Acta hydrotechnica **let/št (20xx)**, Ljubljana
ISSN 1581-0267

Open Access Journal
Odprtodostopna revija

UDK/*UDC*: ######################
Izvirni znanstveni članek – *Original scientific paper*
DOI: 10.15292/acta.hydro.20XX.XX

Prejeto/*Received:* xx.xx.xxxx
Sprejeto/*Accepted:* xx.xx.xxxx
Objavljeno na spletu/*Published online:* xx.xx.xxxx

SIGNIFICANT TRENDS AND STRUCTURAL SHIFTS IN RAINFALL PATTERNS IN NIGERIA

POMEMBNI TRENDI IN STRUKTURNI PREMIKI V VZORCIH PADAVIN V NIGERIJI

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Abstract

Rainfall, with its varying timescales, impacts weather patterns, living conditions, and the environment. This study aims to evaluate trends and structural shifts in monthly rainfall across twenty-four locations in Nigeria spanning 51 years (1960-2010). Utilising the Mann-Kendall test statistic (MK) for trend identification and the cumulative sum method for detecting changes in structure, cyclic patterns, and random components within distributions, the analysis incorporated descriptive statistics, including coefficient of variation, skewness, kurtosis, and the Jarque-Bera test with associated p-values. Descriptive statistics can behave unusually where rainfall peculiarities occur. Despite the nonparametric nature of MK, it occasionally yielded varying values and dissimilar trends between total annual rainfall and total seasonal rainfall, as well as between average annual rainfall and average seasonal rainfall, attributed to high variability. Consequently, a statistically significant trend in total rainfall amounts might not correspond to the trend in mean rainfall amounts. Notably, statistically significant trends may sometimes be accompanied by similar significant structural shifts at every location. However, such trends and shifts are generally more frequent in the northern arid regions, specifically between 9.14°N and 12.53°N. For instance, a statistically significant change in total annual rainfall of 11.15 mm/year was observed in Kano (12.03°N), accompanied by an increasing structural shift around the 40th year of analysis. Conversely, a total annual rainfall significant trend of -3.01 mm/year occurred at Jos (9.52°N), though it was not among the nine locations having diverse significant structural shifts. Analysis of this nature helps in tackling water-related issues and understanding atmospheric phenomena.

Keywords: rainfall trends, Mann-Kendall test statistic, cumulative sum analysis, arid regions, significant trends and shifts

Izvleček

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Padavine s svojimi različnimi časovnimi okviri vplivajo na vremenske vzorce, življenjske razmere in okolje. Namen te študije je oceniti trende in strukturne premike v mesečni količini padavin na štiriindvajsetih lokacijah v Nigeriji, ki obsegajo obdobje 51 let (1960-2010). Z uporabo Mann-Kendallove testne statistike (MK) za identifikacijo trenda in metode kumulativne vsote za odkrivanje sprememb v strukturi, cikličnih vzorcih in naključnih komponentah znotraj porazdelitev je analiza vključevala opisno statistiko, vključno s koeficientom variacije, asimetrijo, sploščenostjo in Jarque-Bera testom s pripadajočimi p-vrednostmi. Opisna statistika se lahko obnaša nenavadno tam, kjer se pojavljajo posebnosti padavin. Kljub neparametrični naravi MK je ta občasno dal različne vrednosti in različne trende med skupno količino letnih padavin in skupno količino sezonskih padavin, pa tudi med povprečno količino letnih padavin in povprečno količino sezonskih padavin, kar se pripisuje veliki variabilnosti. Posledično statistično pomemben trend skupnih količin padavin ne ustreza trendu srednjih količin padavin. Statistično pomembne trende lahko včasih spremljajo podobni pomembni strukturni premiki na vsaki lokaciji. Vendar so takšni trendi in premiki na splošno pogostejši v severnih sušnih regijah, zlasti med 9,14°S in 12,53°S. Na primer, statistično pomembna sprememba skupne letne količine padavin 11,15 mm je bila opažena v Kanu (12,03°N), ki jo je spremljal vse večji strukturni premik okoli 40. leta analize. Nasprotno pa se je značilen trend povprečne letne količine padavin -3,01 mm/leto pojavil v Josu (9,52°N), čeprav ni bil med devetimi lokacijami z različnimi značilnimi strukturnimi premiki. Analiza te narave pomaga pri reševanju vprašanj, povezanih z vodo, in razumevanju atmosferskih pojavov.

Ključne besede: trendi padavin, Mann-Kendallov test statistike, kumulativna analiza vsote, sušne regije, pomembni trendi in premiki

1. Introduction

The climate presents a multitude of inherent trends, features, and periods. However, comprehending all these patterns is often problematic, given that not all are active or distinct. The interconnection of meteorological factors further complicates this, as frequent variability makes it challenging to discern every climate pattern and assess the full impacts of climate change. This underscores the need for comprehensive research to understand the implications of climate change fully. In the West African tropical regions, two primary seasons prevail: the rainy season, characterised by high water vapour concentrations, and the dry season, known for its aridity. The Harmattan season is a subset of the dry season. While the easterly winds from the Atlantic Ocean control the rainy season, the westerly winds from the Sahara Desert dominate the dry season. As atmospheric conditions are characterised by prevailing seasons, human activities vary accordingly. For example, during the Harmattan season in tropical Africa, the atmosphere becomes misty, dry, and dusty, resulting in poor visibility (Odekunle and Adejuwon, 2007; Schwanghart and Schütt, 2008). This period is renowned for frequent rerouted or cancelled flights, extreme hot and cold weather, and peculiar health challenges, such as cough, eye diseases, high blood pressure, and elevated body temperature (Jendritzky et al., 2012; Okeahialam, 2016; Roffe et al., 2023). In addition to the health and living conditions, unprecedented shifts in seasonal hydrological distributions, such as precipitation regimes and streamflow patterns, pose challenges for water resource management, agriculture, disaster management, sustainable development, and environmental conservation (Adger et al., 2003; Vörösmarty et al., 2010; Bello et al., 2012).

