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Modelling Seasonal Rainfall Variability and Climate Change Impacts in Calabar Metropolis: An ARIMA Approach

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Abstract. This study develops a mathematical model to analyse seasonal rainfall patterns and climate change impacts in Calabar Metropolis, Nigeria, using 31 years (1990–2021) meteorological data. The Autoregressive Integrated Moving Average (ARIMA) model was applied to forecast the rainfall, temperature, and relative humidity. The results revealed a slight upward trend in annual rainfall (0.0832 mm/year) and identified July–September as peak rainfall months. The ARIMA model for the rainfall showed a Mean Absolute Percentage Error (MAPE) of 26,690.0, indicating high variability. Increasing rainfall intensity (β = 0.437) contributed significantly to building losses and flooding, exacerbated by inadequate drainage systems. The study underscores the urgency of integrating climate-resilient urban planning and water management strategies to mitigate flood risks in Calabar Metropolis.

Keywords*—Keywords are your own designated keyword which can be used for easy location of the manuscript using any search engines. Keywords must be between 4 – 6 words or phrases in alphabetical order separated by comma.*

I. INTRODUCTION

Flood is a water induced disaster that leads to temporary overflow of dry land and causes serious damage on lives, property, and infrastructures. Flood has created a lot of damaging effect in Nigeria, resulting to the death of people, collapse of buildings, destruction of properties, damage of agricultural produce, loss of land and increased government expenditure. Despite persistent occurrence of this disaster, there is limited research geared at studying the factors that cause flooding and measures to effectively control it. To fill this gap, mathematical models have been developed to predict the patterns and impacts of seasonal rainfall and climate change in Calabar metropolis. These models are essential for predicting rainfall patterns, which can help in planning and decision-making, particularly in agriculture, civil engineering, general construction, and water resources management. Autoregressive Integrated Moving Average (ARIMA) model, has been used to analyse the monthly rainfall pattern of Calabar (Ogbozige, 2022).

The study reveals that the annual rainfall pattern in Calabar does not have a Gaussian distribution and showing an increasing trend in annual rainfall of the study area. Long-term variations in rainfall trends in Calabar have been analysed using indices such as total annual rainfall, number of rain days in the year, total extreme annual rainfall, and number of days of extreme rainfall in the year and long-term rainfall trends in Calabar,

II. LITERATURE REVIEW

The study by Antigha and Ogarekpe (2013) formulated a mathematical model for Intensity Duration Frequency (IDF) curves for Calabar Metropolis in Southern Nigeria using historical rainfall records obtained from the Nigerian Metrological Agency. The IDF curves generated can be used to estimate the maximum intensity of any rainstorm over any return period in Calabar, which can be used to evaluate the quantity of discharge and design of hydraulic structures. The study used the Extreme Value Type 1 (Gumbel) distribution for rainfall data analysis.

The authors also compared their results with other studies in Nigeria and found that the IDF curves for Calabar are similar to those of other cities in the region. The study highlights the importance of IDF curves in the design and management of hydraulic structures and the need for accurate rainfall data for their development. Several studies have been carried out on the monthly rainfall pattern of Calabar using the ARIMA (2, 1, 2) model, with the maximum monthly rainfall occurring between July and September, while the least rainfall fluctuates between December, January, and February. The study also found that the maximum and least monthly rainfall in Calabar does not show a steady increase or decrease yearly, indicating irregular rainfall patterns in the area. Another study analysed the rainfall anomalies and trend in Calabar as an imperative for human adaptation to climate change Amadi et al., (2020). Their work shows that the average annual rainfall for Calabar is 2984.64 mm with a standard deviation of 394.9 mm. The study also revealed consistent fluctuations in the rainfall pattern of Calabar for the past 100 years, with a mean annual rainfall of 2984.64 mm, Ewona et al., (2009).

Similarly, Okonkwo and Mbajiorgu (2010) analysed rainfall intensity-duration-frequency (IDF) for South-eastern Nigeria, using two methods: graphical and statistical. The IDF data developed from the graphical and statistical methods applied were very close for lower return periods of two to ten years, but differed for higher return periods of 50 to 100 years. However, the difference is not significant at the 5% level. The data developed by either of the methods will facilitate planning and design for water resources development in South eastern Nigeria. The study highlights the importance of accurate rainfall data and the use of IDF curves in water resources engineering, Okonkwo et al., (2010).

A. Rainfall

Rainfall has cause devastating effects when in excess (flooding) and when in little quantity (drought) in most area. It is therefore necessary to evaluate its variability as this will enable engineers plan in term of their engineering specifications.

Calabar experience extreme seasonal variation in monthly rainfall, throughout the year in Calabar, the month with the most rain in Calabar is August with an average rainfall of 19.3mm, the month with the least is January with an average rainfall of 0.9 mm.

