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General Extreme Value Fitted Rainfall Non-Stationary Intensity-Duration-Frequency (NS-IDF) Modelling for Establishing Climate Change in Benin City

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Abstract: The study focused on fitting non-stationary rainfall Intensity-Duration-Frequency (IDF) curves based on the General Extreme Value (GEV) distribution function to establish climate change existence in Benin City. The intensity levels were calculated, with the aid of the open-access R-studio software. Four linear behavioural parameter models considered for incorporating time as a covariate had the second model selected for producing the least corrected Akaike Information Criteria (AIC_C). The AIC_C varied from 370.30 to 125.20 for 15 and 1440 minutes, respectively, used in the calibration of the GEV equation. The computed non-stationary intensities produced higher values above those of stationary models, showing that the later IDF models undervalued extreme events. Differences of +15.24% (18.22 mm/hr), +9.4% (7.37 mm/hr), and +12.64% (12.78 mm/hr), for a 2, 10, and 50-year return periods, respectively, are serious underestimation from a stationary IDF model. Having extreme value differences could further aggravate the flood risk more than the design provision for the drainage facilities. The test statistic result confirmed a significant difference at a 95% confidence level between the non-stationary and stationary IDF curves, showing evidence of climatic change influenced by location as the time-variant parameter. The use of shorter-duration storms is advised for design purposes because they produce higher intensities and percentage differences in the extreme values, increasing the flood risk and infrastructural failures to induce climatic change in the study area.

Keywords: Rainfall, Time Series Data, Trend, Non-Stationary, Stationary, Curve Fitting

1. Introduction

Rainfall Intensity-duration-frequency (IDF) models are mathematical formulas derived in hydrology to calculate design storms in terms of the intensity of rainfall against its duration of fall for a given return period or, against the return period for a specified rainfall duration. The graphical representation of the mathematical formulation when values are assigned is known as IDF curves. IDF curves are very important for the design of different types of hydraulic facilities, for example, stormwater drainage systems, culverts, irrigation channels, and Dams.

Rainfall IDF models are applied in the conversion of the rainfall intensities into runoff volume in the design of hydraulic infrastructures. The stationary rainfall IDF model assumes that extremes do not vary significantly over time.

Non-stationary IDF modelling applies dynamic time series data to allow for the use of the sample mean, variance and covariance changes over time. The non-application of Non-stationary concepts in hydrological modelling leads to inaccurate results [1]. The measured rainfall data is checked for a trend to ascertain the presence of dynamic sequential behaviour. When the trend is significant, the location parameters can be evaluated using the non-stationary assumption. The state-of-the-art studies are on the development of IDF curves based on the non-stationary concept [1-4]. Bougadis and Adamowski [2] opined that the simple scaling process of rainfall IDF relationship is more efficient with more accurate estimates in non-stationary IDF modelling than from the stationary approach.

A framework for evaluating climate change impacts on natural and developed infrastructures applying bias-corrected multi-model simulations on historical and projected precipitation extremes was outlined [5]. Changes in rainfall IDF curves and their uncertainty bounds were derived using a non-stationary model integrating Bayesian Inference. Further studies by several authors on IDF modelling show that the Non-stationary framework for IDF modelling gives a better fit to the sample data than the stationary method [1, 6].

This study is focused on the development of a 24-hourly annual maximum series (AMS) non-stationary rainfall IDF model for Benin City using a statistical approach to fit the general extreme value (GEV) distribution function with the aid of non-stationary behavioural parameters to establish climate change existence in the study area. The basic steps for developing a 24-hourly GEV distribution function-based non-stationary model and its stationary-based parameter model counterpart are summarized and presented in a flowchart [7].

2. Materials and Methods

2.1. Study Area

Benin City is the capital of Edo State in the South-Central region of Nigeria. It is located between longitudes 5°34' E – 5°44' E and latitudes 6°52' N – 6°21' N, as shown in Figure 1. See details of the study area description as presented in our earlier publication [8].

