CEDTECH International Journal of Agriculture Research & Life Science
Volume 4, Number 2, June 2023
http://www.cedtechjournals.org
ISSN: 2756-455X

MODELLING AND FORECASTING RAINFALL AND TEMPERATURE FOR UYO, AKWA IBOM STATE, NIGERIA

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ABSTRACT

The monthly air temperature and rainfall time series recorded between January, 1990 -December, 2022 from Nimet station were modeled and forecasted. In our forecasting, we used the methods of the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) model to analyze annual rainfall and maximum temperature of Uyo, Akwa Ibom State and the forecast. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were used to identify the models by aid of visual inspection. From graphical analysis on time plot and Autocorrelation Function (ACF), the series seems not to have a seasonal component and was also non- stationary. Stationary tests were conducted using the Augmented Dickey-Fuller (ADF). In order to attain stationary, first-order and second-order differencing (d = 1, 2) was carried out on rainfall and temperature data respectively. The chosen models were evaluated and validated using Akaike Information Criterion Corrected (AICC) and Schwartz Bayesian Criteria (SBC). Moreover, diagnostic check tests on the residuals of the models on mean rainfall and temperature satisfies the normality, constant variances (homoscedascity), P-P and Q-Q plots assumptions respectively. The best ARIMA model for rainfall for Uyo was (1, 1, 1) with AICC value of 275.15. That of maximum temperature for Uyo was (1, 2, 2) and the corresponding AICC value of 36.92. The model's efficiency was checked using Sum of square error (SSE), Mean square error (MSE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) respectively. In order to assess the relationship between the observed values and the predicted values, Pearson Correlation analysis was employed. The result showed a correlation coefficient (r) of 0.464 and 0.385 between the observed and the predicted rainfall and temperature data respectively indicating a positive correlation between the two variables. The mean, standard deviation, coefficient of variation, skewness and kurtosis of monthly and annual rainfall and temperature was calculated to check the rainfall and temperature variability. Finally, ARIMA (1, 1, 1) and ARIMA (1, 2, 2) were used to forecast mean of monthly rainfall and temperature from the period 2024 - 2028 for Uyo Area, Akwa Ibom State.

Keywords: *ARIMA Model, Modelling, Forecasting, Rainfall, Temperature.*

INTRODUCTION

Modeling and forecasting of weather variables is a challenging task in agriculture and financial economics. The global economy is highly influenced by weather and climatic condition of an area. Among the components of hydrological cycle, rainfall is utmost important (Ramana*et. al*., 2013). It is the result of many complex physical processes that induce particular features and make its observation complex [Akroure*t al.* 2015]. In predicting meteorological information, investigating and analyzing rainfall is very crucial (Radhakrishnan, Dinesh 2006) and accurate forecasting of precipitation is essential to improve management of water resources particularly in arid environment [Feng *et al.* 2015]. According to Somvanshi*et al.* (2006), rainfall is a natural climatic phenomenon and predicting it remains a challenging issue as a result of climatic variability. The forecast of precipitation is particularly relevant to agriculture, growth of plants and development, which profoundly contribute to the world economy. Time series analysis plays a significant role in modelling of meteorological data such as humidity, temperature, rainfall and other environmental variables (Collischonn*et al*., 2005; Hung *et al.*, 2009; Meher&Jha, 2013; Kanna*et al*., 2010; Mahsin et al., 2012; Ansari, 2013; Htike&Khalifa, 2010). Rainfall forecasting is crucial for making important decisions and performing strategic planning. Being able to predict and forecast rainfall quantitatively provides a guide in the management of water related problems such as extreme rainfall conditions like flood and drought, among other issues (Htike&Khalifa, 2010; Ansari, 2013; Kanna et al., 2010; Meher&Jha, 2013). Kapoor and Bedi [2013] reported that considering all the climatic variables, forecasting of temperature variability is very essential for diverse applications. Applications of temperature prediction are for climate monitoring, drought detection, agriculture and production, planning in energy industry and many others. In a related study by Kenitzer*et al.* (2007), they argued that temperature forecasting is the most essential services delivered by the meteorologist to safeguard life and property of dwellers in a locality and also to improve the efficiency of operations as well as to aid individuals to plan a wide range of activities daily. Prediction of hydrological variables such as rainfall and run-off flow serves as a key area in water resources planning. These hydrological variables are usually measured longitudinally across time. This makes times series analysis of their occurrences in discrete time appropriate for monitoring and simulating their hydrological behaviors (Ansari, 2013). Rainfall is one of the complicated components of the hydrological cycle that poses a challenge to model and forecast due to its various dynamic and environmental factors and random spatial and temporal variations. (Htike&Khalifa., 2010).

Time series data forecasting is a part of statistical modelling that is widely used in various departments such as weather stations, finance, banking, and healthcare departments such as covid-19 data analysis because of its benefits in decision- making. Time series forecasting analysis has several objectives, namely; forecasting, modelling, and managing. Forecasting is an element that is important in managing activities because whether or not an effective decision is made depends on several factors that influence, although hidden, when a decision is taken. The essence of employing time series forecasting model is to predict the future values of certain variables that range with time using its past values. Forecasting is related to the generation of models and methods that can be used to construct a good forecast. In time series data, the doings of past events can be used for forecasting because it is expected that, in the future, the impact of the doings of past events will still occur. Generally, time series research uses linear time series models, specifically the autoregressive integrated moving average (ARIMA) model. Many of the time series forecasting methods being employed are based on the analysis of historical data. Time series can be defined as an ordered sequence of values at equal spaced-time intervals (Box et al, 2008). Time series models are mathematical representation of the time series. Time series models have been the basis for the study of behavior of a process over a period of time. Time series models have been discovered to be one of the most effective methods of forecasting when it comes to decisions that involves factor of uncertainty of the future. Most often, future course of actions and decisions for such processes will depend on what would be the anticipated results. In literature, ARIMA models have been widely used for various applications such as medicine, business, economics, finance and engineering. Moreover, ARIMA models have become, in last decades, a major tool in numerous meteorological applications to understand the phenomena of air temperature and precipitation.

Predicting of future courses of meteorological quantities based on historical time series is crucial for agro-physical modelling (Lamorski*et al.*, 2013, Baranowski*et al.*, 2015, Murat *et al.*, 2016, Krzyszczak*et al.*, 2017a).Box-Jenkins (ARIMA) modelling has been successfully applied in various water resources and environmental management applications (Nail & Momani, 2009). ARIMA model is fundamentally a linear statistical technique for modelling the time series and rainfall forecasting with ease. Though rainfall estimation is an important component of water resources planning, its accurate assessment at locations where rainfall stations are scarce can be very difficult. This makes estimate of rainfall a valid concern using the right method. In agricultural planning, the understanding of rainfall variability and its prediction has great significance in the agricultural management and helps in decision making process. The Box-Jenkins approach possesses many appealing features that allows the manager who has only data on past years quantities such as rainfall to forecast future ones without the need to look for other related time series data such as temperature. Box- Jenkins approach also allows for the use of several time series, for example temperature, to explain the behavior of another series, for example rainfall, if these other time series data are correlated with a variable of interest and if there appears to be some cause for this correlation. The Box-Jenkins methodology applies ARMA, ARIMA or SARIMA to establish the best fit of a time series historical values to make forecasts. Box-Jenkins methodology involves four stages, namely: model identification, estimation of model parameters, diagnostic checking for the identified model appropriate for modelling and application of the model (i.e. forecasting).

The main aim of this research is to model and forecast rainfall and temperature for Uyo, Akwa Ibom State for the period of five years (2024 – 2028).

MATERIALS AND METHODS

Description of the Study Area

The study was carried out in Uyo Local Government Area of Akwa Ibom State. Uyo Local Government Area lies between Latitudes 4° 30’ and 5° 32° North and Longitudes 7° 30’ and 7° 36° East, within the tropical rainforest belt with evergreen vegetation. It is the capital city of Akwa Ibom State and presently occupies a total land mass of 1,250,000km^2 of which a substantial percentage is used for agriculture. About 50, 000ha of its area are affected by gully erosion, with gully sites and ravine wide spread over the area (nona.net, Uyo (Nigeria) map, 2011).

Fig. A: Map of Akwa Ibom State showing the location of the study area and the meteorological station.

Climate

The area is situated within the hot humid tropical region and the climate is characterized by two distinct seasons; dry and wet seasons. The wet season starts from April to October and the dry season starts from November to March. The rainfall is bimodal with peaks in July and September and of high intensity coupled with moisture stress period between 2 - 3 weeks in August. The rainfall characteristics of Coastal Akwa Ibom tends to indicate a pattern of three months, maximum in March, July and September, in contrast to the general two maxima pattern of rainfall associated with the overhead passage of the sun resulting in very heavy rainfall which varies from more than 3000mm along the coast to about 2000mm in the northern fringes (UNIUYO CONSULT LTD, 2003). The temperature across the State ranges from a mean daily minimum of 20°C in December to a mean daily maximum of 35°C in March. The mean monthly temperature remains fairly constant throughout the year.

Soil and Vegetation

The geological formation in Uyo is the Coastal Plain Sands, which occupies more than 75% of Akwa Ibom State soils. The soils are derived from the parent materials and are highly weathered and dominated by low activity clays; the dominant soils in Akwa Ibom State are of inter-fluvial slope with a pattern of increase in clay content down the profile and are generally of low organic matter content (OMC), low water storage capacity, low CEC and highly susceptible to erosion (SLUK-AK, 1989; E. J. Udo & J. Sobulo, 1981). The dominant forest types in Akwa Ibom State include the saline water swamp, fresh water swamp forest and the rain forest. The native vegetation has been completely replaced by secondary forest of predominantly oil palms, woody shrubs such as grasses.

