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Non-Stationary Trend Change Point Pattern Using 24-Hourly Annual Maximum Series (AMS) Precipitation Data

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Abstract

This paper mainly investigated the basic information about non-stationary trend change point patterns. After performing the investigation, the corresponding results show the existence of a trend, its magnitude, and change points in 24-hourly annual maximum series (AMS) extracted from monthly maximum series (MMS) data for thirty years (1986-2015) rainfall data for Uyo metropolis. Trend analysis was performed using Mann-Kendall (MK) test and Sen's slope estimator (SSE) used to obtain the trend magnitude, while the trend change point analysis was conducted using the distribution-free cumulative sum test (CUSUM) and the sequential Mann-Kendall test (SQMK). A free CUSUM plot date of change point of rainfall trend as 2002 at 90% confidence interval was obtained from where the increasing trend started and became more pronounced in the year 2011, another change point year from the SQMK plot with the trend intensifying. The SSE gave an average rate of change in rainfall as 2.1288 and 2.16 mm/year for AMS and MMS time series data respectively. Invariably, the condition for Non-stationary concept application is met for intensity-duration-frequency modeling.

Keywords

Precipitation, Data Series, Trend Analysis, Mann-Kendall Test, Change Point

1. Introduction

The prediction of precipitation trends accurately no doubt plays a major role in enhancing the prevention and mitigation of the effect of excessive rainfall which is a major contributor to flood event that could wreak serious havoc on lives and properties. Precipitation time series have been reported to be far more difficult to forecast trends than predicting temperature trends [1]. Significant attention has also been paid by different researchers to studying trends and variation in precipitation time series of some meteorological parameters in many countries [2]-[14].

Nigeria has also attracted similar extensive studies from different authors on trends and variations of different meteorological parameters including precipitation [15]-[25]. Interestingly, most recent studies on climate change have focused mainly on long-term temperature and rainfall variability, which are considered the most important climate change indicators. Evidence of climate change in Nigeria's eco-system indicates an increasing rainfall trend in the coastal region and a decreasing rainfall inland [26] [27] [28] [29] [30].

Time-series analysis is an applied tool for detection and quantitative description of the generating process, which is characteristic of a given set of observations. The generative process of the time series possesses both gradual and abrupt changes that are described as either a trend or trend change point. Thus, trend analysis captures the art of evaluating gradual future events from past measured data, while change point detection is related to determining the unexpected, structural, changes in the time series data properties like mean or variance. There are several parametric and non-parametric approaches in the literature to use in estimating both trend and change-point. A change-point analysis is dependent on the mean or variance of the data series [31] [32]. While the parametric test is helpful and serves as a powerful tool, the condition for its application requires in trend analysis of a given data set should be both independent and normally distributed. Interestingly, this condition had to occur in hydrological time series. The non-parametric test also requires that the data should be independent, and tolerant of outliers. The most commonly applied non-parametric test for trend analysis in time series which will be adopted for this study is the Mann-Kendall test [31] [33] [34] [35] [36], while the Sen's Slope estimator is used for quantifying the trend magnitude and similarly obtaining its intercept [37].

Non-stationary intensity-duration-frequency (NS-IDF) modeling requires the establishment of the time-series data to have a trend otherwise the IDF modeling remains a stationary approach. After executing trend analysis, it is important to confirm such trend analysis for validity and this is where trend change-point analysis is of key value. Different techniques in the literature for the analysis of trend change points available are wild binary segmentation, the Bayesian analysis of change points, the E-Agglomerative algorithm, and iterative robust detection methods [38] [39] [40] [41] [42]. However, other methods of trend change-point analysis that will be applied in this study will be the distribution-free cumulative sum (CUSUM) and the Sequential Mann-Kendall (SQMN) tests [43] [44] [45].

Therefore, the main objective of this study is to investigate the basic information on trend, its magnitude, and change points in 24-hourly AMS extracted data from monthly maximum series (MMS) for thirty years (1986-2015) rainfall data for Uyo in Nigeria. Trend analysis was performed using the Mann-Kendall test, Sen's slope estimator was applied to obtain the trend magnitude, and the trend change point analysis was conducted using the distribution-free cumulative sum test (CUSUM) and the sequential Mann-Kendall test (SQMK). Two different open-source software packages are the "python statsmodel library-pymannkendall" [46] [47] [48]. This study will verify if the data series from this station satisfied the condition for the application of Non-stationary Intensity-Duration-Frequency (IDF) modeling.