Trends in hydrological and climatic time series, such as ambient, land, and surface sea temperatures, streamflow, and rainfall, are often analysed using two broad categories of statistical measures, namely parametric tests (e.g., the t-test, analysis of variance, and regression analysis) and nonparametric tests (e.g., Mann-Kendall test statistic, Wilcoxon signed-rank test, and Kruskal-Wallis test). Parametric tests rely on the normality and equal variances of a given dataset, making them sensitive to measurement magnitudes and giving them greater statistical power. In contrast, nonparametric tests are impervious to data distribution and, thus, unaffected by outliers, making them suitable for skewed, categorical, and irregular measurements. Therefore, nonparametric tests are often preferred since they do not adhere to clear mathematical patterns but consider the order within a dataset. The Mann-Kendall test statistic is a popular nonparametric trend analysis method that identifies increasing, decreasing, or stationary trends. It assesses their statistical significance by ranking a dataset's magnitudes of chronological pairs. Moreover, this test is relatively simple and straightforward, capable of handling the influence of serial correlation on time series (Hamed and Ramachandra Rao, 1998; Yue et al., 2002; Mumo et al., 2019). However, beyond trend identification, the Mann-Kendall test statistic and similar tests do not provide insights into inherent cycles or random periods nor detect upturn occurrence in trends. In contrast, the cumulative sum algorithm can furnish information on structural shifts and periods in lengthy hydrological time series (Regier et al., 2019; Esit et al., 2023).

Several climatic trends have been identified in Africa. Hulme et al. (2001) observed a cooling effect in West Africa, particularly around Nigeria/Cameroon and coastal margin regions compared to other continental sections. This cooling effect could significantly impact local ecosystems and communities, affecting agricultural practices and water availability. Furthermore, the Equatorial region exhibits less pronounced changes in wetness, as it is slow to adapt to alterations. Warming across Africa is characteristic, with the Equatorial region experiencing a temperature increase of 2℃ over the next 100 years, while other areas may see an increase of about 5℃. These temperature increases could lead to more frequent and severe heatwaves, impacting human health and agricultural productivity. Projections suggest that sea levels in the coastal African region are expected to rise by approximately 0.5 to 2.0 metres in 100 years, primarily due to climate change, glacial melt, and human activities (Agossou et al., 2022; IPCC, 2021). This rise in sea levels could threaten coastal communities and ecosystems. In Nigeria, rainfall trends, dependent on the period and length of the data analysed, may also be influenced by other factors such as temperature and vegetation type (Bello et al., 2012; Akinsanola and Ogunjobi, 2017) and regional climate, resulting in varying impacts (Hess et al., 1995; Ati et al., 2007; Obot et al., 2010; Oguntunde et al., 2011; Bello et al., 2012; Ogungbenro and Morakinyo, 2014).

While climate exhibits temporal and spatial variations across multiple timescales, climate change becomes evident when significant variations occur over a defined period. Apart from land and sea temperatures, solar radiation, sea level, and atmospheric gas concentrations, precipitation can also serve as indicators to assess the occurrence of climate change. Climate change can result from two main factors. Firstly, natural cycles of climatic factors (e.g., solar cycles) occasionally have substantial effects, and secondly, human activities have disrupted the climate balance since the advent of civilisation. Nevertheless, diverse viewpoints regarding the sun's contribution to climate change have emerged. Some argue that solar activities are responsible for climate change, while others propose alternative explanations without discounting the sun's influence. Lean et al. (2002) demonstrated that solar activities, such as geomagnetic and cosmogenic indices, sunspot numbers, and total irradiance cycles, increased over different timescales from around 1940 to 2000. Despite the increase in solar activity over the past 400 years, it is important to recognise that various human-made activities predominantly drive climate change. These activities, such as ozone layer depletion, allow more radiation to penetrate the Earth's surface (Fröhlich and Lean, 1999). While natural factors like solar radiation influence the climate, the impact of greenhouse gas-induced climate forcing far outweighs the effect of the increasing phase of solar irradiance. Anthropogenic activities have been scientifically linked to adverse effects on regional rainfall variability, such as changing patterns, frequent heavy event occurrences, and decreasing rainfall intensity (Betts et al., 2004; Ramanathan et al., 2001). However, Haarsma et al. (2005) suggest that these activities can also enhance rainfall in specific regions, such as the Sahara. This enhancement is attributed to the interplay between sea-level pressure and land surface air temperature from 1980 to 2080.

This study employs the Mann-Kendall test statistic to assess rainfall trends in 24 locations across the six geopolitical zones in Nigeria. It also engages the cumulative sum algorithm to identify structural changes in rainfall patterns between 1960 and 2010. Additionally, Sen's slope is utilised to determine the rate of change in trends. At the same time, descriptive statistical methods, such as the coefficient of variation and kurtosis, are employed to evaluate variability in the dataset. The inherent findings could provide valuable insights into rainfall dynamics, trend identification, and methodologies for detecting shifts. Consequently, this can contribute to an improved understanding of the implications of changing rainfall patterns and facilitate informed, adaptive decision-making in addressing rainfall-related challenges.

2. Materials and Methods

2.1 Data and study area

The monthly rainfall data from 1960 to 2010 for twenty-four locations across the six geopolitical zones in Nigeria (Figure 1) were sourced from the

Nigerian Meteorological Agency (MINET) in Oshodi, Lagos. The descriptive statistics of the rainfall data and coordinates of the locations are provided in Table 1. Even when two locations exhibited a year of missing data, the integrity of this study was ensured by employing the four-year monthly averages, encompassing two years before and another two after the affected period, to substitute the absent data. These instances occurred in Yola and Katsina in the year 1967. This straightforward method for filling in missing data, intentionally used here, ensures relative stability, avoids potential inaccuracies associated with predictive techniques, and does not introduce trends or characteristics linked to neighbouring stations.

Nigeria is renowned for its diverse rainfall patterns (Odjugo, 2006; Odekunle and Adejuwon, 2007). The duration of the rainy season fluctuates from three months in the north to eight months in the south, and the dry season invariably follows the rainy season. Given the variations in rainfall duration across the locations under investigation, the seasons are categorised as follows: the first dry season spans from January to March, the first rainy season extends from April to June, the second rainy season encompasses July to September, and the second dry season covers October to December. Although Nigeria is located in the tropics, it partially falls within the Equatorial region, known for its high rainfall and humidity due to its proximity to the Equator. Some areas of Nigeria lie below 10°N, which is the boundary for the Equatorial region. Locations between 0 and 10 degrees north or south are classified as Equatorial.

Comparatively, those falling within 0 to 23.4 degrees north or south are considered part of the Earth's tropical regions. In West Africa, Nigeria has a latitudinal range extending from 3 to 14 degrees north of the Equator and an approximate eastward range from the Greenwich Meridian. Nigeria's unique geographical features, including its latitudinal range and the distribution of water and land, make it a fascinating subject of study. While approximately 13,000 km² of Nigeria is covered by water, the land area encompasses 910,768 km².