Meteorological Station

The network stations in the Uyo metropolis which climatic data (rainfall and temperature) was analysed was Uniuyo meteorological station, Akwa Ibom State; located within Latitude 5°02’60.00” N and Longitude 7°55’59.99” E of the Greenwich Meridian. This is a standard meteorological station owned and managed by professional Nimet staff which assist in measuring the most conventional meteorological variables such as temperature and rainfall. The common meteorological instruments of measure are thermometer and rain gauge.

Materials for the Study

The data for this study is the average monthly rainfall series (mm) and maximum temperature data (°C)retrieved from the records of Nimet Synoptic Weather Station for the period of January, 1990 to December, 2020 for temperature and January, 1990 to December, 2022 for rainfall in Uyo, Akwa Ibom State.

METHODOLOGY

The climatic data of 32 years for the period 1990 – 2022 for Uyo Metropolis was organized and tabulated in Excel spreadsheet. Minitab Statistical Software Version 18 was used to model the mean annual rainfall and maximum temperature for the period 1990 to 2022 for Akwa Ibom State. Time series data collected in hydrology, climatic fields, environmental and so on are best described by Box-Jenkins method. This method is the most general way of approaching to forecast unlike other models. The procedure for the Autoregressive Integrated Moving Average (ARIMA) model is described below:

Box-Jenkins Methodology

The Box–Jenkins method of ARIMA modelling was used in this study. The procedure adopted by Box and Jenkins in the ARIMA modelling was an iterative process the best models were determined through trial and error. But, the iterative process has been made easy by the aid of statistical software packages. The said model has three parts and they are: autoregressive (AR), integrated (I) and moving-average (MA). The AR part denotes the autocorrelation between current and past observations while the MA part describes the autocorrelation structure of error (residuals). In the report of HASMIDA [2009], the integrated part denotes the level of differencing needed to transform a non-stationary series into a stationary series.

The general ARIMA (*p*, *d*, *q*) model is:

$$U_t = \emptyset_1 U_{t-1} + \emptyset_2 U_{t-2} + \cdots + \emptyset_p U_{t-p} + \varepsilon_t - \theta 1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots \theta_q \varepsilon_{t-q} \quad (1)$$

$$U_t = X_t - X_{t-d} \quad (2)$$

Where: $\emptyset_p$ = autoregressive parameter; εt= residual or white noise; θ_q= moving average parameter; X_t= dependable variable; U_t= d^{th} difference of the dependable variable.

The first step in building the model will be to establish whether there is any stationarity in the observed data. Visual inspection of the ACF (autocorrelation function) and PACF (partial autocorrelation function) will indicate whether the series is stationary or not.

Stationarity Tests

The foundation of time series analysis is stationarity. Stationary series are characterized by a kind of statistical equilibrium around a constant mean level as well as a constant dispersion around that mean level (Box, G. E. P. *et. al*., 1976). According to BOX *et al.* [2015] if a series is non-stationary, then it necessitates a differencing to be carried out to transform it to a stationary series in order to continue with the ARIMA modelling. The tests that will be carried out to identify that consist of: The unit root's presence in the time series data was carried out. The standard tests for unit root is the augmented Dickey–Fuller (ADF) test. This test is based on estimates from an augmented autoregression. The selection of lag length k is one of the key issues in the ADF test [Huang *et al.* 2016]. The presence of a unit root is an indication of non-stationarity of the series. The test was carried out at 5% significant level. If the series is non-stationary, differencing will be required to convert it to a stationary data.The Mann–Kendall (MK) test is principally conducted to test for a trend in the time series data. The presence of a trend in the series will indicate a non-stationary series and must be transformed into a stationary series for an ARIMA process to continue. On the other hand, if the series is stationary then the series will be modelled as an ARMA process which will not require a differencing to be conducted [Huang *et al.* 2016].

Differencing

It is required in fitting ARIMA model to attend stationarity in both the mean and variance. To attend stationarity in the data, it could be done by log transformation and differencing of the original data [Huang *et al.* 2016]. In this study, stationary second difference ($d = 2$) of the original data will be carried out to achieve stationarity. The ACF and PACF of the differenced data will be observed and tested for stationarity.

Analysis of ACF and PACF

One of the techniques that was used to identify the models was the visual inspection of the series, which included the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). Autocorrelation (AC) and Partial Autocorrelation (PAC) Function are a type of graphs that contain correlations of different time lags. They can be used to determine whether the series are stationary or not, have seasonal pattern and to identify the number of components (lags or parameters) in an ARIMA model. The number of significant spikes in the ACF indicates the number of MA parameters in the model, while the number of significant spikes in PACF indicates the number of AR parameters in the model. The mean annual rainfall and temperature data was used as the input variable. The auto covariance function, the autocorrelation coefficients and the partial correlation coefficients was computed from the said input variables and the series with its ACF and PACF wasplotted using Minitab software.

Model Diagnostic

To evaluate the model in order to select the best model for each category of data, the criteria used by KHADR [2011], for selecting the best model was used. Generally, in the selection of goodness of fit among candidates of model under the Box-Jenkins methodology, the criteria that will be used will be Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). The Akaike information criterion corrected (*AICC*) was established by AKAIKE [1974] to choose the best model among the class of plausible models. The model with minimum Akaike Information Criteria (AIC) and Bayesian Information will be considered as the best model and will be used for the forecasting. The equation governing the above mentioned criteria [SCHWARZ 1978] is:

$$AICC\ (p,\ q,\ P,\ Q) = N\ln(\sigma^2) + \frac{2(p+q+P+Q+1)N}{(N-p-q-P-Q-2)} \qquad (3)$$

Where: N = the number of observations; δ = the mean square error.

The study of Mishra and Desai [2005] and Alam*et al.* [2014] indicated that *AICC* which is the revised version of AIC acts well even by low number of samples.

Model Diagnostic Analysis

In order to be sure that the model will be representative for the observed rainfall and temperature data and can be used to forecast the future data, the model will be subjected to diagnostic tests. The best chosen models with their corresponding model parameter values will be presented. Diagnostic checks will be carried out to determine whether the models fit the data very well. If the model fits well the residuals should be uncorrelated (white noise) with a constant variance and also the residuals should be normally distributed [Huang *et al.* 2016].

Model Specifications

One of the most popular and frequently used stochastic time series models is the Autoregressive Integrated Moving Average (ARIMA) developed by Box, G. Jenkins model in (1970). The basic assumption made to implement this model is that the considered time series is linear and follows a particular known statistical distribution, such as the normal distribution. ARIMA model has several components, such as the Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA models.

Model Estimation

In order to establish the model that best fits the data being analyzed, model estimation is required. This was achieved by observing the ACF and the PACF of the differenced data. The models were considered with both *p* and *q* starting from zero to two. The models that were tested are: (0, 1, 1), (0, 1, 2), (1, 1, 0) (1, 1, 1), (1, 1, 2), (0, 2, 1), (1, 2, 0), (1, 2, 1), (1, 2, 2), (2, 2, 0), (2, 2, 1), (2, 2, 2). The model having the lowest *AICC* value was chosen as the best for the station.

Model Forecasting

Statistical methods and for that reason ARIMA models are good for short-term forecasting because the historical data normally exhibit inertia and do not show drastic changes [Montgomery *et al.* 2008]. One of the primary objectives of time series analysis is to forecast future value of the series, especially forecasting in weather data is great importance. In this regard, a decision needs to be made at current time t and the optimal decision depends on expected future value of a random variable, the value being predicted or forecast. The number of time points forecast into the future forecast horizon is called the lead time, h. A forecaster would like to obtain a prediction as close as possible to the actual value of the variable in question at the concurrent or future temporal point of interest.

Plot of Residuals of ACF and PACF.

After establishing the appropriate model with the above mentioned criteria, goodness of fit of the model will be determined by plotting ACF and PACF of the residuals. A white noise residuals was an indication of the model fit being adequate. A residual with a zero mean and uncorrelated is termed white noise.

Performance Evaluation Criteria

The model was evaluated and validated using the following performance criteria: Root mean square error (*RMSE*), Sum of squares error (*SSE*), Mean square error (*MSE*) and Mean absolute percent error (*MAPE*). At the forecasting stage, the estimated parameters were tested for their validity using the above error statistics.

Statistical Analysis

For modeling ARIMA model, a statistical software known as Minitab version 18 was used. The best model generated was used to forecast the rainfall and temperature trend of the studied area for the next five years (2024 – 2028). The descriptive statistics of rainfall and temperature such as the mean, SD, Coefficient of Variation (CV), kurtosis and skewness was also analyzed using Excel Spreadsheet. The Product Moment Correlation Coefficient (r) was used to test the relationship between the observed values and the predicted values of the historical data. The Product moment correlation coefficient (r) is the ratio of the joint variation of two variables to the total variation. The technique assumes that both variables came from normally distributed populations.

RESULTS AND DISCUSSION

AVERAGE ANNUAL RAINFALL TREND ANALYSIS

Mean monthly and annual rainfall data of Uyo for the period 1990 – 2022 were analyzed as shown in Fig. 1. The annual total and average rainfall were calculated for each year and the average rainfall plotted against its corresponding year as shown in Fig. 2. The average annual rainfall for the 32 – year period is 238.2mm. The highest total annual average was 319.8mm in 2012 followed by 297mm in 2020 and coming third with 283.1mm in 2018. Within the 32-year period, the lowest average annual rainfall was in 2022 when only 135.4mm of rainfall fell; 2000 with 149.6mm and 1997 with 160.1mm.

