Climate Change and Trend Analysis of 24-Hourly Annual Maximum Series Using Mann-Kendall and Sen Slope Methods for Rainfall IDF Modeling.

ABSTRACT

The focus of this study centered on the establishment of the existence of trend and variability on a typical 24-hourly sorted thirty years (1986-2015) annual maximum series (AMS) and maximum monthly series (MMS) rainfall data for Uyo metropolis downscaled into shorter durations of 0.25, 0.5, …,12 hours. The statistical tool applied for the study was the Mann-Kendall (MK) test and Sen Slope estimator. The results showed that there exists increasing trend for all durations analyzed with consistency in the test statistic results. The MK statistic $|Z|$ for the AMS varied between 3.1701 and 3.2827 while that of MMS was 4.756, were greater than critical Z = 1.96. Also, the computed p-value for the AMS varied between 0.0012 and 0.0015, and were lower than the significant level of alpha, $\propto = 0.05$. Thus, the null hypothesis of no trend was rejected. Similarly, the Sen Slope estimator gave an average rate of change in rainfall as 2.1288 and 2.16 mm/year for AMS and MMS time series data, respectively. The result from the Sen Slope estimator indicated that the magnitude of the trend decreased as the duration of rainfall increased such that shorter duration exhibited more trend than higher duration. The results of the MK trend and Sen Slope analysis proved that both test exhibited high degree of consistency with statistically significant positive trend and variability. These results have provided further evidence of an accelerated alarming rate in climate change increasing trend in Uyo metropolis and perhaps the environs. Therefore, planning for effective and accurate rainfall prediction for annual maximum time series data with established variability in trend will require adoption of non-stationary concept to account for the influence of changing climatic parameters in intensity-duration-frequency (IDF) modeling.

Key words: Hydro-meteorological, trends, Annual maximum series (AMS), Monthly maximum series (MMS), precipitation, Mann-Kendall, Sen Slope analysis.

1. INTRODUCTION

Rainfall and other related meteorological parameters are important factors that affect the ecological system and the social-economic development of any country. Agricultural development are highly vulnerable to these factors which contributes immensely to consequent changes in weather conditions. Variability in rainfall and increases in temperature have been identified as major meteorological parameters amongst others that creates climate change impact. The prediction of precipitation trends accurately no doubt plays a major role in enhancing prevention and mitigation of the effect of excessive rainfall - a major contributor to flooding event that could wreck serious havoc on lives and properties. Precipitation time series has been reported by [1] to be far more difficult to forecast trends than predicting temperature trends. Asia in the latter half of the century, was reported to have witnessed both spatial and temporal variation in precipitation trend by the Fourth Intergovernmental Panel on Climate Change [2]. Significant attention have been paid by researchers worldwide to study trends in precipitation time series. While mean annual precipitation have been observed to be on the decreasing trends along the plains and coastal areas of Russia [3, 4], northeast and northern China [5, 6], and Pakistan [7]. Increasing trends were found to exist in the mean rainfall time series data for western and southeast coastal lands of China [5, 6, 8]. In Nigeria the variation of temperature, rainfall, relative humidity and mean sea level show a long-term trend, while rainfall, in particular exhibit some periodicities [9]. Evidence of climate change on Nigeria eco-system indicates trend on variable rainfall that is, increasing rainfall in the coastal region and a decreasing rainfall in the continental interiors [9-12].

1.1 Time Series Analysis

The earth's climate balance is being threatened by emissions of Greenhouse Gases (GHG) and these gases trap heat re-radiated from the earth's surface which would otherwise be reflected to space [9]. Water vapour is intimately involved in the greenhouse question because its concentration is linked with those of other gases through a "feedback mechanism". Warming brought about by other greenhouse gases, increases evaporation and allows the atmosphere to hold more water vapour, enhancing the warming. The impacts include higher sea levels, altered patterns of rainfall and air temperatures, and increased frequency and intensity of severe storms [2].

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 is most conveniently represented by a set of three basic components: trend, periodic or cyclic and stochastic. The trend and periodic components are deterministic, that is, their evolution with respect to time is both regular and predictable. While the stochastic component is both irregular and unpredictable. The trend component may occur as a result of either man-made changes, within the catchment area or natural causes such as climate change. Periodic component in any hydrologic time series can also be attributed to astronomical events, which are also periodic. Comparing between trend and periodic components, the dependence between successive terms of the stochastic component is probabilistic rather than deterministic [13]. Trend analysis through linear regression is able to describe realistic non-stationarity of rainfall local scaled data [14-16].

1.2 Selection of Statistical Technique

Different statistical techniques have been deployed to model trends in precipitation time series in hydrology which are classified as parametric or non-parametric test [17, 18]. While the parametric test is helpful and serve as a powerful tool, the condition for its application requires that the data set should be both independent and normally distributed. Interestingly, this condition rarely occurs in hydrological time series. The non-parametric test also requires that the data should be independent, and are 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 [17, 19-22] and the Sen Slope estimator used for quantifying the trend magnitude and similarly obtain its intercept [23].

Therefore, this study investigated the existence of trends and variation in historically daily (24-hourly) annual maximum series (AMS) generated rainfall data for Uyo metropolis in south-central, Nigeria using Mann-Kendall test and Sen Slope estimator to evaluate the rate of change in variation of trend, if any. A broad overview of rainfall statistics in terms of short durations downscaled from the 24-hourly AMS extracted data for thirty years (1986-2015) inclusive were investigated. The study further verified if the data from this study station satisfied the condition for application in Non-stationary Intensity-Duration-Frequency (IDF) modeling.

2. MATERIALS AND METHODS

2.1 Study Area

The study station is Uyo metropolis located in Akwa Ibom State in south-central Nigeria. The GPS coordinates to locate the study area are Latitude: 5^{o} 2' 20'' N and Longitude: 7^{o} 54'34''E, (see Figure 1). The above mean sea level elevation is 45m with a topography that is characterized by undulating sandy plain terrain, well drained to the Atlantic Ocean in the South. The mean daily maximum and minimum temperatures of Uyo metropolis are 34 ^{0}C and 23^{0}C, respectively, with average humidity of 72% during the month of January. The maximum annual rainfall vary from 1,599.5 to 3,855.5mm in 1983 and 1977, respectively. The mean annual rainfall value is 2,466.6mm with concentration in rainfall occurring in the months of April to October which most often exhibits high intensity of prolonged rainstorm [24].

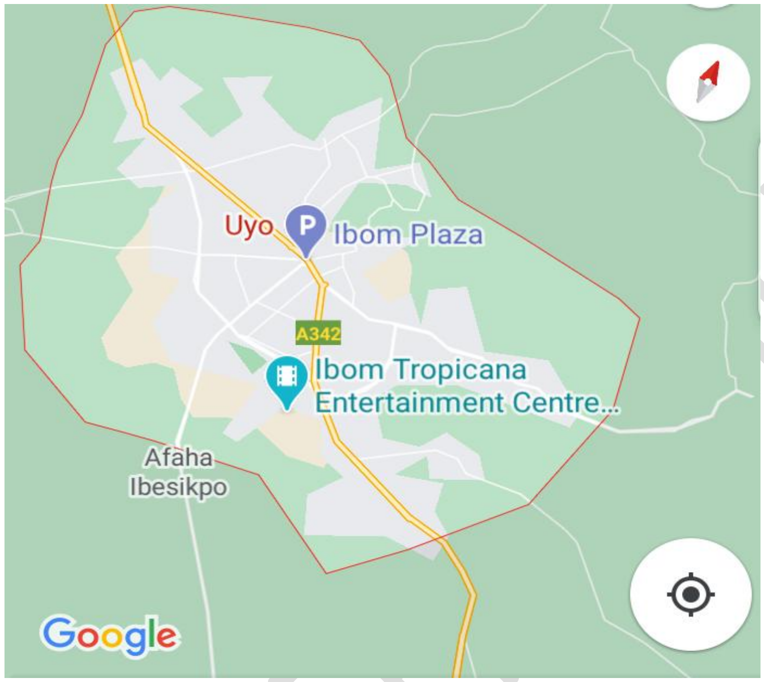

Figure 1: Google map showing Uyo metropolis

2.2 Data Collection

Historical rainfall data for Uyo metropolis spanning 30 years (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 data on rainfall amount collected were recorded in mm against corresponding durations which were in minutes. The data were sorted out by extraction of the maximum daily (24-hourly) rainfall amount from where the maximum for each year was collated to form the annual maximum series (AMS) for the rest of the 30 year interval.