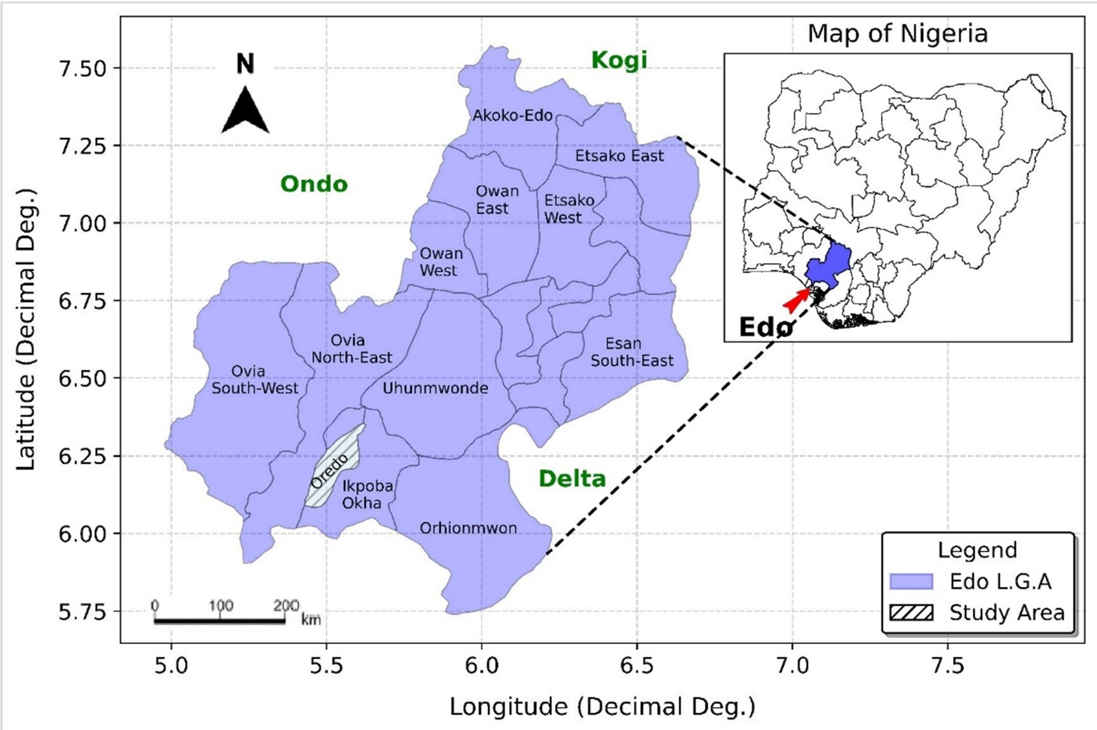

Figure 1. *Map of Edo State showing the study area - Benin City.*

2.2. Data Collection

The observed rainfall data for this study were recorded for about three and a half decades precisely 36 years (1982-2017), from the Nigeria Meteorological Agency (NIMET) gauge station at Benin City. The data collected were sorted out by extracting the 24-hourly annual maximum series (AMS) rainfall time series data from the maximum monthly series (MMS) for each year for the rest of the 36-year interval. The 36-year 24-hourly AMS data were further downscaled into shorter durations using the relationships established by the Indian Meteorological Department (IMD) and the Modified Chowdhury Indian Meteorological Department (MCIMD) scaling methods. See more details of the calibration and scaling process in the author's earlier publications [8, 9].

2.3. Climatic Trends Check in the Time Series Data

Non-stationary IDF modelling (NS-IDF) requires the testing for non-stationarity signals on the measured rainfall data as a precondition. For the detection of whether the trends are statistically significant or not in the time series data, the rank-based non-parametric Mann-Kendall (MK) method with the Sen's Slope Estimator (SSE) was applied to the data [10-12]. The details of the procedure can be found in our earlier publications [8, 13].

2.4. Fitting Non-Stationary IDF Curves with Generalized Extreme Value (GEV) Distribution Function

The introduction of the time-dependent parameters into the general intensity-duration-frequency relationship was the basis of the GEV distribution functions [14]. The standard cumulative distribution function (CDF) of the GEV is shown in Equation (1) [15], with more information on the procedure also available in our earlier study [8].

$$F(x) = \exp\left[-\left(1+\ \xi(t)\frac{x-\mu(t)}{\sigma(t)}\right)^{-1/\xi(t)}\right] \text{ for } \xi \neq 0 \quad (1)$$

Where F(x) = Cumulative Distribution Function, ξ = shape parameter, μ = mean and σ = standard deviation.

2.5. Deriving GEV Time-Variant Parameter Models

The extreme value theory of stationary random series assumes that statistical properties of extremes such as distribution parameters $\theta = (\mu, \sigma, \xi)$ are independent of time [16]. In contrast, for a non-stationary process, the parameters of the fundamental distribution function are time-dependent and have time-varying properties [17]. To represent a dynamic distribution, the location and scale parameters are assumed to be linear functions of time to account for non-stationarity, with the shape parameter kept constant [4, 14, 16, 18, 19]. Thus, the time-varying covariates are incorporated into GEV location and both location and scale parameters respectively, thereby describing trends as a linear function of time in years.

This study considered four different linear model combinations of the GEV parameters by assuming a case of linear trend for location and linear trend for scale parameters and their different combinations as in the literature [9, 20]. We have Model type $GEV_t - 0$ = where all parameters are assumed constant for stationary case; GEV_t – I is $\mu(t) = \mu_o + \mu_1 t$; GEV_t – II is $\sigma(t) = \sigma_o + \sigma_1 t$; and GEV_t – III is $\mu(t) = \mu_o + \mu_1 t$, and $\sigma(t) = \sigma_o + \sigma_1 t$. Given a typical rainfall duration of values $X = X_1, X_2, \ldots, Xn$, for n years of the annual maximum time series. The log-likelihood for the Stationary is expressed as written in Equation (2) based on the condition of Equation (3).

$$\log L(\mu, \sigma, \xi \mid X) = -n\, l\, o\, g\, \sigma - \left(1+\frac{1}{\xi}\right)\sum_{i=1}^{n} log\left[1+\xi\left(\frac{x_i-\mu}{\sigma}\right)\right] - \sum_{i=1}^{n}\left[1+\ \xi\left(\frac{x_i-\mu}{\sigma}\right)\right]^{-1/\xi} \quad (2)$$

$$\text{For } \xi \neq 0 \text{ and } 1+\xi\left(\frac{x_i-\mu}{\sigma}\right) > 0, \quad (3)$$

Where, the Maximum Likelihood Estimates (MLEs) parameter values allow for the extension to the non-stationary case, in which the parameters of the GEV distribution depend on time, t [21]. To obtain the parameters of extreme distributions as the GEV is by minimizing the negative log-likelihood function evaluated using iterative numerical method.