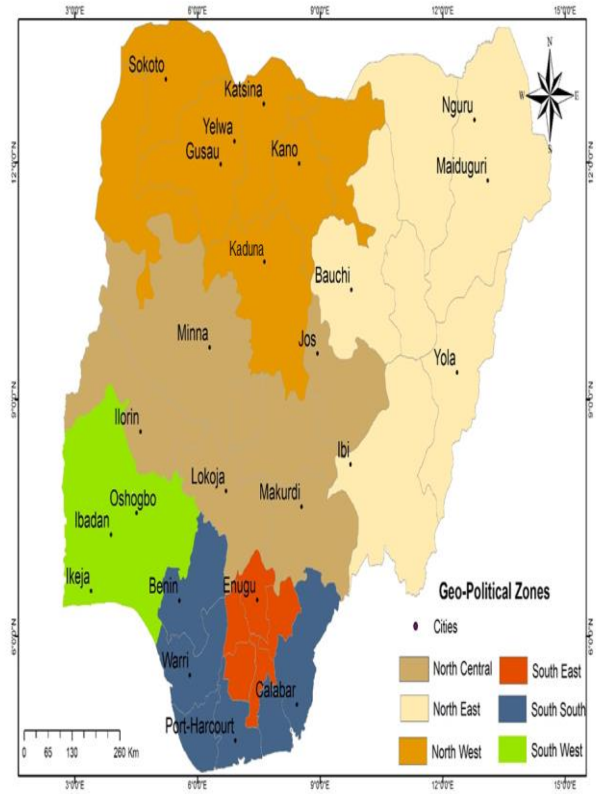

Figure 1: Map of the study area

2.2 Mann-Kendall test statistic

The nonparametric Mann-Kendall test statistic (MK) (Esit et al., 2023; Kendall, 1938; Mann, 1945) was utilised to evaluate the seasonal and annual trends in the data. For a given data series, denoted as $y_1 = x_1, x_2, \ldots, x_n$ measured at times 1, 2, …, n respectively, the sign of the difference between successive values can be given as $\emptyset = sgn\,(x_j - x_i)$, where i precedes j. The sign for $\emptyset$ is equal to + 1 for $x_i > x_j$, - 1 for $x_i < x_j$, and 0 for $x_i = x_j$, indicating a tied pair with no contribution to MK. If the lag-1 serial correlation coefficient (r_1) is statistically significant at a 5% level, the initial data is pre-whitened to remove the serial effect before computing MK. The new time series resulting from pre-whitening is given by: $y_2 = x_2 - r_1 x_1, x_3 -$

$r_1 x_2, \ \ldots, x_n - \ r_1 x_{n-1}$. The Mann-Kendall statistic S is calculated as follows:

$$S = \sum_{j=1}^{n-1} \sum_{i=j+1}^{n} \emptyset \quad (1)$$

$$\text{where } \emptyset = \begin{Bmatrix} +1 & if & \emptyset > 0 \\ 0 & if & \emptyset = 0 \\ -1 & if & \emptyset < 0 \end{Bmatrix} \quad (2)$$

The mean of the statistic S is zero, and its variance, $VAS(S)$, is expressed as:

$$VAS(S) = \frac{1}{18}\left[n\,(n-1)(2n+1) - \sum_{p=1}^{q} t_p(t_p - 1)(2_p + 5)\right] \quad (3)$$

where q is the number of tied groups, and t_p is the number of data values in a particular p group.

The standardised test statistic Z for MK is computed as:

$$Z = \begin{Bmatrix} \dfrac{S-1}{\sqrt{VAS(S)}} & if\ \ S > 0 \\ 0 & if\ \ S = 0 \\ \dfrac{S+1}{\sqrt{VAS(S)}} & if\ \ S < 0 \end{Bmatrix} \quad (4)$$

A Z value of zero indicates a lack of trend, a positive value indicates an increasing trend and a negative value indicates a decreasing trend. Under the condition that $n \geq 10$, MK is considered statistically significant if Z exceeds the critical value at a specified level of significance (e.g., $\alpha = 0.05$) for a two-sided test for trend. Consequently, the null hypothesis of no trend is rejected in favour of the alternative hypothesis for a monotonic trend. For a 95% confidence level (i.e., $\alpha = 0.05$), the critical Z value from the standard statistical table is 1.96.

Furthermore, a corresponding nonparametric method for assessing the rate of change in a trend was also employed. Sen's slope (Sen, 1968), which is robust to outliners and does not assume normality, can be evaluated using:

$$\text{Sen's slope } = median \left[\frac{x_j - x_i}{j-i}\right] \quad (5)$$

2.3 Cumulative sum

The cumulative sum (CUSUM) method was employed to identify significant change points in the annual rainfall dataset. CUSUM is a sequential statistical technique that accumulates the means, deviations, and distribution functions of subgroups or individual measurements of a given parameter to detect shifts at specific significance levels (Esit et al., 2023; Page, 1954). CUSUM utilises a nonparametric approach, and the parameters it employs to identify shifts can be in days, months, or years.

In this section, considering a total sample size of n and m subgroups, where x_{ij} represents an independent measurement denoted as the j^{th} sample of the i^{th} subgroup, the mean of the i^{th} subgroup is calculated as:

$$\bar{x}_{ij} = \sum_{j=1}^{n} x_{ij}/n \quad (6)$$

The grand average of all subgroups, referred to as the reference or targeted mean, is expressed as:

$$\mu_{target} = \sum_{i=1}^{m}\sum_{j=1}^{n_i} x_{ij} \Big/ \sum_{i=1}^{m} n_i \quad (7)$$

However, if the subgroups are all equal, then the grand targeted mean becomes:

$$\mu_{target} = \frac{\sum_{i=1}^{m} \bar{x}_i}{m} = \frac{\bar{x}_1 + \bar{x}_2 + \cdots + \bar{x}_m}{m} \quad (8)$$

The subgroups must follow a normal distribution with a constant mean and variance for this method to be valid. The mean or targeted standard deviation can be determined using the ranges, means, or weighted approach (Chen et al., 2020). If the weighted approach is used (Mahmoud and

Maravelakis, 2010), then the standard deviation for the weights is:

$$S_{wighted} = \sqrt{\frac{1}{m}\sum_{i=1}^{m} S_i^2} \tag{9}$$

where S_i is the unbiased standard deviation of each sample i.

