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Research Article

Development of Rainfall Intensity Duration Frequency Curves for Debre Tabor Town, Ethiopia Using Non-stationary Method

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Abstract

Stationary rainfall intensity duration frequency curves have historically influenced urban infrastructure designs. In contrast to the stationary model, which takes constant parameters into account throughout the observation periods, the non-stationary method takes into account changes in the extreme parameters that determine the distribution of precipitation over time. The parameters were estimated using maximum likelihood estimator method. The best model were computed using the R-studio software by comparing information criteria then model parameters, return levels, rainfall intensity are computed. The National Meteorological Agency, situated in Addis Ababa, Ethiopia, provided the essential historical rainfall data of the Debre Tabor rainfall station for this study, Tests and trends were looked for in the rainfall data. Due to its ability to produce the lowest Akaike, corrected Akaike information criteria, and diagnosis test of goodness of fitness Model Type-MV was chosen for Debre Tabor stations. The parameters of the best models were used to forecast the return levels for each of the following return periods: 2, 5, 10, 25, 50, and 100 years. Because the non-stationary technique has varied intensity levels over time, the annual maximum rainfall from the best appropriate model was calculated using its exceedance probability. Using the 95% of exceedance of the return level, the highest rainfall in each fit was determined. In comparison to the stationary model, the non-stationary model produced higher rainfall intensity values. Therefore, when developing IDF curves, the non-stationary approach should be taken into consideration.

Keywords

Stationary Model, Non-stationary Model, R-Studio, Debre Tabor Town, Diagnostic Test

1. Introduction

Instead of being developing for every town or area, Ethiopia is geographically divided into different distinct rainfall regions. The current design standards for rainfall intensity duration frequency curves developed by regional intensity duration frequency curves (ERA) for Debre Tabor did not consider changes in the country's climate or the effects of urbanization into account [3, 39]. Therefore, the likelihood of floods and infrastructure damage is high because Debre Ta-

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bor’s topography is exposed to flooding and its rainfall intensity patterns are significantly underestimated. However Thanks to modern statistical method, the town is now better prepared for extreme weather events like flooding, even with inadequate rainfall data. An improved modeling of rainfall that takes account to climatic changes, effect of urbanization and rainfall change patterns of the town is essential, to design a more efficient and effective water management system. Therefore a method that incorporates probabilistic models to better account different duration of rainfall variability, and design a system that can estimate extreme events became mandatory choice. These are the reasons to study different days, hourly and sub-hourly IDF curves for Debre Tabor town using non-stationary method of IDF curves development in order to control flooding of the town and nearby area by constructing different hydraulic and hydrologic structures. Developing intensity duration frequency curves from daily, hourly and sub hourly rainfall data is a good way of quantifying rainfall intensity for Debre Tabor’s town by using different durations and return periods of the design flood. Short duration IDF curves have advantages than regional IDF and daily IDF curves to design the drainage and other water structures in the Debre Tabor town and nearby areas.

These days to design hydraulic and hydrologic Structures at Debre Tabor town, Engineers must use the regional intensity duration frequency curves developed from different towns but rainfall intensities vary with location and altitude this results miss consideration of different characteristics of rainfall. This interns results flooding of roads due to under design of rainfall computed from regional IDF [37]. With the help of this research, we can better understand how Debre Tabor's rainfall characteristics are changing. This knowledge will help engineers and planners create more robust infrastructure and efficiently manage water resources. Determining that flooding is a significant and persistent issue that has impacted the town's ecology is therefore a necessary endeavor. Flooding has damaged the town's infrastructure and caused property losses, but it has also affected social stability and the town's economy.

Therefore, intensity duration frequency curves should be developed by using non-stationary methods of intensity development method in order to regulate floods over streets, parking footpaths, and other payment structures.

2. Materials and Methods

2.1. Study Area

The town of Debre Tabor is situated in Ethiopia's Amhara region. It serves as South Gonder's administrative center. The approximate geographic coordinates of Debre Tabor town are 10 °0’0” to 15 °0’0’N latitudes and 35 °0’0” to 40’0’0” E longitudes. On average it gets roughly 1300 mm of rainfall; most of the time in June and September [1, 5]. The 20015 G. C (2007 E. C) national population census indicates that Debre Tabor town is home to about 46,000 people [4] and has been the subject of several hydrological research, including those that examine rainfall intensity duration frequency (IDF) curves, which are essential for managing water resources and building hydraulic infrastructure [3].