2. Methodology

2.1. Study Area

The study station Uyo metropolis is located in Akwa Ibom State in the South-South region of Nigeria. The study area lies between latitudes 4˚52'N - 5˚7'N and longitudes 7˚50'E - 8˚0'E, as shown in **Figure 1**. The area has above a mean sea level elevation of 45 m. Uyo experiences extreme seasonal monthly rainfall throughout the year. The month with the most rain is September with an average rainfall of 386.08 mm while the month with the least rainfall is January with an average rainfall of 17.78 mm. Also, the mean daily maximum temperature occurs in the months of January and March at about 31˚C, with the minimum temperature taking place between December and January of the succeeding year at about 21˚C [49].

2.2. Data Collection

The measured historical rainfall data for the Uyo metropolis spanning 30 years

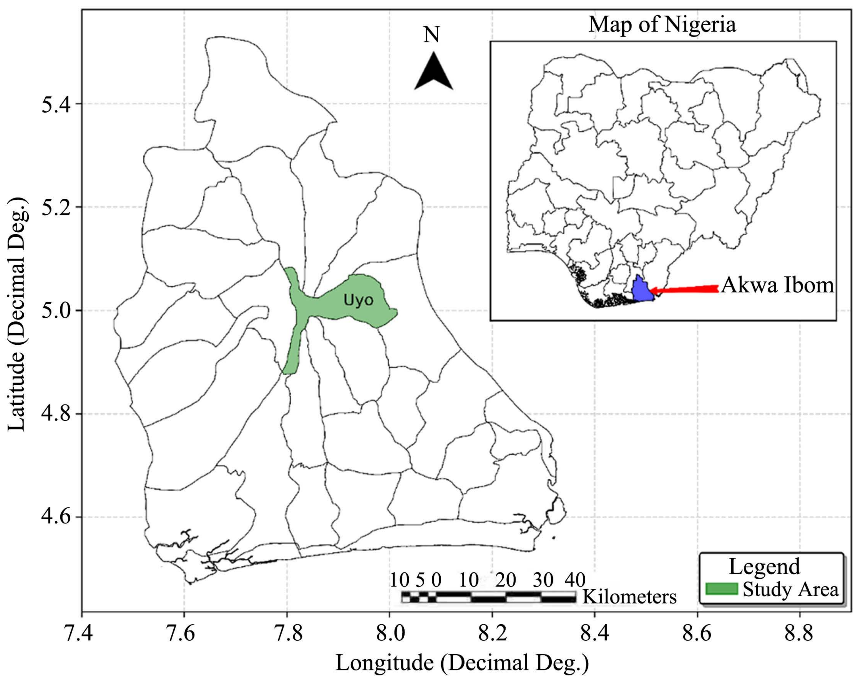

Figure 1. Map of Nigeria showing Uyo in Akwa Ibom state [50].

(1986-2015) used for the study were collected from the Department of Oceanography and Regional Planning of the University of Uyo, meteorological gauge station. The collected data on rainfall amount was recorded in mm against corresponding durations recorded in minutes. Thereafter, the data were sorted out by extraction of the maximum daily (24-hourly) rainfall amount for each month from where the maximum for each year was extracted to form the annual maximum series (AMS) for the rest of the 30 year interval [51].

2.3. Downscaling 24 Hours into Shorter Durations Time Series Data

Maximum daily rainfall data which were collated for each month of the year for 30 years were used for trend analysis of the hydrologic time series. The maximum 24-hourly annual maximum series (AMS) rainfall data extracted were further downscaled into shorter duration rainfall as detailed in Sam, *et al.*, (2021) for the trend study. The formula applied was the proposed Indian Meteorological Department (IMD) initially proposed by [52] and the Modified Chowdhury Indian Meteorological Department (MCIMD) [53] presented in Equations (1) and (2), respectively. Equation (3) provided the basis for conversion of rainfall amount to its intensity equivalent;

$$R_t = R_{24}\left(\frac{t}{24}\right)^n \tag{1}$$

$$R_t = R_{24}\left(\frac{t}{24}\right)^n + C \tag{2}$$

$$I = R_t / t \tag{3}$$

where: R_t is the required rainfall depth in mm for durations less than 24 hours, R_{24} is the daily rainfall depth (mm), t is the required duration (hours), n is an exponential constant = 1/3; and n and C were constants determined for the MCIMD method, while I denotes the rainfall intensity (mm/hr).