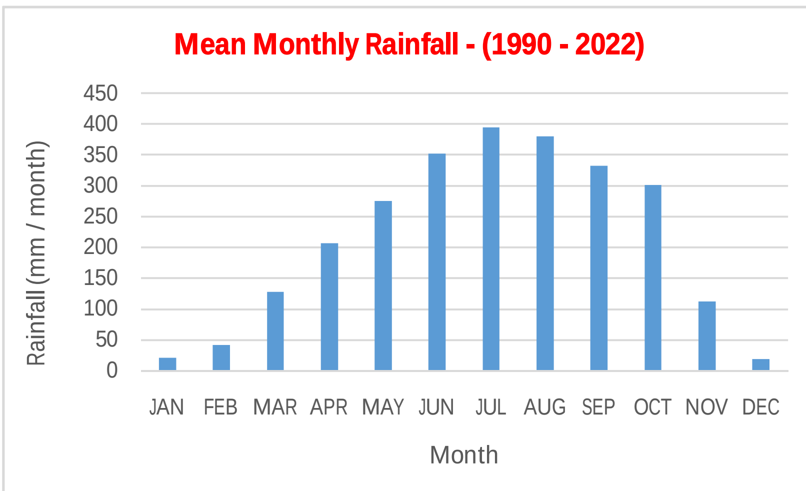


Fig. 1: Mean Monthly Rainfall for Uyo Area

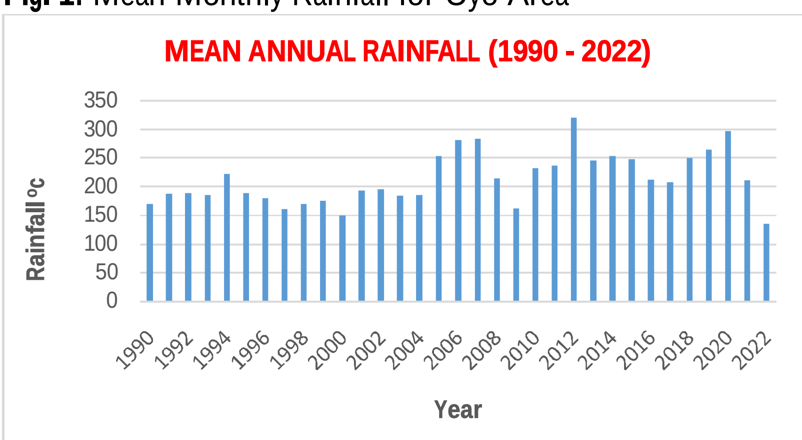


Fig. 2: Mean Annual Rainfall for Uyo Area

STATISTICAL ANALYSIS OF RAINFALL

Table 1 shows the statistical parameters of Uyo rainfall data set for the 32 years (1990 -2022). For the 32 year period, July shows the highest monthly rainfall followed by August, June and September. The average annual rainfall of Uyo for the period analyzed was 2556.16mm. The standard deviation of March, April, till November has a high value which shows high uncertainty in rainfall data. The coefficient of variance of April, May, June, July, August, September, October and November is less than 0.6 which indicates lower variability from the mean. The coefficient of variance of annual rainfall is 0.68 which is high. All positive kurtosis value of data indicates a peaked distribution of rainfall data while negative kurtosis value of data indicates a flat distribution of rainfall data. Also, all positive values of the skewness indicates that data are skewed to the right to normal distribution.

Table 1: Statistical Summary of Rainfall data for Uyo

Parameters	Total	Mean	S.D.	C.V.	Skewness	Kurtosis
January	681.4	20.65	28.33	1.37	2.42	7.20
February	1346.0	40.79	43.71	1.07	1.24	1.39
March	4174.1	126.49	77.60	0.61	0.96	0.64
April	6795.1	205.91	91.28	0.44	0.13	-0.38
May	9035.7	273.81	90.37	0.33	0.12	-0.71
June	11598.4	351.47	139.28	0.39	0.59	-0.23
July	12999.5	393.92	167.19	0.42	1.20	1.84
August	12521.0	379.42	136.60	0.36	1.71	4.13
September	10964.2	332.25	141.04	0.42	0.57	0.78
October	9929.3	300.89	149.37	0.50	1.40	2.86
November	3695.6	111.99	65.92	0.59	0.80	0.54
December	612.8	18.57	29.38	1.58	2.41	6.85
Annual		2556.16	143.79	0.68	-0.20	-1.70

Source: Computed by the researcher using 1990 to 2022 climatic data retrieved from the Meteorological Station, Uyo.

RELATIONSHIP BETWEEN THE OBSERVED AND THE PREDICTED RAINFALL DATA

From Fig. 3, it is shown that the Pearson correlation coefficient (r) is 0.431, which indicates a moderate relationship between the two variables. This implies that as the value of the observed rainfall increases, the value of the predicted rainfall also tends to increase. This is shown by the upward slope of the scatter plot. It indicates a positive correlation between the two variables and the strength of association is small. This implies that there is a moderate relationship between the observed rainfall and the predicted rainfall.

Table 2:Showing the values of the observed and the predicted rainfall

Year	Observed Rainfall	Predicted Rainfall
1990	169.4	198.8
1991	187.2	192.4
1992	188.1	191.7
1993	185.8	192.9
1994	222.4	194.7
1995	188.7	196.8
1996	178.8	198.9
1997	160.1	201.0
1998	169.5	203.2
1999	174.9	205.3
2000	149.6	207.5
2001	193.1	209.6
2002	195.1	211.8
2003	183	213.9
2004	185.1	216.1
2005	252.5	218.2
2006	281.1	220.4
2007	283.1	222.5
2008	213.3	224.7
2009	161.2	226.8
2010	231.8	229.0
2011	235.9	231.1
2012	319.8	233.3
2013	245.3	235.4
2014	252.2	237.6
2015	247.3	239.7
2016	211.3	241.9
2017	207	244.0
2018	249.3	246.2
2019	264.4	248.3
2020	297	250.5
2021	210.7	252.6
2022	135.4	254.8

Source: Computed by the researcher from Field Survey data (2023)

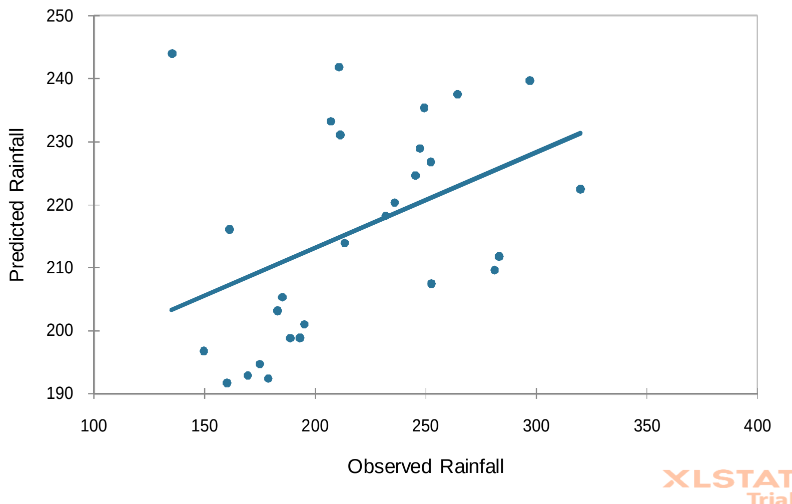


Fig. 3: Relationship between observed rainfall and predicted rainfall

AVERAGE ANNUAL MAXIMUM TEMPERATURE TREND ANALYSIS

Mean monthly and annual temperature data of Uyo for the period 1990 – 2020 were analyzed as shown in Fig. 4. Also, average monthly and average yearly temperature were analyzed for the period 1990 – 2020 as shown in Fig. 5. The average maximum temperature for the 1990 – 2020 period was 31.3°C while the three hottest years were 2009 with 32.2°C, 2008 and 1998, both had a temperature of 32.1°C. The lowest average annual maximum temperatures of 30.5°C were recorded in 2012 and 2013, followed by 30.6°C for 2011 and 2014. Monthly average maximum temperatures were highest in the months of February with 34.2°C, March with 33.1°C and January with 33°C while August, July and September recorded average monthly temperatures from the coldest of 28.5°C, 28.8°C and 29.4°C respectively.

