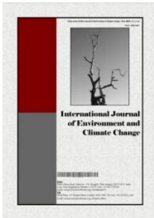

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A Review Study on Stationary and Non-Stationary IDF Models Used in Rainfall Data Analysis around the World from 1951-2020

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Authors' contributions

This work was carried out in collaboration between both authors. Author ILN wrote the protocol, managed and supervised the review article. Author MGS wrote the first draft of the manuscript, the literature searches and documentation. Both authors read and approved the final manuscript.

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ABSTRACT

This article focuses on an overview of the processes of generating rainfall intensity-duration-frequency (IDF) models, the different types and applications. IDF model is an important tool applied in the design of either hydrologic or hydraulic design such as prediction of rainfall intensities to estimate peak runoff volumes for mitigation of flooding. IDF models evolved from stationary – parametric (empirical) and non-parametric (stochastic) models, to non-stationary models in which variables vary with time. Each category controls the ways models predict rainfall intensities, and reveals their strength and weaknesses. IDF models must therefore, be chosen in terms of the project objective, data availability, size of the study, location, output needed, and the desired simplicity. For instance, while the parametric model predicts better for shorter durations and return periods only, the non-parametric models predict better for both shorter and longer durations and return periods. For projects requiring change of input data over time and evaluation of uncertainty bounds, risk assessment, including incorporation of changes in extreme precipitation, the non-stationary model approach must be selected. Also, of importance for catchments without rainfall amount and corresponding duration records but has daily (24-hourly)

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record of rainfall depth, the Indian Meteorological Department (IMD) method of shorter duration disaggregation can be adopted to generate in-put data for the development of IDF curves for such a location. Therefore, each model type has limitations that may make it unsuitable for some projects. Reviewing input data and output requirements, and simplicity are all necessary to decide on which model type should be selected.

Keywords: Stationary; parametric; non-parametric; non-stationary; PDF; IDF models; rainfall-runoff; data.

1. INTRODUCTION

Rainfall is the major component of the hydrologic cycle and is the primary source of runoff which is essentially required to fulfil various demands in human life and his environment. It is a natural phenomenon occurring due to atmospheric and oceanic circulation with local convection, frontal or orographic pattern and has large variability at different spatial and temporal scales [1]. Many attempts have been made to model and predict rainfall behavior using various empirical, statistical, numerical and deterministic techniques. The models may include other input variables, like temperature, information on the catchment or others. Rainfall-runoff models can be classified within several different categories. They can be distinguished between event-based and continuous-simulation models, empirical, conceptual or process (physically) based models, lumped or distributed models, and several others. The classifications are not rigid as sometimes a model may not be clearly assigned to one category [2].

The state-of-the-art monitoring of urban precipitation is based on either a network of rain gauge(s) or weather radars [3]. The application of a single rain gauge as precipitation input carries lots of uncertainties regarding estimation of runoff, because they are point precipitation data. This creates problems for the discharge prediction, especially if the rain gauge is located outside the basin. Rainfall generated runoff is very important in various activities of water resources development and management, such as: flood control and its management, design of irrigation and drainage works, design of hydraulic structures, hydro-power generation, etc. The method of transformation of rainfall to runoff is highly complex, dynamic, nonlinear, and exhibits temporal and spatial variability. This review is therefore, within the context of transformation of rainfall to runoff achieved through the development of intensities-duration-frequency (IDF) models as in the flowchart (diagram) shown in Fig. 1.

A rainfall IDF model is an empirical equation representing a relationship among maximum rainfall intensity (as dependent variable) and other parameters of interest such as rainfall duration and frequency (as independent variables). The simplest type of these models is a relationship between *r*ainfall intensity and duration for a given return period. The severity and frequency of extreme climatic events are growing by the day, thereby calling to question the adequacy of our water resources infrastructures to deal with these changes.

Current infrastructure designs are basically on rainfall Intensity-Duration-Frequency (IDF) models with the so-called stationary assumption, meaning extremes will not vary significantly over time. Stationary IDF relationships are currently constructed based on at-site frequency analysis of rainfall data separately for different durations. These relationships are inaccurate and unreliable because they depend on many assumptions such as distribution selection for each duration; they require a large number of parameters which are not time-dependent. The integration of required parameters led to the evolution of parametric IDF models which have many disadvantages. Examples of parametric IDF models are the quotient, power law and quotient-power models. In order to improve the limitations imposed by the years of data collection in the frequency analysis of rainfall data, the non-parametric IDF models evolved which are probability distribution function (PDF) based IDF models. The frequency analysis of the non-parametric (PDF) based models can be projected beyond the years of rainfall data collection which can be from 2 to 100 year return period. Common PDFs in use include the Gumbel Extreme Value Type-1 (GEVT-1), Log-Pearson Type-3 (LPT-3), Pearson, Normal and Log-Normal distributions in the frequency analysis.