2.4. Mann-Kendall Trend Test

Mann Kendall test [31] [33] [54] is a rank-based statistical test that helps to check if there is a monotonous upward or downward trend existing in a time series data. Mann Kendall (MK) test is a non-parametric test in which the distribution of the data must not be normally distributed with no serial correlation (autocorrelation) in the data set. There is the opinion that although the Mann-Kendall test is relatively effective and robust, it still requires that the data set should be independent enough against serial autocorrelation. Treatment and the conditions required to achieve a relatively error-free MK test result are well documented in the literature [55] [56] [57] [58]. Trend Free Pre-Whitening (TFPW) was adopted in this study to remove serial correlation where it exists in the rainfall intensity. [59] outlines the detailed procedure used in performing the Mann-Kendall test to evaluate if a monotonous upward or downward trend exist in the time series data. If serial correlation exists in the set the Trend Free

Pre-Whitening (TFPW) can be applied to remove the serial correlation. [57] gave details on how to manually apply TFPW to time series data but where the ACF is not significant MK test can be applied directly to the original data set. The python statsmodel library—pymannkendall [46] was used to compute both the ACF for lag 1 and in applying TFPW to the time series data set before MK test was performed on the pre-whitened data set. The magnitude of the trend and intercept was computed using the Sen Slope estimator. Microsoft xlstat 2016 and python pymannkendall library was used in computing the Sen Slope and intercept.

2.5. Trend Change-Point Test

The identification of trends, time of trend change, and the starting time play a significant role in precipitation parameters and time-series studies. In order to carry out the trend change-point analysis, two non-parametric testing methods, the Distribution-free cumulative sum (CUSUM) test [43] and the Sequential Mann-Kendall test [44] [45] were used. The free CUSUM test uses a cumulative sum chart, while the sequential Mann-Kendall (SQMK) test utilizes each sample point sequence sequentially treated in both prograde and retrograde procedures. The package "trendchange" was used for change-point analysis. The software package is an open-source library freely available via the CRAN repository and version 1.2 [47] [48].

2.5.1. Distribution-Free Cumulative Sum Test

The distribution-free cumulative sum (CUSUM) test checks that differences in the mean values in two parts of a series are different for an unknown time. The median value of the series is compared with successive values in order to detect the change after a number of observations [43]. From the beginning the test statistic of the series is given as the maximum value of the cumulative sum (CUSUM) of the differences from the median which is a series of +1 or −1 in such a manner that for a time series $X_t = x_1, x_2, \cdots, x_n$, the test statistic +1 will be:

$$V_k = \sum_{i=1}^{k} sign\left(x_i - x_{median}\right) \quad \text{for,} \quad k = 1, 2, \cdots, n \tag{4}$$

where, $k = 1, 2, \cdots, n$ and $sign\left(x_i - x_{median}\right)$ is calculated from;

$$sign\left(x_i - x_{median}\right) = \begin{cases} -1 & \text{if } \left(x_i - x_{median}\right) < 0 \\ 0 & \text{if } \left(x_i - x_{median}\right) = 0 \\ 1 & \text{if } \left(x_i - x_{median}\right) > 0 \end{cases} \tag{5}$$

where; V_k, distribution is in the form of the Kolmogorov-Smirnov two-sample statistic. Given as, $KS = \left(\frac{2}{n}\right) \max \Big/ V_k$ for critical values produced at various levels of significance (see Equation (6));

$$\begin{matrix} 1.22\sqrt{n} & \text{at } \alpha = 0.10 \\ 1.36\sqrt{n} & \text{at } \alpha = 0.05 \\ 1.63\sqrt{n} & \text{at } \alpha = 0.01 \end{matrix} \tag{6}$$

2.5.2. Sequential Mann–Kendall Test

Considering a given time series $X_t = x_1, x_2, \cdots, x_n$ the sequential Mann–Kendall test identifies the change point in the time series [44] [45]. In the first place, the series is arranged in a ranked order for estimating the test statistic;

$$t_j = \sum_i^j n_j \tag{7}$$

where n_j is equivalent to the numbers of times $x_j > x_i$, when $j > i$ with $j = 1, 2, \cdots, n$ and $i = 1, 2, \cdots, j-1$. The test statistic distribution is asymptotically normal with mean $E(t_j) = \frac{j(j-1)}{4}$ and variance $VAR(t_j) = \frac{j(j-1)(2j+5)}{72}$.

