}_{t+h} = \hat{S}_{t+h} + \hat{Y}_{t+h}^{SA} \quad (17)$$

Where $\hat{S}_{t+h}$ is the forecasted seasonal component corresponding to the future period and $\hat{Y}_{t+h}^{SA}$ is the forecast generated by ARIMA model for the seasonally data.

STL–ARIMA Hybrid Modeling Framework

The forecasting algorithm is founded on a hybrid modeling architecture that combines Loess-based Seasonal-Trend decomposition techniques (STL) with the Autoregressive Integrated Moving Average (ARIMA) model to capture the complex temporal structure of rainfall time series (Figure 2). This approach integrates the strengths of decomposition methods and stochastic time series modeling to improve predictive accuracy and model interpretability.
Within this framework, STL decomposition is first applied to disaggregate the original rainfall series into three additive components: the trend, seasonal, and remainder (residual) components. The trend component represents long-term changes in rainfall behavior, the seasonal component reflects repetitive periodic patterns driven by climatic cycles, and the remainder component captures non-periodic, irregular, and unpredictable fluctuations that cannot be explained by the trend or seasonal structures (Figure 2).
Each component is then modeled independently in a manner consistent with its statistical characteristics. The trend component is modeled using an ARIMA(1,1,0) process, which represents long-term persistence and gradual changes in rainfall dynamics. The seasonal component is addressed through seasonal mapping, which preserves and extrapolates the recurring structure of the rainfall cycle. The remainder component is modeled using an ARIMA(2,0,1) process to capture short-term dependencies and stochastic variability (Figure 2).
Following component-wise modeling, forecasting and recombination are performed by additively integrating the forecasts of the trend, seasonal, and remainder models. This recombination follows the additive structure of the STL decomposition, ensuring that long-term trends, seasonal variations, and stochastic disturbances are collectively expressed in the final forecast output (Figure 2).
By isolating and modeling distinct temporal dynamics independently, the hybrid STL-ARIMA architecture enables more accurate and stable rainfall prediction without forcing a single model to represent all underlying processes. This methodology strengthens predictive performance, enhances interpretability, and improves robustness in non-stationary climatic environments. Consequently, it is particularly well suited for applications in hydroclimatic forecasting, climate risk assessment, and resilience planning, as conceptually illustrated in Figure 2.