2.3 Segregation of Shorter Durations Rainfall Series

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. Furthermore, the maximum 24-hourly annual maximum series (AMS) rainfall data collated were also downscaled into shorter duration rainfall as detailed in [25] for the trend study. The formula applied were those of Indian Meteorological Department (IMD) and the Modified Chowdhury Indian Meteorological Department (MCIMD) presented in Equations (1) and (2), respectively. Equation (3) provided the basis for conversion of rainfall amount to its intensity equivalent.

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

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

And, $I = R_t / t$ (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 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 Analysis

Mann Kendall test [17, 19, 26] is a rank based statistical test that help 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 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 Mann Kendall test is relatively effective and robust, it still requires that the data set should be independent. In other words, the Mann Kendall test is not robust enough against serial autocorrelation. The tendency with serial correlation in the data set when performing Mann Kendall is that it results to a Type I error, in which the null hypothesis of no trend is rejected. Serial correlation in the time series data does erroneously leads to establishing the existence of a trend when actually none exist. [27] in their publication showed the influence of autocorrelation on the ability of MK test to detect trend in hydrological series. Several methods have been proposed by researchers to aid in removing the autocorrelation before applying Mann Kendall to the data set. [28] proposed that the data set should undergo pre-whitening in other to remove the autocorrelation before Mann Kendall can be applied to the data set. Pre-whitening of the time series data is the removal of auto-correlation, and have been used by several authors in trend detection studies [18, 29, 30]. Though pre-whitening of the data set help in removal of auto-correlation none the less, it still has its short coming. [31] suggested that though pre-whitening aid in the removal of the autocorrelation which significantly reduce the Type I error, it leads to increase of Type II error (that is, accepting the null hypothesis when it should be rejected). Because the presence of a trend alters the estimate of the magnitude of serial correlation and the power of Mann Kendall will thus, deteriorate after pre-whitening. [31] advocated that the trend in the time series be removed first before pre-whitening is applied to the data set, which is known as the "Trend Free Pre-Whitening (TFPW)". [32] in a different approach in removal of serial correlation in a data set proposed correction of the variance, S by using an effective sample size (ESS) that reflects the effect of serial correlation on the variance of S. TFPW was adopted in this study in removal of serial correlation where it exist in the rainfall intensity.

2.4.1 Autocorrelation and Trend Free Pre-Whitening (TFPW)

Autocorrelation coefficient (r_1) of the rainfall intensity can be computed using Equation (4), while the Confidence interval of the autocorrelation function are computed using a two-tailed test Equation (5).

$$r_1 = \frac{\sum_{i=1}^{n-1}(X_i - \bar{X})(X_{i+1} - \bar{X})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} \tag{4}$$

$$r_1(95\%) = \frac{-1 \pm 1.96\sqrt{(n-2)}}{n-1} \tag{5}$$

The slope (β) of a trend in sample data was estimated using the approach proposed by [23]. The original sample data X_t were unitized by dividing each of their values with the sample mean $E(X_t)$ prior to conducting the trend analysis [27]. By this treatment, the mean of each data set is equal to one and the properties of the original sample data remain unchanged. The trend was assumed to be linear, and the sample data are de-trended by using Equation (6).

$$Y_t = X_t - T_t = X_t = \beta.\mathrm{t} \tag{6}$$

Pre-whitening as suggested by [33] has been used to reduce the influence of an AR(1) component on the application of the MK test by using Equation (7) on the data series.

$$Y_t' = Y_t - r_1 Y_{t-1} \tag{7}$$

2.4.2 Description of Mann-Kendall (MK) Trend

The Mann-Kendall trend test [17, 19] is based on the correlation between the ranks and sequences of a time series. The null hypothesis state that there is no trend in the data set overtime while the alternative hypothesis state that a trend exist in the data set overtime. The test statistic S, for Mann Kendall was computed applying Equation (8).

$$\mathrm{S} = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sig\left(x_j - x_i\right) \tag{8}$$

Where; x_j and x_i are the time series observations in chronological order, n is the length of time series. $sig\left(x_j - x_i\right)$ is obtained using Equation (9) when the condition is satisfied.

$$sig\left(x_j - x_i\right) = \begin{cases} +1 & if\ \left(x_j - x_i\right) > 0 \\ 0 & if\ \left(x_j - x_i\right) = 0 \\ -1 & if\ \left(x_j - x_i\right) < 0 \end{cases} \quad (9)$$

The variance which is used in computing the MK standardized test statistic (Z) is computed using Equation (10) while the standardized test statistic (Z) is computed applying Equation (11).

$$\mathrm{V}(S) = \frac{1}{18}\left[n\ (n-1)(2n+5) - \sum_{p=1}^{q} t_q\left(t_q - 1\right)\left(2t_q + 5\right)\right] \quad (10)$$

$$Z\ = \begin{cases} \frac{S-1}{\sqrt{V(S)}},\ If\ S > 0 \\ \frac{S+1}{\sqrt{V(S)}},\ If\ S < 0 \end{cases} \quad (11)$$

Where: t_q = number of ties for p^{th} values; q = number of tied value; and Z = Standardized Mann Kendall statistic. A trend is detected in the time series data if the absolute standardized Mann Kendall statistic $|Z|$ is greater than the critical z-score $Z_{1-\alpha/2}$ or if the p-value is less than the level of 5% significance.

Assumptions for Mann-Kendall (MK) analysis:-The following assumptions underlie the MK test; (i) When no trend is present, the measurements (observations or data) obtained over time are independent and identically distributed. The assumption of independence means that the observations are not serially correlated over time. (ii) The observations obtained over time are representative of the true conditions at sampling times. (iii) The sample collection, handling, and measurement methods provide unbiased and representative observations of the underlying populations over time. Thus, there is no requirement that the measurements should be normally distributed or that the trend, if present, is linear. This means the MK test can be computed if there are missing values and values below the one or more limits of detection (LD), although, the performance of the test will be adversely affected by such events. The assumption of independence requires that the time between samples be sufficiently large so that there is no correlation between measurements collected at different times.

2.5 Sen Slope Analysis

Sen's Slope is a nonparametric test initially proposed by [23] and later modified by [34], used to estimate the magnitude of trends in the time series data. Equations (12) and (13) are used in evaluating the Sen Slope.

$$T_i = \frac{x_i - x_j}{j-k} \tag{12}$$

Where: x_i and x_j = data values at time j and k, respectively. Also,

$$Q_i = \begin{cases} T_{(N+1)/2}, & N \text{ is odd} \\ 1/2\left(T_{N/2} + T_{(N+2)/2}\right), & N \text{ is even} \end{cases} \tag{13}$$

Where: If Q_i is positive it represents an increasing trend, while a negative sign denotes decreasing trend over time. The slope or steepness indicates the value or magnitude of the trend.