Subsequently, the overall or targeted standard deviation is obtained as:

$$\sigma_{target} = \frac{S_{weighted}}{c_4(m(n-1)+1)} \tag{10}$$

where c_4 is the correlation factor given as:

$$c_4 = \sqrt{\frac{2}{n-1}}\frac{\Gamma\left(\frac{n}{2}\right)}{\Gamma\left(\frac{n-1}{2}\right)} \tag{11}$$

The target value is derived from the following expression:

$$z_i = \frac{\overline{\mu_i} - \mu_{target}}{\sigma_{target}} \tag{12}$$

For i = 2 to n, the recursive formula for the CUSUM chart at each point i is calculated as:

$$C_i = max\,(0, C_{i-1} + z_i - k) \tag{13}$$

where k is the allowable slack or drift parameter that determines the sensitivity of the CUSUM chart to changes in the mean.

CUMSUM was implemented with codes in MATLAB®. Typically, the CUSUM chart displays series on the horizontal axis and the computed CUSUM values on the vertical axis. Horizontal lines representing the upper and lower control boundaries are incorporated based on the targeted mean μ_{target}, targeted standard deviation σ_{target}, and drift parameter k. At a 5% significance level, the null hypothesis, H_0, which assumes constancy throughout the time series, is rejected (while the alternative hypothesis, H_1, indicating a change, is accepted) if the continuous CUSUM plot exceeds the lower or upper boundaries. Crossing the upper boundary suggests a significant increase, whereas crossing the lower boundary indicates a significant decrease. A reset to zero is activated at a predefined threshold to prevent the continuous growth of the CUSUM value.

3. Results

3.1 Descriptive statistics

The regional distribution of total annual rainfall was assessed using four key descriptive statistics, which include the coefficient of variation (CV), skewness, kurtosis, and the Jarque-Bera test with the p-value (Table 1). The CV quantifies the relative variation in the distribution by comparing the standard deviation to the mean. A high CV indicates a substantial degree of dispersion, while a low value suggests a minimal dispersion. The CV spans approximately 36% at Kano in the north to a minimum of 10% at Warri in the south. Notably, neither location is situated at the extremities of their respective geographical regions. However, with more locations, the north appears to have higher average CV values than the south.

Skewness reveals whether a distribution is symmetrical or asymmetrical. A positive skewness indicates a longer tail on the right side of the distribution, while a negative value implies a longer tail on the left side of the dataset. Skewness ranges from approximately -0.03 to 1.15 across the 24 sites, with nine locations displaying an asymmetric distribution. Despite considering annual rainfall instead of seasonal data, which can exhibit a hyperbolic rain pattern, the kurtosis values are positive, indicating peaked distributions. These values typically fall within the range of 2.1 to 6.3. While a typical kurtosis range extends from -3 to +∞, a positive kurtosis value suggests a peaked distribution or a heavy tail with numerous outliers, a negative kurtosis value implies a flat distribution or a light tail with few outliers, and a value of 0 denotes a normal distribution.

Table 1: Rainfall locations across Nigeria and descriptive statistics for total annual rainfall

s/n	Location	Region	Lat. (°N)	Lon. (°E)	CV (%)	Kurtosis	Skewness	Jarque-Bera statistic	p-value
1	Katsina	North	13.01	7.41	28.17	2.5351	0.1403	0.6264	0.7311
2	Sokoto	North	13.01	5.15	22.73	4.2726	0.7225	7.8793	0.0195
3	Nguru	North	12.53	10.28	26.59	2.1356	-0.0795	1.6413	0.4401
4	Kano	North	12.03	8.12	35.79	3.6456	-0.3502	8.8001	0.0103
5	Gusau	North	12.03	6.42	18.66	4.5102	1.1504	16.0952	0.0003
6	Maiduguri	North	11.51	13.05	25.02	2.7035	-0.0581	0.2155	0.8978
7	Yelwa	North	10.53	4.45	17.60	4.8445	0.7360	11.8348	0.0269
8	Kaduna	North	10.35	7.27	13.63	2.4099	-0.3502	1.7825	0.4101
9	Bauchi	North	10.17	9.49	18.38	3.9260	0.8995	8.6991	0.0129
10	Jos	North	9.52	8.45	13.15	4.1639	-0.0324	2.8876	0.2360
11	Minna	North	9.37	6.32	13.29	3.5335	-0.3033	1.3867	0.4999
12	Yola	North	9.14	12.28	19.41	4.7168	-0.7950	11.6353	0.0030
13	Ilorin	North	8.29	4.35	19.77	4.5103	1.1504	0.6554	0.7206
14	Ibi	North	8.11	9.45	16.33	2.1994	0.2559	1.9188	0.3831
15	Lokoja	North	7.47	6.44	17.06	2.7659	0.4004	1.4792	0.4773
16	Makurdi	North	7.44	8.32	17.82	2.7867	0.0783	0.1488	0.9283
17	Oshogbo	South	7.41	4.29	16.51	3.0689	0.1759	0.2730	0.8724
18	Ibadan	South	7.26	3.54	21.44	2.7080	0.2611	0.7606	0.6837
19	Ikeja	South	6.35	3.20	22.47	6.2597	1.1343	33.5164	5.27E-8
20	Enugu	South	6.28	7.33	15.87	3.5973	-0.5765	3.5830	0.1667
21	Benin	South	6.19	5.06	15.81	3.5876	-0.4349	2.3417	0.3101
22	Warri	South	5.31	5.44	10.18	2.6403	0.0092	0.2757	0.8712
23	Calabar	South	4.58	8.21	12.41	3.0210	0.5147	2.2527	0.3242
24	Port Harcourt	South	4.51	7.01	13.05	2.6185	0.0749	0.3571	0.8365

Conversely, the Jarque-Bera test, a statistical test that employs skewness and kurtosis, is used to assess the normality assumption of a dataset. In the context of rainfall data analysis, this test helps us understand whether the distribution of rainfall across the regions follows a normal distribution pattern. A dataset is assumed to deviate from normality if the Jarque-Bera statistic value is significant, with a p-value of less than 0.05. While not absolute, the Jarque-Bera statistic and the p-value exhibit an inverse relationship, such that significantly high Jarque-Bera values correspond to exceedingly low p-values and vice versa. The Jarque-Bera statistical test ranges from 0.1488 to 33.5164, while the p-value ranges from $5.27 * 10^{-8}$ to 0.9283 for analysed rainfall locations. The minimum value for the Jarque-Bera test and maximum value for the p-value occur at Makurdi, a northern site at a latitude of 7.44 degrees north, and the maximum and minimum values of both statistics, respectively, appear at Ikeja, a southern location at 6.35 degrees north. Nevertheless, seven locations have a p-value less than 0.05, with their Jarque-Bera test values exceeding 7.85, although Ikeja is the sole southern site among them.