A reduced variable referred to as the pro-grade series $u(t)$ is calculated for each of the test statistic variables, as;

$$u(t) = \frac{t_j - E(t_j)}{\sqrt{VAR(t_j)}} \tag{8}$$

In a similar way, a retrograde series $u'(t)$ is calculated from the end of the series. Where there is the presence of a significant trend and the point of intersection for both series is identified, the pro-grade and the retrograde indicate the trend change point whereas in the absence of a trend the series intersects at several locations.

3. Results and Discussion

3.1. Results

3.1.1. Rainfall Data Set from 24-Hourly Annual Maximum Time Series

The process of detecting a trend was carried out for three sets of data. The first data set was precipitation obtained from downscaling 24-hourly rainfall data of Uyo metropolis (see Table 1) using the IMD formula in Equations (1) and (3),

Table 1. 24-hourly annual maximum series (AMS) rainfall data for Uyo (1986-2015).

Year	Rainfall Amount (mm)	Year	Rainfall Amount (mm)	Year	Rainfall Amount (mm)
1986	113.4	1996	133.8	2006	141.1
1987	91.5	1997	108.4	2007	117.4
1988	139.2	1998	117.4	2008	117.4
1989	95.4	1999	99.4	2009	98.1
1990	87.3	2000	118.5	2010	145.9
1991	111.3	2001	76.8	2011	180
1992	83.4	2002	87.3	2012	137.5
1993	120.3	2003	139.2	2013	164.5
1994	129.2	2004	139.2	2014	238.9
1995	148.5	2005	148.5	2015	197.3

while the second data set was precipitation obtained from downscaling 24-hourly rainfall data of Uyo metropolis using the MCIMD formula in Equations (2) and (3) with results shown in **Table 2**. The third data set constitutes the initial sorted 24-hourly monthly maximum series (MMS) for the 30-year (1986-2015) study period.

Table 2. Result of trends and rate of rainfall intensity variations obtained for Uyo.

Time (hrs)	Statistic	IMD	MCIMD
		Value	Value
0.25	Z	3.245	3.245
	p-value	0.001	0.001
	Q_i	1.856	2.690
	Intercept	77.384	136.176
0.5	Z	3.245	3.245
	p-value	0.001	0.001
	Q_i	1.168	1.602
	Intercept	48.75	78.792
0.75	Z	3.245	3.245
	p-value	0.001	0.001
	Q_i	0.894	1.183
	Intercept	37.191	57.318
1	Z	3.207	3.245
	p-value	0.001	0.001
	Q_i	0.737	0.954
	Intercept	30.706	45.770
2	Z	3.245	3.245
	p-value	0.001	0.001
	Q_i	0.463	0.568
	Intercept	19.377	26.680
6	Z	3.170	3.245
	p-value	0.001	0.001
	Q_i	0.218	0.249
	Intercept	9.336	11.411
12	Z	3.282	3.245
	p-value	0.001	0.001
	Q_i	0.138	0.148
	Intercept	5.892	6.699
24	Z	3.170	3.245
	p-value	0.001	0.001
	Q_i	0.088	0.088
	Intercept	3.661	3.941

Level of significance, $\alpha = 0.05$, where Z = standardized Mann Kendall statistic, Q_i = Sen Slope (mm/hr/year), Critical Z-value = 1.96.

3.1.2. Mann-Kendall (MK) Trend Change Analysis

The performance of the MK test operation initially commenced with the computation of the autocorrelation function (ACF) which result indicated that the ACF was significant at 95% Confidence level. This result warranted the application of TFPW first on the original time-series data before the implementation of the MK test for trend detection. The results of the MK test are presented in Table 2. The $|Z|$ value for MCIMD method data were the same for all durations as 3.245 with slight variations for the IMD method data ranging from 3.170 to 3.282. All MK statistic $|Z|$ values were greater than the Critical Z-value of 1.96. Similarly, the p-value for the MCIMD method data produced a common value of 0.001 for all durations, while the IMD method data p-value were also 0.001. These p-values obtained were all below alpha, α = 0.05 level of significance. Therefore, the foregoing reinforces the existence of trends in the various downscaled short-duration data.