2.6 Flow Chart for Computing Mann-Kendall Test Statistic

The flow chart used in evaluating if a monotonous upward or downward trend exist in the time series data is shown in Figure 2. The process starts from evaluating the autocorrelation function (ACF) of the time series at lag 1, required to establish if the rainfall /precipitation has serial

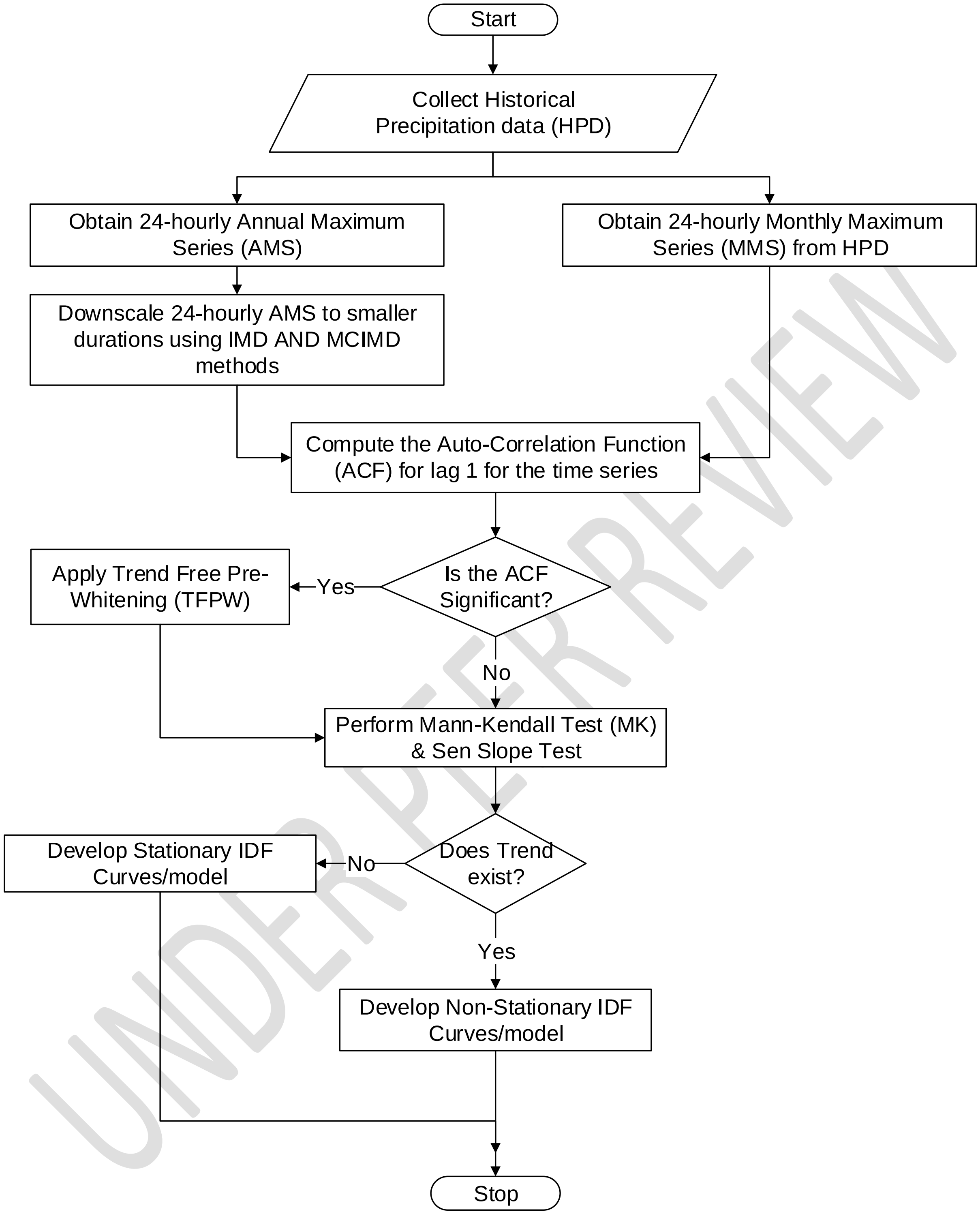

Figure 2: Flow Chart for Performing Mann-Kendall Test

Correlation. When serial correlation is found in the time series data it forces MK test to a Type-1 error, which erroneously establish that there is a trend in the data set. The ACF for lag 1 was computed with the aid of Minitab software and confirmed with python statsmodels.tsa library. If the ACF value is outside the confidence interval calculated, the ACF is considered significant, meaning serial correlation exist in the data set. If serial correlation exist in the data set the Trend Free Pre-Whitening (TFPW) can be applied to remove the serial correlation. [27] gave details on how to manually apply TFPW to time series data but where the ACF is not significant MK test can be applied to the original data set. The python library pymannkendall was used 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 Sen Slope estimator. Microsoft xlstat 2016 and python pymannkendall library were used in computing the Sen Slope and intercept.

3. RESULTS AND DISCUSSION

3.1 Analysis of Results

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

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

3.1.2 Graphical Plots of Downscaled Shorter Duration Rainfall Intensities

The result for the trend graph plotting of the 24-hourly annual maximum series (AMS) rainfall for Uyo for both short and long duration are presented in Figures 3 and 4, respectively. In other to verify if the rainfall intensity is non-stationary, the rainfall intensity was tested using Mann-Kendall test. Figure 2 outlined the steps required in other to carry out Mann Kendall test.

3.1.3 Correlogram and TFPW of Rainfall Intensities

Figure 6 shows the autocorrelation at lag 1 for different rainfall intensity durations. It can be observed that the ACF at lag 1 all exceeded the 95% Confidence interval. The presence of autocorrelation at lag 1 for all durations would result to a Type 1 error if Mann Kendall test is applied on the original time series data to detect the trend, thereby erroneously leading to one confirming that a trend exist when actually there is no trend in the rainfall intensity. Therefore, the original rainfall intensity data was subjected to Trend Free Pre-Whitening (TFPW) before Mann Kendall was used to detect trend existence applying Equations (4) to (7).

Also, subjected to TFPW was the original historical data of rainfall intensities sorted out in 24-hourly Monthly Maximum Series (MMS). The autocorrelation graph in Figure 7 showed that the autocorrelation of the rainfall intensities from 1986 to 2015 at lag 1 exceeded the confidence interval. TFPW was similarly applied to the original rainfall data before Mann Kendall test was performed.

Table 1: Downscaled Rainfall Intensity Using IMD Method for Uyo

Year No	*0.25hr*	*0.5hr*	*0.75hr*	*1hr*	*2hrs*	*6hrs*	*12hrs*	*24hrs*
1	99.1	62.4	47.6	39.3	24.8	11.9	7.5	4.7
2	79.9	50.4	38.4	31.7	20	9.6	6.1	3.8
3	121.6	76.6	58.5	48.3	30.4	14.6	9.2	5.8
4	83.3	52.5	40.1	33.1	20.8	10	6.3	4
5	76.3	48	36.7	30.3	19.1	9.2	5.8	3.6
6	97.2	61.3	46.7	38.6	24.3	11.7	7.4	4.6
7	72.9	45.9	35	28.9	18.2	8.8	5.5	3.5
8	105.1	66.2	50.5	41.7	26.3	12.6	8	5
9	112.9	71.1	54.3	44.8	28.2	13.6	8.5	5.4
10	129.7	81.7	62.4	51.5	32.4	15.6	9.8	6.2
11	116.9	73.6	56.2	46.4	29.2	14	8.8	5.6
12	94.7	59.7	45.5	37.6	23.7	11.4	7.2	4.5
13	102.6	64.6	49.3	40.7	25.6	12.3	7.8	4.9
14	86.8	54.7	41.7	34.5	21.7	10.4	6.6	4.1
15	103.5	65.2	49.8	41.1	25.9	12.4	7.8	4.9
16	67.1	42.3	32.3	26.6	16.8	8.1	5.1	3.2
17	76.3	48	36.7	30.3	19.1	9.2	5.8	3.6
18	121.6	76.6	58.5	48.3	30.4	14.6	9.2	5.8
19	121.6	76.6	58.5	48.3	30.4	14.6	9.2	5.8
20	129.7	81.7	62.4	51.5	32.4	15.6	9.8	6.2
21	123.3	77.7	59.3	48.9	30.8	14.8	9.3	5.9
22	102.6	64.6	49.3	40.7	25.6	12.3	7.8	4.9
23	102.6	64.6	49.3	40.7	25.6	12.3	7.8	4.9
24	85.7	54	41.2	34	21.4	10.3	6.5	4.1
25	127.5	80.3	61.3	50.6	31.9	15.3	9.7	6.1
26	157.2	99.1	75.6	62.4	39.3	18.9	11.9	7.5
27	120.1	75.7	57.7	47.7	30	14.4	9.1	5.7
28	143.7	90.5	69.1	57	35.9	17.3	10.9	6.9
29	208.7	131.5	100.3	82.8	52.2	25.1	15.8	10
30	172.4	108.6	82.9	68.4	43.1	20.7	13	8.2