B. Seasonal ARIMA Process

Similarly, Bacastow et al., (1994) study the non-stationary processes, analysing a type of lack of stationary in the mean that is frequently found in practice: seasonal behaviour. Seasonality makes it so that the mean of the observations is not constant, but instead evolves according to a cyclical pattern: For example, in a series of monthly temperatures in Europe, the mean temperature is not constant, since it varies by month, but for the same month in different years, we can expect a constant average value.

The most typical case is that we can incorporate seasonality into the ARIMA model multiplicatively, so that we obtain a multiplicative seasonal ARIMA model.

We say that a series which has no trend is seasonal when its expected value is not constant, but varies in a cyclical pattern. Specifically, if

E (zt) = E (zt+s)

We say that the series has seasonality of periods.

The simplest model for seasonality is when it is modelled as a constant effect that is added to the values of the series. For example, let us assume a series that, except for its seasonal effect, is stationary. We can write the series as a sum of a seasonal component S(s), and a stationary process, nt, in such a way that the model for the series is:

Zt = St(s) = nt (1)

This series is not stationary, since if we take expectations

E(zt)=E (2)

Where μ is the mean of the process nt.

Since by definition the seasonal component does not take the same value in all of the periods, the series is not stationary because it does not have a constant mean. Therefore, each month has a different average behaviour, which is what characterizes a seasonal series. We can consider different hypotheses regarding the behaviour of the seasonal process S(s). The first is that seasonality is a deterministic process, that is, a constant function for the same month in different years:

St(s) =k = ± 2 (3)

For example, seasonal coefficients can follow a sinusoidal function, which occurs in climate series due to the Earth's rotation. This suggests treating seasonality with sinusoidal functions but these functions are not very efficient when the seasonality follows a deterministic, but not sinusoidal, pattern. Representing this seasonality using sinusoidal functions would be very inefficient. Deterministic seasonality can always be modelled by introducing 11 dummy variables, one for each month of the year as you will see in second module. Nevertheless, many time series do not have deterministic seasonality. Instead, the seasonal pattern, like other properties, also evolves over time. The second way to model seasonality is to assume that the evolution is stationary, that is, the seasonal factors are not constant, but follow a stationary process, oscillating around an average value in accordance with the representation. The third way to model seasonality is to allow it to change over time with no fixed average value. In this case, seasonality follows a non-stationary process. For example, the simplest model is to assume that it evolves according to a random walk:

If we apply this operator to a series, we obtain a transformed series which is the result of replacing at each point in time, t, the value of the series with the difference between the value at time, t, and the value of the series at time t − s:

$$\nabla szt = (1 - Bs)zt = zt - zt{-}s. \tag{4}$$

Therefore, if we apply this operator ∇sin (117), we have:

$$\nabla szt = \nabla sSt \quad + \nabla snt \tag{5}$$

and we are going to prove that the series ∇szt is then stationary.

Let us consider the three cases we have studied.

C. The ARIMA Seasonal Model

We have seen that we can convert non-stationary series into stationary ones by taking regular differences, that is, the difference from one period with respect to the next. We also saw that we can eliminate seasonality by means of seasonal differences. Combining both results we conclude that, in general, we can convert a non-stationary series with seasonality into a stationary one by using the transformation:

$$wt = \nabla D \nabla dzt, \tag{6}$$

where D is the number of seasonal differences (if there is seasonality, we almost always have D = 1, if there is no seasonality D = 0) and d is the number of regular differences ($d \leq 3$). When seasonal dependence exists, we can generalize the ARMA model for stationary series incorporating both the regular dependence, which is that associated with the measurement intervals of the series, as well as the seasonal dependence, which is that associated with observations separated by s periods. We will discuss next how to model these two types of dependence. The first solution is to incorporate seasonal dependence into the regular, adding Bs terms to the AR or MA operators in the B operator, in order to represent the dependence between observations separated by s periods. The inconvenience of this formulation is that it would lead to very large polynomials in the AR and MA part: For example, with monthly data, s = 12, if a month is related to the same month in three previous years, we need an AR or MA of order 36 to represent this dependence.

A simpler approach, and one which works well in practice, is to model the regular and seasonal dependence separately, and then construct the model incorporating both multiplicatively. ARIMA model is based on the central hypothesis that the relationship of seasonal dependence is the same for all periods. Experience indicates that this situation, although frequent, is not always true so it is advisable, whenever sufficient data are available, to test it by constructing the models and checking to see if all of them are equal. The urban area of Calabar is particularly vulnerable to flooding due to its low-lying topography and inadequate drainage systems. Improved infrastructure resilience is crucial to withstand the impacts of extreme weather events (Ekpoh and Nsa, 2020; UNDP, 2021). In other regions, correlating with global climate change phenomena (IPCC, 2021; Oladipo, 2018). Studies have shown that increased rainfall variability is a common indicator of climate change, resulting in more frequent and intense weather events (NIMET, 2021).