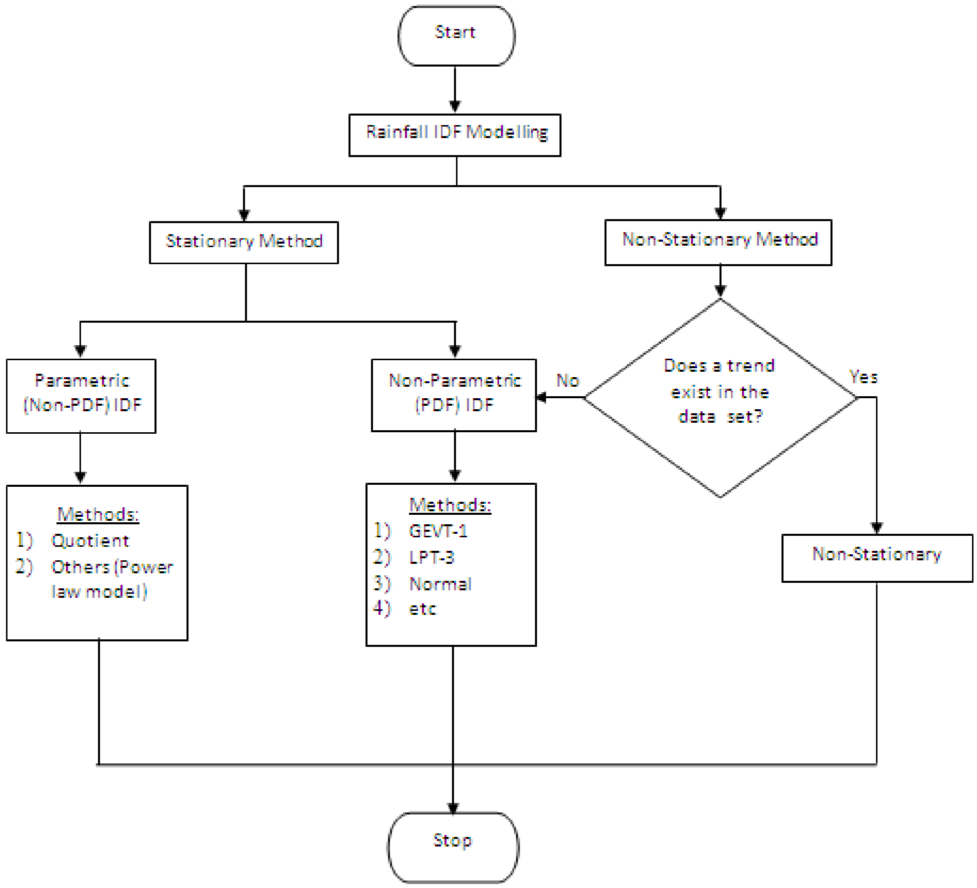

Fig. 1. Flowchart for developing rainfall intensity duration frequency models

On the other hand, non-stationary IDF modeling is one with a dynamic data series in which the statistics of the sample (mean, variance and covariance) change over time. Studies are now focusing on non-stationary IDF modeling in meteorological time series. The implication is that neglecting to incorporate non-stationarities in hydrological models will likely lead to inaccurate results [4]. Significant trend check of the measured rainfall data is required. This is detected using non-parametric rank based Mann-Kendal (MK) test. The null hypothesis of no trend remains rejected if the test statistic is significantly different from zero to 0.05 significance level. If a significant trend is detected, the location parameters will be evaluated based on non-stationary assumption. Thus, allowing the estimation of rainfall quantities which is consistent with the ideal characteristics of the measured precipitation extremes. Otherwise, the non-parametric (PDF) modeling approach is applied as indicated in the flowchart (Fig. 1).

2. TREND IN RAINFALL-RUNOFF MODELLING

Modeling runoff helps gain a better understanding of hydrologic phenomena and how changes affect the hydrological cycle. Runoff models visualize what occurs in water systems due to changes in pervious surfaces, vegetation, and meteorological events [2,5,6] defines a runoff model as a set of equations that aid in the estimation of the amount of rainfall that turns into runoff as a function of various parameters used to describe the watershed. In this paper, the relationship between the IDF models and how it contributes to rainfall-runoff estimation is explored.

2.1 Rational Method

The first widely used runoff method is the Rational Method published by Thomas Mulvaney in 1851, which employed rainfall intensity, drainage area, and a runoff coefficient to determine the peak discharge in a drainage basin [1,5]. In the United States, Kuichling in 1889 applied the rational method to urban drainage designs successfully. Also, in the United Kingdom, the method is often ascribed as the Lloyd-Davis method published in 1906 [7]. Widely accepted by hydraulic engineers, the method is based on the theory that, for a given storm frequency, the maximum runoff rate results from a rainfall intensity of duration equal to the time of concentration of the particular basin. The simplicity of the equation is misleading because "the critical value of the rainfall intensity which can be estimated from IDF models or curves, through the medium of concentration time, entails a consideration of such factors as basin size, shape, and slope; channel length, shape, slope, and conditions; as well as variation in rainfall intensity, distribution, duration, and frequency; all of which can and should be considered in determining its value" [8].

According to [9] recommends the use of Rational method for estimating the design-storm peak runoff from small basins with area up to 200 acres (2ha) and for up to 300 acres (3ha) in low-lying tidewater areas. The Rational method uses an empirical equation that incorporates basin and precipitation characteristics to estimate peak discharges. The method is relatively simple to apply; however, its concepts are sophisticated. Considerable engineering knowledge is required to select representative hydrologic characteristics that will result in a reliable design discharge [9]. Validation of the Rational Method is difficult because direct measurement of some hydrologic characteristics used in the method is not easily obtained. The application of the method requires some assumptions provided by Merit in 1976 [10]. The rational formula is given by the equation:

$$Q = 0.278\, CIA \tag{1}$$

Where; Q is the quantity of runoff in (m^3/s), C is a dimensionless runoff coefficient, I is the rainfall intensity in (mm/hr) corresponding to a particular duration and average recurrence interval (ARI), and A is the tributary or catchment area involved (km^2). For the application of Equation (1), C, I and A must be known, and if A is in (m^2), then; Q becomes:

$$Q = CIA\ (m^3/s) \tag{2}$$

The Rational method uses a rainfall intensity to represent the average intensity for a storm of a given frequency for a selected duration [11]. As noted, assumptions of the method include that the rainfall intensity is constant over the entire basin and uniform for the time of concentration. Amongst the assumptions associated with the Rational method, is that of constant, uniform rainfall intensity that are the least valid in a natural environment. However, the variability of rainfall intensity during a storm and over a basin becomes less as the size of the basin decreases such that these assumptions become more valid. The variability of rainfall intensity in time and space is a major reason for an upper limit on basin size when using the Rational method to estimate peak flow.

Rainfall intensity is selected from an intensity-duration-frequency (IDF) curve generated from point rainfall data collected in a given area. This is, however, possible if both duration and the return period are known. These curves are generated by fitting annual maximum rainfall intensities for specified durations to a Gumbel-probability distribution, usually by plotting the data on extreme-value-probability paper. The rainfall intensity is estimated by transferring the basin time of concentration as duration in minutes through the desired storm frequency curve. The major disadvantages of the rational method is the need for reliable IDF relationship. Secondly, the recurrence interval is assumed to be uniform over the whole catchment.