3.2 Rainfall trends

Table 2 comprises the Mann-Kendall test statistic results for the total annual rainfall amounts, while Table 3 provides that for the average annual rainfall amounts. Furthermore, Tables 4 and 5 present Sen's slope values for the respective rainfall data types of Tables 2 and 3. Due to considerable variability, the order of magnitude of the total rainfall frequently differs from the average rainfall data. Consequently, as ranking is the method employed, MK values rarely align between the average rainfall dataset and the total rainfall data, and there are instances where the trends also diverge. As a result, a statistically significant trend for a particular form (e.g., total) of a given dataset may be insignificant for another form (e.g., average) of the same dataset. However, there are a few cases where MK remains unchanged, albeit rarely.

With a confidence level of 95% in the analysis of this study, statistically significant year-round trends were observed in two stations, namely Kano and Jos, in the case of the total rainfall amounts (Table 2). In Kano, there was an increasing trend with a change rate of 11.15 mm per year, while Jos exhibited a decreasing pattern with a Sen's slope of -3.01 mm/year (Table 4). Furthermore, five stations had diverse statistically significant trends in the first dry season (Kaduna, Minna, Makurdi, Enugu, and Benin) and four locations had them in the first rainy season (Kano, Kaduna, Bauchi, and Yola), while three sites had such in the second rainy season (Katsina, Ibi, and Jos) and the second dry season (Jos, Ibi, and Port Harcourt), respectively. From the above, some locations, e.g., Kano, Kaduna, and Jos, have significant trends over several seasons.

Based on the average annual and seasonal rainfall data (Table 3), three locations have year-round statistically significant trends (Kano, Kaduna, and Enugu), four stations have them during the first dry season (Kano, Kaduna, Bauchi, and Benin), three sites have it in the second dry season (Kano, Kaduna, and Bauchi), while three stations (Jos, Lokoja, and Port Harcourt) also have statistically significant trends in the second dry season. Like with total annual and seasonal rainfall, there are also instances where stations like Kano, Kaduna, and Bauchi have up to two or more statistically significant trends for different seasons. Notably, locations with contrasting statistically significant trends between total annual and seasonal rains and average annual and seasonal rains include Kaduna, Jos, and Enugu (refer to a footnote for Tables 2 and 3).

Table 2: Mann-Kendall Z-statistic for the total rainfall amounts (1960–2010), with bold values indicating statistically significant trends.

Location	Year-round	1st dry season	1st rainy season	2nd rainy season	2nd dry season
Katsina	-1.54	-0.15	0.21	**-2.05***	1.34#
Sokoto	0.49	0.49#	-0.65†	0.24#	0†
Nguru	-1.82	0.62	-1.61	-1.28	1.35#
Kano	**3.62**	-1.73#	**2.20**	**3.54**#	0.98#
Gusau	1.27	-1.36#	0.60	0.80#	0.55
Maiduguri	0.36	-0.85	-0.36	0.43	0.97
Yelwa	1.18	0.34	0.73†	-0.19†	0.10
Kaduna	-1.90*	**-2.37**#	**-2.03**#	-0.75	1.51
Bauchi	0.62	0†	**2.23**	0.26	0.80
Jos	**-2.13**	-0.51	0.81	**-3.44**	**2.24**
Minna	0.32	**-2.14**	0.74	-0.35	0.46
Yola	-0.31†	0.97	**-2.87**	-0.59	-0.49
Ilorin	-0.05	-1.21	-0.53	-0.10#	-0.53
Ibi	-0.88	-1.71	-1.49	0.58#	**-2.41**
Lokoja	0.05	0.25	0.89	-0.19#	0.43
Makurdi	-1.41	**-2.65**	-0.76#	-0.71#	-0.02
Oshogbo	0.34	-1.50	-0.44#	0.58#	0.52
Ibadan	0.63	1.14	-0.65#	1.18	-0.35
Ikeja	-0.96	-1.07	-1.49#	-0.97#	0.68
Enugu	0.96	**-2.53***	1.72	1.84	-0.09
Benin	1.59	**2.22**	1.58	-0.11	1.75
Warri	-1.20	0.32	0.32	-0.96	-0.34
Calabar	-0.07	0.44	0.69	0.22	-1.36
Port Harcourt	-1.10	0.06	0.66#	-0.16#	**-2.26**

Table 3: Mann-Kendall Z-statistic for the average rainfall amounts (1960–2010), with bold values indicating statistically significant trends.

Location	Year-round	1st dry season	1st rainy season	2nd rainy season	2nd dry season
Katsina	-1.84	-0.14	-0.02	-1.64*	1.34[#]
Sokoto	0.89	0.49	0.02[†]	0.24	0.04
Nguru	-1.51	0.60	-1.02	-1.53	1.35
Kano	**3.66**	-1.73[#]	**2.49**	**3.54**[#]	0.98
Gusau	1.33	-1.36[#]	0.86	0.80[#]	0.50
Maiduguri	0.58	-0.84	-0.02	0.44	0.96
Yelwa	0.93	0.05	-0.53[†]	0.06[†]	0.63
Kaduna	**-2.13***	**-2.37**[#]	**-2.03**[#]	-0.74	1.58
Bauchi	0.55	-0.97	**2.04**	0.26	0.80
Jos	**-0.44***	-0.34	0.80	**-3.12**	**2.17**
Minna	0.42	**-2.02**	0.75	-0.36	0.45
Yola	0[†]	0.98	-0.28*	-0.68	-050
Ilorin	-0.45	-1.19	-1.23	-0.10[#]	-1.24
Ibi	-0.96	-1.78	-1.50	0.58[#]	**-2.28**
Lokoja	0.34	0.35	0.89	-0.19[#]	0.41
Makurdi	-0.96	**-2.62**	-0.76[#]	-0.71[#]	-0.04
Oshogbo	0.57	-1.47	-0.44[#]	0.58[#]	1.17
Ibadan	0.77	1.04	-0.65[#]	1.19	-0.25
Ikeja	-0.27	-0.89	-1.49[#]	-0.97[#]	1.79
Enugu	**2.52***	-1.93*	1.80	1.79	0.72
Benin	1.62	**2.06**	1.58	-0.11	1.59
Warri	-0.34	0.71	0.32	-0.96	-0.23
Calabar	0.18	0.71	0.69	0.22	-1.53
Port Harcourt	-0.89	0.15	0.66[#]	-0.16[#]	**-2.27**

Footnote:

* A statistically significant trend occurs in either Table 2 or Table 3

Z remains unchanged in both Tables 2 and 3

† A trend changes form in both Tables 2 and 3

3.3 Structural changes

By default, the CUSUM chart in MATLAB flags a positive or negative significant structural change by marking circled data around the boundary, represented by a straight horizontal dashed line, when the CUSUM drift (or standard errors) exceeds five standard deviations from a targeted mean. The targeted mean (μ_{target}) and targeted standard deviation (σ_{target}) are based on the first 25 instances. The CUSUM plots utilise consecutive periodic values, or years in this case, for their computations. Based on the dates used for this analysis, the first year corresponds to 1960, while the 51st year corresponds to 2010. Figure 2 presents the CUSUM plot for the sixteen northern locations, where eight sites have significant shifts, while Figure 3 illustrates the plot for the eight southern sites, where only one site demonstrates a significant structural shift.