Increased rainfall and flooding can damage infrastructure, including roads, buildings, and drainage systems. Changes in rainfall patterns can disrupt planting and harvesting cycles, leading to reduced crop yields and food insecurity. Recent studies indicate that unpredictable rainfall can result in either drought conditions or excessive flooding, both of which adversely affect crop production (Adger et al., 2021; Adejuwon, 2021). Farmers in Calabar need to adopt climate-smart agricultural practices to mitigate these impacts (Ozor and Cynthia, 2019). Climate change can exacerbate health issues by increasing the prevalence of waterborne diseases such as malaria and cholera, particularly during flooding events. Enhanced healthcare infrastructure and proactive measures are necessary to address these challenges (IPCC, 2021; Boko et al., 2018). Similarly, changes in climate can affect local ecosystems and biodiversity. Altered rainfall patterns can disrupt the natural habitats of various species, leading to shifts in biodiversity and ecosystem services. Conservation efforts are essential to preserve the region's rich biodiversity (Adger et al., 2021).

III. Methods And Materials

A. *Description of the Study Area*

The materials used and the methodology adopted for the forecasting, selection of study area, meteorological data extraction and verification for the selected study years, coupling with statistical methodologies, with the use of Auto-Regressive Integrated Moving Average (ARIMA).This study aimed at examining the nature of rainfall pattern and the climatic conditions in Calabar over a period of 31 years (1990-2021). Calabar is situated in the Southern Nigeria with latitude of 40 53' 41.10" to 50 7' 37.57" North and longitude 80 14' 14.90" to 80 25' 14.03" East, occupying an approximate area of 158 km^2. It is the capital of Cross River State and a well-known city for tourism in Nigeria, comprising two Local Government Areas (LGAs) of the state known as Calabar Municipal and

Calabar South LGAs. The city shared common boundary with two other LGAs of the state known as Odukpani and Akpabuyo as could be seen in Figure 1.

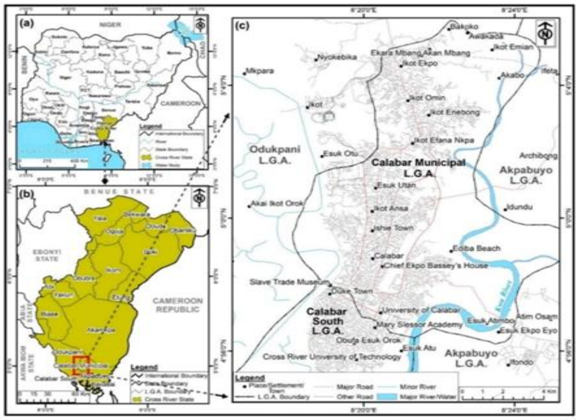

Figure 1: Map of Study Area (Source: CRGIA, 2020)

B. The Box-Jenkins Method

The Box–Jenkins's modelling method, named after the statisticians Box and Jenkins (1970), was adopted in this work which describes the stationary time series and incorporate the Autoregressive Moving Average (ARMA) or Autoregressive Integrated Moving Average (ARIMA) models to find the best fit of a time series to past values of this time series to make forecasts. The methodology involved five-step processes to identify, selecting, and assessing conditional mean models (for discrete, univariate time series data).

i. Determine whether the time series is stationary. If the series is not stationary, successively difference it to attain stationarity. The sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of stationary series decay exponentially (or cut off completely after a few lags).

ii. Identify a stationary conditional mean model for the series. The sample ACF and PACF functions can help with this selection. For an autoregressive (AR) process, the sample ACF decays gradually, but the sample PACF cuts off after a few lags. Conversely, for a moving average (MA) process, the sample ACF cuts off after a few lags, but the sample PACF decays gradually. If both the ACF and PACF decay gradually, consider an ARMA model.

iii. Create a model template for estimation, and then fit the model to the series. When fitting non-stationary models in Econometrics Toolbox™, you do not need to manually difference the series and fit a stationary model. Instead, you can use the series on the original scale, and create an ARIMA model object with the desired degree of non-seasonal and seasonal differencing. Fitting an ARIMA model directly is advantageous for forecasting: forecasts are returned on the original scale (not differenced).

iv. Conduct goodness-of-fit checks to ensure the model describes the series adequately. Residuals should be uncorrelated, homoscedastic, and normally distributed with constant mean and variance. If the residuals are not normally distributed, you can change the innovation distribution to a student.

v. After choosing a model and checking its fit and forecasting ability you can use the model to forecast or generate Monte Carlo simulations over a future time horizon.

C. Difference the Data

Take a first difference of the data, and plot the differenced series.

Get

```
dY = diff(y);
figure
plot(dY)
h2 = gca;
h2.XLim = [0,T];
h2.XTick = 1:10:T;
h2.XTickLabel = datestr(dates(2:10:T),17);
title('Differenced Log Quarterly Calabar CPI')
```

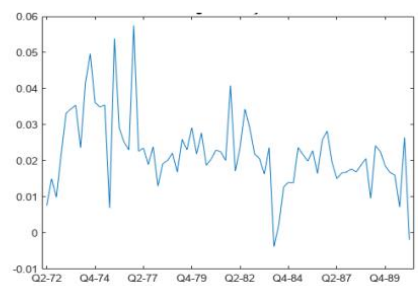

FIGURE 2: DIFFERENCING REMOVES THE LINEAR TREND.