More recently, the unit hydrograph concept was introduced to conceptualize a catchment's response to a storm event based on the superposition principle [1,5]. The unit hydrograph made it possible to separate base-flow and storm event runoff from stream flow. With increased computing power and a deeper understanding of hydrological processes, runoff models have become more sophisticated.

In general design work, the major advance following the Rational method was the development of computer models for drainage system design and analysis. A number of urban storm water simulation models have been developed after the rational method and the unit hydrograph methods. Some of the frequently used models are: Chicago Hydrograph method (CHM), Road Research Laboratory method (RRL), Illinois Urban Drainage Area Simulator (ILLUDAS), Storm Water Management Model (SWMM) and others [11]. The progress in urban storm water drainage modeling has not been uniform in time and across different countries and regions. Furthermore, the various models may give different solutions to the same problem. Therefore, communities that are experiencing urbanization and climate change may develop their own urban drainage model and local drainage design practice.

2.2 Soil Conservation Service – Curve Number (SCS-CN) Method

The SCS-CN method was developed by the United States Department of Agriculture, Soil Conservation Services (SCS) in 1969. The purpose of the curve number is to describe average condition for design purposes. The curve number was originally developed for agricultural watersheds with a land slope of 5% and an initial abstraction of rainfall of 20% due to infiltration. The initial abstractions consist of interception loss, surface storage, and infiltration prior to runoff.

The SCS-CN method is a simple predictable, and stable conceptual method for estimation of direct runoff depth based on storm rainfall depth. It relies on rainfall amount and curve number (CN). The curve number is based on the area's hydrologic soil group, land use, treatment and hydrologic condition. The first two requirements are of utmost importance. The general equation for the SCS-CN method is an empirical equation expressed in the form:

$$Q = (P - Ia)^2 /[(P - Ia) + S] \tag{3}$$

Where: Q = runoff (mm); P = rainfall (mm); S = potential maximum retention after runoff begins; and Ia **=** initial abstractions. The initial abstraction, Ia can be defined as a percentage of S as shown in Equation (4) giving rise to Equation (5)

$$Ia = 0.2S \tag{4}$$

$$Q = (P - 0.2S)^2/(P - 0.8S) \tag{5}$$

Equation (5) is easily evaluated by substituting S with Equation (6).

$$S = \frac{1000}{CN} - 10) \tag{6}$$

The parameter CN is a transformation of S, and it is used to make interpolation, averaging, and weighting from the linear relationship as indicated in Equation (6). The curve number are therefore determined from chart based on the inputs of the hydrologic soil group, land cover type, and hydrologic condition. Four soil groups are defined as A, B, C, and D according to the infiltration rates. Cover types are determined by photographs and land use maps, ranging from developed surfaces to agricultural and forest areas. The weighted curve number method computes the weighted average of all the curve numbers in the area of interest to provide one curve number for runoff calculation [2].

Once the CN is determined, Equation(5) is employed with known amount of rainfall and initial abstractions to calculate the amount of rainfall translated into surface runoff. The CN method assumes the ratio of actual runoff to potential runoff is equal to the ratio of actual to potential retention. This is a purely empirical process for determining runoff. There is no temporal resolution within the CN calculation in order to consider rainfall duration and intensity. The application of the SCS-CN Weighted Curve Number method is used for ungauged areas and within other models such as the Soil and Water Assessment Tool (SWAT) [12].

Long-term observations on streamflow are generally not available at desired locations, and these records often contain missing data attributable to variety of reasons. Therefore, many hydrological models have been developed in the past [13] for transformations of rainfall into streamflow because of easy availability of rainfall data for longer time periods at different locations. In many of these models, soil conservation service curve number (SCS-CN) model has been widely used for surface runoff computations.

3. ANNUAL MAXIMUM RAINFALL ANALYSIS

3.1 Extreme Value Theory

The field of extreme value theory was pioneered by Leonard Tippett (1902-1985), but in 1958 [14] codified the theory in his book: "Statistics of Extremes" including the Gumbel distribution in his name. Extreme value theory is a branch of the probability that studies the stochastic behavior of the extremes of a set of random variables [15]. The extreme value theory has emerged as one of the most important disciplines of applied science in the last 50 years and it has been used in various fields of science, such as: Climate change, Oceanic modeling, and Hydrology.

Extreme values are selected maximum values of data sets. For example, the annual maximum discharge of a given location is the largest recorded discharge value during a year, and the annual maximum discharge values for each year of historical record make up a set of extreme values that can be analyzed statistically. Distributions of the extreme values selected from sets of samples of any probability distribution converge to one of the three forms of extreme value distributions called types 1, 2, and 3 respectively, when the number of selected extreme value is large. The three limiting forms are special cases of a single distribution called the General Extreme Value (GEV) distribution. It is given by [16] thus:

$$F(x) = exp\left[-\left(1 - k\,\frac{x-u}{\alpha}\right)^{\frac{1}{k}}\right] \tag{7}$$

Where: k, u and α are parameters to be determined. The three limiting cases are: for k = 0 (the Extreme Value Type 1 distribution); for k < 0 (the Extreme Value Type 2 distribution) for which Equation (7) applies for $(u + \alpha/k) \leq x \leq \infty$. For k > 0 (the extreme Value Type 3 distribution) for which Equation (7) applies for: $-\infty \leq x \leq (u + \alpha/k)$. In all three cases, α is assumed to be positive for EV 1 distribution, x is unbounded, while for EV 2, x is bounded from below by $u + \alpha/k$.

The characterization of rainfall and its intensity is important for the estimation of design storm values. Historical time series are analyzed in either of the two following ways being Partial Duration Series (PDS) or Annual Maximum Series (AMS).