Sequel to the derivation of the GEV parameter model values, the next step is to identify which of the GEV parameter models best represents the original data. To select the best model, the corrected Akaike Information Criteria (AICc) is preferable, because it penalizes the minimized negative log-likelihood for the number of parameters estimated [21]. The AICc is recommended in practical applications because it outperforms the original AIC and helps to avoid over-fitting the data [22].

2.6. Deriving Stationary & Non-Stationary Intensity Duration Frequency Curves

The fitting of Non-stationary IDF curves based on the GEV distribution function requires the determination of the best GEV behavioural extreme parameters for substitution into the CDF formula in Equation (1). So that to enable the evaluation of the rainfall intensities, x_T, assuming stationarity (i.e., constant value) of the behavioural parameters, Equation (1) is solved by inversion of the CDF to have the subject of the equation as written in Equation (4) [3, 15]:

$$x_T = \left[\left(-\frac{1}{In\,P}\right)^{\xi} - 1\right] \text{x}\ \frac{\sigma}{\xi} + \bar{\mu},\ (\xi \neq 0) \quad (4)$$

Where x_T = rainfall intensity exceedance value, and T = return period. The return periods and return levels of extremes in Equations (4) are determined by expressing return levels as a function of the return period T as in Equation (5) [6]

$$T = \frac{1}{1-\text{P}} \quad (5)$$

Where p is the non-exceedance probability of occurrence in a given year, assumed constant under the stationary IDF concept. Also, for each return period and duration, the intensity values are calculated with IDF curves plotted.

However, by estimating the model parameters on the conditions of Non-stationarity in terms of the behavioural parameter extremes, it can be extended to estimate the Non-stationary return level or rainfall intensity as given in Equation (6):

$$\bar{x} = Q_K(\mu_{t1}, \mu_{t2}, \ldots, \mu_{tn}),\ (\mu(t) = \mu_1 t +\ \mu_o)$$

$$x_T = \left[\left(-\frac{1}{In\,P}\right)^{\xi} - 1\right] \text{x}\ \frac{\sigma}{\xi} + \bar{\mu},\ (\xi \neq 0) \quad (6)$$

Where x_T = rainfall intensity exceedance value, and T = return period. The return levels are also translated into intensities for each return period and duration, with the IDF curves plotted.

For example, let us compute the rainfall intensity values for both Stationary and Non-stationary GEV fitted Curve given 15-minute rainfall at 2-year return periods for a daily annual time series data collected for 30 years just like the case of Benin City.

For Stationary Case – Using the intensity formula from Equation (4) with the computed GEV parameters from Table 1: location, μ=146.178; scale, σ = 35.22, and shape, ξ =0.0304 for T = 2 years return period. The rainfall intensity, x_T can be obtained by making necessary substitutions;

$T = \frac{1}{1-P} \Rightarrow P = 1 - \frac{1}{T} = \frac{2-1}{2} = \frac{1}{2} = 0.5$; ie, From Equation (5), so that the rainfall intensity.

$$x_T = \left[\left(-\frac{1}{In\ 0.5}\right)^{0.0304} - 1\right] \times \frac{35.22}{0.0304} + 146.178 = 12.98 + 146.178 = 159.16 \text{ mm/hr}$$

For Non-stationary Case - From Table 1, the GEV_t - I parameter model is the best selected with the least AIC_C and the parameters are obtained as follows; Location, $\mu(t) = 118.019 + 1.495t$; Scale, $\sigma(t) = 28.11$, and Shape, $\xi = 0.1722$, with data collection time, t = 36 years. Substituting the time, t = 30 years we have; $\mu(t) = 118.019 + 1.495 \times 36 = 171.849, \sigma(t) = 28.11$, and $\xi = 0.1722$.

Therefore, substituting the values of the calculated parameter estimates into Equation (6) for Non-stationary rainfall intensity computation for 2 year return period for the 15-minute duration we have;

$$x_T = \left[\left(-\frac{1}{In\ 0.5}\right)^{0,1772} - 1\right] x\ \frac{28.11}{0.1722} + 171.849 = 10.634 + 171.849 = 182.48 \text{ mm/hr}$$

2.7. Comparing Non-Stationary Against Stationary Predicted Rainfall Intensities

Graphical plots of computed rainfall intensities against durations were carried out for a given return period, with the return period against duration at a given duration. The statistically significant differences between the best non-stationary model and the stationary models were evaluated using the Wilcoxon signed rank sum non-parametric test. Acceptance is given to the null hypothesis if the critical value corresponding to alpha, $\propto = 0.05$ at reduced sample size, n, were greater than the computed statistic value. The statistical significance of the best non-stationary model compared to the stationary model was measured by the p-value of the Wilcoxon signed rank statistic test at a 5% level of significance [24].