Table 2: Downscaled Rainfall Intensity Using MCIMD Method for Uyo

Year No	*0.25hr*	*0.5hr*	*0.75hr*	*1hr*	*2hrs*	*6hrs*	*12hrs*	*24hrs*
1	167.6	97.5	71.1	56.9	33.3	14.3	8.4	5.0
2	139.9	81.0	58.9	47.1	27.5	11.8	6.9	4.1
3	200.3	117.0	85.5	68.5	40.2	17.4	10.2	6.1
4	144.8	83.9	61.1	48.8	28.5	12.2	7.2	4.2
5	134.5	77.8	56.6	45.2	26.3	11.3	6.6	3.9
6	164.9	95.9	70.0	56.0	32.8	14.1	8.3	4.9
7	129.6	74.9	54.4	43.4	25.3	10.8	6.3	3.7
8	176.3	102.7	75.0	60.0	35.2	15.1	8.9	5.3
9	187.6	109.4	79.9	64.0	37.5	16.2	9.5	5.6
10	212.0	124.0	90.7	72.7	42.7	18.5	10.9	6.4
11	193.4	112.9	82.5	66.1	38.8	16.7	9.9	5.8
12	161.3	93.7	68.3	54.7	32.0	13.7	8.1	4.8
13	172.7	100.5	73.4	58.7	34.4	14.8	8.7	5.1
14	149.9	86.9	63.3	50.6	29.6	12.7	7.5	4.4
15	174.1	101.3	74.0	59.2	34.7	14.9	8.8	5.2
16	121.2	69.9	50.8	40.5	23.5	10.0	5.9	3.5
17	134.5	77.8	56.6	45.2	26.3	11.3	6.6	3.9
18	200.3	117.0	85.5	68.5	40.2	17.4	10.2	6.1
19	200.3	117.0	85.5	68.5	40.2	17.4	10.2	6.1
20	212.0	124.0	90.7	72.7	42.7	18.5	10.9	6.4
21	202.7	118.4	86.6	69.3	40.7	17.6	10.4	6.1
22	172.7	100.5	73.4	58.7	34.4	14.8	8.7	5.1
23	172.7	100.5	73.4	58.7	34.4	14.8	8.7	5.1
24	148.2	86.0	62.6	50.0	29.2	12.5	7.4	4.3
25	208.7	122.0	89.2	71.5	42.0	18.1	10.7	6.3
26	251.9	147.7	108.2	86.8	51.1	22.2	13.1	7.8
27	198.1	115.7	84.5	67.7	39.8	17.2	10.1	6.0
28	232.3	136.0	99.6	79.9	47.0	20.3	12.0	7.1
29	326.5	192.1	141.0	113.3	66.9	29.1	17.2	10.2
30	273.8	160.8	117.8	94.6	55.7	24.2	14.3	8.5

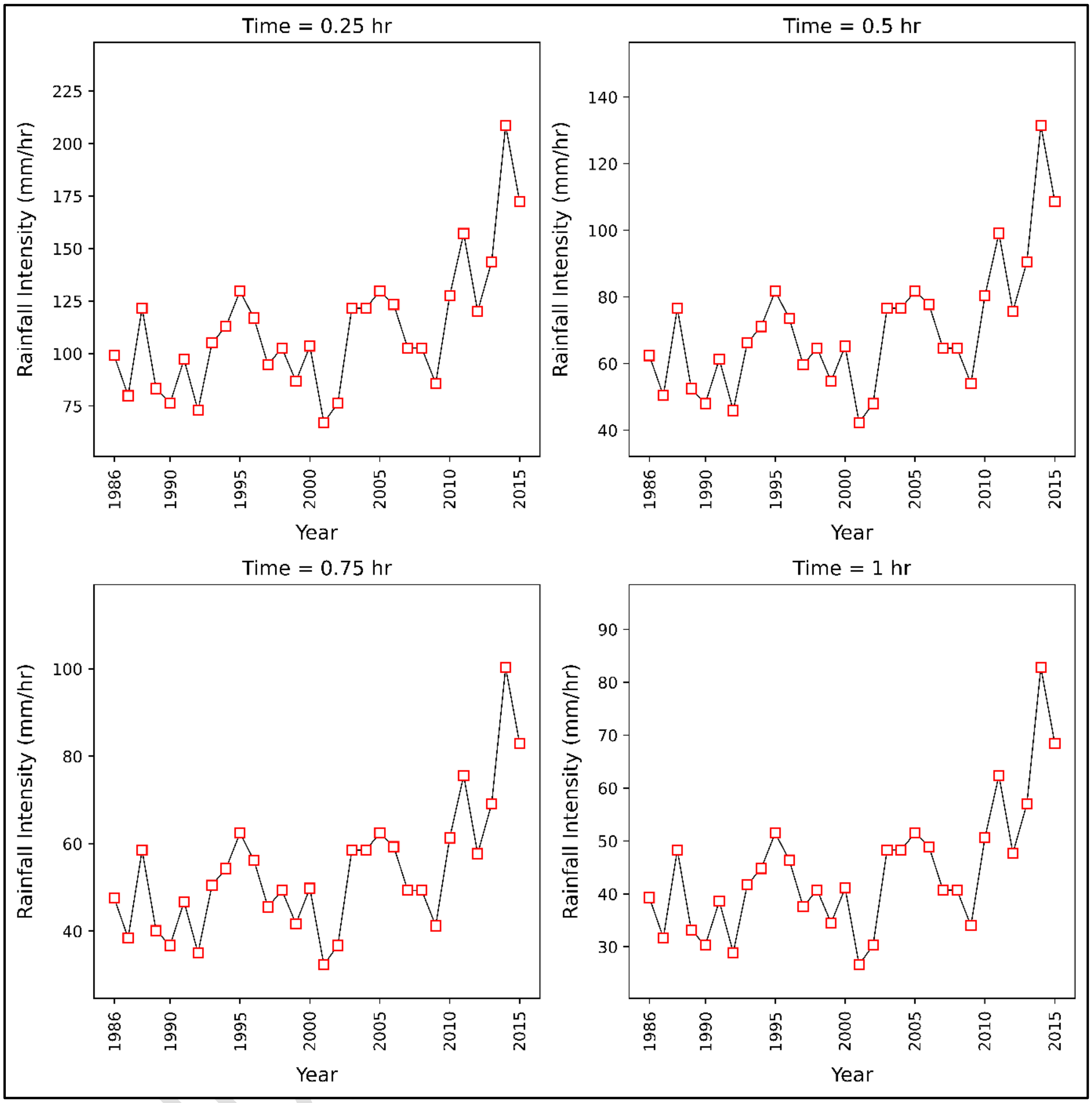

Figure 3: 24-Hourly AMS Rainfall Intensities versus Time for Uyo Metropolis (1986-2015) for Shorter Durations from Table 1.

