**Modeling Rainfall Intensity-Duration-Frequency (IDF) and Establishing Climate Change Existence in Abakaliki-Nigeria Using a Non-Stationary Approach**

**Abstract**

Rainfall Intensity Duration Frequency (IDF) models are essential tools for obtaining the rainfall intensity necessary for designing hydraulic structures. Underestimation of rainfall intensities from stationary rainfall models can lead to inadequate designs. Stationary models fail to account for the changing variations in climatic parameters. This study aims to develop non- stationary IDF curves for Abakaliki, Nigeria, using a 31- year rainfall record (1992-2022) obtained from the Nigerian Meteorological Agency (NIMET). The 24- hour rainfall data from NIMET were downscaled to shorter durations using the Indian Meteorological Department (IMD) formula. Non- stationarity in the rainfall data was identified using the Mann-Kendall test, a non-parametric method. Abrupt changes in the rainfall data were detected using two change point tests: Distribution- free CUSUM and Sequential Mann- Kendall. The General Extreme Value distribution was employed to develop the non-stationary IDF rainfall models. Three distinct General Extreme Value (GEV) distribution models were assessed to determine the best-fitting non-stationary model according to the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). For the trend change, results from the Mann- Kendall test provided sufficient evidence that rainfall in Abakaliki shows an increasing trend (p-value = 0.0059). The findings suggest that the statistical parameters are not constant over time and that non-stationary approaches are required for IDF modelling in Abakaliki. The change point test identified 2010 and 2012 as probable points of change in the rainfall trend. Out of the three models assessed, GEVt- III displayed the best performance across most duration intervals (10-1440 minutes) indicated by its lowest AIC values ranging from 218.897 to 328.818. For the 5- minute duration, GEVt- I was the best non-stationary model with the lowest AIC of 207.946. A generalised non-stationary IDF model was created, demonstrating exceptional predictive ability (R² = 0.996, MSE = 37.00). These results emphasise the necessity of incorporating non-stationary methods in infrastructure design in Abakaliki, as conventional stationary approaches may significantly underestimate rainfall intensities in the era of climate change.

**Keywords**: Rainfall Intensity-Duration-Frequency (IDF), Climate change, Stationary, Non-stationary modeling, General Extreme Value (GEV) distribution, Mann-Kendall trend analysis, Change point detection

**1. Introduction**

The rising occurrence and severity of extreme precipitation events are critical issues in hydrology and civil engineering, especially regarding infrastructure design and urban drainage management. Rainfall Intensity-Duration-Frequency (IDF) curves provide relationships between rainfall intensity, storm duration, and their occurrence frequency, making them essential in the design of hydraulic structures (Endreny & Imbeah, 2009; Ganguli & Coulibaly, 2017). Traditionally, these IDF relationships have been established based on the assumption of stationarity, which means that the statistical characteristics of extreme rainfall are assumed to remain constant over time (Sam et al., 2023). However, this foundational assumption has come under increased scrutiny as climate change continues to alter precipitation patterns globally (Milly et al., 2008; Tramblay et al., 2013; Ekwueme et al., 2025).

Climate change is anticipated to intensify the hydrological cycle, as the Clausius-Clapeyron relationship states that the atmospheric capacity to hold water increases by about 7% for every 1°C of warming (Trenberth, 2011; Lenderink & van Meijgaard, 2008). This physical relationship directly influences precipitation intensity, potentially increasing the frequency and severity of extreme rainfall events (Cheng & AghaKouchak, 2014; Westra et al., 2013). The changes in precipitation patterns lead to nonstationary, meaning that the statistical characteristics of extreme rainfall vary over time, which necessitate a time component to be introduced to IDF model development to account for the variations of the statistical parameters over time.