3. Results

3.1. Generalized Extreme Value (GEV) Behavioural Parameter Models Evaluation

Thirty-six years of measured rainfall data were collected and sorted into 24–hourly Annual Maximum Series (AMS) for each year. The data were disaggregated using the IMD and MCIMD downscaling models into shorter durations as in our earlier published work [9, 13].

The condition for non-stationary IDF modelling requires evidence of trend existence in the time series data which was a positive trend. The performances of the different linear parameter models selected are shown in Table 1. They are expressed as functions of time with their derived values. The best in performance of the non-stationary models was chosen based on the corrected Akaike Information Criteria (AICc) obtained to represent the time series data. The selected linear parameter models were substituted into Equations (4) and (6) for the evaluation of the rainfall intensities.

3.2. Fitting GEV Distribution Function IDF Curves

The open-access R Studio software package was used to develop the rainfall IDF curves [25]. The CDF of the GEV formula given in Equation (1) was used for fitting both the stationary and the non-stationary IDF curves. The GEV distribution has the combination of the Gumbel, Frechet and Weibull distributions which constitutes the necessary and required condition expressed in Equation (3). Thus, the formulation of Equation (1) enabled the optimization of the log-likelihood function of Equation (2) which allowed for its extension to the non-stationary modelling, in which the parameters of the GEV distribution depend on time *t*. The GEV Equation (1) when inverted results in Equations (4) & (6) used for the computation of the rainfall intensity values. The parameters of the GEV formula were obtained by minimizing the negative likelihood function through an iterative numerical approach. Subsequently, Non-stationarity was introduced by expressing one or more of the parameters of the GEV as a function of time that were selected.

The rainfall intensity values were computed for the non-stationary IDF curves based on the selected best model. The linear model with the least AIC_c presented in Table 1 is GEVt-I., on the basis for which the rainfall intensities were estimated. The results of the rainfall intensities computed for both the stationary and non-stationary models were plotted together. Figure 2 shows the plots of the GEV distribution fitted non-stationary and stationary against duration IDF curves on the same graph paper for given return periods, while Figure 3 shows the GEV distributionfitted non-stationary and stationary against return period IDF curves plotted on the same graph paper for given durations, respectively.

3.3. Percentage Differences Between Non-Stationary and Stationary IDF Curves

The graphical plots of rainfall intensity values against duration, and return period presented in Figures 2 and 3, respectively, show a visual difference between the non-stationary and the stationary models at each plotting point. However, it is important to verify if the differences were statistically significant. The computed rainfall intensity values for stationary and non-stationary obtained were evaluated to obtain their percentage differences. The Wilcoxon non-parametric paired test of significance was carried out to verify this fact if the percentage differences were significant at a 95% Confidence level.

Table 1. *Performance of GEV Parameters Evaluated for Non-Stationary and Stationary Models for Benin.*

Time (mins)	Model	Location Parameter	Scale	Shape Parameter	AIC	AIC_c
15	GEV_t – 0	146.178	35.22	0.0304	376.74	377.49
	GEV_t – I	118.019 + 1.495t	28.11	0.1722	369.01	*370.30*
	GEV_t – II	149.704	45.231 – 0.653t	0.1842	377.13	378.42
	GEV_t - III	117.743 + 1.511t	27.785 + 0.0194t	0.1718	371.011	373.01

Time (mins)	Model	Location Parameter	Scale	Shape Parameter	AIC	AIC_c
30	GEV_t – 0	84.753	20.997	0.0297	339.47	340.22
	GEV_t – I	68.003 + 0.890t	16.773	0.1717	331.71	*333.00*
	GEV_t – II	89.937	27.110 – 0.395t	0.1856	339.86	341.15
	GEV_t - III	67.854 + 0.899t	16.597 + 0.0094t	0.1713	333.71	335.71
45	GEV_t – 0	61.751	15.493	0.0301	317.57	318.32
	GEV_t – I	49.407 + 0.655t	12.773	0.1725	309.86	*311.15*
	GEV_t – II	63.326	19.978 - 0.290t	0.1861	317.967	319.26
	GEV_t - III	49.280 + 0.662t	12.237 + 0.0073t	0.1722	311.857	313.86
60	GEV_t – 0	49.345	12.487	0.0305	302.036	302.79
	GEV_t – I	39.405 + 0527t	9.971	0.172	294.33	*295.62*
	GEV_t – II	50.6118	16.074 - 0.233t	0.185	302.429	303.72
	GEV_t - III	39.293 + 0.534t	9.849 + 0.0066t	0.1719	296.327	298.33
120	GEV_t – 0	28.809	7.447	0.0295	264.801	265.55
	GEV_t – I	22.868 + 0.316t	5.947	0.1707	257.055	*258.35*
	GEV_t – II	29.57	9.594 - 0.129t	0.1844	265.199	266.49
	GEV_t - III	22.802 + 0.319t	5.876 + 0.0039t	0.1704	259.052	261.05
360	GEV_t – 0	12.339	3.277	0.0284	205.655	205.66
	GEV_t – I	9.737 + 0.138t	2.623	0.1678	197.984	*197.98*
	GEV_t – II	12.671	4.217 - 0.061t	0.183	206.05	206.05
	GEV_t - III	9.706 + 0.140t	2.589 + 0.0018t	0.1675	199.98	201.98
720	GEV_t – 0	7.258	1.952	0.0289	168.386	169.14
	GEV_t – I	5.681 + 0.084t	1.551	0.1758	160.488	*161.78*
	GEV_t – II	7.464	2.529 - 0.037t	0.1878	168.745	170.04
	GEV_t - III	5.677 + 0.00838t	1.545 + 0.0003t	0.1754	162.488	164.49
1440	GEV_t – 0	4.268	1.173	0.0269	131.606	132.36
	GEV_t – I	3.331 + 0.0497t	0.9358	0.168	123.911	*125.20*
	GEV_t – II	4.387	1.5078 - 0.022t	0.1796	132.016	133.31
	GEV_t - III	3324 + 0.0501t	0.9304 + 0.0004t	0.1664	125.99	127.99