D. Plot the Sample ACF and PACF of the Differenced Series

Plot the sample ACF and PACF of the differenced series to look for behaviour more consistent with a stationary process.

Get

```
figure
subplot(2,1,1)
autocorr(dY)
subplot(2,1,2)
parcorr(dY)
```

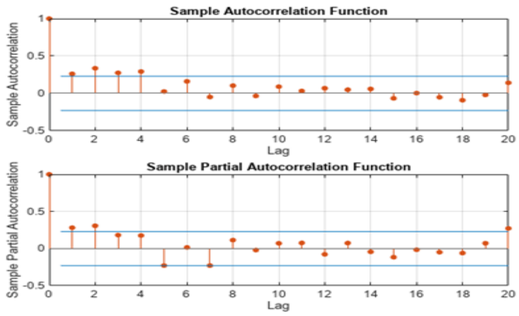

FIGURE 3: THE SAMPLE ACF OF THE DIFFERENCED SERIES DECAYS MORE QUICKLY.

IV. RESULTS AND DISCUSSION

A. Trend Analysis of Rainfall

The trend analysis indicated a slight increase in the amount of rainfall at a rate of 0.0832 mm/year over the 31-year period. This was evidenced by the trend line plot (Figure 4) from January 1990 to December 2021. Increased rainfall and flooding can damage infrastructure, including roads, buildings, and drainage systems.

B. Discussion on Climate Change Impacts in Calabar Metropolis

In this study, we plotted the graph of original rainfall data from January, 1990 to December, 2021 called time trend plot. The time plot revealed features of rainfall data collected over a period 31 years. The time plots showed a pattern that repeat s itself every Twelve month. From our time plot, rainfall is usually low in the months of January, February, and March and gradually increased in intensity from May, June and picked in the month of July. The rainfall starts reducing from August and least amount of rainfall is usually recorded for November and December. This cycle repeats every year as shown in Figures 4 to 5.

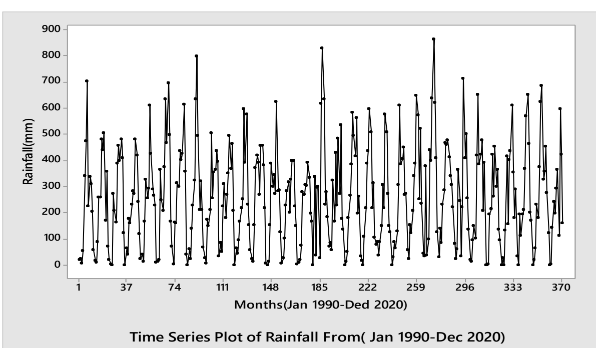

Figure 4: Time series of rainfall

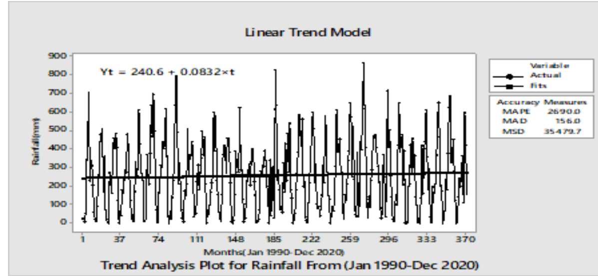

Figure 5: Linear Trend Model

In order to determine the trend of rainfall in the period of 31 years under study, we fit a trend model in the original data. The trend model suggests that there is slightly upward trend in the amount rainfall recorded. The measure of accuracy of the trend model are given as Mean Absolute Percentage Error (MAPE)=2690.0, Mean Absolute Deviation (MADE) = 156.0 and Mean Standard Deviation (MSD)=35479.7. The search results provide information about the trend analysis plot for rainfall from January 1990 to December 2020. The plot suggests a slightly upward trend in the amount of rainfall recorded in Calabar metropolis during the period under study. The accuracy measures of the trend model are given as Mean Absolute Percentage Error (MAPE) = 2690.0, Mean Absolute Deviation (MAD) = 156.0, and Mean Standard Deviation (MSD) = 35479.7.