3.1.3. Evaluation of the Trend Magnitude

Evaluation of the magnitude of the trend was carried out using Sen's slope estimator, as the trend line intercept and slope, Q_i indicated in Figures 2-4 and values presented in Table 2. The result of the slope shows decreasing positive values of 1.856 (at 0.25 hour) to 0.088 (at 24 hour) and 2.690 (at 0.25 hour) to 0.088 (at 24 hours) for IMD and MCIMD models, respectively. The intercept for the IMD method also decreased from 77.384 to 3.661 at 0.25 and 24 hours, respectively. The MCIMD data produced higher intercept values which similarly decreased from 136.176 to 3.941 at 0.25 to 24 hours, respectively. The result obtained for the 24-hourly MMS data collaborated the trend and magnitude test results. The |Z| value obtained was 4.756 which was greater than Critical Z-value of 1.96 with slope value as 0.00376 and intercept 1.4955.

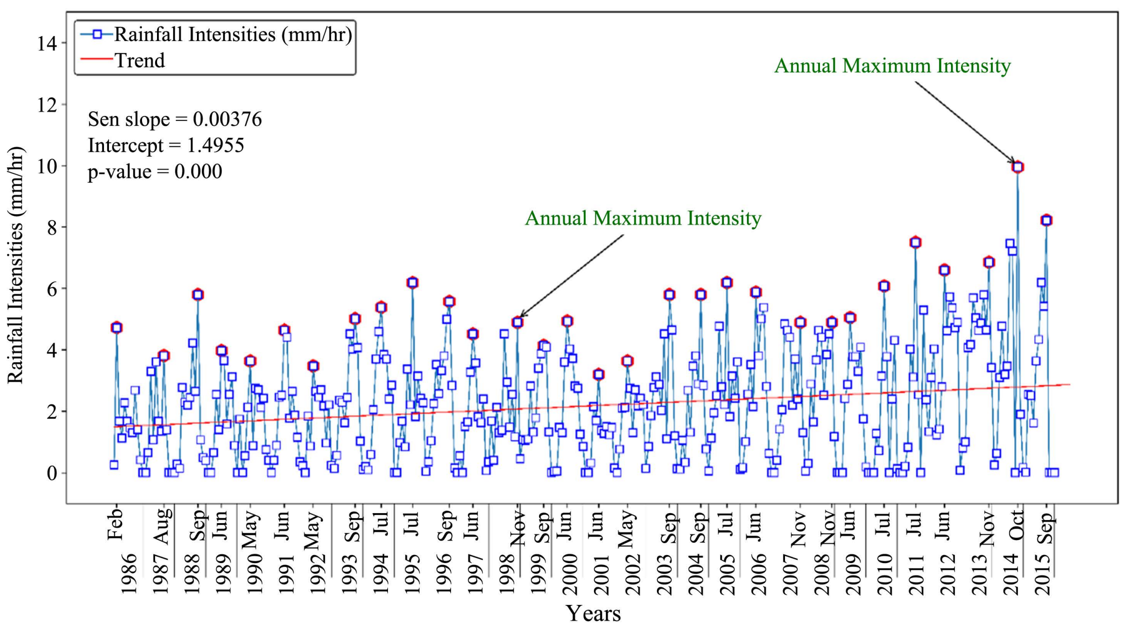

Figure 2. Trend pattern for 24-hourly MMS rainfall intensity versus time plots for Uyo metropolis (1986-2015).

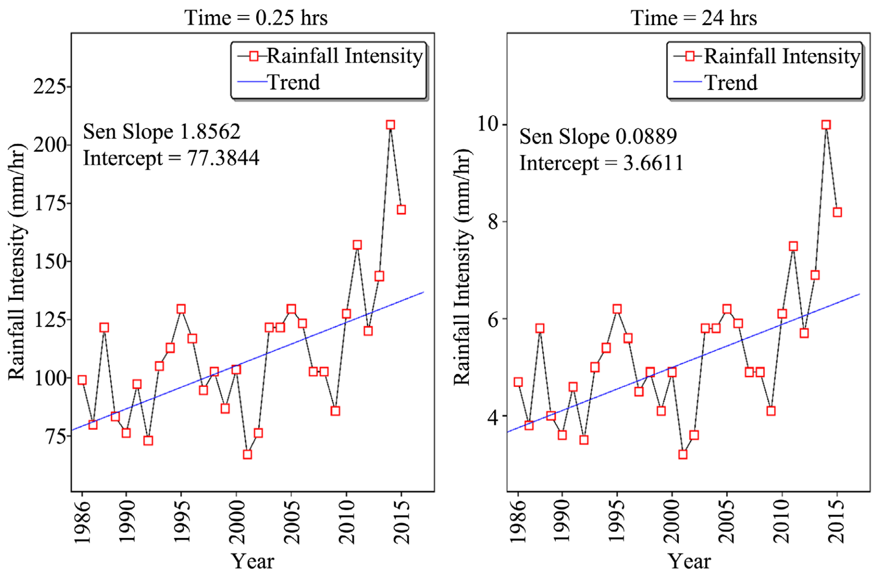

Figure 3. Trend pattern for 24-hourly AMS rainfall intensity versus time plots IMD model downscaled durations for Uyo metropolis (1986-2015).