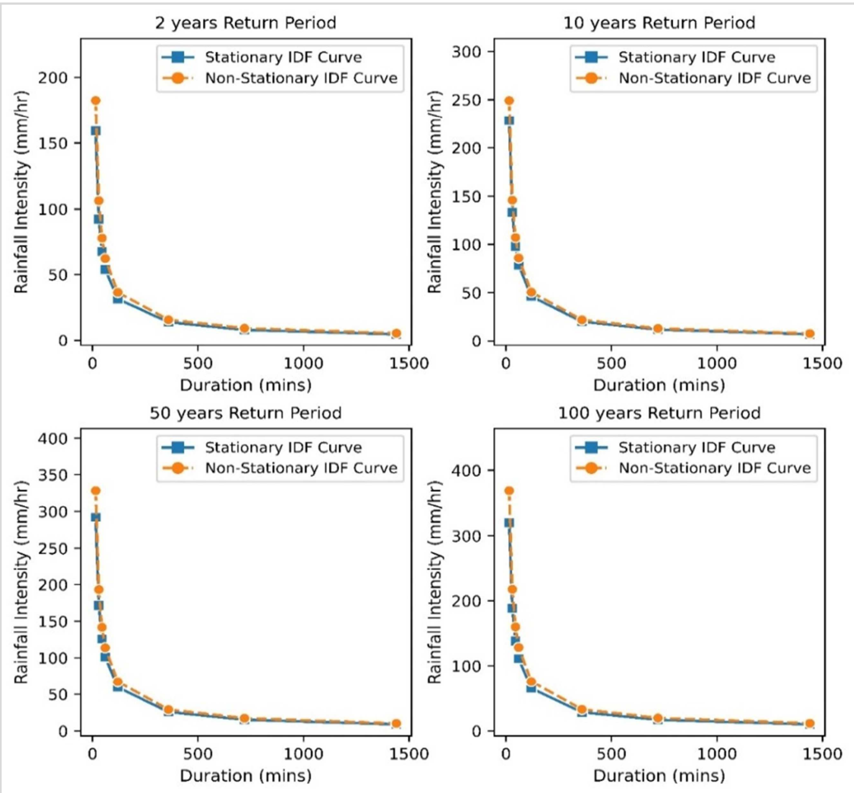

Figure 2. *GEV Distribution Fitted Non-stationary versus Stationary IDF Curves for Different Return Periods for Benin.*

Table 2. *Percentage Difference of Rainfall Intensities between Non-Stationary and Stationary IDF Curves for Benin.*

Duration (mins)	Return Period (years)					
	2	5	10	25	50	100
15	14.65±	9.85	9.15	10.31	12.37	15.30
30	15.04	10.08	9.36	10.53	12.60	15.57

Duration (mins)	Return Period (years)					
	2	5	10	25	50	100
45	15.13	10.11	9.39	10.63	12.67	15.67
60	15.24	10.14	9.40	10.55	12.64	15.62
120	15.53	10.36	9.54	10.67	12.75	16.06
360	13.43	10.54	9.72	10.77	12.80	15.72
720	16.29	10.73	9.91	11.23	13.44	16.60
1440	16.38	10.89	9.87	10.87	13.09	16.08
Av. %tage Difference	15.21	10.34	9.54	10.69	12.79	15.83