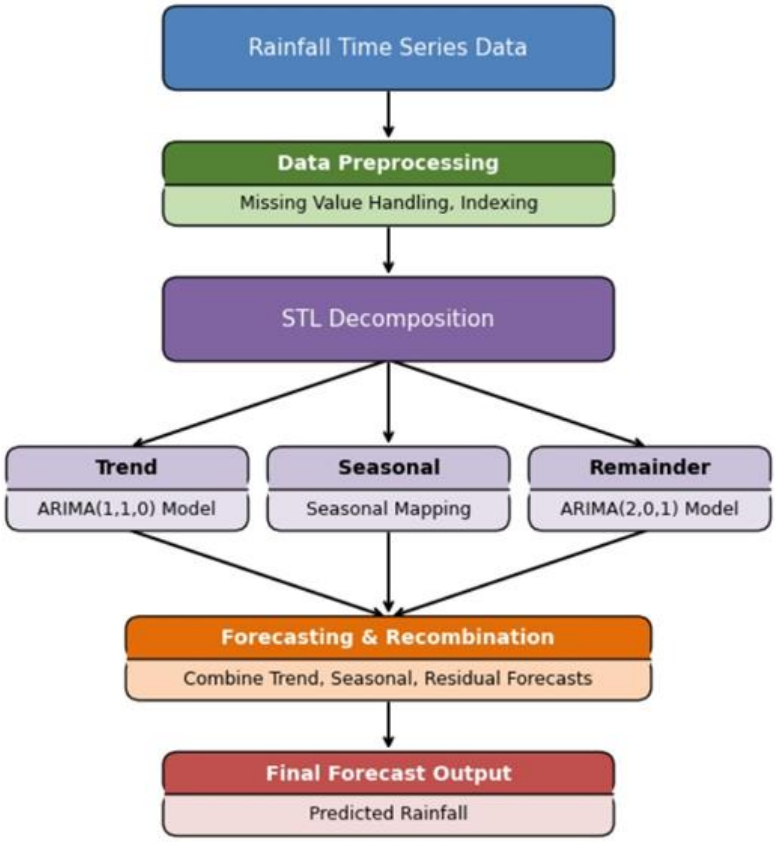

Figure 2: Methodological flowchart of the STL-ARIMA hybrid forecasting framework

Statistical Evaluation

Evaluating the performance of a predictive model is a critical component of the modelling process, particularly when its effectiveness is assessed relative to alternative modelling approaches. This process typically depends on the use of particular statistical measures. Nevertheless, models can have almost identical results for a particular measure, using only one measure might not give a comprehensive view of the performance of the model. Each measure identifies only a specific feature of the model's capacity to mimic actual data. Hence, it is advisable to employ a set of statistical measures to achieve a more complete and accurate assessment of model performance so that more meaningful comparisons between various modelling techniques can be made. Among the most frequently used are MSE, RMSE and MAE.

$$RMSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(x_i - \hat{x}_i)} \quad (18)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i| \quad (19)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \quad (20)$$

Where; x_i: is the actual value, $\hat{x}_i$: is the fitted value, n: is the number of observations

RESULTS AND DISCUSSION

Data Source and Description

Figure 3 demonstrates how precipitation varied every month in Maiduguri during the period. It also has a pronounced seasonality with the rainfall being clustering in a limited number of months annually and it has near zero values at the dry season. Some years have record-breaking rainfall and this is especially the case after 2000 which demonstrates higher intermittency and intensity of rainfall. This high seasonality and non- stationary nature warrants use of decomposition-based and hybrid forecasting model e.g. STL-ARIMA.