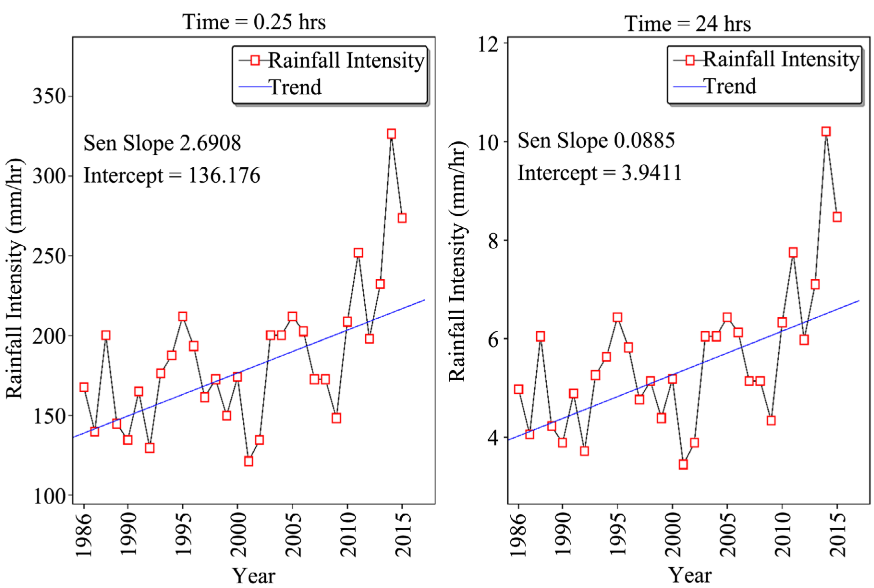

Figure 4. Trend pattern for 24-hourly AMS rainfall intensity versus time plots MCIMD model downscaled durations for Uyo metropolis (1986-2015).

3.1.4. Trends Change-Point Analysis for Time Series Data

The result for the trend graph plots of the 24-hourly AMS rainfall intensities for Uyo for both short and long duration are presented in Figure 3 and Figure 4, respectively. Also, trend change-point analysis was carried out for all downscaled duration time series and the results of both distribution-free CUSUM tests are shown in Table 3 & Table 4. Figure 5 and Figure 6 show distribution-free CUSUM plot and Sequential Mann-Kendall plot for 24-hourly AMS rainfall intensity for Uyo, respectively. Obtained via the "trendchange" software package [47] [48].

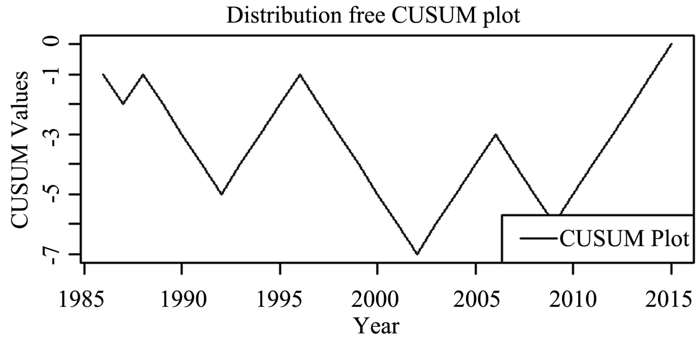

Figure 5. Distribution-free CUSUM plot for 24-hourly AMS rainfall intensities for Uyo.

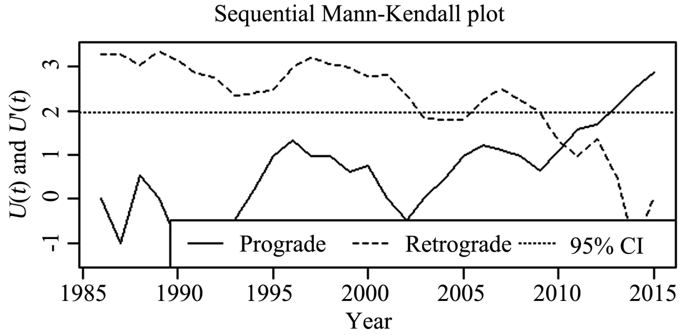

Figure 6. Sequential Mann-Kendall plot for 24-hourly AMS rainfall intensity for Uyo.