In Nigeria, especially in the southeast around Abakaliki, the effects of climate change are becoming more apparent through changes in rainfall patterns and intensities (Ekwueme et al., 2024). Traditional IDF curves that do not account for non-stationarity can significantly underestimate future rainfall extremes. The utilisation of a stationary IDF model for design could result in insufficient infrastructure design and a heightened flood risk (Cheng & AghaKouchak, 2014). Cheng and AghaKouchak (2014) showed that conventional stationary methods for IDF development may underestimate extreme precipitation by up to 60% in areas undergoing substantial climate change. This difference underscores the essential requirement for nonstationary methods considering temporal variations in rainfall patterns. Several researchers have proposed frameworks for developing nonstationary IDF curves, incorporating time-varying parameters in extreme value distributions (Cheng & AghaKouchak, 2014; Agilan & Umamahesh, 2016; Ganguli & Coulibaly, 2017; Ekwueme et al., 2024). The General Extreme Value (GEV) distribution has emerged as a particularly useful model for incorporating nonstationarity, as it allows for temporal changes in distribution parameters (Tramblay et al., 2013; Ganguli & Coulibaly, 2017). Studies have employed various approaches to model nonstationary, including linear trends in distribution parameters and incorporating covariates such as global temperature anomalies, urbanisation indicators, and climate indices (Agilan & Umamahesh, 2016; Ali & Mishra, 2017).

Despite the progress in nonstationary IDF model development, nonstationary IDF methods are still not widespread in Nigeria, especially in the southeast. Nwaogazie and Sam (2020) found that most IDF studies in Nigeria continue to depend on stationary methods, even as evidence of climate change's effects becomes more apparent. This study aims to address this knowledge gap by developing nonstationary IDF curves for Abakaliki, Nigeria, using a 31-year rainfall record spanning from 1992 to 2022.

**2. Materials and Methods**

**2.1 Study Area**

Abakaliki, the capital of Ebonyi State, is in southeastern Nigeria, specifically in the South-Eastern region, at coordinates 6.3231°N latitude and 8.1120°E longitude. The city has a tropical climate with a rainy season from March to October and a dry season from November to February. Its climate is shaped by its position in the Guinea Forest-Savanna mosaic ecoregion, which typically yields substantial annual rainfall, rendering it prone to flooding and other rain-related issues. The city's rapid urbanisation in recent years has increased its exposure to climate change effects, particularly regarding alterations in rainfall patterns.

A map of nigeria with a yellow and green map

AI-generated content may be incorrect.

**Figure 1**: Map of the study Area

**2.2 Data Collection**

The research employed long-term Abakaliki historical rainfall data spanning thirty-one years. A 31-year rainfall dataset covering the period from 1992 to 2022 was acquired from the Nigerian Meteorological Agency (NIMET) for analysis in Abakaliki. The data obtained was the 24-hour monthly rainfall record for Abakaliki. To obtain smaller durations, the Indian Meteorological Department (IMD) formula, which is given by Equation (1) was utilised (Sam & Nwaogazie, 2021). The shorter duration records obtained included 5, 10, 20, 30, 60, 120, 360, and 720 minutes.

= (1)

Where = Downscaled rainfall precipitation, = daily rainfall precipitation (mm), t = time.

**2.3 Trend and Change Point Detection**

The trend and change point analysis was done before developing the rainfall intensity duration frequency models. The trend analysis was carried out to determine how the statistical parameters of rainfall fluctuated over time and to support the development of a non-stationary IDF model. Mann-Kendall test, which is a non-parametric test, was utilised in assessing whether there is a trend in the rainfall data. The following Mann-Kendall equations were used in computing for the Mann Kendall statistic (Mann, 1945; Kendall, 1948).