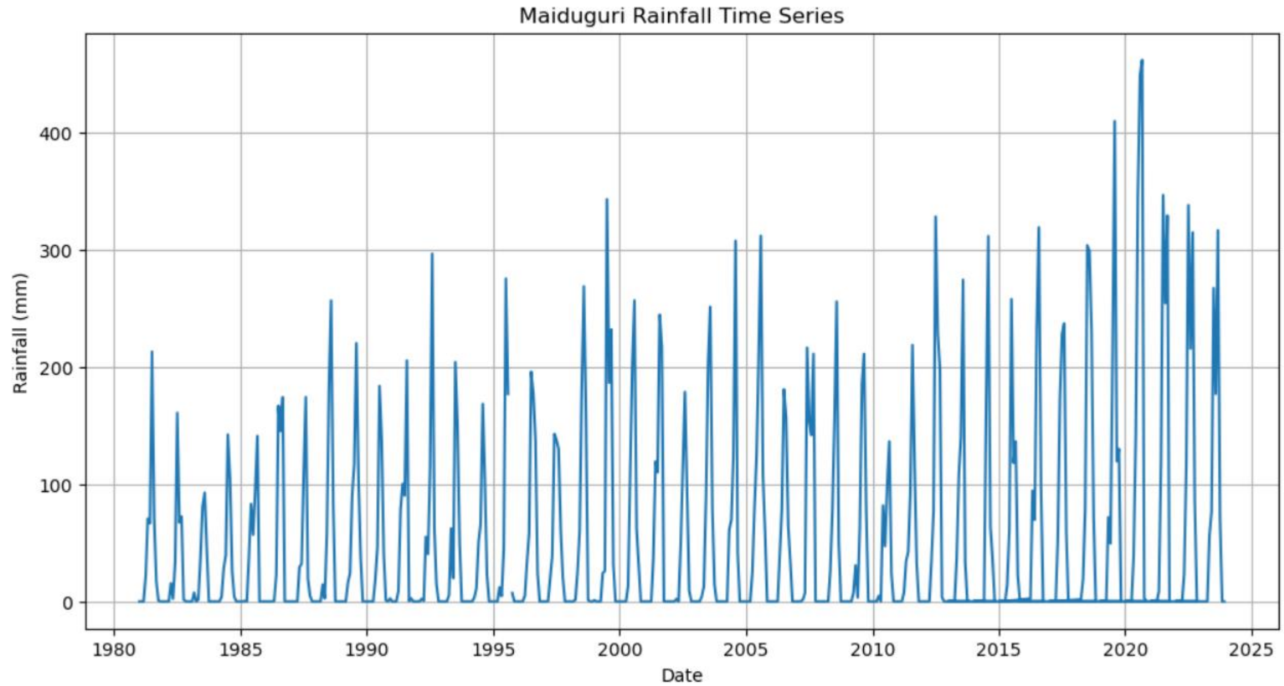

Figure 3: Monthly rainfall time series plot for Maiduguri (1981–2023)

Figure 4 has demonstrated an average rainfall in Maiduguri on monthly basis and it is evident that there is a strong seasonality on the data. It receives a lot of rainfall during May to September with July and August recording the highest and the other months receiving the little or no rain. It is understandable that seasonal lag features can be incorporated in machine learning models when seasonality is as prominent as this.

Figure 5 shows the annual change in total rain per year between the years 1981 and 2023 which is erratic and in other cases there are excessive years of rainfall. The observation of high variability and non-stationarity of the time series argues that the common time-series modelling methods might not be sufficient to discover the underlying patterns.

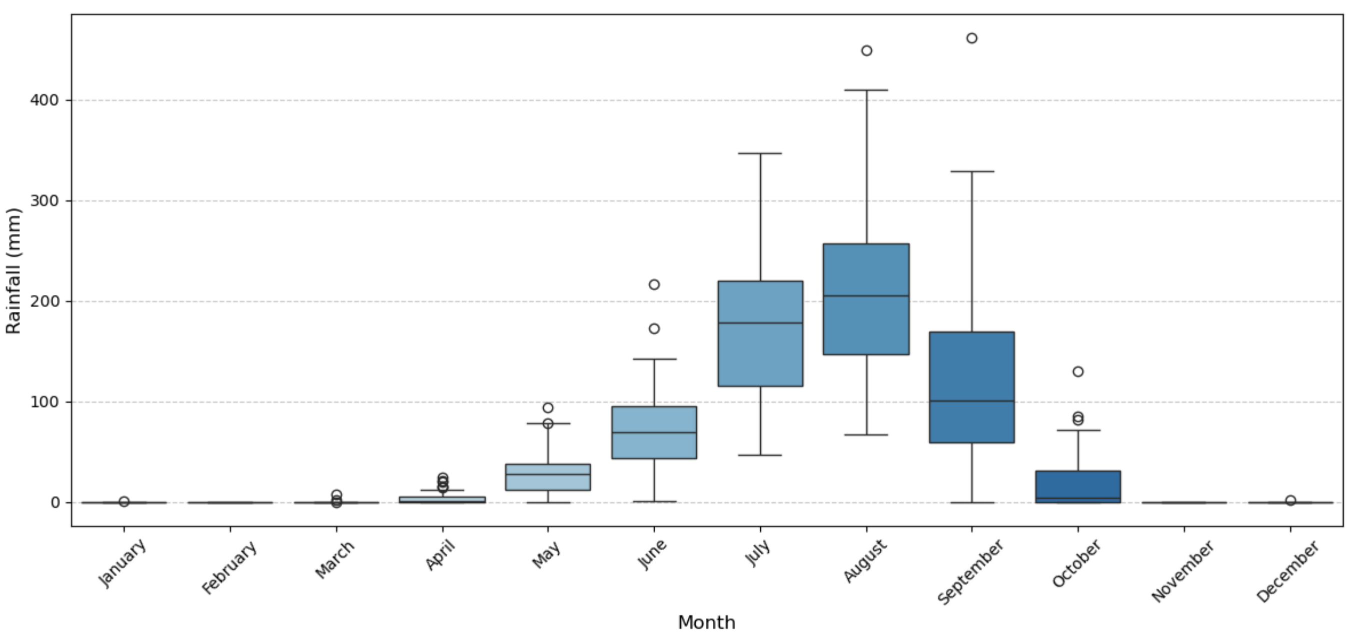

Figure 4: Monthly Rainfall Distribution – Maiduguri (1981-2023)