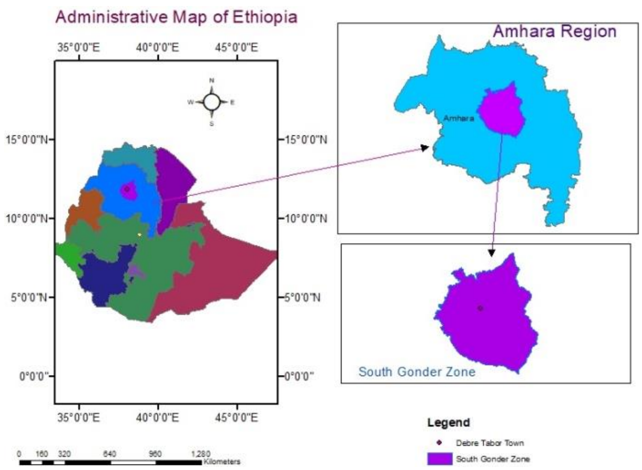


Figure 1. *Location of study area.*

2.2. Data Collection

The Ethiopian Meteorological Agency (EMA), which is located in Addis Ababa, Ethiopia, provided the daily rainfall statistical data. The Central Statistical Agency of Ethiopia was also the source of the geographic data, meaning that the information came from many offices. The GPS positions of the station are included in the geographic data, which can be used for many other rainfall data adjustment works, including the calculation of missing data, if the inverse distance method of missing data filing is approved by criteria. The rainfall station was chosen based on a number of criteria, such as its ability to have automatically record rainfall, the length of its record for a particular year, and its environmental resemblance to the research area. Following the sorting of the daily rainfall records, the matching rainfall data were converted into annual maximum daily rainfall values for use in particular procedures and needs. The rainfall amounts in millimeters were also noted. Prior to the subsequent study, the daily annual maximum series for chosen station, from the year 1988-2022 years were retrieved on a daily basis for all years. Other subsequent process followed the extraction of annual maximum daily rainfall data.

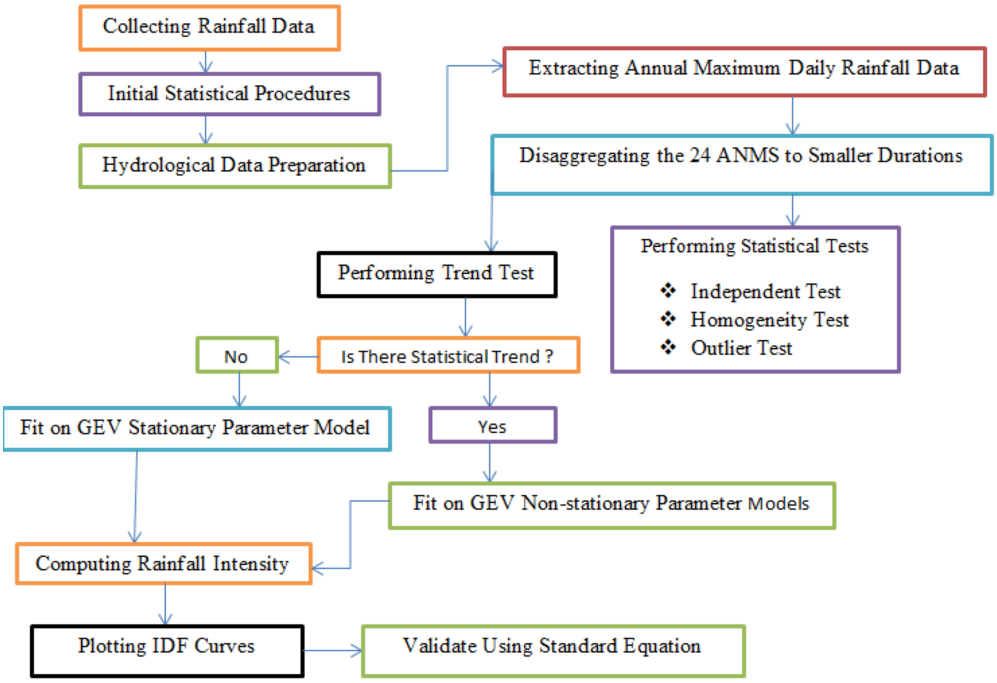


Figure 2. Overall Structure of the Research.