*S* = (2)

= (3)

V = (4) (5)

Where x = observed data values (e.g., monthly or annual rainfall amounts), n = total number of observations in the time series, S = Mann-Kendall test statistic, sign(xⱼ − xᵢ) = sign function, V(S) = variance of the test statistic S, tₚ = number of tied values in the p-th tied group, q = total number of tied groups in the data, Z = standardized normal statistic used to determine the significance of the trend

Change point analysis was performed to pinpoint significant shifts in the rainfall data. The distribution-free CUSUM (McGilchrist & Woodyor, 1975) and Sequential Mann-Kendall (Sneyers, 1990) methods were used to identify the change point year. The change point tests were conducted utilized R-studio Trendchange library.

**2.4 Development of Non-Stationary IDF Model**

The General Extreme Value Distribution was utilised in developing the non-stationary IDF model. The Generalised Extreme Value (GEV) distribution has been implemented for the modelling of various behavioural extremes through its three distribution parameters: location, scale, and shape (Cheng et al., 2014; Akanbi, 2020). The standard cumulative distribution function (CDF) of the GEV distribution, as formulated by Coles et al. (2001), is expressed in Equation (6). This statistical framework provides a parametric approach for quantifying the probability of extreme events across multiple domains of inquiry.

(6)

Where F(x) = Cumulative distribution function, = mean (location), = standard deviation (scale) and, = shape parameter are three behavioural parameter extremes.

The maximum likelihood estimator served as the statistical method for estimating distribution parameters, as it can be readily adapted for non-stationary evaluations. Non-stationarity arises from expressing one or more statistical parameters of the GEV as a function of time (Coles et al., 2001; Katz, 2013). Three linear non-stationary expressions were used to develop the IDF models, as shown in Table 1. The optimal non-stationary model was chosen based on the goodness of fit indicated by AIC and BIC. Among these, the model exhibiting the lowest AIC and BIC was considered the best match for the rainfall's non-stationarity. R-studio facilitated the retrieval of model parameters and the calculation of rainfall intensity.

**Table 1:** Types of Selected GEV Linear Parameter Models

|  |  |  |
| --- | --- | --- |
| **Model Type** | **Parameter Combination** | **Remark** |
| (i) GEVt – 0 |  | Stationary parameter model |
| (ii) GEVt – I |  | Non-stationary parameter model |
| (iii) GEVt – II |  | Non-stationary parameter model |
| (iv) GEVt – III |  | Non-stationary parameter model |

Source: Silva and Simonovic (2020)

**2.5 Calibration of the Generalised Sherman IDF model.**

The computed rainfall intensity obtained after developing the IDF non-stationary model was fitted to the Sherman IDF model, which is given in Equation (7). David et al. (2019) detailed how the Sherman model is calibrated utilising Microsoft Excel Solver. The Least Squares method is utilised in fitting the rainfall intensity to the Sherman model Equation. The Solver optimises for the best model parameter values that produce the highest R2 and least Mean Squared Error.

I = (7)

Where: I = Rainfall intensity; Tr =return period; Td =rainfall duration; a, m and c are model parameters/constants.

**3. Results**

Table 2 shows the trend outcomes for Abakaliki. The Mann-Kendall test indicated a statistically significant upward trend in rainfall, with a test statistic of 2.7534 and a p-value of 0.0059. The result from the Mann-Kendall provides sufficient evidence that the rainfall at Abakaliki is on the rise, and the statistical parameters of the rainfall will change over time. The result prompts the use of a non-stationary approach for modelling the rainfall. The change point analysis results in Table 3 demonstrate that both methods yield similar findings. The CUSUM test pinpointed 2010 and 2012 as potential change point years, though these points were not statistically significant at 90% and 95% confidence levels. This was further supported by the Sequential Mann Kendall (SQMK) test, which identified 2010 as a change point. The close occurrence of these change points (2010-2012) indicate a potential shift in rainfall patterns during this timeframe for Abakaliki. The results from both the Mann-Kendall and change point analyses strongly suggest that climate change is impacting rainfall precipitation in Abakaliki; therefore, a non-stationary method should be applied to develop the IDF model.