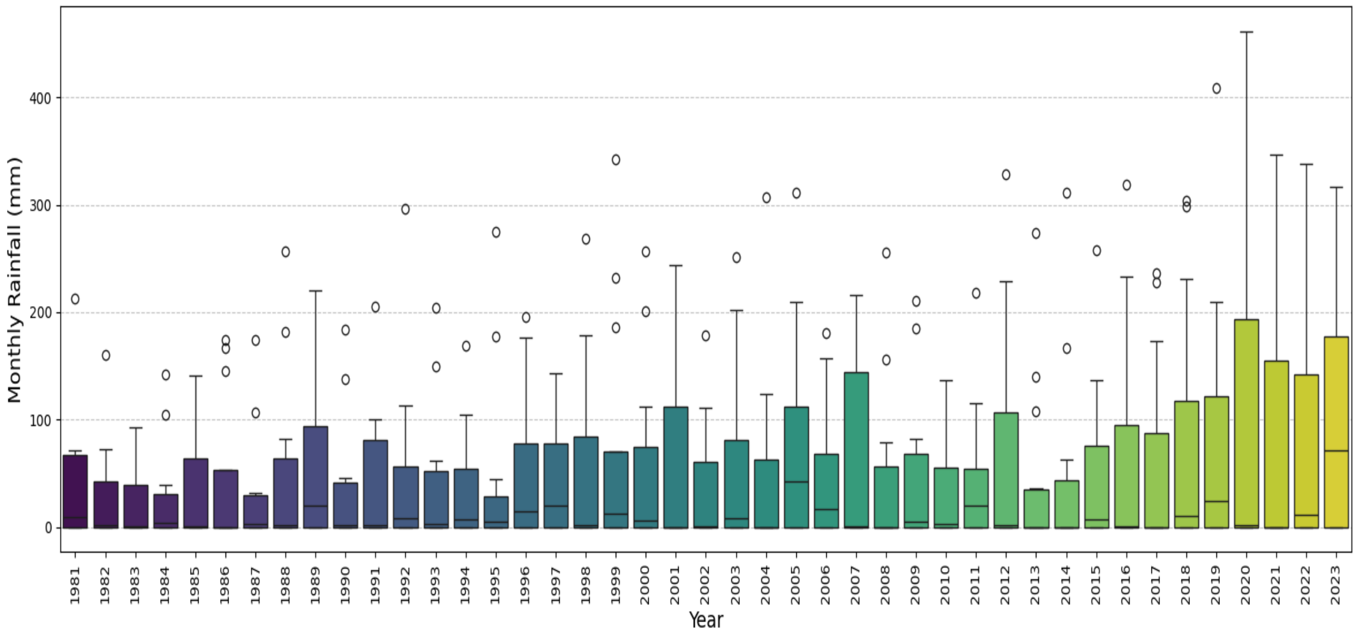

Figure 5: Rainfall Distribution by Year – Maiduguri

STL Decomposition

Figure 6 shows the Seasonal-Trend decomposition (STL) of the monthly rainfall based on Loess (STL) applied on the monthly rainfall series throughout the study time. According to this approach, the observed rainfall is broken down into four additive factors, that is, the original series, long-term trend, seasonal term, and a residual factor, which measures the irregular variations.

As indicated by the original rainfall sequence in the top panel, there is a high rate of temporal variability whereby intense rainfall occurs in the wet season, with very long dry months of minimum rainfall. These peaks become clearly more pronounced in the latter part of the record, which can be interpreted as evidence of the magnification in the level of rainfall in the recent years.

The trend component of the second panel shows the process of the long run development of rainfall when seasonal effects have been eliminated. Instead of the simple linear trend, the trend is multi-decadal with up and down swings at different time intervals. A clear increase can be seen towards the end of 2010s, and then a steady decline towards the end of the series. Such behaviour indicates the impact of more widespread climatic forces and indicates non-steadiness of long-term rainfall variability.