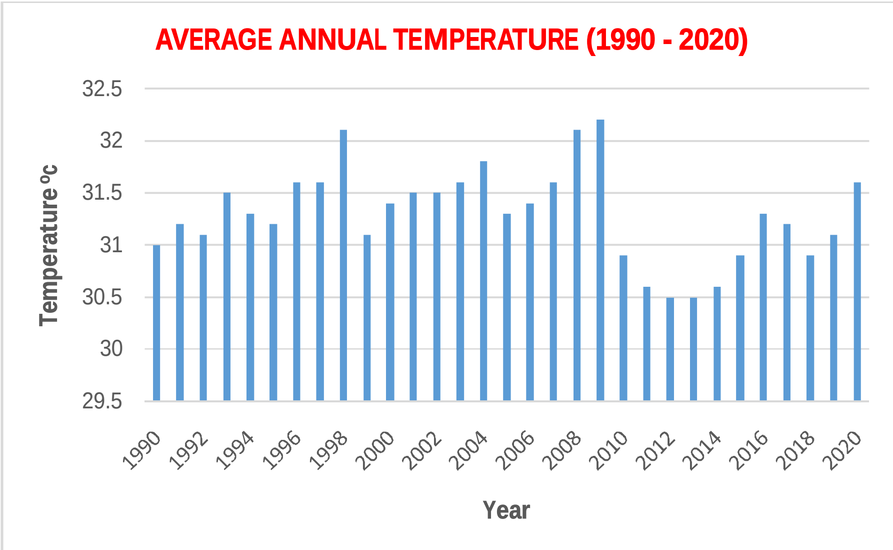


Fig. 4: Average Annual Temperature Uyo

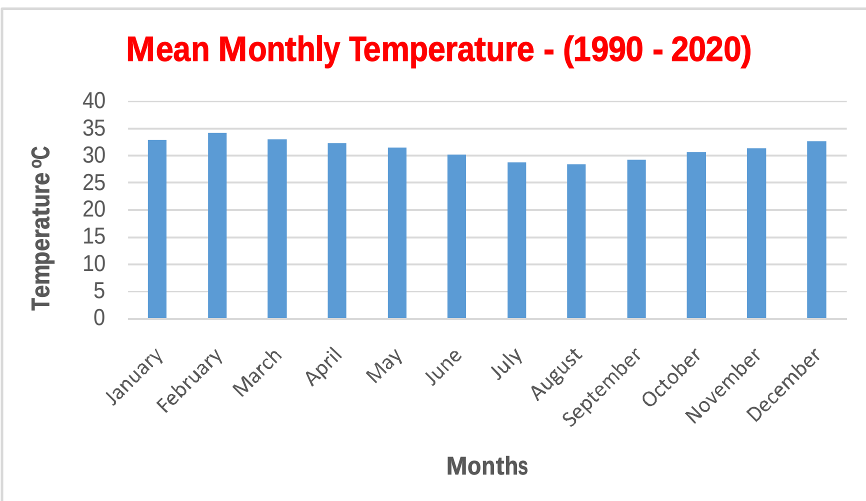


Fig. 5: Mean Montly Temperature Uyo

Table 3: Statistical Summary of Temperature data for Uyo

Parameters	Total	Mean	S.D.	C.V.	Skewness	Kurtosis
January	1021.3	32.95	0.72	0.02	-0.49	1.68
February	1060.1	34.20	0.02	0.00	-5.57	31.00
March	1025.2	33.07	0.98	0.03	0.67	0.50
April	1000.9	32.29	0.54	0.02	1.03	2.80
May	979.7	31.60	0.53	0.02	1.00	2.65
June	936.0	30.19	0.71	0.02	-0.15	-0.52
July	892.3	28.78	0.86	0.03	0.04	-1.50
August	882.2	28.46	0.71	0.03	-0.11	-0.79
September	909.7	29.35	0.82	0.03	0.98	0.00
October	950.9	30.67	0.62	0.02	-0.27	-1.15
November	974.5	31.44	0.96	0.03	0.87	1.78
December	1012.8	32.67	0.84	0.03	1.43	3.47
Annual		375.67	1.84	0.06	-0.19	-1.06

Source: Computed by the researcher using 1990 to 2022 climatic data retrieved from the Meteorological Station, Uyo.

RELATIONSHIP BETWEEN THE OBSERVED AND THE PREDICTED TEMPERATURE DATA

From Fig. 6, it is shown that the Pearson correlation coefficient is 0.385 indicating a positive correlation between the two variables and the strength of the relationship is moderate. This implies that as the value of the observed temperature data increases, the value of the predicted temperature tends to increase. This is shown by the upward slope of the scatter plot.

Table 4: **Showing the values of the observed and the predicted temperature**

Year	Observed Temperature	Predicted Temperature
1990	31.0	31.3
1991	31.2	31.3
1992	31.1	31.4
1993	31.5	31.4
1994	31.3	31.5
1995	31.2	31.5
1996	31.6	31.5
1997	31.6	31.5
1998	32.1	31.6
1999	31.1	31.6
2000	31.4	31.6
2001	31.5	31.6
2002	31.5	31.6
2003	31.6	31.6
2004	31.8	31.6
2005	31.3	31.6
2006	31.4	31.6
2007	31.6	31.6
2008	32.1	31.5
2009	32.2	31.5
2010	30.9	31.5
2011	30.6	31.4
2012	30.5	31.4
2013	30.5	31.3
2014	30.6	31.3
2015	30.9	31.2
2016	31.3	31.2
2017	31.2	31.1
2018	30.9	31.0
2019	31.1	30.9
2020	31.6	30.9

Source: Computed by the researcher from Field Survey data (2023)

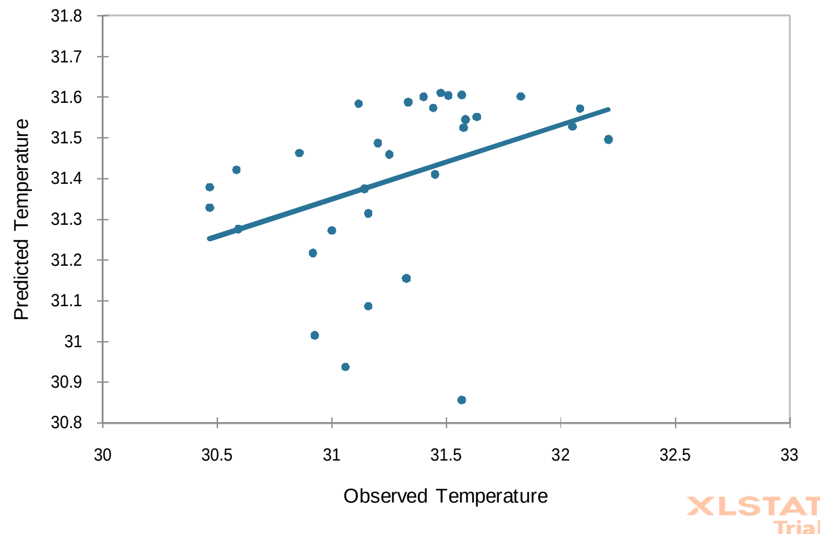
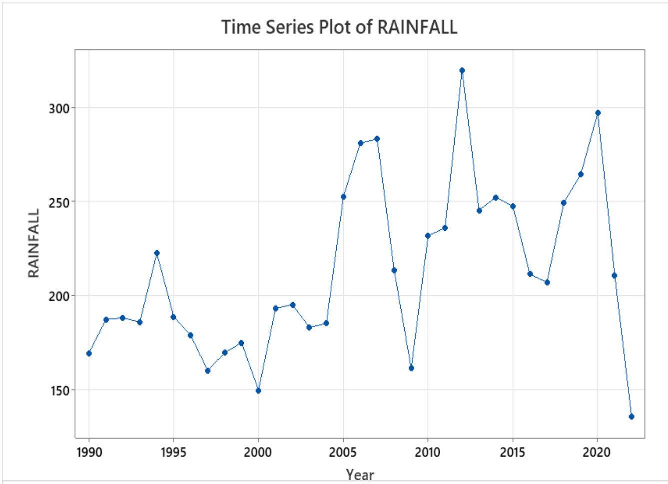


Fig. 6: Relationship between observed temperature and predicted temperature

The data of Ibesikpo network station was chosen as a sample for calculations. Data from January 1990 to December 2022 was used in deriving stochastic and forecasting models. The first step in the application of the methodology was to check whether the time series (mean monthly rainfall and temperature) is stationary and has seasonality. The time series plot of Fig. 7 and 8 of mean annual rainfall and mean annual temperature of Uniuyo and Ibesikpo network station encounters problem of non-stationarity. In Fig. 9 and 10, the graph trend of original data of rainfall and temperature showed non-stationary data, because the data is decreasing and increasing along the axis of time respectively. The graph of original data of (ACF) and (PACF)in Fig. 11 – 14, showed that the rainfall and temperature data are non-seasonal and non-static, where both ACF and PACF have significant values at different lags. A stationary time series has a constant mean and has no trend over time. However, it could satisfy stationary in variance by having log transformation and satisfy stationary in the mean by having differencing of the original data in order to fit an ARIMA model. In order to use the ARIMA procedure for the modelling, the non-stationarity was removed by differencing to make the data set stationary. The time series plot portray an increasing but waving mean annual rainfall.