The study found that the annual rainfall pattern of Calabar does not have a Gaussian distribution, but the b value of 58.40 (or trend) was significant, indicating an increasing trend in annual rainfall in the study area during the period under study. The study also found that the annual rainfall intensity with beta coefficient of 0.437 contributed more to the total cost of building loss to rainfall anomalies than annual rainfall duration, with beta coefficient of -0.063. Therefore, the linear trend model suggests a slightly upward trend in the amount of rainfall recorded in Calabar metropolis during the period under study, with an increasing trend in annual rainfall and annual rainfall intensity contributing more to the total cost of building loss to rainfall anomalies than annual rainfall duration. Here is an interpretation of the accuracy measures for the trend model: Mean Absolute Percentage Error (MAPE): MAPE is a measure of prediction accuracy of a forecasting model. A MAPE value of 2690.0 suggests that, on average, the trend model's predictions of rainfall amounts deviate by approximately 2690% from the actual values. A lower MAPE value would indicate a more accurate model. Mean Absolute Deviation (MAD): MAD is a measure of the average absolute difference between the predicted and actual values. A MAD value of 156.0 indicates that, on average, the trend model's predictions deviate by 156 units from the actual rainfall amounts. Lower MAD values indicate a better predictive model. Mean Standard Deviation (MSD): MSD measures the average amount of variability or dispersion in the data points around the trend line. A higher MSD value of 35479.7 suggests that the data points are spread out further from the trend line. Lower MSD values would imply less variability in the data around the trend. In summary, while the trend model suggests a slightly upward trend in rainfall over the 31-year period, the relatively high MAPE value and MAD value and a high MSD value indicate that there may be room for improvement in the accuracy of the model's predictions. Further analysis or adjustments to the model may help in refining its predictive capabilities as presented in Figures 6 to 7.

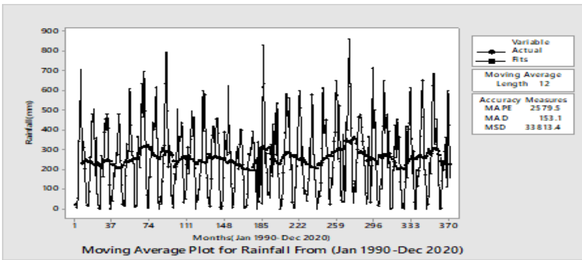

Figure 6: Moving average plot for rainfall

Next, we try to smoothen the time plot by superimposing the 12 – point cantered moving average on the original rainfall data. The 12 – points cantered moving average is the thick dark line running across the time plot. The measure of accuracy of the moving model are given as Mean Absolute Percentage Error (MAPE)=2579.5, Mean Absolute Deviation (MADE)=1531.0 and Mean Standard Deviation (MSD) = 33813 According to Figure 6 moving average plot for rainfall, the trend analysis of rainfall in Calabar shows that rainfall has been increasing by 16.23 mm per annum over the past 31 years. This suggests that the average annual rainfall duration in Calabar is also increasing, as more rainfall means that it is likely to last for a longer period of time. Further, discusses the use of the rescaled range (R/S) statistic, cantered moving average (CMA), and detrended fluctuation analysis (DFA) to analyse monthly rainfall data in Nigeria. It further suggests that these methods can be used to analyse rainfall trends and patterns in the region finally, discusses the development of non-stationary rainfall intensity-duration-frequency curves for Calabar City, Nigeria. This study suggests that the rainfall pattern in Calabar is non-stationary, meaning that it changes over time. This further supports the idea that the average annual rainfall duration in Calabar is likely to be increasing.

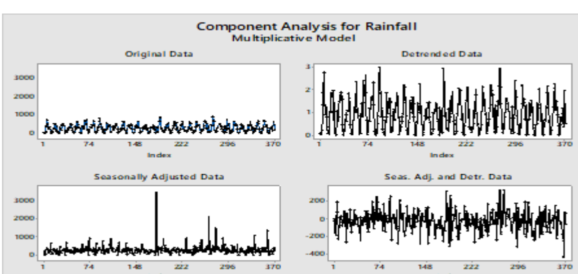

Figure 7: Component analysis for rainfall multiplicative model

The graphs show detrended and deseasonalized data and the component analysis for the rainfall examining the original data, detrended data, and seasonally adjusted data. The multiplicative model is used to analyse these components. Original data represents the raw data without any adjustments or modifications. Detrended data involves removing the trend component from the original data to focus on fluctuations around the trend. Seasonally adjusted data accounts for seasonal variations in the data, providing a clearer picture of the underlying patterns, by analysing these components, researchers can have better understand about the trends, fluctuations, and seasonal variations in the rainfall data, aiding in forecasting the trend analysis as shown in Figures 8 to 9, 5% significance limits for the autocorrelations.

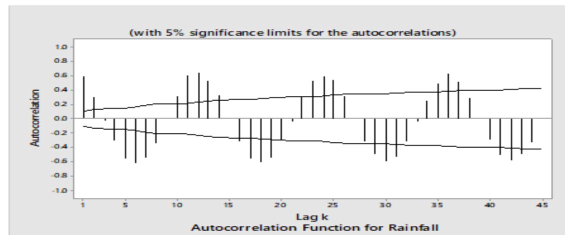

Figure 8: 5% Significance limits for the autocorrelations

The autocorrelation function (ACF) of original rainfall data revealed pattern of consistent with seasonality. Most of the spikes fall outside 95 percent confidence interval as depicted in Figures 8 to 9. Certainly, there is seasonal variation that must be taken care of during modelling. Autocorrelation is the correlation of a time series with its own past and future values, also known as lagged correlation or serial correlation1. It is a measure of the similarity between observations as a function of the time lag between them. Autocorrelation can be positive, negative, or zero. Positive autocorrelation indicates that observations close in time are more similar than those further apart, while negative autocorrelation indicates the opposite. Zero autocorrelation indicates that observations are uncorrelated regardless of the time lag. In the context of the given data, the autocorrelation function for rainfall is plotted against lag k. The autocorrelation function shows the correlation between the current rainfall and the rainfall at different time lags. A strong positive autocorrelation at lag 1 would indicate that rainfall on a given day is highly correlated with rainfall on the previous day.