The third (seasonal) panel shows that the annual cycle is quite strong and highly regular in nature, which confirms that seasonality is the aspect of rain pattern that is still dominant. Although the occurrence of seasonal peaks and troughes largely remains unchanged over the period of the study, there is observed to be a gradual rise in seasonal amplitude over the last few decades which exhibits increased rainfall within peak rainy months.

Short-term variation not accounted by both the trend and the seasonal pattern is reflected in the residual component presented on the bottom panel. Though these residuals tend to mean zero, in the end, they are getting more and more dispersed, bigger, more frequent deviations can be observed in recent years. This broadening dispersion indicates growing variations in rainfall, which are presumably due to local convection, short-lived atmospheric disturbances.

On the whole, the STL decomposition shows that a non-dominant but recurring seasonal cycle only serves as an indicator of obvious non-stationarity of both long-run trend and residual variability of the rainfall series. Such characteristics suggest a challenge to the assumptions of traditional linear time-series models and are the best reason to use hybrid or nonlinear forms of modeling to better forecast rainfall and assess flood risks.

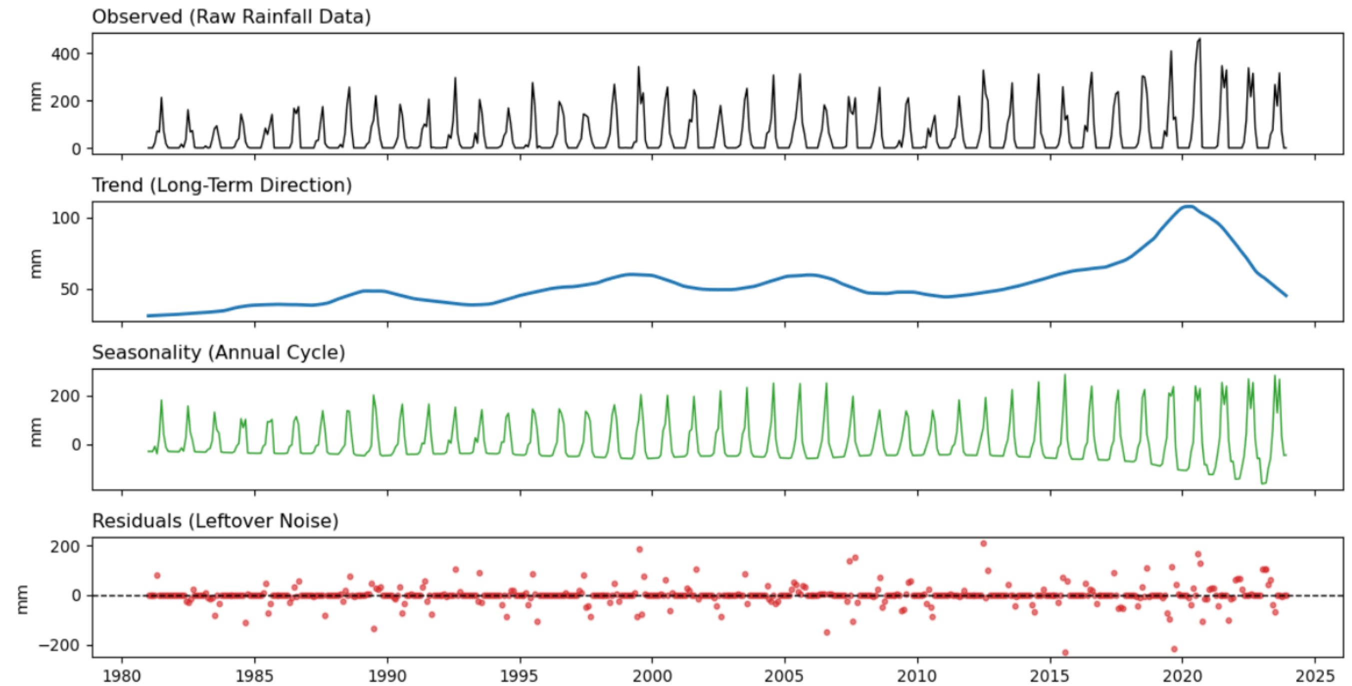

Figure 6: STL Decomposition

Figure 7 gives the residual diagnostics results of the fitted model ARIMA(2,0,1) and gives an indication regarding the suitability of the model at explaining the underlying structure of the time series of rainfalls.