**Table 2: Mann-Kendall test and Sen’s Slope estimates result for Abakaliki.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Time** | **Z-Value** | **p-value** | **Qi** | **Intercept** | **Status** |
| 5mins | 2.7534 | 0.0059 | 0.3457 | 5.0052 | increasing |
| 10mins | 2.7534 | 0.0059 | 0.4352 | 6.3117 | increasing |
| 20mins | 2.7368 | 0.0062 | 0.5483 | 7.9561 | increasing |
| 30mins | 2.7534 | 0.0059 | 0.6278 | 9.1026 | increasing |
| 60mins | 2.7534 | 0.0059 | 0.7909 | 11.4770 | increasing |
| 120mins | 2.7534 | 0.0059 | 0.9965 | 14.4622 | increasing |
| 360mins | 2.7534 | 0.0059 | 1.4374 | 20.8491 | increasing |
| 720mins | 2.7534 | 0.0059 | 1.8109 | 26.2670 | increasing |
| 1440mins | 2.7534 | 0.0059 | 2.2817 | 33.0939 | increasing |

**Table 3**: Change Point for Abakaliki

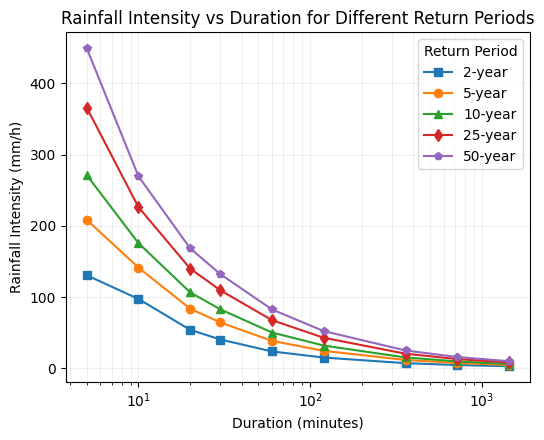
| **Test Type** | **Statistic** | **p-value** | **Trend/Change Point** | **Remark** |
| --- | --- | --- | --- | --- |
| CUSUM | 5.0 | - | 2010 and 2012 | Not Significant (CI: 90%, 95%) |
| SQMK | - | - | 2010 | Steady positive increase from 2013 to 2019 |

Table 4 presents the development of the non-stationary IDF model. Analysing the GEV parameters uncovers intriguing patterns across various time durations from 5 to 1440 minutes. For 5-minute duration, the GEVt- I model exhibited the best fit, achieving an AIC of 207. 946 and a BIC of 213. 682. However, as durations extended to 10 minutes or more, the GEVt- III model consistently outperformed others with the lowest AIC values- such as 218. 897 for the 10- minute duration versus 223. 555 for GEVt- I. In te intermediate range of 20 to 60 minutes, the GEVt- III model continued to show superiority. Specifically, for the 20- minute duration, the model performed optimally with an AIC of 238. 470. This trend persisted for the 30- minute period (AIC = 247. 691) and the 60- minute duration (AIC = 262. 103). The adjustments in both the location and scale parameters over time indicate that both the central tendency and variability of extreme rainfall events in Abakaliki are evolving.

For the longer durations of 120 to 1440 minutes, the trend remained with GEVt- III consistently yielding the best fits. The analysis for the 720- minute duration recorded an AIC of 314. 329 for GEVt- III, while the 1440- minute duration showed an AIC of 328. 818, both representing the lowest values in their respective duration categories. Figure 2 shows the calculated rainfall intensity for all durations and return periods. This figure serves as a practical resource for engineers to determine rainfall intensity for any duration and return period relevant to Abakaliki. A general IDF model was created to facilitate ease in obtaining rainfall intensity for any duration and return period, as shown in Table 5. This model demonstrated exceptional predictive capability with a high coefficient of determination (R ² = 0. 996) and a relatively modest Mean Square Error (MSE = 37. 00). The elevated R² value indicates that the model accounts for approximately 99.6% of the variability in rainfall intensity, suggesting high reliability for predicting rainfall intensities across various durations and return periods.