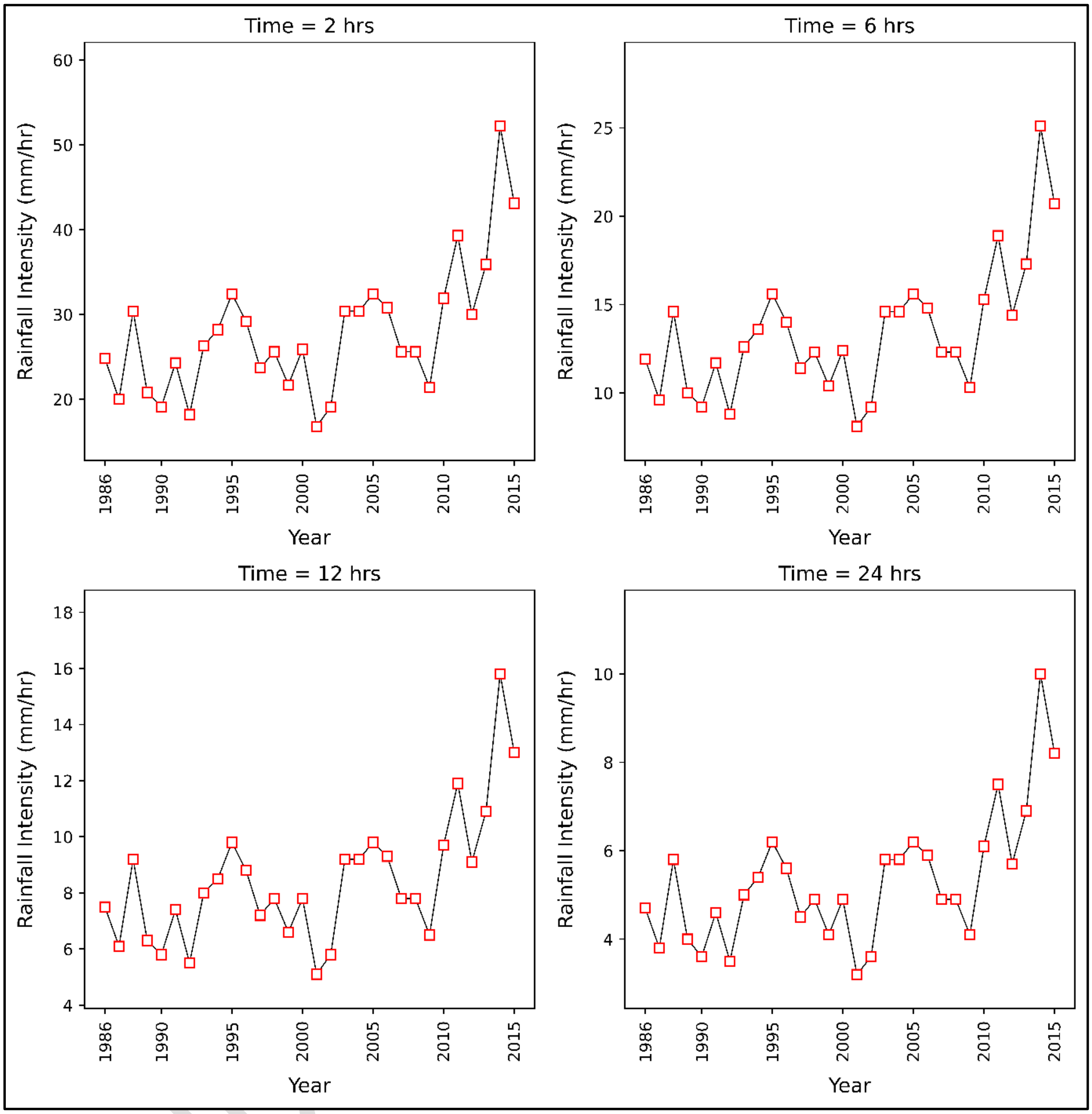

Figure 4: 24-Hourly AMS Rainfall Intensities versus Time for Uyo Metropolis (1986-2015) for Longer Durations from Table 1.

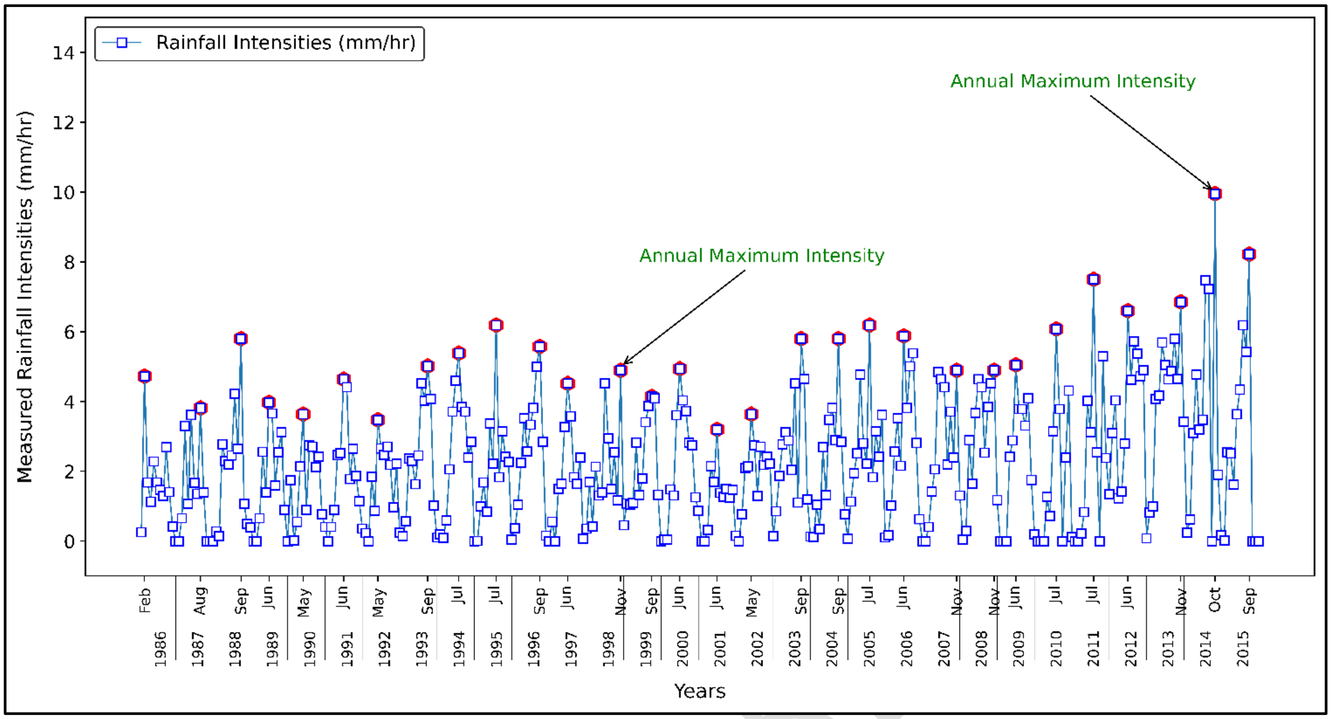

Figure 5: 24-Hourly MMS Rainfall Intensities versus Time for Uyo Metropolis (1986-2015).

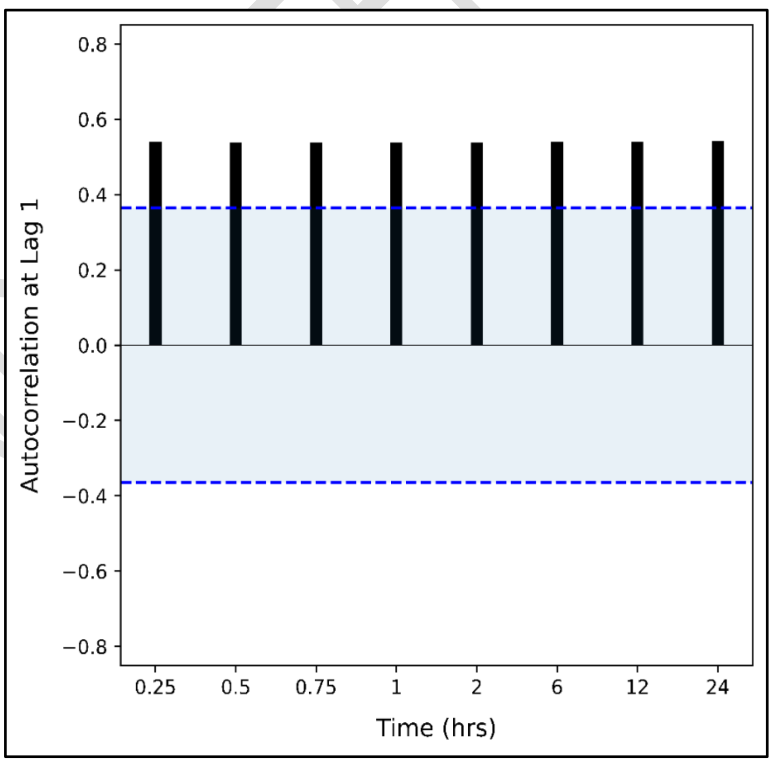

Figure 6: Correlogram of ACF at Lag-1 for various 24-Hourly AMS IMD Method Downscaled Durations