The plot on the upper panel shows the plot of residuals against time. The series of residuals reflects a random movement around a zero mean and no observable pattern or tendency implying that the model has captured the primary linear dynamics in the data. Even though one or two sporadic positive and negative spikes are noted especially in the elderly, these deviations are occasional as opposed to chronic, which points to the fact that the structure has not been misspecified.

The mid-panorama depicts a Autocorrelation Function (ACF) of the residues. With the exception of the insignificant spike at the lag zero, all the autocorration coefficients fall within the 95% confidence limits. This shows that the remaining series of residuals does not exhibit any statistically significant serial correlation which means that the ARIMA(2,0,1) model has successfully succeeded in eliminating any linear dependence of the series.

On the same lower panel, there is also the Partial Autocorrelation Function (PACF) of the residuals. All the non-zero autocorrelations are negligible and fall within the confidence limits further supporting that there is no further autoregressive structure that is not explained by the model.

In general, the diagnostics of the residual indicate that the ARIMA(2, 0,1) model is well elaborated. The residual values seem to resemble white noise and meet the major assumptions of independence and zero mean. Accordingly, there is a possibility to assume that the analyzed model is statistically sufficient and effective in forecasting in the circumstances of the rainfall data under consideration.

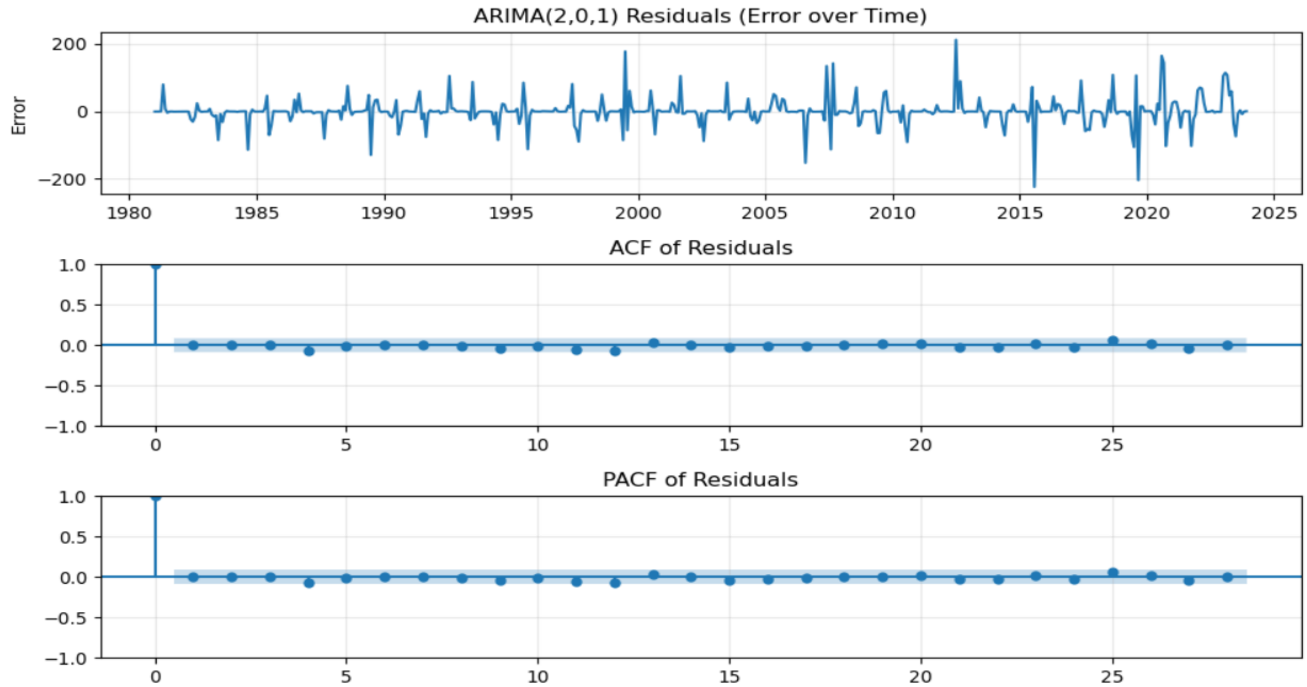

Figure 7: ACF and PACF of the remainder after decomposition

Comparative Forecasting Performance

In order to compare the predictive power of the proposed hybrid framework with already known hydrological forecasting models, the STL-ARIMA model was compared to two of the already known hydrological forecasting models Seasonal ARIMA (SARIMA) and the Exponential Smoothing of Holt-Winter. Mean squared error (MSE), Root mean square error (RMSE) and, Mean absolute error (MAE) were used to measure the performance of various models.