Similarly, a strong positive autocorrelation at lag 12 would indicate that rainfall in a given month is highly correlated with rainfall in the same month of the previous year. The autocorrelation function can be used to identify patterns in the data and to assess the stationarity of the time series. A stationary time series has constant statistical properties over time, including constant mean, variance, and autocorrelation. Non-stationary time series have changing statistical properties and may require differencing or other transformations to achieve stationarity before analysis. In the given data, the autocorrelation function shows a strong positive autocorrelation at lag 1, indicating that rainfall on a given day is highly correlated with rainfall on the previous day. The autocorrelation decreases as the lag increases, but remains positive for several lags, indicating a persistence in the rainfall pattern. The significance limits for the autocorrelations can be used to assess whether the observed autocorrelations are statistically significant or due to random chance. In this case, the significance limits are set at the 5% level, meaning that there is a 5% chance that the observed autocorrelations are due to random chance. Autocorrelations outside of the significance limits are considered statistically significant and indicate a pattern in the data.

In summary, autocorrelation is a measure of the similarity between observations in a time series as a function of the time lag between them. The autocorrelation function can be used to identify patterns in the data and to assess the stationarity of the time series. Significance limits can be used to assess the statistical significance of the observed autocorrelations.

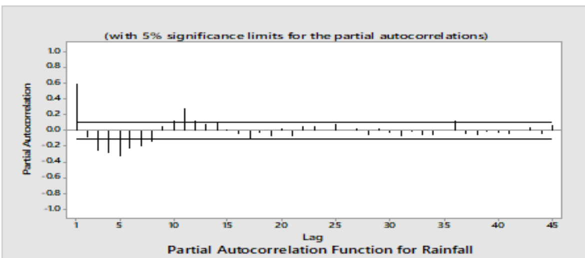

Figure 9: 5% Significance limits for the partial autocorrelation

The partial autocorrelation function (PACF) is another tool used for the model identification. There are some spikes that are lie outside the 95 per cent confidence interval. Next, we shall go ahead to fit a model that will take into consideration 12 monthly periodicity. The partial autocorrelation function (PACF) is a measure of the correlation between an observation in a time series and observations at prior time steps, after removing the effect of any correlations due to intermediate time steps. The PACF is used to identify the order of an autoregressive (AR) model, which is a type of time series model that uses past observations to predict future observations. In the given data, the partial autocorrelation function for rainfall is plotted against lag k. The partial autocorrelation decreases as the lag increases, indicating that the correlation between rainfall and its past values decreases as the time lag between them increases.

The significance limits for the partial autocorrelations can be used to assess whether the observed partial autocorrelations are statistically significant or due to random chance. In this case, the significance limits are set at the 5% level, meaning that there is a 5% chance that the observed partial autocorrelations are due to random chance. Partial autocorrelations outside of the significance limits are considered statistically significant and indicate a pattern in the data. The PACF can be used to identify the order of an AR model by finding the lag at which the partial autocorrelation becomes statistically insignificant. In this case, the partial autocorrelation becomes statistically insignificant at lag 3, indicating that an AR (3) model may be appropriate for modelling the rainfall data.

In summary, the partial autocorrelation function is a measure of the correlation between an observation in a time series and observations at prior time steps, after removing the effect of any correlations due to intermediate time steps. The PACF can be used to identify the order of an autoregressive model and to assess the statistical significance of the observed partial autocorrelations.

C. Seasonal ARIMA Model

The model most appropriate for this kind of data is seasonal Autoregressive Integrated Moving Average (SARIMA). SARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model. The model is given as

$$ARIMA \quad \underbrace{(p, d, q)}_{\text{Non seasonal part of the model}} \quad \underbrace{(P, D, Q)_m}_{\text{Seasonal part of the model}}$$

Where

Where

$p =$ Non-seasonal AR order

$d =$ Non-seasonal differencing

$q =$ Non-seasonal MA order

$P =$ Seasonal AR order

$D =$ Seasonal differencing

$Q =$ Seasonal MA order

$m =$ Time span of repeating seasonal pattern

Without differencing operators, the model could be written more formally as

$$\Phi(B^m)\phi(B)(y_t - \mu) = \Theta(B^m)\theta(B)u_t \tag{6}$$

The non-seasonal components are

AR

MA $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ (7)

$\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$ (8)