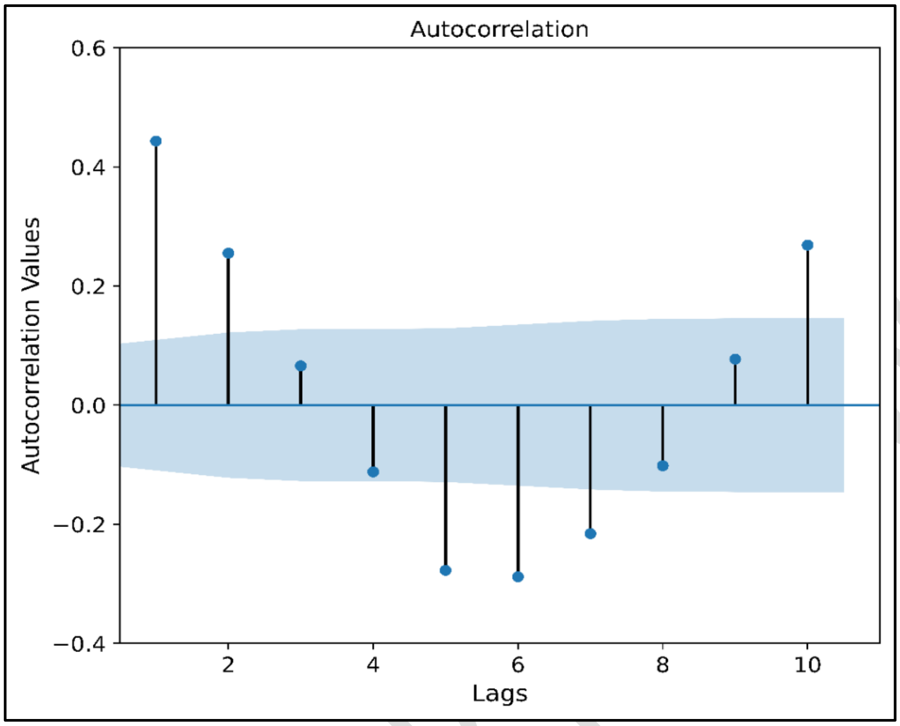

Figure 7: Correlogram of ACF at Lag-1 for 24-Hourly MMS Rainfall Intensities (1986-2015)

3.1.4 Mann-Kendall (MK) Test Statistic Results

The flow chart presented in Figure 2 guided the procedure for the performance of the MK test. The operation initially the computation of the autocorrelation function (ACF) which result indicated that the ACF was significant at 95% Confidence level as evidenced in Figures 6 and 7. This outcome 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 test are presented in Table 3. The MK test was evaluated based on the correlation between the ranks and the sequences of the time series data using the formula given in Equations (8) to (11) to obtain the test statistic.

The $|Z|$ value for MCIMD method data were the same for all durations as 3.2451 with slight variations for the IMD method data ranging from 3.1701 to 3.2827. All MK statistic $|Z|$

value were greater than the Critical Z-value of 1.96. Similarly, the p-value for the MCIMD method data produced common value of 0.0012 for all durations, while the IMD method data p-value varied from 0.0012 to 0.0015. These p-values obtained were all below alpha, $\propto = 0.05$ level of significance. Therefore, the foregoing reinforces the existence of trend in the various downscaled short duration data.

3.1.5 Sen Slope Estimator Results

Evaluation of the magnitude of the trend were carried out using the formula in Equations (12) and (13) computed in terms of the trend line intercept and slope, Q_i as indicated in Figures 8 to 10 and presented in Table 3. The result of the slope shows a decreasing positive values of 1.8562 (at 0.25 hour) to 0.0889 (at 24hour) and 2.6908 (at 0.25 hour) to 0.0885 (at 24 hour) for IMD and MCIMD methods, respectively. The intercept for the IMD method also decreased from 77.384 to 3.6611 at 0.25 and 24 hours, respectively. The MCIMD data produced higher intercept values which similarly decreased from 136.1760 to 3.9411 at 0.25 to 24 hours, respectively.

The result obtained for the 24-hourly MMS data collaborated the MK test and Sen Slope test results. The $|Z|$ value obtained was 4.756 which was greater than Critical Z-value of 1.96 with slope value as 0.090 and intercept 35.89.

Table 3: Result of Mann-Kendall Test and Sen Slope Estimates for Uyo

Time (hrs)	Statistic	IMD	MCIMD
		Value	Value
0.25	Z p-value Q_i Intercept	3.2451 0.0012 1.8562 77.3844	3.2451 0.0012 2.6908 136.1760
0.5	Z p-value Q_i Intercept	3.2451 0.0012 1.1687 48.753	3.2451 0.0012 1.6022 78.7928
0.75	Z p-value Q_i Intercept	3.2451 0.0012 0.8937 37.1906	3.2451 0.0012 1.1830 57.3189
1	Z p-value Q_i Intercept	3.2076 0.0013 0.7375 30.7063	3.2451 0.0012 0.9540 45.7703
2	Z p-value Q_i Intercept	3.2451 0.0012 0.4636 19.3773	3.2451 0.0012 0.5680 26.6804
6	Z p-value Q_i Intercept	3.1701 0.0015 0.2182 9.3364	3.2451 0.0012 0.2497 11.4112
12	Z p-value Q_i Intercept	3.2827 0.1385 5.8923	3.2451 0.0012 0.1487 6.6991
24	Z p-value Q_i Intercept	3.1701 0.0015 0.0889 3.6611	3.2451 0.0012 0.0885 3.9411

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

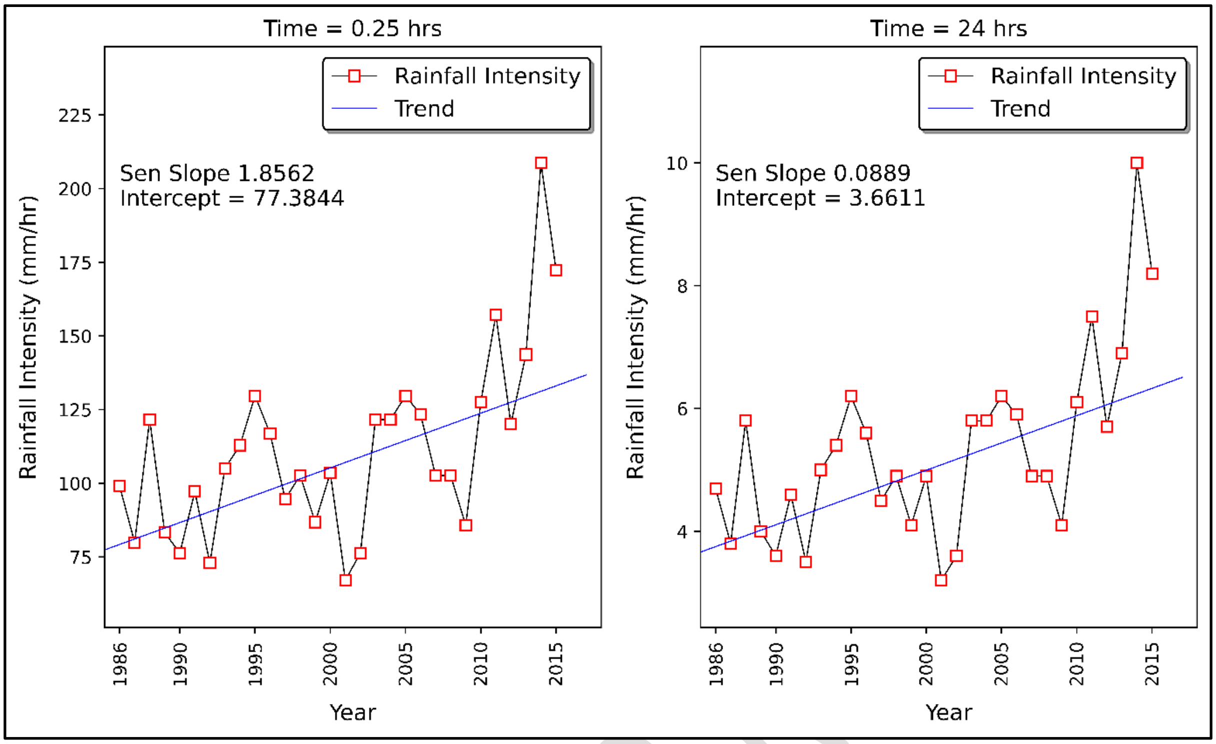

Figure 8: 24-Hourly AMS Rainfall Intensities versus Time Showing Trend Line for IMD Method Downscaled Durations