Table 1: Comparative Error Metrics of Forecasting Models

Model	MSE	RMSE	MAE
SARIMA	1931.08	43.94	25.22
Holt-Winter	1849.60	43.01	25.87
STL-ARIMA	872.63	29.54	16.77

The STL-ARIMA hybrid model proved to be the most effective one as it outperformed all measures of error, as shown in Table 1. The classical SARIMA model had the worst error rates (MSE = 1931.08), presumably because of its inability to capture the non-linear volatility which has characterized the past few decades in the Maiduguri index of rainfall. Although the method of HOLT-Winter offered a slight decrease (MSE = 1849.60) in that the multiplicative seasonality is well embraced, it still did not cover the issue complexities of trend dynamism.

Conversely, the STL-ARIMA hybrid model minimized the MSE than SARIMA by nearly 55%. The RMSE decreased to 29.54mm versus the original 43.94mm meaning that the hybrid model will make significantly closer predictions to those of the observed values of the rainfalls. This significant decrease in error ascertains that by splitting the series, more specific modelling of the different trend and residual designs that individual modelling often mixture can be achieved.

Component Fitting Analysis

The strength of the hybrid method is that it is able to model the trend and the residual components on their own using optimised ARIMA structures. The decomposition could be used to model effectively, as shown in Figure 8:

Trend Component An ARIMA(1,1,0) was estimated on the trend extracted by STL. As the plot (Fig 8, top panel) reveals, this specification is sensitive to the non-linear variation in the rainfall over the long-term that is best recorded in the multi-decadal increase and decrease, which would go unnoticed by static regression models.

Residual Component: ARIMA(2, 0, 1) was also fitted to the remaining series. Figure 8 (bottom panel) shows that this model can effectively produce the irregular noise and transient shocks so that the end result (forecast) is not merely a repeat of seasonal averages but rather a dynamic reaction to the recent shocks.