Table 4: Sen's slope values for the corresponding total rainfall amount of Table 2

Location	Year-round	1st dry season	1st rainy season	2nd rainy season	2nd dry season
Katsina	-2.57	0	0.21	-3.27	0
Sokoto	0.86	0	-0.55	0.33	0
Nguru	-2.08	0	-0.63	-1.03	0
Kano	11.15	0	2.46	9.12	0
Gusau	1.67	0	0.46	0.90	0.08
Maiduguri	0.56	0	-0.13	0.68	0
Yelwa	1.98	0	0.52	-0.23	0.00
Kaduna	-2.79	-0.05	-1.52	-0.74	0.75
Bauchi	1.23	0	1.66	0.38	0.17
Jos	-3.11	0	0.70	-4.87	0.81
Minna	0.61	-0.13	0.90	-0.44	0.33
Yola	-0.48	0	-1.14	-0.29	-0.06
Ilorin	-0.26	-0.34	-0.51	-0.26	-0.51
Ibi	-1.63	-0.23	-1.41	0.60	-1.33
Lokoja	0.06	0.05	0.97	0.27	0.26
Makurdi	-2.91	-0.68	-0.83	-1.44	-0.02
Oshogbo	0.69	-0.74	-034	0.87	0.42
Ibadan	1.95	0.75	-0.76	2.40	-0.32
Ikeja	-0.48	-0.75	-2.36	-2.21	0.58
Enugu	2.25	-1.32	2.37	3.24	-0.10
Benin	5.07	1.27	2.24	-0.26	2.20
Warri	-3.84	0.33	0.60	-2.91	-0.71
Calabar	-0.09	0.39	1.13	0.44	-1.54
Port Harcourt	-3.44	0.04	0.88	-0.44	-2.10

Table 5: Sen's slope values for the corresponding mean rainfall amount of Table 3

Location	Year-round	1st dry season	1st rainy season	2nd rainy season	2nd dry season
Katsina	-0.31	0	-0.01	-0.62	0
Sokoto	0.12	0	0.02	0.08	0
Nguru	-0.15	0	-0.14	-0.43	0
Kano	1.01	0	0.93	2.28	0
Gusau	0.15	0	0.24	0.23	0.03
Maiduguri	0.07	0	-0.00	0.17	0
Yelwa	0.13	0	0.15	0.2	0.01
Kaduna	-0.29	-0.02	-0.51	-0.18	0.25
Bauchi	0.11	0	0.51	0.10	0.06
Jos	-0.04	0	0.24	-1.03	0.28
Minna	0.07	-0.04	0.32	-0.11	0.11
Yola	-0.00	0	-0.07	-0.19	-0.06
Ilorin	-0.10	-0.13	-0.55	-0.07	-0.36
Ibi	-0.14	-0.81	-0.47	0.15	-0.44
Lokoja	0.06	0.03	0.32	-0.07	0.09
Makurdi	-0.16	-0.23	-0.28	-0.36	-0.01
Oshogbo	0.16	-0.25	-0.11	0.22	0.39
Ibadan	0.20	0.21	-0.25	0.60	-0.10
Ikeja	-0.08	-0.24	-0.79	-0.55	0.61
Enugu	0.52	-0.34	0.80	0.74	0.20
Benin	0.43	0.43	0.75	-0.06	0.75
Warri	-0.08	0.19	0.20	-0.73	-0.04
Calabar	0.08	0.23	0.38	0.11	-0.62
Port Harcourt	-0.24	0.03	0.29	-0.11	-0.70

Overall, no significant structural change occurred in fifteen locations across the entire region (Figures 2 and 3). However, a positive significant change occurred in four locations—Kano, Gusau, Yelwa, and Bauchi—in the north (Figure 2). Conversely, a negative significant pattern change occurred in five locations—Katsina, Nguru, Maiduguri, Kaduna, and Benin—where Benin is the only southern station. These significant changes occurred at different times but were always beyond the 25th year (i.e., 1984). For instance, around the 50th year of this analysis (i.e., 2009), significant shifts occurred at Katsina (positive) and Bauchi (negative), while around the 30th year (1989), shifts were observed at Nguru, Gusau, Maiduguri, and Benin. Meanwhile, the change at Gusau was positive, while those at the other locations were negative. However, the U-turn around the 40th year (1999) at Kano and Yelwa persisted throughout the subsequent ten years. The shift may also rapidly reverse itself (as seen in Maiduguri and Benin), last for as long as 20 years (e.g., Gusau between 1990 and 2010), or fluctuate above and below the control boundary (as in Nguru) over an extended period.

A potential association may exist between the statistically significant trends identified by the Mann-Kendall test statistic and the significant structural changes indicated by the CUSUM chart in this region. Table 6 compares the MK and CUSUM results. Although twelve locations showed no statistically significant change in rainfall trends and fifteen locations exhibited no significant shift in the CUSUM analysis, locations with any significant trend in MK also show corresponding significance in CUSUM where this occurred in both tests. For example, Kano, with three instances of increasing rainfall trends, shows a positive shift in CUSUM. However, an exception to this pattern is found in the southern region, where Benin is the only location with a significant shift in rainfall patterns, yet displays contradictory results between MK and CUSUM.