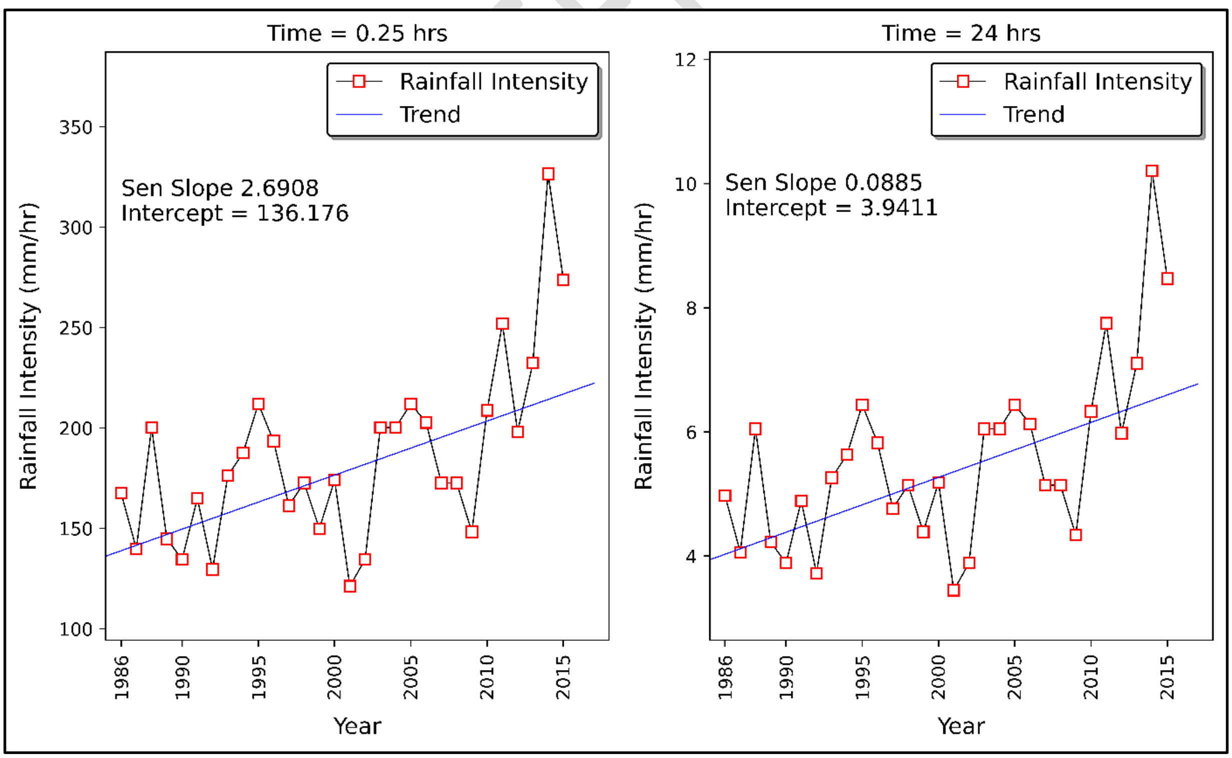

Figure 9: 24-Hourly AMS Rainfall Intensities versus Time Showing Trend Line for MCIMD Method Downscaled Duration

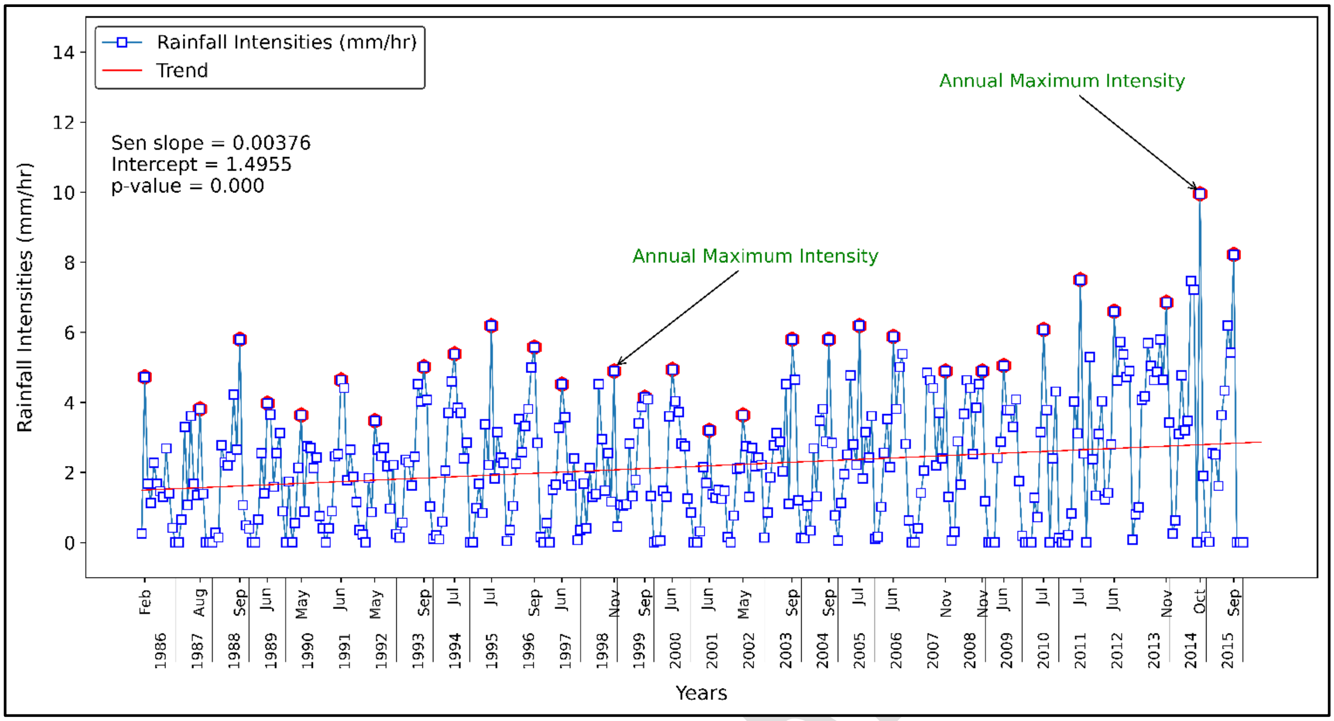

Figure 10: 24-Hourly MMS Rainfall Intensities versus Time indicating Trend Line for Uyo Metropolis (1986-2015).

3.2 Discussion of Results

3.2.1 Analysis of Trend in 24-Hourly AMS Rainfall Intensities

The purpose of this study was to establish the existence of hydro-meteorological trends and variation in 24-hourly AMS extracted data from the 24-hourly Monthly Maximum Series (MMS) historical precipitation records collected for Uyo metropolis by using Mann-Kendall trend test and Sen Slope estimator for evaluation of its magnitude. This information is expected to guide in 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 trend) when established.

Three sets of hydro-meteorological time-series data were applied. The IMD method (see Table 1) and MCIMD method (see Table 2) downscaled shorter duration rainfall intensities and those of the initially extracted MMS rainfall intensities records. Their curves were plotted of rainfall intensity against time (in years) for each shorter durations of 0.25, 0.5, 0.75, and 1 hour as shown in Figure 3. Similarly, those of longer durations of 2, 6, 12 and 24 hours were also plotted as in Figure 4. 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 repeating itself for the MMS in Figure 5, which was actually the parent population of the 24-hourly AMS extraction. From the graph it can be subjectively deduced that the rainfall intensity from 1986 to 2005 exhibited some form of stationarity, while non-stationarity was exhibited in the rainfall intensity from 2005 to 2015. However, introduction of a trend line as presented in Figures 8, 9 and 10 indicated an increasing trend in rainfall intensity. It is important to note that the observed uniformity in the plotted rainfall distribution curves gives reason for stationarity assumption, that is, where all statistical parameters of the sample data are assumed constant. But when trend exist, proving non-stationarity, the changing sample statistical parameters (sample mean, shape and location parameters) are computed in segments for IDF modeling.