2.3. Disaggregation of Annual Maximum Daily Rainfall Data into Shorter Durations

After calibration, the modified Chodhury Indian Methodological Department equation was used to disaggregate the sorted annual maximum daily rainfall values with time scale less than 24 hours. This reduction was initially achieved using the equation originally intended by the Indian Methodological Department [7, 28, 33, 34, 40].

$$\mathrm{Rt} = R24(\tfrac{t}{24})^{n} \tag{1}$$

The Original Indian meteorological Equation, Where n= $\frac{1}{3}$

Rt = The required rainfall in millimeters less than a day

t= the required time in hours

R24 = Rainfall depth per day, measured in millimeters

Modified Indian Methodological Department of Chodhury After the initial equation, another equation appeared [7].

$$\mathrm{Rt} = R24(\tfrac{t}{24})^{n} + C \tag{2}$$

It is an adjustment to the equation mentioned above. Where n is an exponential and C is the calibrated constants. This research was conducted using 35 years of rainfall data from a nearby station by using modified Indian Methodological Department of Chodhury equation.

2.4. Different Tests on Rainfall Data

In order to ensure the quality and completeness including its representativeness of the rainfall data in the advance of the subsequent steps necessary to construct IDF curves, a number of tests were carried out after the rainfall data was collected, estimation of missing values was made, maximum annual daily rainfall data series was extracted to the corresponding years, Disaggregation of annual maximum daily rainfall values to smaller durations was done, and then rainfall data quality check was performed using various methods.

2.4.1. Von-Neumann's Independent Test

If the occurrence of one event has no relationship on the occurrence of other event, then the two events are said to be independent. The Probability that events A and B would occur equally is provided by the following equation [14].

$$\mathrm{Pr}(A \cap B) = \mathrm{Pr}(A) * \mathrm{Pr}(B) \tag{3}$$

If the series X_1, $X_2 \ldots X_n$ are independent and normally distributed the value of the function P(x) will be two [17].

$$P(x) = \frac{\sum_{i=1}^{n-1}(\mathrm{Xi+1-Xi})^2}{\sum_{i=1}^{n}(\mathrm{Xi-Xavg})^2} = 2 \tag{4}$$

Where X_{avg}=average value of the series $X_i \ldots X_n$

2.4.2. Mann-Whitney's Homogeneity Test

Using Mann-Whitney technique, one can verify that every component of the data series came from the same population and can follow the same probability distribution. Two ranked portions are created from the data series using this procedure; in such a way that $q + p = n$, $\mathrm{p} \leq \mathrm{q}$

Next, the smaller of V and W will be the value of U and calculated with the following formula:

$$V = S - \frac{P*(P+1)}{2} \qquad W = q * p - V \quad (5)$$

S =Sum of ranks that are common for total series (N) and the first group ranks (p) that are highlighted by colors in chapter four. The values of Ū and Var (U) are competed as follow as

$$\bar{U} = \frac{p*q}{2}, \mathrm{Var(U)} = \left[\frac{P*q}{N*(N-1)}\right]\left[\frac{N^3-N}{12}\right] + \sum_{I=0}^{n} \mathrm{Ti} \quad (6)$$

$$u = \frac{\mathrm{U}-\bar{\mathrm{U}}}{\mathrm{var(U)}(\frac{1}{2})} \quad (7)$$

Where Ti, refers ties in the groups

In Mann-Whitney U test, ties refer to situations where two or more observations from different groups have the same value. When encountering ties; the average rank is assigned to each tied observation. The presence of ties affects the calculation of the expected value and variance of U. Special formulas are used to account for ties in these calculations [9, 17, 37].

2.4.3. Outliers Tests

Outlier indicates the deviation of an observation from the rest of rainfall data because of different reasons such as errors in data collection, recording and measurement, and occasional event from a single population. This problem results in difficulties when fitting the distribution to the data. There are different methods to test the outliers including: Z-score method, Box Plot method, Quality control test, Stedinger method and Grubbs-Beck (G-B) methods. High and low outliers have different effects on the analysis of rain fall data [8, 10, 17, 37]. The following formulas are used to determine the X_H and X_L values.

$$XH = EXP(\bar{X} + KN * S) \quad (8)$$

$$XL = EXP(\bar{X} - KN * S) \quad (9)$$

Where, X_H =Upper outlier, X_L =Lower outlier, $\bar{X}$ and S denote the sample's natural logarithm mean and standard deviation, respectively. At 10% significant level KN is determined by the following formula.

$$KN = -3.62201 + 6.28446N^{1/4} - 2.49835N^{1/2} + 0.491436N^{3/4} - 0.037911N \quad (10)$$

Where N=Sample size and 5≤N≤150 in this research case N=35, Higher outliers are defined as samples with values larger than X_H, and lower outliers are defined as samples with values less than X_L. Therefor data series bigger than X_H and smaller than X_L are flagged as an outlier data.