3.2 Partial Duration Series (PDS)

PDS include all the values that occur within the period of record as long as they are higher than some threshold value. PDS data used for frequency analysis typically yields higher values for a given frequency than using AMS data. The difference in values is greater in the more frequent events such as 2-year, 5-year and 10-year, and decreases as the recurrence interval increases. For less frequent events such as 25-year, 50-year and 100- year, the difference in values is minimal between the two series. Using a PDS to analyze event frequency increases the sample size by capturing more events of interest, but requires that each data point used represents an independent event. The value of the threshold value also affects the distribution parameters, so special care are taken to choose a good threshold.

3.3 Annual Maximum Series (AMS)

The annual maximum series daily rainfall is defined as an extreme instance with critical duration for a water shed, catchment area, river basin, state or region, with immediate consequences to agriculture, soil conservation, roads, dams and drainage [17]. In many statistical applications the interest is directed towards the estimation of the central features such as mean value, a variable based on random samples from the population under study and draws on ideas that have such key moments which are approximately normal distribution, with theorems of analysis based on the central limit theory. However, as in many applied areas, the climatological characterization of the annual maximum series daily rainfall requires a suitable choice of methodology. These events are not in a central position in the probability distribution. The interest is to identify the occurrence of extreme events, that is, maximum values. The information about the probability of extreme values occurrence is fundamental to the society to prepare for extremes like heavy precipitations events.

AMS include only the highest values that occur within each year of the period of record and AMS are preferable in frequency analysis. As a direct consequence of the increasing trends of daily maximum rainfall, there is an increase of soil loss, increase in carrying out of sediments, and increase loss of fertility resulting in decreased agricultural production. Thus, necessitating the need for recording daily or 24 hourly rainfall data for obtaining extreme value records. The daily annual maximum series when collated are subjected to analysis.

Different approaches have therefore been used for the construction of daily AMS rainfall data in the form of classical highest precipitation amount for different precipitation duration method, and the Indian Meteorological Department (IMD) method of shorter duration rainfall downscaling.

3.3.1 Conventional annual maximum series (CAMS) method

This is the most common approach used for construction of AMS that is applied in rainfall analysis and Intensity-Duration-Frequency (IDF) modeling the world over. The analysis is anchored on ground-based observations of precipitation extremes being the annual maxima. The annual maxima series is constructed by the extraction of the highest precipitation amount for different durations. Thus, numerical analysis is performed on AMS for storm durations such as 5, 10, 15, and 30 minutes which are typical time of concentration for small urban catchments and 1, 2, 6, 12, and 24 hours, also typical time of concentration for larger rural watersheds.

In the USA, [18] adopted the AMS rainfall analysis method to develop a scaling model of a rainfall IDF relationship; [19] used the AMS construction method to develop a generalized framework for estimating IDF curves and their uncertainties using Bayesian inference. Like in USA and other Countries, the AMS method as the most prevalent rainfall analysis method has been of immense utility by Nigerian scholars to develop IDF models for Nigerian cities [20,21,22,23,24].

3.3.2 Indian meteorological department (IMD) method

The availability of observed hourly rainfall data is limited by very poor network of such rain gauges. By analyzing data at some locations where both hourly and daily rainfall data are available [25] proposed a relationship adopted by Indian Meteorological Department (IMD), to disaggregate daily rainfall to a given *'t'* hour rainfall in the form:

$$R_t = R_{24}\left(\frac{t}{24}\right)^{0.33} \tag{8}$$

Where: R_t is the required precipitation depth for the duration *t*-hour in mm, R_{24} is the daily precipitation in mm and *t* is the time duration in hours for which precipitation depth is required.

Using this relationship, daily (24 hourly) rainfall data commonly found in both urban and rural locations especially in developing Countries, can be converted to peak hourly rainfall as may be required for analysis. Thus, from the annual maximum series (AMS) daily (24 hourly) rainfall data recorded for any gauge station, disaggregation can be performed using the IMD empirical formula to shorter durations such as 0.16, 0.33, 0.5, 1, 2, 6 and 12 hours. The derived rainfall values of shorter durations serve as representative values of the various durations from the statistical population of the annual daily extreme values for the gauge station [26]. The IMD method was applied by [27,28] to develop IDF models for Cities in Iraq while [29] applied a modified version of the empirical formula for frequency analysis, infilling and trends for extreme precipitation for Jamaica (1895-2100).

4. RAINFALL INTENSITY-DURATION-FREQUENCY (IDF) MODELING

This section of the review shall focus on the trend of evolution of IDF types from the stationary to non-stationary, their strength and weaknesses including their applications in hydrologic designs.

4.1 Stationary IDF Modeling

Under the assumption of a stationary climate, the concepts of return level and return period provide critical information for design, decision-making, and assessing the impacts of rare weather and climate events such as the return level with a *T*-year return period representing an event that has 1/*T* chance of occurrence in any given year [30]. Infrastructure design concepts have long relied on stationary return levels, which assume no change to the frequency of extremes over time [31]. Frequency distribution and analysis methods is a key feature in differentiating types of stationary IDF modelling that can be classified as either parametric (empirical) or non-parametric (stochastic) IDF modelling.

4.1.1 Parametric IDF modeling

In parametric IDF modeling the parameter of the IDF relationship assume fixed values. In other words, the variables are defined by model parameters. The models are therefore deterministic and continuous; because the variables are not detached but represented in a continuous manner. Empirical continuous probability distribution function (ECPDF) are applied to determine the return period of the rainfall AMS events for historical measured rainfall data. The probability of exceedance of the AMS events are determined by the rank-order method. This method involves ordering the events from the largest events ranked as 1 to the lowest as *m*, being the sample size of events [32,33].

The observed cumulative frequency is computed by the use of the Weibull's plotting position formula:

$$p = m/(n+1) \tag{9}$$

Where; *p* is the exceedance probability for an event with rank *m, m* is the rank of the event and *n* is the sample size. The empirical return period (*T*) of each event is determined as the inverse of its exceedance probability:

$$T = 1/p \tag{10}$$

Major source of uncertainty in the IDF relationship are insufficient quantity and quality of data leading to parameter uncertainty due to the distribution of the data. Thus, it is important to study these uncertainties and propagate them to future for accurate assessment of return levels for future [34]. Also, another major short coming of the IDF models developed from return period *T* obtained from this method of empirical continuous probability distribution function (ECPDE) are that they are return period specific and are seriously limited by the years of data collection. The IDF models showed higher prediction at lower durations of 10 – 40 minutes [23]. Typical empirical equations calibrated for IDF modeling are those of power and quotient-power governing equations.