3.2.2 Analysis of Autocorrelation and TFPW on 24-Hourly AMS Rainfall Intensities

The statistical tool adopted for non-stationarity check, that is if trends exist in the time-series data was the Mann-Kendall test which required autocorrelation analysis at 95% Confidence level. The result from the Correlogram in Figure 6 showed that the ACF at lag 1 was statistically significant for all downscaled rainfall durations, which indicated that the original rainfall intensity at the various durations can be predicted by the rainfall intensity at lag 1. Similarly, the 24-hourly MMS data subjected to autocorrelation as in graph of Figure 7 exhibited same features as that in

Figure 6. Thus, to eliminate the Type-1 error the rainfall intensity time-series data were subjected to Trend Free Pre-Whitening (TFPW) before Mann-Kendall test was performed to detect trend using Equations (4) to (7) as earlier described. Thus, TFPW applied to each of the original time-series data before Mann Kendall was used to remove serial autocorrelation dependency.

3.2.3 Analysis of Trend and Variations in MK Test and Sen Slope Estimator Statistics

The results of the Mann Kendall test are presented in Table 3. The hypothesis considered for Mann-Kendall test are that for H_0: Null hypothesis, there is no trend in the rainfall intensity over time; and for Ha: Alternate hypothesis, there is a trend in the rainfall intensity over time. From Table 3 at computed p-value of 0.0012 for MCIMD data series with range of value from 0.0012 to 0.0015 for IMD data series, the p-value were lower than the significant level of alpha, $\propto = 0.05$, the null hypothesis H_0 was rejected, because trend was found to exist in the rainfall intensity.

Also, if the Standardized Mann-Kendall statistic /Z/ > Critical Z value the null hypothesis H_0 was also rejected. From Table 3, it can be observed that the rainfall intensity for all durations exhibited a monotonous upward trend, that is, variation from 3.1701 to 3.2827 and 3.2451 for IMD and MCIMD data, respectively. The standardized Mann-Kendall statistic were all greater than the critical Z value of 1.96. Another verdict is that trend was also detected in the time series data with the absolute standardized Mann Kendall statistic, $|Z|$ being greater than the Critical Z-value. The result from the Mann-Kendall suggest that when developing Intensity Duration Frequency (IDF) curves the change in the hydrological parameters must be accounted for in the IDF model. Non-stationary IDF modeling applies as more appropriate in developing IDF curves for all rainfall durations for Uyo metropolis.

The result from the Sen Slope in Table 3 also showed an interesting relationship. It proved that the magnitude of the trend tends to decrease as the duration of rainfall increased. This implies that shorter duration tend to exhibit more trend than higher duration. The result from the Sen's slope as shown in Figures 8, 9 and 10 indicates that the non-stationary IDF modeling is more pronounced for application in shorter durations. The implication remains that having met the condition for non-stationary modeling doing otherwise the IDF curves of short storms for such time series as in Uyo will produce unreliable and shortfall in rainfall intensity predictions for shorter and longer durations. Most infrastructures are commonly designed with short rainfall duration, meaning that checking the stationarity of a time series is vital before developing IDF curves. This is in agreement with earlier findings of [35]. Therefore, there exist the need to improve the short comings inherent in the assumption of stationarity in hydro-meteorological time series analysis as in the case of the study area for enhanced intensity prediction. The incorporation of time-varying hydro-meteorological parameters such as location, scale and shape function separately or as combined have been recommended to be considered as co-variates in modeling temporal changes applicable in non-stationary IDF modeling [36-38].

The result after the Mann Kendall test for the 24-hourly MMS also confirmed that the test statistic (4.756) was greater that the critical Z value of 1.96, which translated to the monotonous cumulative increase in the rainfall precipitation from 1986 to 2015. The Sen Slope and intercept was 0.090 and 35.89 respectively. These later results is not surprising as it gave credence to the fact that the downscaled rainfall intensities came from the same statistical population. The 24-hourly AMS data could provide an adequate representative time series data for a more accurate IDF modeling for prediction of rainfall intensity of any catchment area.

3.2.4 Comparison of Rate of Change in Magnitude and Trend of Evaluated Test Statistic

The results of the MK trend and Sen Slope analysis presented in Table 3 also proved that both test exhibited high degree of consistency. They both showed statistically significant positive trend increase in their values of evaluated parameters for 24 hours higher duration to 0.25 hour in lower duration. The observed performance in consistency of both test are in conformity with some published work [27, 29, 39].

The magnitude in positive trend variation are statistically significant as presented in Table 3. The Sen Slope estimator quantified the rate of change in magnitude of rainfall intensity at 24 hour duration for IMD as 0.0889 mm/hr per year and for MCIMD as 0.0885 mm/hr per year which translate to an average of 2.1288 mm/year or 21.288mm/decade. This result is in agreement with the publications of earlier authors such as [40] who got 13mm/decade for Ghana and [9] who had 55.2 mm/decade for gauge station in the Niger Delta. Both work were coastal stations located along the Gulf of Guinea. However, the results were in disagreement with those of [30] whoes work focused in the Nigerian hinterland. They found a negative (decreasing) trend in the rate of variability of rainfall amount (mm/year) and in MK test statistic. This is an evidence that confirms the assertion of climatic change variability in Nigeria of trend on rainfall increasing in the coastal region and vice versa in the continental interiors [9-12].

3. CONCLUSION

The study established hydro-meteorological trend and variability existence in 24-hourly AMS and MMS time series data for Uyo metropolis. Curves of rainfall intensity (mm/hr) plotted against time (in years) for downscaled shorter durations, visually showed a uniform distribution of the rainfall intensity from 1986 to 2005 with a sharp increase noticed from 2005 to 2015 for both AMS and MMS data. The rainfall intensity from 1986 to 2005 exhibited stationarity, while 2005 to 2015 exhibited non-stationarity. The statistical tool adopted for non-stationarity check, was the Mann-Kendall (MK) test, performed after Trend Free Pre-Whitening (TFPW) to remove serial autocorrelation at 95% confidence level. The results of the MK test gave computed p-values of 0.0012 for MCIMD data with a range from 0.0012 to 0.0015 for IMD data series. The p-values were lower than the significant level of alpha, $\propto = 0.05$. The rainfall intensity for all durations exhibited a monotonous upward trend that varied from 3.1701 to 3.2827 and 3.2451 for IMD and MCIMD data, respectively. The standardized MK statistic were all greater than the critical Z value of 1.96 confirming trend in the time series data with the MK statistic, $|Z| >$ Critical Z-value. The null hypothesis H_0 was accordingly rejected, because trend was found to exist. The MK test statistic of 4.756 for the 24-hourly MMS also confirmed trend in the time series data which translated to the monotonous cumulative increase in the rainfall precipitation from 1986 to 2015. The Sen Slope and intercept obtained was 0.090 and 35.89 respectively. These later indices proved the fact that the downscaled rainfall intensities came from the same statistical population. This means that the 24-hourly AMS data was representative of the population and provided an adequate and reliable time series data for IDF modeling for prediction of rainfall intensity.

The result from the Sen Slope estimator indicated that the magnitude of the trend decreased as the duration of rainfall increased such that shorter durations exhibited more trend than higher durations. The results of the MK trend and Sen Slope analysis proved that both test exhibited high degree of consistency with statistically significant positive trend and variability. The Sen Slope estimator quantified the rate of change in magnitude of rainfall intensity at 24 hour duration for IMD and MCIMD an average of 2.1288 mm/year or 21.288mm/decade. From the foregoing, planning for IDF modeling for accuracy and effective rainfall prediction delivery will no doubt require 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.

COMPETING INTERESTS DISCLAIMER:

Authors have declared that no competing interests exist. The products used for this research are commonly and predominantly use products in our area of research and country. There is absolutely no conflict of interest between the authors and producers of the products because we do not intend to use these products as an avenue for any litigation but for the advancement of knowledge. Also, the research was not funded by the producing company rather it was funded by personal efforts of the authors.

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