Table 3. Distribution free CUSUM result for Uyo.

Parameters	Values
Maximum CUMSUM value	7.00
Critical value at 90% CI	6.68
Critical value at 95% CI	7.45
Critical value at 99% CI	8.93
Date of Change	2002

Table 4. Trend change point for different downscaled duration rainfall intensities for Uyo.

Rainfall Durations (mins)	CUSUM	SQMK
15	2002*	2011
30	2002*	2011
45	2002*	2011
60	2002*	2011
120	2002*	2011
360	2002*	2011
720	2002*	2011
1440	2002*	2011

*Significant change point at 90% confidence interval.

3.2. Discussion of Results

3.2.1. Derivation of 24-Hourly Time Series Rainfall Data

The purpose of this study was to establish the existence of trends and variation in 24-hourly AMS extracted data from the 24-hourly Monthly Maximum Series (MMS) measured historical precipitation records collected for the Uyo metropolis by using the Mann-Kendall trend test and Sen Slope estimator for evaluation of its magnitude. This information is expected to guide an informed decision in the selection of the type of intensity-duration-frequency modeling applicable for a time-series data of a typical gauge station such as Uyo metropolis in a given catchment area. This could be either stationary (no trend) or Non-stationary (there is a trend) when established. The dynamics of the trend process also require validation and confirmation by applying trend change point analysis.

3.2.2. Establishing Trends and Variations in the Rainfall Data

The results of the Mann-Kendall test are presented in **Table 2** show that From at computed p-value of 0.001 for the MCIMD and IMD data series, the p-value was lower than the significant level of alpha, =0.05, this implies a trend exists in the rainfall intensity data series. From **Table 2**, it can be observed that the rainfall intensity for all durations exhibited a monotonous upward trend, varying from 3.170 to 3.283 and constant value at 3.245 for IMD and MCIMD data, respectively. The standardized Mann-Kendall statistic was all greater than the critical Z value of 1.96. This result indicates that trend was also detected in the time series data with the absolute standardized Mann-Kendall statistic, being greater than the Critical Z-value. The result from the Mann-Kendall suggests that when developing Intensity Duration Frequency (IDF) curves the change in the precipitation parameters must be accounted for in the IDF model. Uyo time series data passed the requirement for Non-stationary IDF modeling as more appropriate in developing IDF curves for all rainfall durations.

The result from the Sen Slope analysis in **Table 2** also proved that the magnitude of the trend tends to decrease as the duration of rainfall increases. This means that shorter duration tends to exhibit more trends than higher duration. **Figures 2-4** indicate that the Non-stationary IDF modeling is more appropriate for application in shorter durations. Most infrastructures are commonly designed with shorter rainfall duration. Trend check Non-stationarity of such a time series data is vital before developing IDF curves to avoid under designing issues and enhance your intensity prediction. This is in agreement with the earlier findings of [60]. The incorporation of time-varying parameters such as location, scale, and shape function separately or combined as co-variates have been recommended in modeling temporal changes applicable in Non-stationary IDF modeling [61] [62] [63].

The trend test for the 24-hourly MMS also confirmed the test statistic, 4.756 to be greater that the critical Z value of 1.96, which translated to the monotonous cumulative increase in the rainfall trend from 1986 to 2015. The trend variation rate was 0.090 mm/hr/year (2.16 mm/year) which lends credence to the fact that the downscaled rainfall intensities came from the same statistical population. Therefore, the 24-hourly AMS data could provide adequate representative time series data for a more accurate IDF modeling for the prediction of rainfall intensity for any catchment area.

3.2.3. Comparison of Trend Statistic and Rate of Change in Magnitude

The trend statistic and the rate of variation of change in magnitude as presented in **Table 2** indicated a high degree of consistency. The statistically significant positive trend increase in their values was observed for 24 hours to 0.25 hours duration. There is an agreement in the observed performance in the consistency of both tests which conforms to some published work [58] [64] [65].