Studies conducted in Nigeria on IDF development are all site specific and are also based on the stationary concept [20,21,35,36, 37]. Most of the studies applied short precipitation records varying between 10 to 13 years except for those of [37] which were between 17 – 35 years term. The various studies focused on derivation of deterministic IDF models where the variables are defined by the parameters of the calibrated equations.

4.1.2 Non-parametric (stochastic) IDF modeling

When IDF model's relationship has variables which are not defined by the model parameters but rather by the state of the system such as probability distribution functions such a model is said to be stochastic. The sampled data when plotted in a normality graph paper does not exhibit a normal shape but are better described as a non-parametric shape giving either a positive or negative coefficient of skewness. Frequency analyses of the hydrologic data therefore, use probability distributions to relate to the magnitude of extreme events to their frequency of occurrence. The most common and important probability distributions in use are the Normal, Log-Normal, Exponential, Gamma, Pearson Type 1, 2, and 3, Log Pearson, General Extreme Value 1 (Gumbel), General Extreme Value 2 (Frechet), and General Extreme Value 3 (Weibull). The Normal and Log-Normal distribution generally fits to the annual flows of rivers [16].

To deal with frequency analysis of rainfall, emphasis is laid on frequency of occurrence of the events. Thus, probability distribution functions (PDFs) are the basis for analysis. Computing the magnitudes of the extreme random events using the PDF methods requires that the PDFs be given a value for any given return period, (*T*) or [$F(X_T)$ = *T*/(*T*-1)], that can enable corresponding event value X_T , to be computed. The magnitude X_T of any hydrologic event such as rainfall intensity or flooding can be evaluated from Equation (11):

$$X_T = \mu + \Delta X_T \tag{11}$$

Where μ = the mean, and ΔX_T the departure of the variate from the sample mean which can be written as $\Delta X_T = K_T S$; where: *S* = standard deviation, and K_T= distribution factor.

These two parameters are rather functions of return period and PDF type. Equation (11) can be written in the form;

$$X_T = \mu + K_T S \tag{12}$$

Similarly, [16] also proposed that the same formulae applies to the statistics for the logarithmic data, in the form:

$$\log X_T = \log \bar{x} + K_T S_{logx} \tag{13}$$

Where, $\log \bar{X}$ = logarithmic mean and S_{logx} = standard deviation. And the required rainfall intensity, X_T is found taking the antilog of $\log X_T$.

Frequency analysis of any event starts with calculation of the statistical parameters (the mean($\bar{x}$), standard deviation (*S*), and coefficient-of-skewness (C_S)) needed for an intended probability distribution by using methods of moment from the observed data [32]. Equations describing the relationship of the frequency distribution factors (K_T) are provided in literature with their applicable PDFs as applied for generation of relevant frequency distribution factors (K_T) substituted for eventual calculation of the required rainfall intensity values [16,38]. The model varies directly with the probability or inversely with the return period, for a two parameter distribution and coefficient of skewness for a skewed distribution. Frequency factor (K_T) is a function of standard deviation and return period. Recently in Nigeria, pioneering effort has been observed in the use of the stochastic IDF modeling approach to develop IDF models for some cities such as Lokoja, Port Harcourt, Akure and Abeokuta [22, 23, 24]. [23] in their study found that the probability distribution function (PDF) IDF models showed higher prediction at higher durations of 50 – 120 minutes and also predicted higher rainfall intensities for longer return period of 25, 50, and 100 years that were far beyond years of data collection.

4.2 Non-Stationary IDF Modeling

Classical frequency analysis provides adequate engineering design values when the data series from which the probability distribution parameters are to be estimated come from a stationary distribution and the observations are independent or weakly dependent. In contrast to its classical alternative, a dynamic data series is one in which the statistics of the sample (mean, variance and covariance) change over time technically referred to as non-stationary. Non-stationary in hydrologic records can be attributed to local anthropogenic impacts, such as deforestation and other land use change, or to global climate change and low frequency climate oscillations [4,39].

A commonly used tool for the design of water resources infrastructure are rainfall Intensity-Duration-Frequency (IDF) models or curves. Studies are now focusing on non-stationary IDF modeling in meteorological time series. The implications means that neglecting to incorporate non-stationarities in hydrological models will likely lead to inaccurate results [4].

4.2.1 Extreme Value theory in non-stationary IDF modeling

Non-stationary models are generally fit on data series of specific durations. A single model with a separate functional relation with the return period and rainfall duration can be used. The Generalized Extreme Value (GEV) and the Gumbel Extreme Value Type 1 (Gumbel EVT-1) distributions are also used as the time dependent functions in the general IDF relationship [19]. The GEV distribution is a combination of Gumbel, Frechet, and Weibull distributions and is based on the limit theorems for block maxima or annual maxima [40].

The standard cumulative distribution function (CDF) of the GEV as in Equation (7) can be rewritten as expressed by [41]

$$F(X|\mu,\sigma,K) = \exp\left[-\left(1+K\left(\frac{x-\mu}{\sigma}\right)\right)^{\frac{-1}{K}}\right] \quad (14)$$

Where *F(x)* is defined for $1+K\left(\frac{x-\mu}{\sigma}\right) > 0$; where sometimes, *F(x)* is either 0 or 1 [42]. The GEV distribution has the location parameters (μ), the scale parameter (σ) and the shape parameter (*K*) to specify the center of the distribution, the deviation, about μ and the tail behavior of the GEV distribution, respectively. For $K \rightarrow 0$, $K < 0$, and $K > 0$, the GEV leads to the Gumbel, Weilbull and Frechet distributions, respectively.