The seasonal components are

Seasonal AR

$$\Phi(B^m) = 1 - \Phi_1 B^m - \Phi_2 B^{2m} - \cdots - \Phi_P B^{Pm} \quad (9)$$

Seasonal MA

$$\Theta(B^m) = 1 + \Theta_1 B^m + \Theta_2 B^{2m} + \cdots + \Theta_Q B^{Qm}$$

(10)

D. ARIMA Model: Rainfall

The parameters estimation was achieved for each iteration for the model development for rainfall forecast for Calabar Municipality as presented in Figures X to XI respectively.

$$\Phi(B^m)\phi(B)(1 - B^m)^D(1 - B)^d(y_t - \mu) = \Theta(L$$

$$D = 1, d = 1, \quad m = 12 \text{ and } \quad x_t = y_t - \mu$$

$$\Phi(B^{12})\phi(B)(1 - B^{12})(1 - B)x_t = \Theta(B^{12})\theta(B)u$$

(11)

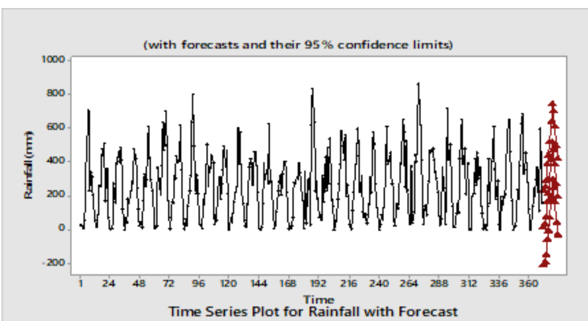

FIGURE 10: PLOT OF FORECASTS AND THEIR 95% CONFIDENCE LIMITS

The time series plot of rainfall data shows a seasonality pattern without any trends, indicating that rainfall reaches its higher value at the end of the year until January (rainy season) and decreases from March to August (dry season). This pattern is repeated annually during the 2006-2018 period. To forecast rainfall, decomposition of time series data into trend, seasonality, and remainder components can be used. The ARIMA and ETS models can be used for forecasting, and they share similar movement based on the plot with the lowest value of rainfall occurring during August. The forecast can be useful for farmers who want to know the best month to start planting and for dry and rainy season prediction to determine the right time for various activities.

This graph shows the original rainfall data and forecast for Jan 2021- December, 2022

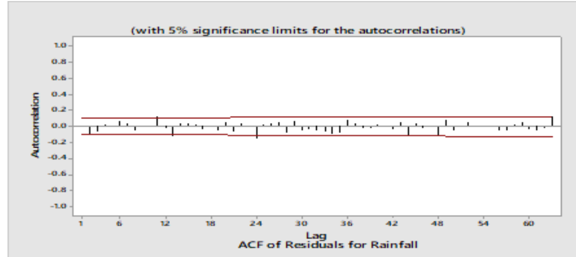

FIGURE 11: 5% SIGNIFICANCE LIMITS FOR THE PARTIAL AUTOCORRELATION

Most of the spikes of autoregressive correlation function (ACF) of the residuals fall within 95 per cent confidence interval which suggest the model is adequate for the rainfall data as shown in Figures 12 to 13 respectively. The concept of spatial autocorrelation is crucial in understanding the behaviour of data across different locations. It is a measure of the similarity or dissimilarity between the values of a variable at different locations as a function of the distance between them. This concept is particularly important in fields such as geography, ecology, and epidemiology, where the spatial distribution of data can have significant implications. The document discusses the use of auto covariate models to account for spatial autocorrelation in the analysis of data. These models estimate how much the response variable at any one site reflects response values at surrounding sites, indicating the degree of spatial dependence in the data. However, the document notes that these models were not able to remove all spatial autocorrelation from the data, suggesting the presence of an aggregation mechanism in the errors 1. The document also discusses the impact of ignoring the autocorrelation structure of the vector process on the eigenvalues, suggesting a spurious impact of the time-correlation on the eigenvalues. To mitigate this impact, a pre-filtering procedure to whiten the data is applied

In summary, spatial autocorrelation is an important concept in the analysis of data, particularly in fields where the spatial distribution of data is critical. Auto covariate models can be used to account for spatial autocorrelation, but they may not be able to remove all spatial autocorrelation from the data, indicating the presence of other factors influencing the data. Pre-filtering procedures can be used to mitigate the impact of spatial autocorrelation on the analysis of data as presented in Figures 11 to 14, five percent (5%) significance limits for the partial autocorrelation.