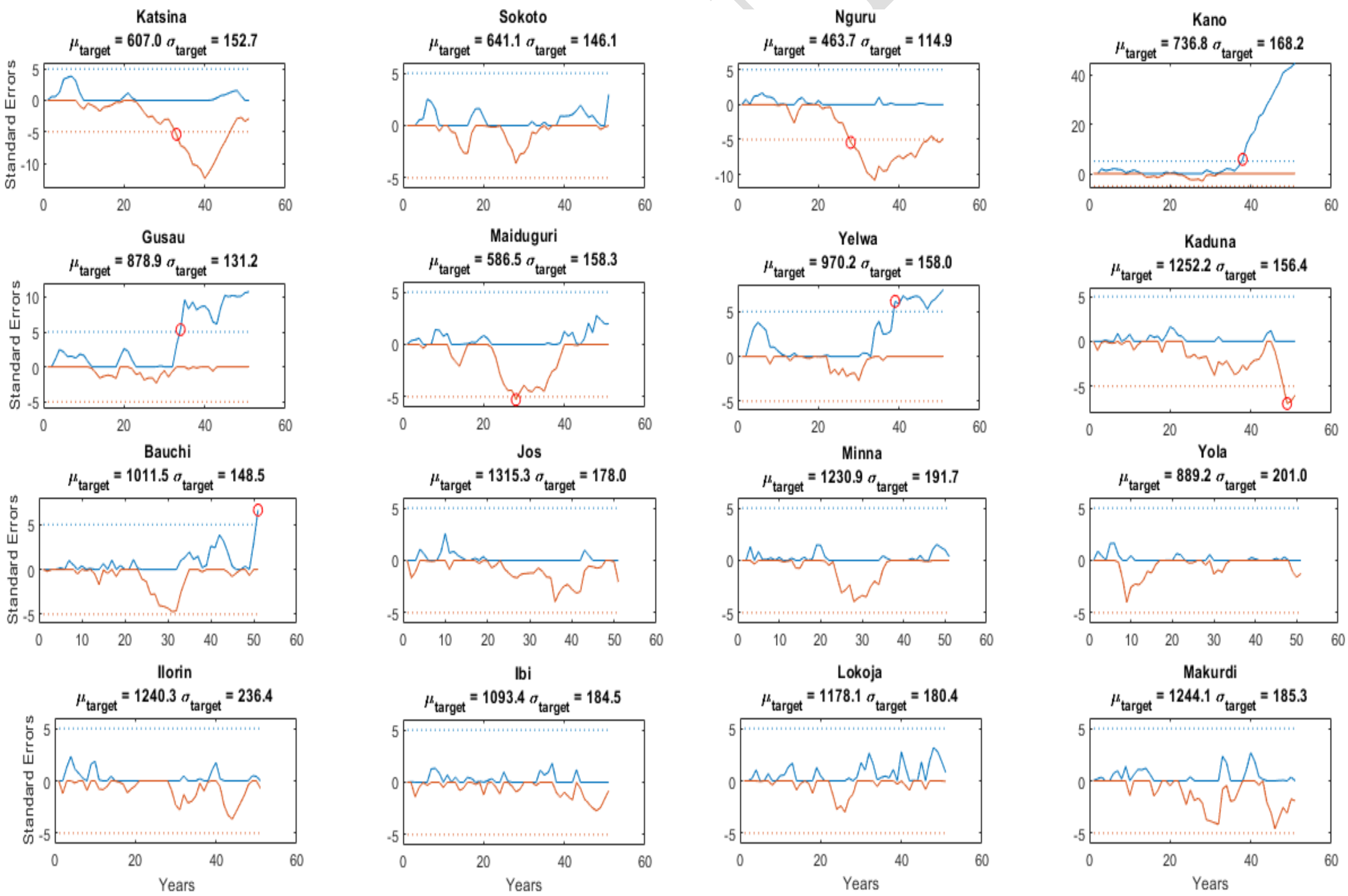

Figure 2: CUSUM plot for the northern stations in Nigeria considered in this study

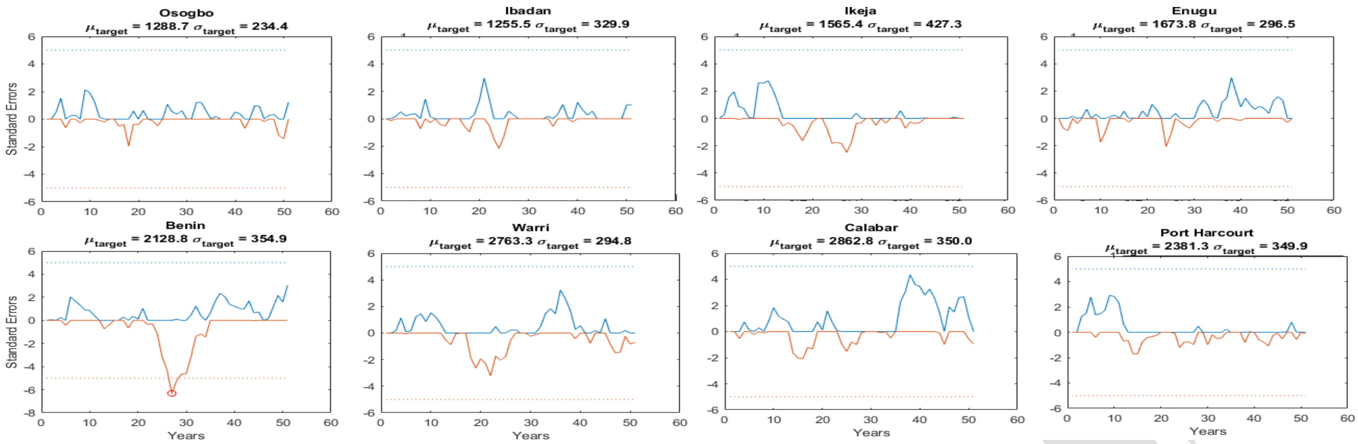

Figure 3: CUSUM plot for the southern locations in Nigeria evaluated in this study. As applicable to Figures 2 and 3, the fluctuating blue line in the upper section around the baseline represents the positive shift in the CUSUM, while the dashed blue line indicates the positive boundary level. Similarly, in the lower section of the baseline, the fluctuating red line represents the negative shift in the CUSUM, while the dashed red line indicates the negative boundary level.