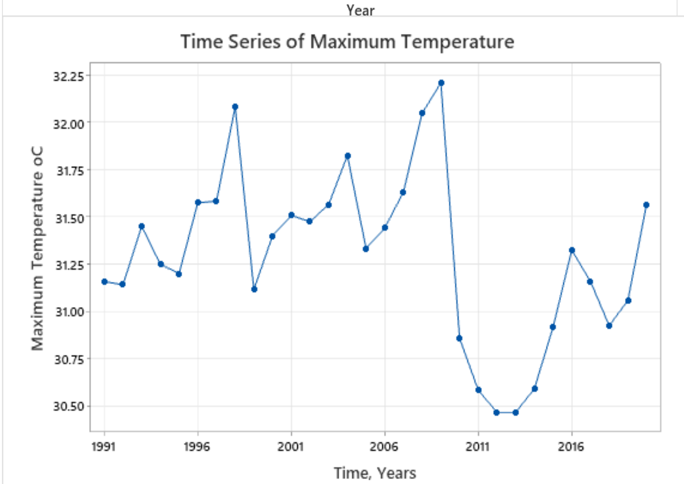
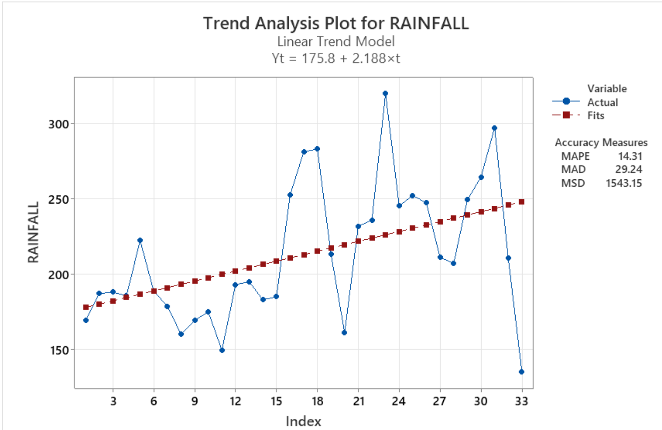


Fig. 7: Time series plot of mean annual rainfall (1990 – 2022)
Fig. 8: Time series plot of mean annual temperature (1990 – 2020)



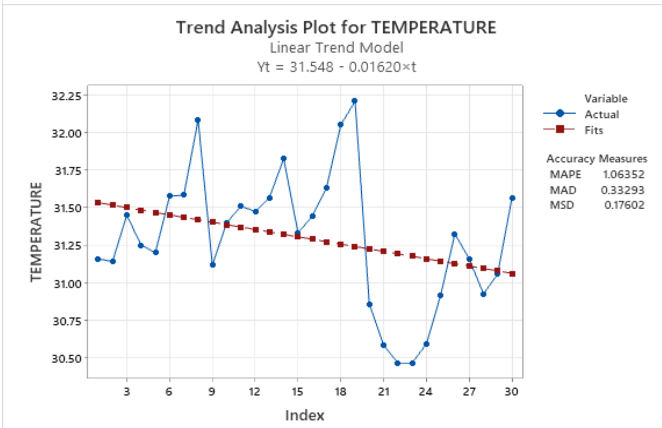
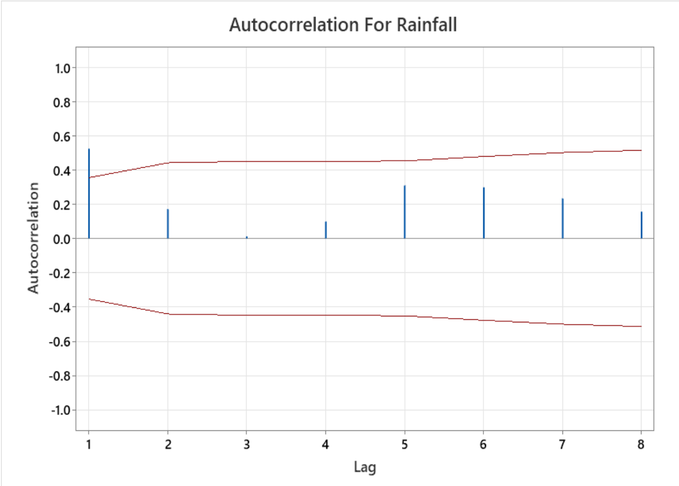


Fig. 9: Trend of original rainfall data
Fig.10: Trend of original temperature data

Moreover, we use statistical testing to verify the stationarity of considered series. The stationarity tests were conducted on the mean annual rainfall and the maximum temperature data series to check and confirm the autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis on the non-stationarity of the data series. In doing this, there are two different approaches: stationarity tests such as the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test that consider as null hypothesis that the series is stationary, and unit root tests, such as the Dickey-Fuller test and its augmented version, the augmented Dickey-Fuller test (ADF), or the Phillips-Perron test (PP), for which the null hypothesis is the contrary – that the series possesses a unit root and hence is not stationary. ADF and PP tests verified the non-stationarity of our series with *p*-value greater than 0.01, which was also confirmed by the KPSS test. Additionally, the MK test also revealed a trend in the data series which further buttressed the non-stationarity.



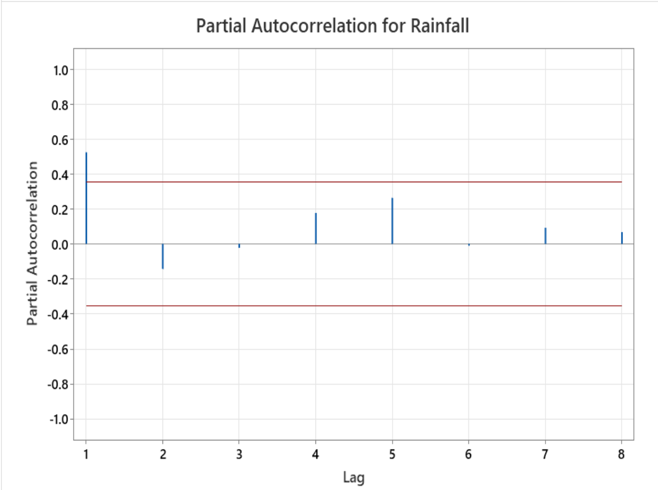
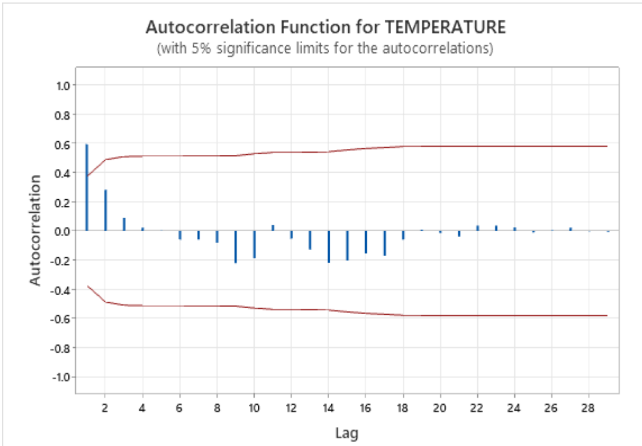


Fig. 11: ACF for original monthly rainfall data.
Fig. 12: PACF for original monthly rainfall data.



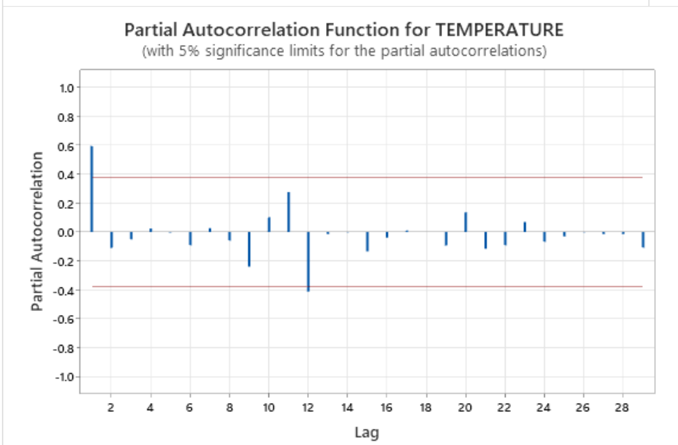


Fig. 13: ACF for original monthly temperature data.
Fig. 14: PACF for original monthly temperature data

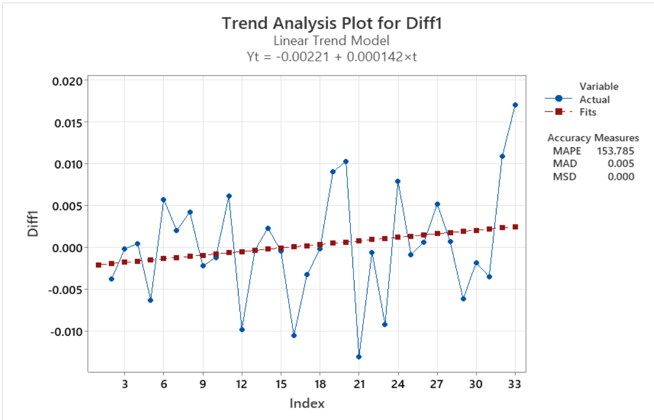
The results of Augmented Dickey–Fuller (ADF), Phillips-Perron (PP), Mann–Kendall (MK) and Kwiatkowski– Phillips–Schmidt–Shin (KPSS) tests respectively are presented in Table 5. The tests justified that all the mean annual rainfall and maximum temperature data series were not stationary. The ADF and KPSS tests indicated the presence of a unit root in the data series. Observing the pattern of the ACF and PACF plots as shown in Figures 11 – 14, it is seen that the mean annual rainfall and the mean maximum temperature series were non-stationary. The patterns exhibited a very slow decay which was an indication of possible non-stationarity. Besides, some of the spikes are seen being outside the confidence interval and some very close to it. This indicated the values were significant and were not white noise (Huang *et al.* 2016). Therefore, it was necessary for trend differencing to be carried out on the series. So, in all ARIMA models, we assumed the second regular differencing (d = 2) for temperature and first regular differencing (d = 1) for rainfall to stabilize the variance in mean and remove the trend in order to convert the data to a stationary one. A graph of time series plot of annual rainfall and annual temperature after doing the differencing showed stationary on the value of the data center, whereas the trend is decreasing at a fairly constant rate as shown in Fig. 14 and 15. The above results therefore implies that ignoring non-stationarity of the data series will have led to the selection of sub-optimal model whose estimate may be misleading. This means the accuracy of the model depended on the stationarity information. The assertion is in agreement with the report of Jung and Shah (2015) who study the implication of non-stationarity on predictive models and Hendry and Pretis (2016) who considered the implication of non-stationarity on empirical modelling and forecasting.