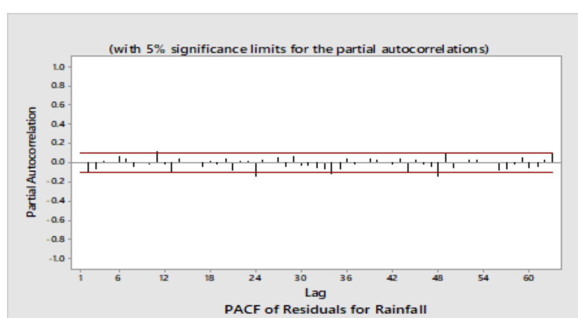

Figure 12: 5% Significance limits for the partial autocorrelation

Most of the spikes of partial auto regressive correlation function (PACF) of the residuals fall within 95 per cent confidence interval which suggest the model is adequate for the rainfall data as depicted in Figure 12. The partial autocorrelation function (PACF) of the residuals for rainfall data indicates that most spikes fall within the 95% confidence interval, suggesting the model is suitable for the data analysis This alignment within the confidence interval implies that the model adequately captures the underlying patterns in the data, as shown in Figure 12.

In this study, we plotted the graph of original maximum temperature data from January, 1990 to December, 2020 called time plot. The time plot revealed features of maximum temperature data collected over a period 31 years. The time plot showed a pattern that repeat s itself every Twelve month as presented in Figure 12. From our time plot, temperature l is usually high in the months of January, February, and March and gradually decreases in intensity from May, June and picked in the month of July. The temperature starts increasing from August and least amount of temperature is usually recorded for November and December. This cycle repeats every year, as presented in Figures 13 to 14.

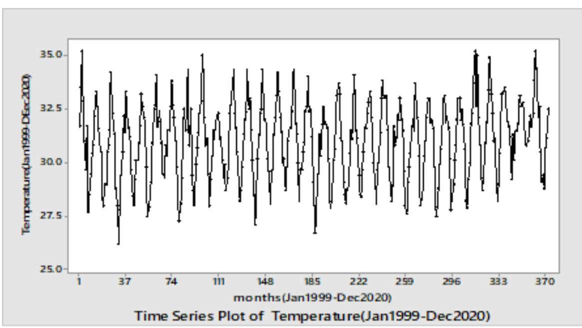

Figure 13: Time series plot of temperature

The provided search results do not contain a direct answer to the question about the time series plot of temperature from January 1999 to December 2020. However, the search results do provide Time series analysis is a statistical technique used to analyse data collected over time, with the aim of identifying patterns, trends, and relationships between variables. It is widely used in fields such as economics, finance, engineering, and environmental science to make predictions and inform decision-making. The search results mention the use of models to estimate the parameters of a time series, as well as the importance of checking for autocorrelation and partial correlation in the residuals. The use of sine and cosine functions to represent periodic sequences is also discussed, which is relevant for analysing data with seasonal patterns. In summary, while the search results do not provide a direct answer to the question about the time series plot of temperature, they do provide useful context and background information about time series analysis and its importance in various fields.

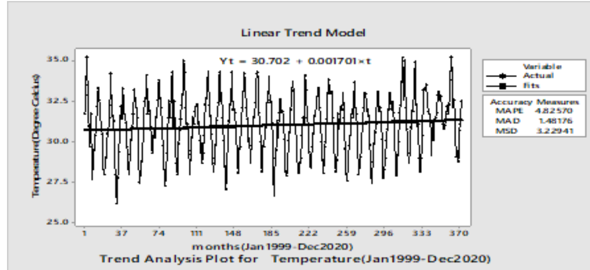

Figure 14: Linear trend model

In order to determine the trend of rainfall in the period of 31 years under study, we fit a trend model in the original data. The trend model suggests that there is slightly upward trend in the amount rainfall recorded. The measure of accuracy of the trend model are given as Mean Absolute Percentage Error (MAPE)=4.82570, Mean Absolute Deviation (MAD)=1.48176 and Mean Standard Deviation (MSD)=3.22941. The concept of spatial autocorrelation is crucial in understanding the behaviour of data across different locations. It is a measure of the similarity or dissimilarity between the values of a variable at different locations as a function of the distance between them. This concept is particularly important in fields such as geography, ecology, and epidemiology, where the spatial distribution of data can have significant implications.

V. Conclusion And Recommendation

A. *Conclusion*

The in-depth analysis of rainfall patterns in Calabar reveals significant implications for climate change. The variability in rainfall, temperature trends, and relative humidity all contribute to the city's vulnerability to climate-related challenges. By understanding these impacts and integrating findings into policy and planning, Calabar can better prepare for and adapt to the effects of climate change. Effective forecasting models, such as ARIMA, are essential tools for predicting future trends and aiding in planning and decision-making processes.

B. *Recommendations*

Water management experts should develop robust water management systems that account for variability in rainfall. This could include improved storage facilities and efficient water usage practices. Incorporate climate projections into urban planning to mitigate the impacts of flooding and heat waves. This might involve enhancing drainage systems, designing flood-resistant infrastructure, and increasing green spaces. Implement public health strategies to address heat-related health risks and ensure that healthcare facilities are prepared for climate-related emergencies. Infrastructure resilience enhances flood management infrastructure to mitigate risks associated with increased rainfall, including the construction of better drainage systems and flood barriers. Investing in resilient infrastructure is crucial for minimizing the impacts of extreme weather events.

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