The extreme value theory of stationary random sequences assumes that statistical properties of extremes such as distribution parameters $\theta = (\mu, \sigma, K)$ are independent of time [43]. However in a non-stationary process the parameters of the underlying distribution function are time-dependent and the properties of the distribution would vary with time [44]. In order to represent a dynamic distribution, the location and scale parameters can be assumed to be linear functions of time to account for non-stationarity, with the shape parameter kept constant [40,43,45,46,47]. Then, μ and σ can be defined as;

$$x_t = \mu_a + K_T\sigma_a \quad (15)$$

$$\sigma(t) = \sigma_1 + \sigma_0 \quad (16)$$

Where *t* is the time in years, x_t denotes the intensity of the *T*-years return period event, K_T is the frequency factor, μ_a and σ_a are the mean and the standard deviation of the set of AMS, respectively. While $\beta = (\sigma_1, \sigma_o)$ are the regression parameters.

The equation for fitting the Gumbel EVT-1 distribution to precipitation of AMS for different return periods *T* is similar to Equation (12) [16], with the frequency factor K_T as:

$$K_T = \frac{\sqrt{6}}{\pi}\left[0.5772 + In\left(In\left(\frac{T}{T-1}\right)\right)\right] \quad (17)$$

4.2.2 Significant trend check in non-stationary IDF modeling

Testing historical records of intensity, data for non-stationary signals are required. The rank-based non-parametric revised Mann-Kendall [48,49,50] method is applied on the data to detect statistically significant trends.

The null hypothesis of no trend remains rejected if the test statistic is significantly different from zero to 0.05 significance level. If a significant trend is detected, the location parameters will be evaluated based on non-stationary assumption. Thus allowing the estimation of rainfall quantities which is consistent with the ideal characteristics of the measured precipitation extremes. The aim of the MK test is to ensure the avoidance of implementing a time varying extreme value analysis in a data that do not indicate a significant change in extremes over time. However, the same method can be technically applied to all data sets regardless of their trend where a subjective significance measure is unnecessary.

4.2.3 Evaluation of time-variant parameters and return level/period

Temporal scaling function for simultaneous determination of trend in frequency parameters (location μ, scale σ, and shape *k*, respectively) for time in years (*t*) for varying growth functions (*i*=0 is no growth, *i*=1 is linear and *i*=2 is power), hence;

$$\widehat{U}(t)=\mu_o+\sum_0^{i=2}\mu_i.t^i \quad (18)$$

$$\hat{\sigma}(t)=\sigma_o+\sum_0^{i=2}\sigma_i\, t^i \quad (19)$$

$$\hat{k}(t)=k_o+\sum_0^{i=2}k_i\, t^i \quad (20)$$

The model parameters are used to estimate the non-stationary precipitation intensity or equivalent return levels. Using the GEV distribution, the return periods and return levels of extremes in Equations (18) to (20) are determined by expressing return levels as a function of the return period *T* [51]:

$$T=\frac{1}{1-\mathrm{P}} \quad (21)$$

Where *p* is the non-exceedance probability of occurrence in a given year, assumed constant under stationary. The *p*-return level q_p derived from the GEV distribution can be expressed as [41,46]:

$$q_p=\left[\left(-\frac{1}{In\,P}\right)^k-1\right]\times\frac{\sigma}{k}+\mu, \quad (K\neq 0) \quad (22)$$

For non-stationary GEV model, time varying covariates are incorporated into GEV location as per Gumbel EVT-1, to describe trends as linear function of time in years, that is, $\mu(t)$ = $\mu_1 t$ + μ_o as in Equations (18). Modeling temporal changes, shape and scale parameters requires long term records, that means, where there are short-term records these two parameters are assumed constant. Therefore, for estimation of GEV parameters, a Bayesian inference is performed combined with Differential Evolution Markov Chain (DE-MC) Monte Carlo (MC) simulation as proposed by [19,46,47]. For the AMS, the parameters are derived by computing 50th (median), 5th and 95th (lower and upper bounds) of the DE-MC sampled GEV parameters. The model parameters are then used to estimate the non-stationary return level as follows:

$$\bar{x}=Q_K(\mu_{t1,}\,\mu_{t2},\ldots.,\,\mu_{tn}),\ (\mu(t)=\mu_1 t+\mu_o) \quad (23)$$

$$q_p=\left[\left(-\frac{1}{In\,P}\right)^k-1\right]\mathrm{x}\,\frac{\sigma}{K}+\bar{\mu}, \quad (k\neq 0) \quad (24)$$

The computation of non-stationary design storm intensity is similar to the stationary model except the inclusion of time-varying location parameters. The calculation can be performed following [52] using an MATLAB-based software package, non-Stationary Extreme Value Analysis (NEVA), Version 2.0.

A number of studies have been focused on the development of IDF curves with consideration of non-stationary concept [4,18,19,47]. [18] proposed scaling method of rainfall IDF relationship and reported that rainfall follow simple scaling process which is more efficient and gives more accurate estimates in non-stationary IDF modeling than that from traditional techniques.

Severe climatic conditions with potential human and socioeconomic consequences induced decades of observed warming climate with more intense precipitation in some regions of the world likely due to increase in the water holding capacity of the atmosphere require integration in non-stationary IDF development. [53] outlined a framework for quantifying climate change impacts on natural and man-made infrastructures using bias-corrected multi-model simulations of historical and projected precipitation extremes. The approach evaluates changes in rainfall IDF curves and their uncertainty bounds using a non-stationary model based on Bayesian inference. The research went on to show that highly populated areas across California may experience extreme precipitation that is more intense and twice as frequent, relative to historical records, despite the expectation of unchanged annual mean precipitation. [4] in their investigation of non-stationary IDF curves integrating information concerning tele-connections and climate change presented the study result that showed that non-stationary framework for IDF modeling provides a better fit to the data than stationary counterpart. Thus, providing a generalized approach which is more robust than the common methods especially for stations with short rainfall records. In assessment of future changes in IDF curves for Southern Ontario using Northern American (NA) - CORDEX models with non-stationary methods, [54] found that extreme precipitation intensity driven by future climate forcing indicated a significant increase in intensity relative to baseline period and exhibited opposite trend for longer return period. [55] worked on impacts of spatial heterogeneity and temporal non-stationary on IDF estimates – A case study in a Mountainous California – Nevada Watershed. The result presented proved the existence of strong heterogeneity and variability in IDF estimates using high resolution simulation data and discrepancies in spatial variability supports the use of an ensemble of non-stationary approach.