± Percentage Difference of Rainfall Intensities

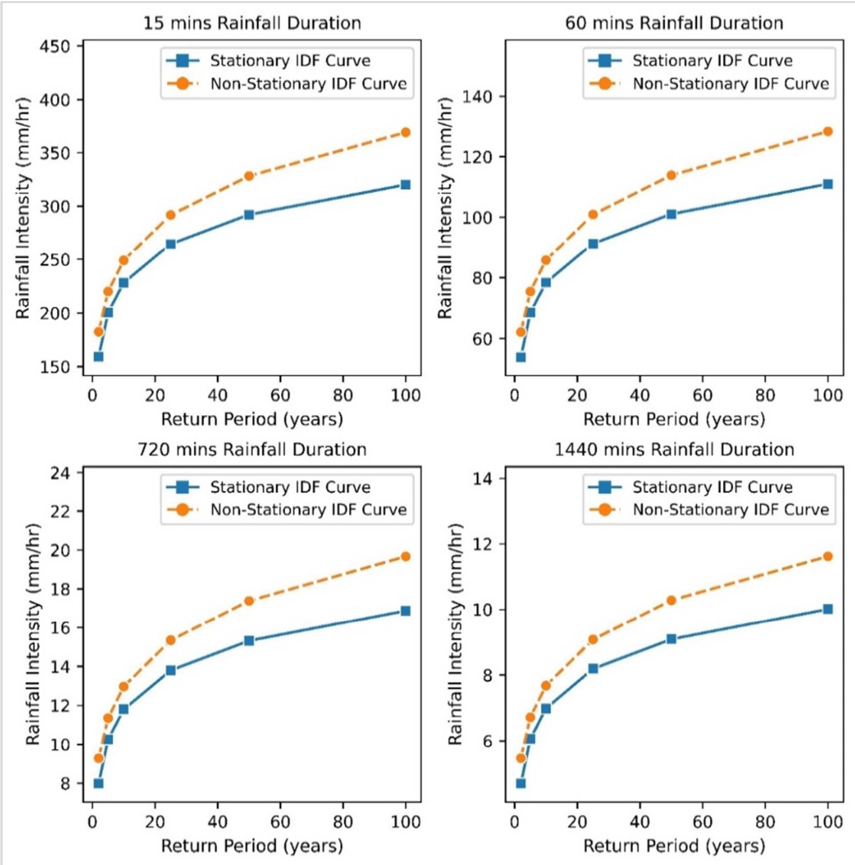

Figure 3. *GEV Distribution Fitted Non-Stationary versus Stationary IDF Curves for Different Durations for Benin.*

The two-tailed statistic test was carried out for rainfall intensities against duration for a given return period and rainfall intensities against return period for the given duration. The Wilcoxon statistic test result was compared with the critical p-value at alpha, ∝ - value of 5% level of significance.

4. Discussion

4.1. Analysis of Evaluated GEV Behavioural Parameter Models

This research study was carried out based on 24-hourly measured annual maximum series (AMS) data constructed using the Modified Chowdhury Indian Meteorological Department (MCIMD) downscaling method. The MCIMD downscaling models produced higher rainfall intensity values than other models for different shorter durations of 0.25 to 1.0 hours typical of urban drainage, and 2 to 24 hours longer duration applied in large-scale or rural infrastructural designs. The downscaled rainfall intensities (mm/hr) plotted against duration (years) showed a strong positive (i e., increasing) trend as obtained in our earlier publication [13].

The behavioural parameters considered were scale, location, and shape, expressed in four different linear models for the integration of time as co-variate in the calibration of the GEV distribution Equation (1). The GEVt – 0 is the first linear model applied at constant values of the various parameters, the same as the stationary assumption model of the Gumbel Extreme Value 1 (GEVT-1). The second model, GEVt – I have time as a co-variate with location as the behavioural parameters while the scale and shape parameters remain constant. The GEVt – II is the third model, having time as a co-variate with scale parameters, while location and shape parameters are constant. The fourth model, GEVt – III has the shape parameter constant while the time is co-varying with both location and scale parameters.

For the Benin City meteorological station, the best-performed linear model was the model with the least AIC_C, chosen as reasonable and representing the non-stationarity better. Therefore, the second model, GEVt – I was chosen as the best parameter model for the calculation of the parameters required for calibration of the GEV Equation (1). The equation was adopted in the calculation of the non-stationary rainfall intensities for various durations in a given return period, and also for different return periods in a given duration.

4.2. The Analysis of Evaluated GEV Distribution Function Fitted IDF Curves

The R-studio software was applied for all the computations to obtain the rainfall IDF curves fitted based on the GEV distribution function. The formula for obtaining the cumulative distribution function for the GEV distribution has a family of three distribution functions controlled by the shape function when it is either zero, more than zero or less than zero, given in Equation (1). The expression of the equation into the log-likelihood form in Equation (2) provided the basis for computing the parameters of the GEV distribution function for both stationary, vis-a-vis the extension of the principles to the non-stationary condition where time is integrated as a co-variate [22]. The parameters were, therefore, calculated on the satisfactory condition of Equation (3) through optimization of the minimization of the negative log-likelihood achieved by iteration.

The intensity levels for various downscaled durations for any given return period were computed from Equation (1), inverted to derive Equation (6) which were applied with the values of the best linear parameter model substituted to obtain the non-stationary intensities. The intensities of the stationary model were also calculated based on model 1, that is, GEVt – 0 which is the stationary counterpart. The intensity levels computed for both stationary and Non-stationary models were plotted against duration for a given return period on the same normal graph paper, to obtain the IDF curves shown in Figure 2. Also, the plot of the computed intensities was made against the different return periods for a given duration presented in Figure 3.

4.3. Analysis of Percentage Difference Between Non-Stationary & Stationary IDF Curves

The plotted curves in Figures 2 and 3 show glaring visual differences for intensity levels against both return levels and duration, respectively. However, the plots in Figure 2 may require further confirmation in terms of the percentage differences. The calculated percentage differences presented in Table 2 showed that for the plots in Figure 2, the intensity values for the non-stationary distributions produced higher values above those of stationary distributions for Benin City. This implies that the stationary distribution function delivers IDF curves that underestimate extreme events as in the literature [3]. For example, considering a 1-hr storm duration event gave the percentage difference between the non-stationary and stationary extreme rainfall of +15.24% (18.22 mm/hr), +9.4% (7.37 mm/hr), and +12.64% (12.78 mm/hr), for a 2, 10, and 50 year return periods, respectively. Such differences of 18.22 mm/hr, 7.37 mm/hr, and 12.78 mm/hr, rainfall intensities in a 1-hour duration storm for a small catchment area could lead to serious underestimation of the peak flood from a stationary IDF curve. The obtained extreme value differences could worsen the flood risk more than the design provision. These under estimations signify that if the stationary intensities were applied for infrastructural designs, such a project may not contain extreme hydrologic events as indicated by the non-stationary counterpart to guarantee safety for some particular return periods [3, 4, 20].