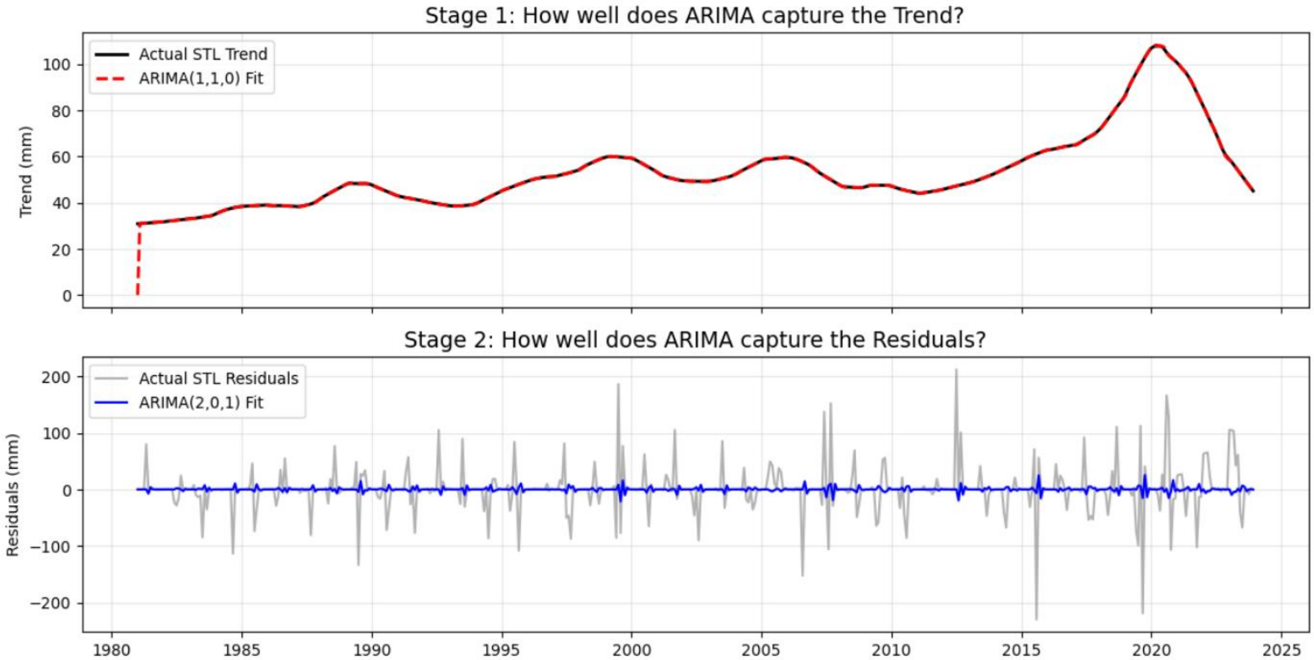

Figure 8: Fitting performance of the Hybrid components. Top: ARIMA(1,1,0) fitted to STL Trend. Bottom: ARIMA(2,0,1) fitted to STL Residuals

Discussion

The results provide significant insights into rainfall variability in Maiduguri. First, the STL decomposition revealed that rainfall variability in the region is driven by a strong seasonal cycle superimposed on a slowly evolving long-term trend, confirming the presence of non-stationary and non-linear behavior. Second, the superior performance of the hybrid STL–ARIMA model indicates that separating these components prior to forecasting significantly improves model interpretability and accuracy. In particular, the hybrid framework demonstrated enhanced ability to capture long-term trend shifts, preserve seasonal structure, and reduce forecast errors relative to SARIMA and Holt–Winters models. These findings suggest that classical single-structure models are limited in handling the complex rainfall dynamics of the Sahelian climate, while component-wise modeling offers a more reliable basis for long-term rainfall forecasting and climate-informed decision-making.

CONCLUSION

This paper had an aim to model an effective rainfall forecasting structure to Maiduguri, Nigeria, which would help manage intricate seasonal and non-linear climatic pattern of the area. The study found that a comparative evaluation conducted over a 42-year period (1981–2023) showed that the hybrid STL–ARIMA model outperformed the traditional SARIMA and Holt–Winters methods in key forecasting tasks, including accurate trend representation, effective seasonal modeling, and improved forecast accuracy better than the traditional SARIMA and Holt-Winter methods.

Key conclusions include:

Best Accuracy levels, SARIMA had higher root mean square error levels (RMSE = 29.54mm), which is more than 30 times higher than the error levels in the STL-ARIMA model.

Methodological Robustness: The analysis/breakdown of the time series indicated that although seasonality is the overriding factor, it is the erratic nature of the residual component where the traditional models fail and the hybrid model prospers.

Operational Relevance: As extreme weather occurrences seem to be a rising phenomenon, including the 2024 floods, the added accuracy of this hybrid model represents an indispensable resource to the policymakers. It provides a scientific foundation to transition between the reactive disaster relief and the proactive climate resilience planning to directly achieve SDG 13 (Climate Action) targets to Nigeria.

In the future, the study can be conducted by incorporating exogenous factors that include sea surface temperature or humidity level to make the predictions of residual components more precise and have a longer forecast horizon on seasonal forecasts.

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