4.3 IDF Model Relationships

Intensity-Duration-Frequency (IDF) relationships provide the basis for estimating the design storm value. IDFs are usually constructed using historical rainfall records under the assumption of stationary, that is, the future rainfall has the same statistical characteristics as the historical rainfall [56]. These relationships can be calculated for both point rainfall and spatial averages. From IDF equations or curves, design rainfall can be derived. Typical empirical IDF relationships usually adopted for calibration found in literature are of the form shown in Equations (25) to (28) [16,57].

Talbot equation, $I(T_d, T_r) = \frac{CT_r^m}{T_d+b}$ (25)

Sherman equation, $I(T_d, T_r) = \frac{CT_r^m}{(T_d+b)^a}$ (26)

Modified Sherman equation, $I(T_d, T_r) = \frac{CT_r^m}{{T_d}^a}$ (27)

Kimijima equation, $I(T_d, T_r) = \frac{CT_r^m}{{T_d}^a+b}$ (28)

Where; I (T_d, T_r) are the intensities for a given aggregation level or duration T_d and or return period T_r. C > 0 is scale parameters b > 0, 0 < a < 1 are shape parameters and for some cases a, assume the value of 1. The modified Sherman's equation was applied in the form given in Equation (27) [8,16,23,58,59,60]. Where: I = rainfall intensities (mm/hr); T_r = return period in years; T_d = duration of rainfall in minutes; and c, a, and m = physiographic constants. The equation depicts probabilities that are conditional of rainfall-intensities averages over duration typical of storm intervals.

Equations (25) to (28) are empirical and show that rainfall intensity is a decreasing function of rainfall duration for a given return period. The equation parameters represent the influence of climatic and physiographic features of the catchments or drainage basin on rainfall. Different organizations and researchers have applied IDF models in any of the listed equation forms. [61] used a model of Equation (25) type to fit rainfall data throughout the United States. The constants (a and b) serve as characteristics features of both the region and the frequency of rainfall occurrence. For instance, [62] used Equation (26) type, which relates rainfall intensity to rainfall duration, along with a table of the coefficients tabulated as a function of recurrence interval for each of the 254 counties of the state. [63] provided intensity-duration relationships for a 10 year recurrence interval based on Equation (25) type. [64,65] used Equation (26) type to develop rainfall IDF models and studies of Urban drainage failures and incidence of flooding in Southern Nigeria, respectively. [66] also adopted Equation (25) model type for fitting rainfall intensities in Nigeria.

4.4 IDF Model Calibration

For efficient and accurate prediction of rainfall intensities in a catchment, model calibration to the specific catchment is required. There are different ways to calibrate an IDF model; the manual process which may include trial-and-error, linearization and graphical method. Manual calibration is time-consuming and experience is needed to obtain a good calibration [5]; difficulty in determining when the best-fit has been achieved is another flaw [67]. Automatic methods using computer based algorithms such as optimization technique speeds up the calibration time and accuracy of predicted intensities. Least squares methods and maximum likelihood methods are examples of goodness-of-fit techniques that put a value on correctness in numerical relationship between observed and predicted rainfall intensities [54].

5. COMPARATIVE MODELS' PERFORMANCE AND GAP ANALYSIS

The trend of research in IDF modeling is herein summarized in tabular format with respect to the authors, title of articles, contributions and gaps (i.e areas not covered in the study).Tables 1a & b present summary account on Non-stationary IDF modeling world-wide and stationary IDF modeling in a developing nation (Nigeria).

Table 1a. Non-stationary IDF modeling

Authors	Title of Article	Contribution(s)	Gap(s)
[18]	Scaling model of a rainfall Intensity-Duration-Frequency relationship.	Results showed that rainfall follow simple scaling process. This is more efficient and gives more accurate estimates in non-stationary IDF modelling than that from traditional techniques.	The study did not account for climate change impact in non-stationary IDF modeling. Research is not in present study area.
[28]	Developing of rainfall IDF model for Sulaimam City.	The study found that the LPT-3 was better than the Gumbel EVT - 1 IDF models developed using IMD method to downscale rainfall data with reduced duration from daily AMS.	The study developed stationary IDF models with sufficient data.
[27]	Drawing curves of the rainfall IDF and assessment equation intensity of rainfall for Nasiriyah City, Iraq.	The study found that the LPT-3 was better than the Gumbel EVT - 1 IDF models developed using IMD method to downscale rainfall data with reduced duration from daily AMS.	36 years rainfall data were used to develop stationary IDF models.
[19]	Non-stationary Precipitation IDF Curves for Infrastructure Design in a changing climate.	The study provided a generalized framework for estimating non-stationary IDF curves and their uncertainties using Bayesian inference.	The study failed to integrate impacts from changing climatic condition and parameters. Work was not in present study area.
[47]	Does non-stationarity in rainfall require non-stationary intensity-duration-frequency curves?	The study revealed that despite signals of non-stationary in rainfall extremes in all locations, the stationary versus non-stationary models do not exhibit any significant difference in the design storm for short intervals. But needs updates of 2-44% in current IDF models.	The research emphasis was not to develop IDF equations nor did it incorporate climate change parameters. The focus was on evaluation of the validity of non-stationary modeling.
[53]	Projected changes in California's precipitation I-D-F curves.	The study approach evaluates changes in rainfall I-D-F curves and their uncertainty bounds using a non-stationary model based on Bayesian inference.	The study did not develop IDF model with empirical equations but computed rainfall intensities to draw IDF curves from GEV-CDF.
[4]	Non-stationary I-D-F curves integrating information concerning Tele-connections and climate change.	Results of study showed that non-stationary framework for IDF modeling provides a better fit to the data than its stationary counterpart. That the generalized approach is more robust than the common methods especially for stations with short rainfall records.	The study did not apply downscaled RCM data from GCM ensemble but applied co-variate of time and climate indices or oscillations, with measured rainfall data to derive non-stationary