Table 6: Summary and comparison of statistically significant trends and significant structural change-point occurrences at each location

Location	MK indicating statistically significance trend	CUSUM significant shift
Katsina	One negative occurrence in Table 2	Negative
Sokoto	-	-
Nguru	-	Negative
Kano	Three positive occurrences in Tables 2 and 3	Positive
Gusau	-	Positive
Maiduguri	-	Negative
Yelwa	-	Positive
Kaduna	Two negative occurrences in Table 2, three negative occurrences in Table 3	Negative
Bauchi	One positive occurrence in Tables 2 and 3	Positive
Jos	Two negative and one positive occurrences in Table 2, one positive and one negative occurrences in Table 3	-
Minna	One negative occurrence in Tables 2 and 3	-
Yola	One negative occurrence in Table 2	-
Ilorin	-	-
Ibi	One negative occurrence in Tables 2 and 3	-
Lokoja	-	-
Makurdi	One negative occurrence in Tables 2 and 3	-
Oshogbo	-	-
Ibadan	-	-
Ikeja	-	-
Enugu	One negative occurrence in Table 2, one positive occurrence in Table 3	-
Benin	One positive occurrence in Tables 2 and 3	Negative
Warri	-	-
Calabar	-	-

Port Harcourt	One positive occurrence in Tables 2 and 3	-

4. Discussion

The 51-year monthly rainfall data in this study reveals that arid regions, in contrast to regions with heavy rainfall, frequently undergo substantial structural changes. This suggests that areas with low rainfall intensity are more susceptible to significant alterations in their rainfall patterns. Certain arid regions exhibit multiple statistically significant trends during annual and seasonal evaluations, a phenomenon not observed in the southern areas (Tables 2 and 3). Among the 24 locations analysed, only three in the northern regions—Sokoto, Ilorin, and Lokoja—displayed no statistically significant trends or significant shifts in either MK or CUSUM test. At the same time, five southern sites showed no significance in both statistics.

Assuming a direct connection between MK and CUSUM, as significances occasionally aligned in both tests, short-lived CUSUM significant shifts could result from a U-turn like a statistically significant trend, transitioning from one form to another. For example, a previous study observed a decreasing trend in Maiduguri (Hess et al., 1999) that later reversed (Obot et al., 2010), albeit using different methods. While the initial reversing trend in Maiduguri was observed over 20 years of annual rainfall data (1978 – 2007), the present 51-year study indicates a steady or insignificant trend. The short-lived negative structural shift identified in CUSUM in Maiduguri may suggest the earlier reported U-turn in a significant trend. Similarly, Benin exhibits a short-lived significant structural shift that contradicts its statistically significant trend, implying an undetected upturn in its rainfall trend.

Periodic trends in the dataset may account for the disparities between MK and CUSUM results under different circumstances (Table 6). While a reversal in a trend, as time progresses, could likely neutralise the overall MK trend, CUSUM, with its threshold reset and predetermined conditions for significant shifts, sometimes indicated significant shifts even in the absence of statistically significant trends in arid northern sites like Nguru, Gusau, Maiduguri, and Yelwa (Table 6). Conversely, regions with statistically significant trends but no significant structural shifts (mostly semiarid and southern areas) may result from opposing trends that do not exert sufficient influence to affect CUSUM's structural shifts due to their magnitudes.

Descriptive statistics reveal the peculiarities of rainfall regimes compared to other factors, such as topography, vegetation cover, and geographical locations, which influence rainfall characteristics. However, these statistics do not correlate with significant trends or shifts in rainfall patterns. Ikeja, despite having the highest coefficient of variation and skewness values among the southern sites, ranking third overall at 0.22 and 1.13, respectively, and exhibiting the highest kurtosis and Jarque-Bera statistic values, shows no significance in either MK or CUSUM test. The extremes in descriptive statistics may be attributed to an unusual interruption in the seasonal rain in Ikeja (Odekunle and Adejuwon, 2007). On the other hand, Makurdi, despite having the lowest Jarque-Bera statistic but the highest p-value, also displays an August break in its rainfall pattern (Isikwue et al., 2012). However, it is the southernmost location in the northern region considered in this study. The descriptive statistics obtained for Makurdi may be influenced by the abrupt break in the intertropical convergence zone (ITCZ) in the south, causing changes in rainfall patterns in the northern region, in addition to the region's susceptibility to climatic variability (Amissah-Arthur and Jagtap, 1999). In contrast to Ikeja, Makurdi exhibits a statistically significant negative trend during the first quarter of the year in both Tables 2 and 3, despite both stations lacking a significant structural rainfall shift pattern. Ikeja and Makurdi fall within the Equatorial region, lying below 10°N latitude (Table 1).

When it comes to policy-making for climate change resilience and adaptation, disaster management, and water resources planning, attention should be given to northern stations like Kano, Kaduna, Bauchi, and Jos that have displayed undeniable statistical significance in their rains more than once (Tables 2 and 3). Coincidentally, regions within the latitudinal range between 9.14°N and 10.35°N are particularly susceptible to statistically significant trends, as evidenced by all stations in that spatial zone exhibiting noteworthy rainfall trends (Tables 1 and 6). Furthermore, it can also be observed that all stations between the geographical latitude from

10.17 to 12.53 degrees north have a significant structural shift. Substantial rainfall activities like trends and shifts are commonplace in Nigeria from 9.14°N to 12.53°N. Moreover, particular emphasis should be placed on southern regions, specifically Enugu, Benin, and Port Harcourt, which demonstrate noteworthy changes, considering the considerable magnitude of their rainfall.

5. Conclusions

This study comprehensively analysed rainfall patterns across 24 locations in Nigeria from 1960 to 2010. The investigation utilised the nonparametric Mann-Kendall test statistic and the cumulative sum test to identify statistically significant trends and structural changes. Additionally, descriptive statistics were employed for in-depth data analysis, including the coefficient of variation, skewness, kurtosis, Jarque-Bera statistic, and p-value. The key conclusions drawn from this study are as follows:

i. Descriptive statistics prove effective in capturing the inherent characteristics of regional rainfall to a large extent. For instance, two locations, namely Ikeja and Makurdi, which have a break within their rainy season, had distinctive kurtosis values, Jarque-Bera statistics, and p-values.

ii. Statistically significant trends, whether present in annual or seasonal data, may vary. The absence of trends in yearly data does not preclude their existence in seasonal data and vice versa.

iii. In instances where both statistically significant trends from the Mann-Kendall test and significant shifts from the cumulative sum test coincide, they are typically similar. An exception to this generalisation is noted in the sole southern location (Benin), where both types of significance were observed.

iv. Notably, stations situated between 12.53°N and 9.14°N exhibit either or both statistically significant trends and significant structural shifts in rainfall. In contrast to the southern regions, northern areas are more susceptible to changes, potentially influenced by lower rainfall amounts and the dynamic nature of the regional atmosphere.

Acknowledgement

The authors are grateful to the Nigerian Meteorological Agency (MINET), Lagos, for the rainfall data used in this study.

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