**Table 4:** Evaluation of the performance of GEV parameters used for non-stationary and stationary models for Abakaliki

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Time (mins)** | **Models** | **Location Parameter** | **Scale** | **Shape Parameter** | **BIC** | **AIC** |
| 5 | GEV₍t₎ – I | -67.764 + 0.038t | 4.703 | 0.209 | 213.682 | **207.946** |
| GEV₍t₎ – II | 8.443 | 5.158 - 0.0002t | 0.185 | 215.689 | 209.953 |
| GEV₍t₎ - III | -145.167 + 0.076t | -3.348 + 0.004t | 0.31 | 215.269 | 208.099 |
| 10 | GEV₍t₎ – I | -24.522 + 0.018t | 5.846 | 0.193 | 229.292 | 223.555 |
| GEV₍t₎ – II | 10.638 | 6.50- 0.0002t | 0.185 | 230.022 | 224.286 |
| GEV₍t₎ - III | -390.026 + 0.199t | -13.12 + 0.009t | 0.177 | 226.067 | **218.897** |
| 20 | GEV₍t₎ – I | -136.164 + 0.075t | 7.457 | 0.167 | 241.987 | 236.251 |
| GEV₍t₎ – II | 13.402 | 8.190 - 0.0007t | 0.219 | 244.343 | 238.607 |
| GEV₍t₎ - III | -118.461 + 0.066t | -0.115 + 0.004t | 0.203 | 245.64 | **238.47** |
| 30 | GEV₍t₎ – I | 6.277 + 0.005t | 8.948 | 0.1841 | 252.609 | 246.873 |
| GEV₍t₎ – II | 15.342 | 9.376 - 0.0003t | 0.1847 | 252.726 | 246.99 |
| GEV₍t₎ - III | -82.163 + 0.049t | 3.017 + 0.003t | 0.1624 | 254.861 | **247.691** |
| 60 | GEV₍t₎ – I | 9.759 + 0.005t | 10.961 | 0.188 | 266.934 | 261.198 |
| GEV₍t₎ – II | 19.329 | 11.813 - 0.003t | 0.228 | 267.044 | 261.3 |
| GEV₍t₎ - III | -86.316 + 0.0528t | 4.843 + 0.0029t | 0.187 | 269.27 | **262.103** |
| 120 | GEV₍t₎ – I | 17.533 + 0.004t | 14.119 | 0.1791 | 281.315 | 275.58 |
| GEV₍t₎ – II | 24.355 | 14.89 - 0.0005t | 0.1848 | 281.372 | 275.636 |
| GEV₍t₎ - III | -180.216 + 0.102t | 1.492 + 0.0060t | 0.2055 | 282.945 | **275.775** |
| 360 | GEV₍t₎ – I | 35.417-- 0.00011t | 20.081 | 0.1836 | 304.081 | 298.345 |
| GEV₍t₎ – II | 35.119 | 21.47 - 0.0007t | 0.1849 | 304.08 | 298.344 |
| GEV₍t₎ - III | -0.1703 + 0.017t | 19.0 + 0.0004t | 0.1954 | 307.297 | **300.127** |
| 720 | GEV₍t₎ – I | 44.635-- 0.0002t | 25.296 | 0.183 | 318.406 | 312.67 |
| GEV₍t₎ – II | 44.252 | 27.05 - 0.0009t | 0.2336 | 318.405 | 312.669 |
| GEV₍t₎ - III | -24.449 + 0.0343t | 22.28 + 0.0011t | 0.2072 | 321.499 | **314.329** |
| 1440 | GEV₍t₎ – I | 56.244 - 0.0002t | 31.872 | 0.3669 | 332.73 | 326.994 |
| GEV₍t₎ – II | 55.759 | 34.08 - 0.0011t | 0.2321 | 332.728 | 326.993 |
| GEV₍t₎ - III | 12.572 + 0.0215t | 31.23 + 0.0003t | 0.1949 | 335.987 | **328.818** |