Authors	Title of Article	Contribution(s)	Gap(s)
			IDF curves. Work was not in study area.
[54]	Assessment of future changes in I-D-F curves for Southern Ontario using Northern American (NA)-CORDEX models with non-stationary methods.	Results indicated that extreme precipitation intensity driven by future climate forcing shows a significant increase in intensity relative to baseline period and exhibited opposite trend for longer return period.	The study did not extend to the formulation and calibration of any empirical equation as a general IDF model for easy application in hydraulic designs. Also, not in present study area.
[55]	Impacts of spatial heterogeneity and temporal non-stationary on I-D-F estimates - A case study in a mountainous California-Nevada Watershed.	Results indicated strong heterogeneity and variability in IDF estimates using high resolution simulation data and discrepancies in spatial variability supports the use of an ensemble of non-stationary approach.	The study did not develop IDF equations but was limited in comparison of different RCM ensemble data IDF curves obtained from PDF-computed rainfall intensities. Work is not in present study location.

Table 1b. Stationary IDF modeling in Nigeria

Authors	Title of Article	Contribution(s)	Gap(s)
[64]	Developing rainfall IDF models for Port Harcourt City.	Results showed two sets of rainfall models: either intensity or frequency against duration.	IDF models were empirical and limited by 10 years of insufficient data collection.
[20]	Developing rainfall IDF models for Calabar City, South-South, Nigeria.	Results showed two sets of rainfall models: either intensity or frequency against duration.	The IDF were empirical types and was limited by 10 years of insufficint rainfall data collection.
[21]	Rainfall Intensity Frequency models for selected cities in Southern Nigeria.	Programmable tools for hydrologic design of structures using 5 equation types.	Less than 25 year rainfall data were used and IDF models were all stationary types.
[35]	Rainfall intensity- duration-frequency modeling and comparative analysis of developed models for Abakiliki.	IDF models developed for Abakaliki used 4 equation types and quotient-power IDF model was the best in rainfall predictions.	IDF models were all stationary type.
[57]	Comparative analysis of rainfall IDF equation types for predicting rainfall intensity in Southern Nigeria.	4 IDF equation types were compared, and the quotient-power IDF model predicted higher rainfall intensity than others.	The IDF equations developed and compared were all stationary types.
[36]	Rainfall intensity- duration-frequency (IDF) models for Uyo City, Nigeria.	Results showed two sets of rainfall models, which were either intensity or frequency against duration.	Return period specified empirical IDF models were developed and were limited by 10 years insufficient rainfall data collection.
[68]	Deriving Rainfall I-D-F relationship for region with	Developed PDF-IDF model for Ikeja, Western Nigeria.	Applied 10 year insufficient rainfall data.

Authors	Title of Article	Contribution(s)	Gap(s)
	inadequate data.		Model was stationary type.
[22]	Rainfall intensity- duration-frequency (IDF) models for Lokoja metropolis, Nigeria.	Developed 5 general PDF-IDF model types with the LPT-3 as the best fit model for design application.	16 years rainfall data was applied. Models developed were stationary types.
[23]	Probability and non-probability rainfall IDF modeling for Port Harcourt metropolis, Nigeria.	Developed PDF and nPDF IDF models for Port-Harcourt using 3 types of equations. PDF-IDF models predicted intensity higher than empirical models.	Applied 16 year of rainfall data and IDF models developed were all stationary types.
[24]	Development of models for rainfall IDF for Akure, South-West, Nigeria.	Developed PDF-IDF models for Akure, South-West, Nigeria.	Applied 25 year rainfall data. Model was stationary type.
[69]	Modeling rainfall intensity by optimization technique in Abeokuta, South-West, Nigeria.	Developed PDF-IDF models for Abeokuta, South-West, Nigeria.	Applied 25 year rainfall data. Model was stationary type.
[70]	Trend in climate change and Vulnerability Assessment of Nigerian Gulf of Guinea.	The result indicated a rising temperature and rainfall, with rise in sea level. Thus, the use of higher return period to account for climate change was recommended.	Vulnerability assessment of climate change was not factored into IDF development for the study area. The models was stationary type.
[71]	Assessment of the impact of climate change on IDF equations in Benin City.	Climate change effect on IDF curves with observed data was insignificant.	Did not apply RCM data and models were only stationary types.
[72]	Rainfall Probability density function (PDF) and non-PDF IDF modeling for Uyo City, Nigeria.	Developed 3 PDF-IDF models types and confirmed the LPT-3 PDF model as the best-fit and predictive model for design application.	10 years rainfall data was applied. Models developed were stationary types.

6. CONCLUSION

Flood mitigation is a major challenge faced by hydrologists who rely on the use of the IDF models, a tool for prediction of rainfall intensities used in the determination of peak runoff volume in a catchment. Various IDF models have emerged over the years with different predictive capabilities. Some IDF models predict rainfall intensities with higher degree of efficiency and accuracy while others performance are limited by insufficiency and quality of measured data, variability and insufficient temporal details of input rainfall data. The incompatibility of different IDF models to different catchment areas requires careful selection.

IDF models must be chosen in terms of the project objective, data availability, study size, location, output needed, and the desired simplicity. For a watershed with short-term historical data, the parametric (empirical) IDF model especially the quotient type is preferable for shorter durations of 10-40 minutes, while for higher durations of 50-120 minutes and above the non-parametric (PDF) IDF models will suffice [23]. If the project involved requires evaluation of the statistics of the input data changing over time with their uncertainty bounds, using a non-stationary model becomes expedient. The IDF curves developed by this method have the potential application in adapting infrastructure design and risk assessment to incorporate projected changes in extreme precipitation [53].

Also, of importance for catchments without rainfall amount and corresponding duration records but has daily (24-hourly) record of rainfall depth, the IMD method of shorter duration disaggregation can be adopted to generate in-put data for the development of IDF curves for such a location. Therefore, each model type has limitations that may make it unsuitable for some projects. Reviewing data requirements, output requirements and simplicity are all necessary to decide on which model type should be selected.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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