Table 5: Stationary Test

Station	**Augmented Dickey-Fuller Test**		**Kwiatkowski-Philips-Schmidt-Shin Test**		**Phillips-Perron Test**		**Mann – Kendall Test**		**Remarks**
	P-value (rainfall)	P-value (max. temp.)	P-value (rainfall)	P-value (max. temp.)	P-value (rainfall)	P-value (max. temp.)	P-value (rainfall)	P-value (max. temp.)	
Uniuyo	0.983	0.396	<0.0001	0.102	<0.0001	0.738	0.005	0.292	Non-stationary

Station	**Augmented Dickey-Fuller Test**		**Kwiatkowski-Philips-Schmidt-Shin Test**		**Phillips-Perron Test**		**Mann – Kendall Test**		**Remarks**
	P-value (rainfall)	P-value (max. temp.)	P-value (rainfall)	P-value (max. temp.)	P-value (rainfall)	P-value (max. temp.)	P-value (rainfall)	P-value (max. temp.)	
Uniuyo	0.028	0.006	0.410	0.969	<0.0001	<0.0001	0.687	0.292	Stationary

Source: Computed by the researcher from Field Survey data (2023)



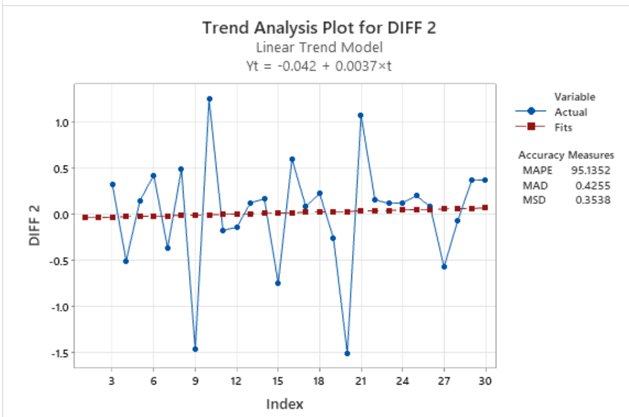


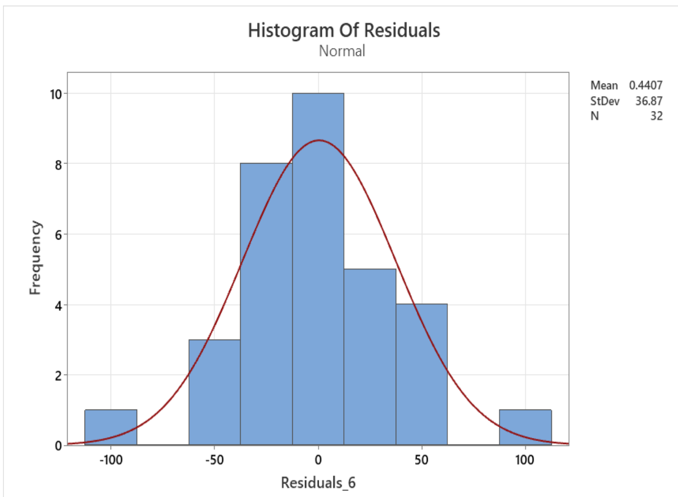
Fig. 15: Plot of trend data for rainfall after in difference
Fig. 16: Plot of trend data for temperature after in difference

The first diagnostic check was the plot of histogram of the residuals (Fig.17 & Fig. 18) which confirmed the normality of the residuals for rainfall and maximum temperature respectively. The other requirement of a good model is that the residuals should be homoscedastic. The homoscedasticity plots were indicated in Figures 4.19 & 4.20 of rainfall and maximum temperature models respectively. The results of Breusch– Pagan test as shown in Table 4.6 confirmed the homoscedascity plots. A residual with constant variance is said to be homoscedastic. Homoscedasticity is a determinant of the model's ability to predict variables consistently. A heteroscedastic residuals cannot provide predictions that are reliable (Huang *et al.* 2016).

Table 6: Results of Breusch-Pagan Test

Station	P-value (rainfall)	P-value (temperature)	Interpretation
Uniuyo	0.070	0.990	Homoscedastic

Test Interpretation: H_o = Residuals are homoscedatic; H_a = Residuals are heteroscedatic
As the computed P-value is greater than the significance level alpha = 0.05, one cannot reject the null hypothesis Ho.
Source: Computed by the researcher from Field Survey data (2023)



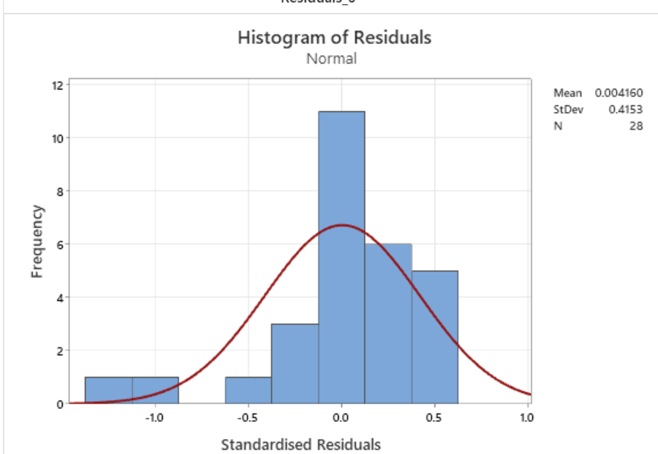


Figure 17: Histogram of Residuals (rainfall)
Figure 18: Histogram of Residuals (temperature)

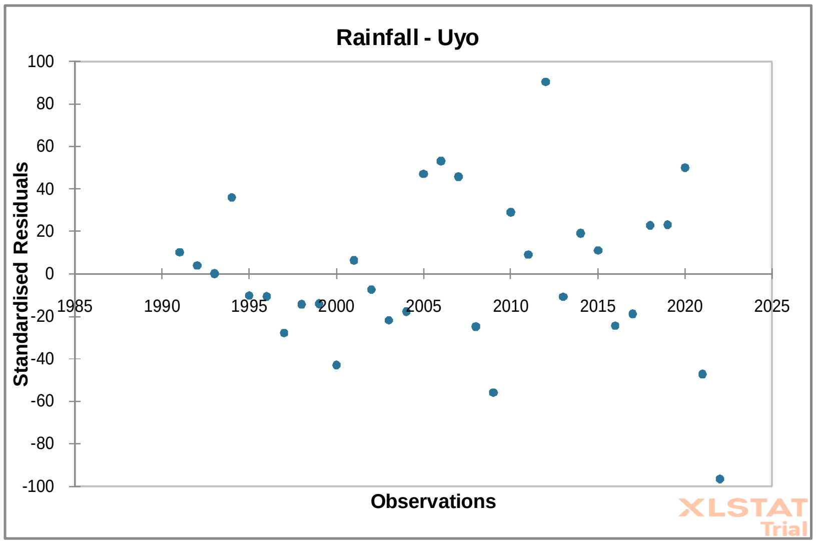


Figure 19: Distribution of standardized residuals (rainfall) for Uyo
Source: Computed by the researcher from Field Survey data (2023)

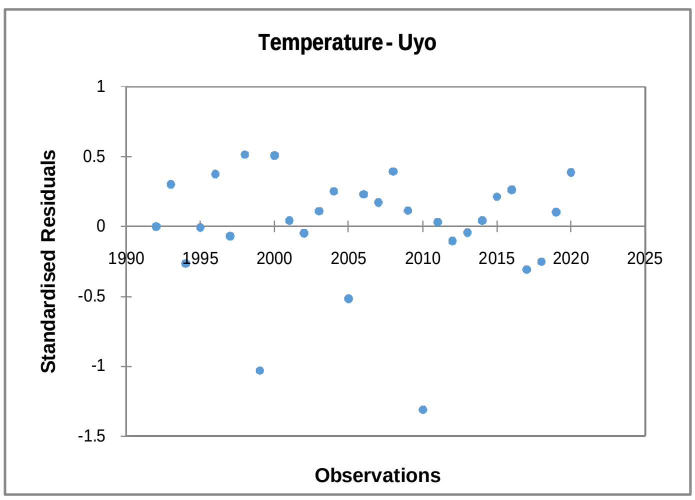


Figure 20: Distribution of standardized residuals (temperature) for Uyo
Source: Computed by the researcher from Field Survey data (2023)

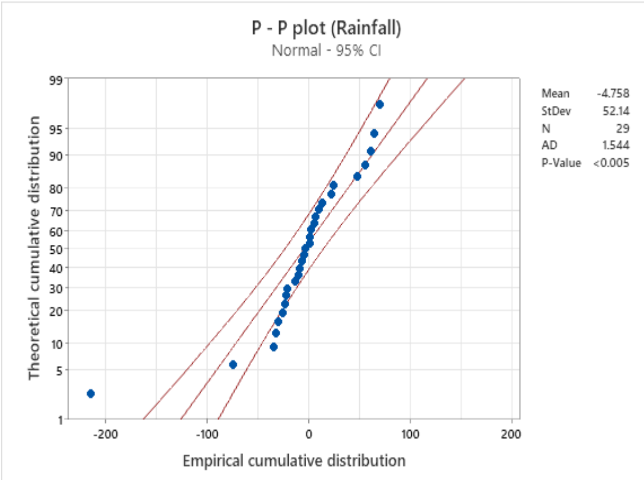
The normality of residuals distribution was essential to produce a satisfactory confidence interval for the forecast. The results of Anderson–Darling, Jarque-Bera, Shapiro–Wilk and Lilliefors tests respectively further confirmed the normality of the residuals (Table 4.7). The *p*-values of the aforementioned tests were more than 0.05 at 95% confidence interval.