From **Table 2**, it can be observed that variation in the rate of change in magnitude of rainfall intensity at 24-hour duration of 0.089 mm/hr per year for both IMD and the MCIMD downscaled data translates to an average of 2.1288 mm/year or 21.288 mm/decade. This result is in tandem with the publications of some researchers such as [8] who got 13 mm/decade for Ghana and [28] who had 55.2 mm/decade for selected stations in the Niger Delta. Both works were carried out along the coastal lines of the Gulf of Guinea. However, the results disagree with those of [66] who focused on the Nigerian hinterland. They found a decreasing trend in the rate of rainfall amount variability. This study also agrees with the assertion of climatic change variability in Nigeria with increasing rainfall trend in the coastal areas while sustaining a reverse in the in-land locations [27] [28] [29] [30].

3.2.4. Trend Change-Point Analysis

Three sets of precipitation time-series data were applied. The IMD and MCIMD methods downscaled shorter duration rainfall data and those of the initially extracted MMS rainfall data. The plots of rainfall intensity against time (in years) for each shorter durations (*i.e.* 0.25, 0.5, 0.75, & 1 hour) those of longer durations (*i.e.* 2, 6, 12, and 24 hours) as typically shown in **Figure 3** and **Figure 4** for both IMD and MCIMD models. Visually, uniform distribution of the rainfall intensity can be observed from 1986 to 2005 with a sharp and higher increase noticed from 2005 to 2015. This scenario was observed initially occurring for the MMS plot in **Figure 2**, which was the parent population of the 24-hourly AMS extraction where the patterns were equally noticed.

The trend change-point analysis identified the abrupt points in the distribution curves that confirmed the reality of trend existence in the time series data. Trend change points for different downscaled duration rainfall intensities for Uyo are presented in **Table 4** showing results for both CUSUM and SQMK tests. **Figure 5** shows the Distribution-free CUSUM plot for 24-hourly AMS rainfall intensity for Uyo which indicates the lowest point of convergence in the year 2002. This is the date of change point occurring when the critical value of 6.68 at a 90% Confidence interval (CI) is less than the maximum CUMSUM value of 7.0. However, the result for the Sequential Mann-Kendall (SQMN) plot presented in Figure 6 shows only one point of convergence of the pro-grade and the retrograde in the year 2011 at 95% CI. Interpreting the plots of both Figure 5 and Figure 6 point out the date of change point of rainfall trend as 2002 at a 90% confidence interval from where an increasing trend started and became significant in the year 2011, a date given by the SQMK test as a change point year too.

From the graph, it can be subjectively deduced that the rainfall intensity from 1986 to 2002 exhibited uniform distribution (*i.e.* some form of stationarity), while the abrupt end in 2002 marked the change point in the rainfall intensity distribution with the increasing trend intensifying beyond 2011. However, the introduction of a trend line as presented in Figures 2-4 indicated an increasing uniform trend in rainfall intensity. It is important to note that the observed uniformity in the plotted rainfall distribution curves gives reason for the stationarity assumption, which means statistical parameters of the sample data are assumed constant. But when a trend is established, proving non-stationarity, the changing sample statistical parameters (sample mean, shape, and location parameters) are treated as co-variate with time for IDF modeling.

4. Conclusions

The study established trends and variability in 24-hourly AMS and MMS time series data for the Uyo metropolis. The rainfall pattern although visually showed a uniform distribution of the rainfall intensity from 1986 to 2005 with a sharp increase noticed around 2005 to 2015 for both AMS and MMS data. The trend change dates were identified as 2002 and 2011 when the trend further intensified for all downscaled shorter durations. The results of the MK test gave computed p-values of 0.001 for the MCIMD and IMD data series. The p-values were lower than the significant level of alpha, =0.05 indicating trend. The rainfall intensity for all durations exhibited a monotonous upward trend that varied from 3.170 to 3.283 and 3.245 for IMD and MCIMD data, respectively, were all greater than the critical Z value of 1.96 confirming the trend in the time series data. The MK test statistic for the 24-hourly MMS of 4.756 with a rate of variation of 2.16 mm/year also confirmed the trend in the time series data which translated to the monotonous cumulative increase in the rainfall precipitation from 1986 to 2015.

The magnitude of the trend decreased as the duration of rainfall increased such that shorter durations exhibited more trends than higher durations. The rate of change in magnitude of rainfall intensity at 24-hour duration for IMD and MCIMD is at an average of 2.1288 mm/year or 21.288 mm/decade. From the foregoing, planning for IDF modeling for accuracy and effective rainfall prediction delivery will no doubt require the application of the non-stationary concept to adequately capture the influence of rate and variation in climatic change parameters which contribute to trends in time series data.

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Conflicts of Interest

The authors declare no conflict of interest regarding the publication of this paper.

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