Further observation revealed that the intensity of rainfall indicated higher differences between non-stationary and stationary at short durations. Because, at a 2-year return period, the rainfall intensity differences between the distributions varied from 8.22 mm/hr to 1.3 mm/hr for 1-hour and 12-hour storm durations, respectively. While at the 100-year return period, the intensity difference at 1 hour is 17.34 mm/hr and reduces to 2.8 mm/hr at 12-hour storm duration, and tends to zero (1.62 mm/hr) at 24-hour storm. This result suggests that emphasis should be laid on shorter duration storm for design purposes because it occurs with higher intensities showing higher differences in the extreme values, which have the potential of increasing the flood risk that causes hydrological facilities failure, consistent with an earlier study [8].

The study also observed differences between the non-stationary and stationary intensities in Benin City to have increased with higher durations from 15 min to 1440 min for 2 and 5-year shorter return periods, but reduced in value at 1440 min for 10, 25, 50, and 100 years return period. This proves that longer-duration events have not changed much for concern over the succeeding years, while shorter-duration events persistently increased [3].

To further establish the existence of a statistically significant difference between both intensity distributions, performance evaluation for a two-tailed sample using Wilcoxon signed rank sum statistic was carried out for given return periods, and also for given duration. The Wilcoxon signed rank sum test statistic calculated was 0.0143 for all return periods, which is less than the critical p-value at alpha, $\propto$ value = 0.05. Also, the Wilcoxon signed rank sum test statistic was calculated as 0.0360 for all durations. These values computed being less than the critical p-value at a 5% level of significance, the result affirms that there are significant statistical differences between the non-stationary and stationary IDF curves.

5. Conclusion

This study has proven that Benin City with a positive trend in the time series data requires non-stationary IDF modelling. Among four linear behavioural parameter models considered for incorporating time as a covariate. The second model, GEVt – I with time as a covariate and location as the behavioural parameter dominating, while the scale and shape parameters are constant in the study area. The linear model produced the least corrected Akaike Information Criteria (AICC) varying between 370.30 to 125.20 for 15 and 1440 minutes, respectively, and was selected for calibration of the GEV equation for the computation of intensity levels. The computed intensities showed that the non-stationary curves were higher than the stationary curves, indicating that the computed stationary intensities underestimate extreme storm events. Where, a 1-hr storm duration rainfall event produced a percentage difference between the non-stationary and stationary of +15.24% (18.22 mm/hr), +9.4% (7.37 mm/hr), and +12.64% (12.78 mm/hr), for a 2, 10, and 50 year return periods, respectively; and for a small watershed could lead to serious underestimation of the peak flood. The test statistic result proved a significant difference at a 95% confidence level between the non-stationary and stationary IDF curves.

This study also shows emphasis should be on shorter duration storms for design purposes because they produced higher intensities and higher percentage differences in the extreme values which could increase the flood risk and infrastructural failures.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Ouarda, T. B. M. J., Yousef, L. A. and Charron, C. (2019) Non-stationary Intensity-Duration- Frequency Curves Integrating Information Concerning Tele-connections and Climatology https://doi.org/10.1002/joc.5953

[2] Adamowski, K. and Bougadis, J. (2006) Detection of Trends in Annual Extreme Rainfall. Hydrological Processes, 17: 3547-3560. https://doi.org/10.1002/hyp.1353

[3] Cheng, L. and AghaKouchak, A. (2014) Non-Stationarity Precipitation Intensity- Duration-Frequency Curves for Infrastructure Design in a Changing Climate. Science Reports, 4, Article No. 7093, 1-6. https://doi.org/10.1038/srep07093

[4] Ganguli, P. and Coulibaly, P. (2017) Does Non-Stationary in Rainfall Require Non-Stationary Intensity-Duration Frequency Curves? Hydrology and Earth System Sciences, 21, 6461-6483. https://doi.org/10.5194/hess-21-6461-2017.

[5] Aghakouchak, A., Ragno, E., Love, C. and Moftakhari, H. (2018) Projected Changes in California's Precipitation Intensity-Duration-Frequency Curves. California's Fourth Climate Change Assessment, California Energy Commission. Pub. No.: CCCA4-CEC-2018-005.

[6] Ren, H., Hou, Z. J., Wigmosta, M., Liu, Y. and Leung, L. R. (2019) Impacts of Spatial Heterogeneity and Temporal Non-Stationarity of Intensity-Duration-Frequency Estimates – A Case Study in a Mountainous California-Nevada Watershed. Water, 11, 1296. https://doi.org/10.3390/w11061296

[7] Sam, M. G., Nwaogazie, I. L and Ikebude, C. 2023a. Establishing Climatic Change on Rainfall Trend, Variation and Change Point Pattern in Benin City, Nigeria. International Journal of Environment and Climate Change, 13 (5): 202-212. https://doi.org /10.9734/IJECC/2023/v13i51761.