Table 7: Results of Normality Test

Stations	Anderson – Darling Test		Jarque-Bera Test		Shapiro – Wilk Test		Lilliefors Test	
	p-value (rainfall)	p-value (temperature)	p-value (rainfall)	p-value (temperature)	p-value (rainfall)	p-value (temperature)	p-value (rainfall)	p-value (temperature)
Uniuyo	0.605	0.450	0.695	0.150	0.803	0.181	0.581	0.100

Source: Computed by the researcher from Field Survey data (2023)

The *P–P* and *Q–Q* plots of the residuals also attested the normality (Figures 20 - 24). The *Q–Q* plot of standardized residuals was based on gamma distribution assumption for a data set. The *Q–Q* plot was used to compare the observed data with the forecasted data by plotting their quantile against each other. The data set almost lying in straight line is an indication that the two distributions were similar. The implication is that the fitted models are correct as their standardized residuals were from the same gamma distribution. From the figures, it is clear that most of the forecast residuals lie within the normal line, with only a few outliers at the beginning and terminals of the time series forecast. The few data points far from the straight line may be due to deviation from the mean stemming from variability of the date set (heavy or low rainfall). From the plot, it can be inferred that the residuals follow a normal distribution pattern. The attribution made is corroborated by George *et al.* (2016). The computed Hessian standard errors and all the estimated model parameters were within the confidence band. The implication of the non-normality of the data series is that the inference or prediction made with the model may be unreliable and misleading. The evidence of normality is corroborated by the histogram of the residuals which is almost bell shape (Figure 17 &18).



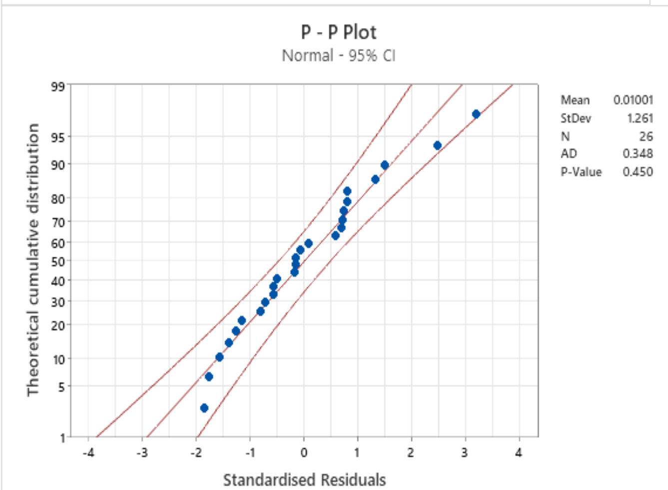


Fig. 21: The P – P plot of residuals (rainfall) for Uyo

Fig. 22: The P – P plot of residuals (temperature) for Uyo

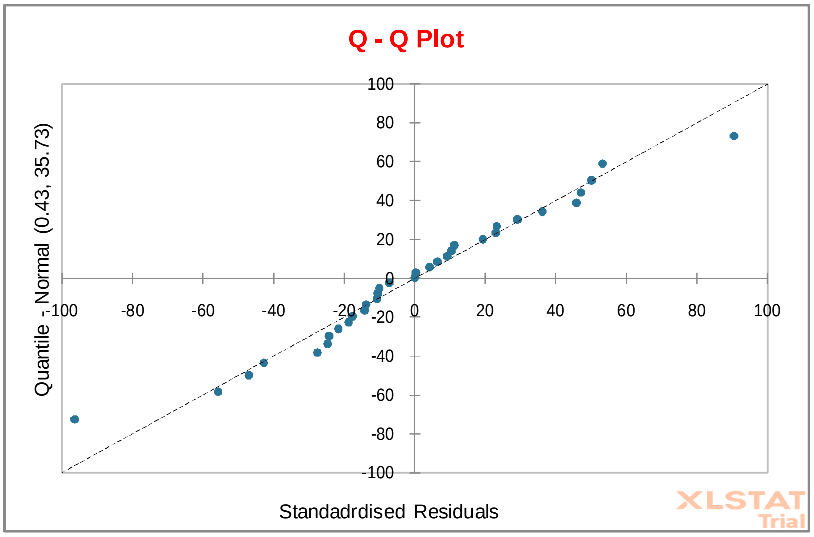


Figure 23: The Q – Q Plot of the residuals (rainfall) for Uyo

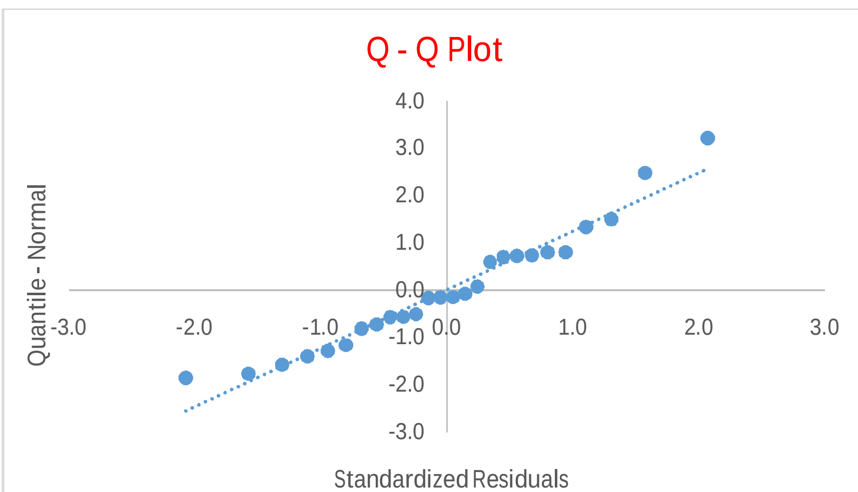


Figure 24: The Q – Q Plot of the residuals (temperature) for Uyo

After fitting the models, the residual plots of ACF and PACF were examined and it was observed that the residuals were within the confidence intervals which is an indication of a good fit and the adequacy of the model. That is correlogram analysis of a plot of ACF and PACF. For a good forecasting model, the residuals left after fitting the model, must satisfy the requirements of a white noise process (Huang *et. al.,* 2016). From Figure 22 and Figure 23, it was clear that the correlogram of the ACF and PACF of the residuals of the stations for both rainfall and temperature data fell within the confidence interval. This was an indication that they were not significant and that the residuals were independent and thus satisfying the residual criterion. Besides no patterns were observed in the residuals which further buttressed the point that the models could be used to represent the observed data. It means the residuals were very small in magnitude and have no pattern or trend. The residual is obtained by the difference between the observed and the forecast data. The implication is that the forecast value is as close as the observe data further indicating the performance efficiency of the model. Residuals are therefore employed to validate models. The study of Nobre and Singer (2007) is consistent with the above assertion. Also, the observed ACF and PACF plots indicated that one order differencing is adequate. Further differencing of higher orders revealed higher standard deviations, an indication of over differencing. Thus the minimum standard deviations were achieved with differencing order two (d = 2) for temperature & differencing order (d = 1) for rainfall. Therefore, the preliminary ARIMA (p, d, q) was selected.

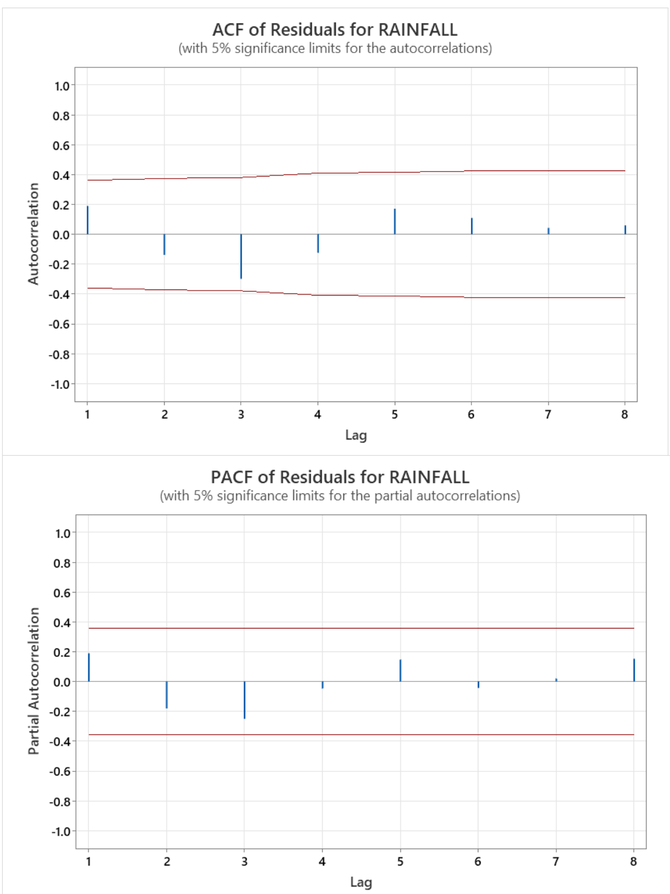


Figure 25: Residual plots of Autocorrelation function and Partial autocorrelation function of annual rainfall.