**Figure 2: Computed Rainfall Intensity Duration Curves for Abakaliki**

**Table 5:** GEV fitted General Non-stationary IDF (GNS-IDF) model for Abakaliki

| **S/N** | **Station** | **IDF Model** | **R²** | **MSE** |
| --- | --- | --- | --- | --- |
| 1 | **Abakaliki** | I = | 0.996 | 37.00 |

**4. Discussion**

Infrastructure design in Abakaliki could face significant challenges if stationary models are used for developing Intensity-Duration-Frequency (IDF) models. The result from the trend analysis using statistical method like the Mann-Kendall test confirmed a significant increasing trend in rainfall in Abakaliki (p-value = 0.0059), with notable change points identified in 2010 and 2012, establishing clear non-stationarity in the rainfall. The results from developing IDF models utilising non-stationary approach for Abakaliki revealed that the GEVt-III model emerged as the optimal non-stationary model for most rainfall durations, while GEVt-I performed best specifically for 5-minute duration events. The superior performance of GEVt-III demonstrates that both location and scale parameters have changed throughout the 31-year study period. This indicates that the precipitation in Abakaliki gradually increases from year to year, and the variation within each year also changes over the study duration. Continuous utilisation of a stationary model for IDF model development in Abakaliki will significantly underestimate the rainfall intensities, as both the increase in rainfall and its variability are not captured in the stationary models.

The underestimation of rainfall intensity in Abakaliki can create a serious risk for drainage infrastructure design, potentially increasing flood vulnerability throughout Abakaliki. Cheng and AghaKouchak (2014) in their study showed that stationary models can underestimate 50-year precipitation events by up to 60% in certain regions. The global trend towards the adoption of non-stationary analysis is evident in the literature. Sugahara et al. (2009) demonstrated that non-stationary models more accurately represent rainfall intensities, especially in regions where evidence of climate change is noticed. There has been a gradual shift in utilising a non-stationary approach for the IDF modelling. However, the adoption of non-stationary approaches in Nigeria has been relatively slow. Few studies have been done on non-stationary models in Nigeria. Nwaogazie and Sam (2020) noted that most Nigerian IDF studies continue using stationary approaches despite mounting evidence of climate change impacts. AghaKouchak et al. (2018) stated that non-stationary approaches are especially crucial in regions experiencing rapid climate change. Willem et al. (2012) found that incorporating non-stationary patterns in urban drainage design could reduce infrastructure vulnerability by up to 30%. These findings suggest an urgent need to update design standards and infrastructure planning approaches in Abakaliki. Continuing to use stationary approaches would underestimate future rainfall intensities and lead to systemic infrastructure inadequacies, particularly in urban drainage system.

**5. Conclusion**

This study aimed to create non-stationary Intensity-Duration-Frequency (IDF) curves for Abakaliki, Nigeria, utilizing a 31-year rainfall dataset (1992-2022) sourced from the Nigerian Meteorological Agency. Trend and change point analyses indicated that climate change affects rainfall patterns in Abakaliki. The identified significant increasing trend in rainfall intensity and the change points detected in 2010 and 2012 provide compelling evidence of non-stationarity in local precipitation patterns. The GEVt-III model outperformed in most duration intervals, while the GEVt-I model excelled at 5-minute duration, highlighting the limitations of traditional stationary methods for modeling rainfall in this area. The findings correspond with global trends regarding climate change's impact on precipitation patterns and emphasize the urgent need to revise design standards and infrastructure planning in the region. The results indicate that relying on stationary IDF curves for infrastructure design in Abakaliki may lead to substantial underestimation of rainfall intensities, potentially resulting in inadequate infrastructure capacity.

**Disclaimer (Artificial intelligence)**

Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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