[8] Sam, M. G., Nwaogazie, I. L., Ikebude, C., Iyang, U. J. and Irokwe, J. O. 2023b Modeling Rainfall Intensity-Duration-Frequency (IDF) and Establishing Climate Change Existence in Uyo-Nigeria Using Non-Stationary Approach. Journal of Water Resource and Protection, 15, 194-214. https://doi.org/10.4236/jwarp.2023.155012

[9] Sam, M. G., Nwaogazie, I. L. and Ikebude, C. (2021). Improving Indian Meteorological Department Method for 24-hourly Rainfall Downscaling to Shorter Durations for IDF Modeling. International Journal of Hydrology, 5 (2), 72-82. https://doi.org/10.15406/ijh.2021.05.00268

[10] Yue, S. and Wang, C. (2004) The Mann-Kendall Test-Modified by Effective Sample Size to Detect Trend in Serially Correlated Hydrological Series. Water Resources Management, 18 (3), 201-218. https://doi.org/10.1023/B:WARM.0000043140.61082.60

[11] Ahmad, I., Tango, D., Wang, T., Wang, M. and Wagan, B. (2015) Precipitation Trends over Time Using Mann- Kendall and Spearman's Rho Tests in Swat River Basin, Pakistan, Advances in Meteorology, 2015, Article ID: 431860. https://doi.org/10.1155/2015/431860.

[12] Okafor, G. C., Jimoh, O. D. and Larbi, K. I. (2017) Detecting Changes in Hydro-Climatic Variables during the Last Four Decades (1975-2014) on Downstream Kaduna River Catchment, Nigeria. Atmospheric and Climate Sciences, 7, 161-175. https://doi.org/10.4236/acs.2017.72012

[13] Sam, M. G., Nwaogazie, I. L. and Ikebude, C. (2022). Climate Change and Trend Analysis of 24-Hourly Annual Maximum Series Using Mann-Kendall and Sen's Slope Methods for Rainfall IDF Modeling. International Journal of Environment and Climate Change, 12 (2), 44-60. https://doi.org/10.9734/ijecc/2022/v12i230628

[14] Cheng, L., AghaKoucak, A. Gilleland, E. and Katz, R. W. (2014) Non-Stationary Extreme Value Analysis in a Changing Climate. Climate Change, 127, 353-369. https://doi.org/10.1007/s10584-014-1254-5

[15] Coles, S., Bawa, J., Trenner, L. and Dorazio, P. (2001). An Introduction to Statistical Modeling of Extreme Values. Springer, London. https://doi.org/10.1007/978-1-4471- 3675-0

[16] Renard, B., Sun, X. and Lang, M. (2013) Bayesian Methods for Non-Stationary Extreme Value Analysis. In Extremes in a Changing Climate; Springer: Dordrecht. The Netherlands, pp. 39-95. https://doi.org/10.1007/978-94-007-4479-0_3

[17] Meehl, G. A. et al. (2000) An introduction on trends in Extreme Weather and Climate Events: Observations, Socioeconomic Impacts Terrestrial Ecological Impacts and Model Projections. B Am Meterol Soc. 81, 413-416. https://doi.org/10.1175/1520-0477(2000)081<0413:AITTIE>2.3.CO;2

[18] Katz, R. (2010) Statistics of Extremes in Climate Change. Climate Change, 100, 71-76. https://doi.org/10.1007/s10584-010-9834-5

[19] Gilleland, E. and Katz, R. W. (2011) New Software to Analyze How Extremes Change Over Time. EOS Trans. Am. Geophys. Union. 92, 13-14. https://doi.org/10.1029/2011EO020001

[20] Silva, D. F., and Simonovic, S. P. (2020) Development of Non-Stationary Rainfall Intensity Duration Frequency Curves for Future Climate Conditions. Water Resources Research Report No: 106. Department of Civil and Environmental Engineering, Western University, Canada, 43 pages. ISBN (print) 978-0-7714-3137-1; (Online) 978-0-7714-3138-8.

[21] Katz, R. W. et al. (2013) Statistical methods for nonstationary extremes. In: Kouchak, A. A., et al. (Eds.). Extremes in a Changing Climate: Detection, Analysis and Uncertainty. Springer, Dordrecht, pp. 15-37. https://doi.org/10.1007/978-94-007-4479-0_2

[22] Sugahara, S., and Rocha, R. P. and Silveira, R. (2009) Non-stationary frequency analysis of extreme daily rainfall in Sao Paulo, Brazil, 29, 1339–1349. https://doi.org/10.1002/joc.1760.

[23] Cooley, D. (2013) Return Periods and Return Levels under Climate Change. Extremes in a Changing Climate, Springer, Netherlands. https://doi.org/10.1007/978-94-007-4479-0_4

[24] Kothari, C. R. and Garg, G. (2014) Research Methodology: Methods and Techniques. 3rd ed. New Age International (P) Limited, Publishers, New Delhi.

[25] RStudio Team (2020) RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.