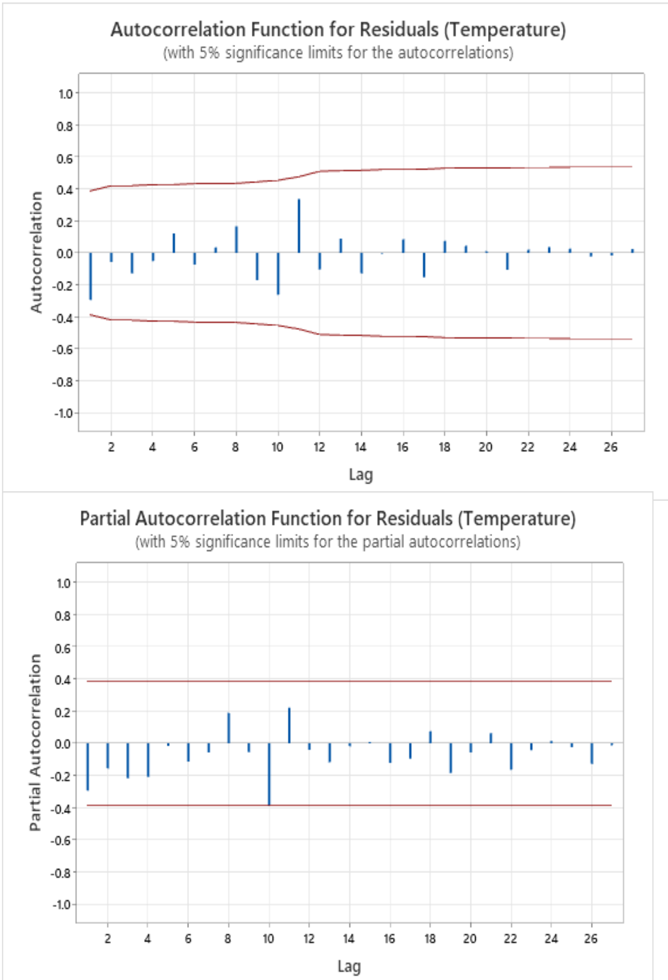


Figure 26: Residual plots of autocorrelation function and partial autocorrelation function of maximum temperature.

We used Box-Jenkin's method to predict annual rainfall and temperature for 2023 – 2027 by analyzing the annual rainfall and temperature series from 1990 – 2022 of which rainfall was annually increasing during the studied period by 4.87mm while temperature was annually decreasing by 0.01620°C. We ignored the last 6 years in order to use it as our model-testing set. In order to identify the best model to represent the data, we found Autoregressive Integrated Moving Average Model (1, 1, 1) as the best forecasting model for rainfall which gives us forecasted rainfall for (2024 - 2025 - 2026 – 2027 - 2028) with (259.07, 261.22, 263.36, 265.51, 267.66) mm values and Autoregressive Integrated Moving Average Model (1, 2, 2) as the best forecasted model for temperature and it gives us forecasted temperature for (2024 – 2025 – 2026 – 2027 - 2028) with (30.48, 30.38, 30.27, 30.15, 30.03) °C after applying the least value of AICC and performing the necessary tests on the model residuals and passing them successfully, whereas the autocorrelation was not found to exist between the series residuals, and taken the natural shape and following the normal distribution. Table 4.8 and 4.9 shows the error ratios between original data and forecasting values of ARIMA models for rainfall and temperature.

Table 8: The table presents the error ratios between original and forecasting data for rainfall

Year	Original	Forecast (mm)	Error Ratio (%)
2017	207.0	233.3	-12.7
2018	249.3	235.4	5.57
2019	264.4	237.6	11.28
2020	297.0	239.7	19.29
2021	210.7	241.9	-14.80
2022	135.4	244.0	-80.21

Source: Computed by the researcher from Field Survey data (2023)

Table 9: The table presents the error ratios between original and forecasting data for temperature

Year	Original	Forecast (mm)	Error Ratio (%)
2015	30.92	31.22	-0.97
2016	31.33	31.16	0.54
2017	31.16	31.09	0.22
2018	30.93	31.02	-0.29
2019	31.06	30.94	0.39
2020	31.57	30.86	2.25

Source: Computed by the researcher from Field Survey data (2023)

To assess the accuracy and the performance efficiency of the models, they were evaluated using four popular metrics: Sum of Squares error (*SSE*), Mean Absolute Percentage Error (*MAPE*), Mean Square Error (*MSE*) and Root Mean Square error (*RMSE*) for both rainfall and temperature models respectively. The values for the respective models are presented in Table 4.10. In the table stated, the (*MAPE*) which is an unbiased statistic was employed to evaluate the ability of the model to predict correctly. Its low value is an evidence of the models adequacy. It is reported in literature that the smaller the value the better the model's performance (Galavi*et al.*2013; Valizadeh*et al.* 2014).

Table 10: Best Autoregressive Integrated Moving Average Models and Goodness of Fit Statistics

Best Model	**Goodness of Fit Statistics**	
	(1, 1, 1) Rainfall	**(1, 2, 2) Temperature**
AICC	275.15	36.92
SBC	278.15	41.47
MAPE	11.16	0.84
SSE	32005.4	4.11
MSE	1185.39	0.18
RMSE	34.43	0.42

Source: Computed by the researcher from Field Survey data (2023)

Table 11: Autoregressive Integrated Moving Average (ARIMA) model parameters

Model	**Parameter**	**Estimate (Coefficient)**	**Hessian standard error**
ARIMA (1, 1, 1) (Rainfall)	Φ_1	-0.33	0.22
	Θ_1	1.03	0.13
ARIMA (1, 2, 2) (Temperature)	Φ_1	-0.89	0.76
	Θ_1	0.15	0.78
	Θ_2	0.98	0.72

Explanations: Φ_1= autoregressive parameters, Θ_1= moving average parameters
Source: Computed by the researcher from Field Survey data (2023)

The models that are therefore developed could assist in water resources planning and management. Effective water management planning and cropping system design can be achieved with an understanding of the statistical properties of long-term records of major climatic parameters like rainfall and temperature. The probable climate change impacts on rainfall and temperature assessment and its forecast is crucial for disaster alertness, planning of irrigation infrastructural and development. The analysis carried out provides vital information in addressing projected climate changes and their impacts on soil physio-chemical properties of the studied area.

CONCLUSION

The annual rainfall and temperature data in Uyo area has been studied using the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) model technology. An annual rainfall and temperature record spanning the period of 1990 – 2022 (for rainfall) of Uniuyo station and 1990 – 2020 (for temperature) of Iwuduta, Ibesikpo station in Akwa Ibom has been used to develop and test the models. The results showed a slight increase in the rainfall for the future up to 2028 (2024 - 2028) in the study area. Maximum temperature forecast also revealed a gentle downward decrease. The downward fluctuating trend in the maximum temperature might be the reason for the increasing rainfall in the study area. However, further comprehensive multivariate analysis employing a digitized data is required for a definite pronouncement on the rainfall and temperature situation. The forecasted temperature data showed a good agreement with the actual recorded data. This gave an increasing confidence of the selected ARIMA model. Air temperature and rainfall modelling and its forecasting pose a challenging task for handling any daily time series. There are many methods for forecasting time series, but Box-Jenkins models is adopted to analyze the time series data, due to its high accuracy and their compatibility with the characteristics of each region and therefore cannot be directly applied to a different area.

The findings from modeling and forecasting of rainfall and temperature for Uyo, Akwa Ibom State can have significant agricultural implications. Some of these implications include:

1. **Planning and decision-making**: Accurate and reliable models and forecasts can help farmers and agricultural planners make informed decisions regarding crop selection, planting schedules, irrigation, and pest management. By having access to reliable information on rainfall and temperature patterns, farmers can optimize their practices and minimize risk.
2. **Crop yield and production**: Understanding the expected rainfall and temperature patterns can help farmers optimize their agricultural practices to maximize crop yields. For example, farmers can adjust their irrigation systems based on anticipated rainfall patterns, ensuring efficient water usage.

Additionally, farmers can select crop varieties that are more resilient to specific temperature conditions, minimizing the risk of crop failure.

3. **Disease and pest management:** Climate conditions, including rainfall and temperature, can influence the prevalence and spread of agricultural pests and diseases. Modeling and forecasting these conditions can help farmers anticipate and prepare for potential outbreaks. This allows for timely implementation of appropriate pest and disease management strategies, reducing crop losses and the need for excessive pesticide use.
4. **Water resource management:** Adequate rainfall is crucial for water availability in agricultural systems. By modeling and forecasting rainfall patterns, farmers can plan for water storage and irrigation. They can also implement water-conservation practices during periods of low rainfall to ensure sustainable water management and mitigate the impact of droughts.
5. **Climate change adaptation:** Modeling and forecasting rainfall and temperature trends can help farmers and policymakers develop effective strategies for climate change adaptation. As climate change alters weather patterns, including rainfall and temperature, it is important to understand these changes and implement measures to adapt agricultural practices accordingly. This may include promoting drought-resistant crop varieties, implementing efficient irrigation systems, or adopting agroforestry practices to provide shade and reduce heat stress on crops.
6. **Economic implications:** Accurate modeling and forecasting of rainfall and temperature can have economic implications for the agricultural sector. With reliable information, farmers can reduce input costs by optimizing resource allocation and minimizing waste.

In summary, the findings from modeling and forecasting rainfall and temperature in Uyo, Akwa Ibom State can provide valuable insights for agricultural planning, decision-making, and mitigation of weather-related risks. By utilizing this information, farmers and policymakers can improve agricultural productivity, reduce losses, and contribute to sustainable and climate-resilient agricultural practices.

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