2.5. Parameter Estimation Techniques

Parameter estimation is the process of finding the values of the parameters of a model that best fit the observed data. It is a fundamental problem in statistics, and there are many different parameter estimation methods, each method has its own advantages and disadvantages. Some of the most commonly used methods include:

2.5.1. Least Square Method

This is the most common parameter estimation technique. It minimizes the sum of the squared errors between the observed data and the model predictions. It is used to study the relationship between two variables. A more accurate way of finding the line of best fit is the least square method. The least square method is used to find the parameters of x and y for the development of empirical equations correlating with intensity and duration of rainfall. The correlation coefficient (R) is used to know the best-fit intensity duration frequency empirical equation. For the specific return period, the equation that gives an R value near 1 is the best fit and a line of best fit is a straight line that is the best approximation of the given set of data [17].

$$y = ax + b \quad (11)$$

$$a = \frac{rsx}{sy}$$

$$\mathrm{b}=\bar{\mathrm{y}}+\mathrm{a}\bar{\mathrm{x}}$$

Where, r=correlation coefficient
y=least square Regression line
a=the slope of the regression lone
b=the intercept point of the regression line and the y-axis
$\bar{x}$=mean of x value
$\bar{y}$=mean of y value
S_x=standard deviation of x
S_y=standard deviation of y value

2.5.2. Root Mean Squared Deviation (RMSD)

To determine the root mean square deviation (RMSD), one takes the square root of the sum of the squared deviations between the actual and projected amounts of rainfall, divided by the total number of observations [30]. The prediction is more accurate the smaller the RMSD value.

$$\mathrm{RMSE} = \frac{\sqrt{(\sum(\mathrm{observed} - \mathrm{predicted})^2)}}{n} \quad (12)$$

Where: Observed is the actual rainfall amount, predicted is the predicted rainfall amount, and n is the number of observations

2.5.3. Methods of Moments

When the moments of the probability density function about the origin equal the corresponding moments of the sample data, those moments are estimated as the parameters of a probability distribution. If the data value are each assigned a hypothetical mass equal to their relative frequency of occurrence ($\frac{1}{n}$) it is imagined that this system of mass is rotated about the origin x=0, then the first moment of each observation xi about the origin is equal to the product of its moment arm xi and its mass $\frac{1}{n}$, and the sum of these moments overall the data is given below [11, 14].

$$\sum_{i=}^{n} \frac{xi}{n} = \frac{1}{n} \sum_{i=1}^{n} xi = \bar{X} \tag{13}$$

The initial moment regarding the origin $= \sum_{n=1}^{\infty} \left(\frac{xi}{n}\right) = \bar{X}$. The method of moments select values for the parameters of the probability density function so that its moments are equal to these of sample data. The corresponding centroid of probability density function is equal to:

$$\mu = \int_{-\infty}^{\infty} x\, f(x) dx \tag{14}$$

2.5.4. Method of Maximum Likelihood

The parameter in the probability distribution function that maximizes the joint probability of the observed sample's occurrence is the best value and should be used. The probability density function X=xi is equal to f(x) if the sample space is divided into intervals of length dx and a sample of independent and identically distributed observations x1, x2,..., xn is taken. The probability that the random variable will occur in the interval including xi is equal to f(x) dx. Since the observations are independent, the product of f1(x) dx f2(x) dx….f (xn) dx=$\prod_{i=1}^{n} f(xi) dx^n$, determines the joint probability of occurrence of the observations. Since the interval size dx is fixed, maximizing the joint probability of the observed sample is equal to maximizing the likelihood function [11].

$$L = \prod_{i}^{n} f(xi) \tag{15}$$

It is sometimes more convenient to work with the log likelihood function because a lot of probability functions are exponential.

$$\ln L = \sum_{i=1}^{n} \ln[f(xi)] \tag{16}$$

2.5.5. The L-moments

It is used to calculate the parameters of GEV distribution and fit to the annual maximum series. L-moments are the modifications of probability weighted moments and use it to estimate the parameters that are easy to interpret. The L-moment, which is a linear combination of the order of statistics of the annual maximum rainfall quantity, is a potent substitute for the moments of distributions. The following equation is used to estimate the probability weighted moments [10]:

$$\text{wo} = n^{-1} \sum_{j=1}^{n} \text{xj} \tag{17}$$

$$w1 = n^{-1} \sum_{n=2}^{n} \left(\frac{j-1}{n-1}\right) xj \tag{18}$$

$$w2 = n^{-1} \sum_{n=2}^{n} \frac{(j-1)(j-2)xj}{(n-1)(n-2} \tag{19}$$

Where, wi is the initial probability weighted moments and xj is the ordered sample of the annual maximum series. The following equations can then be used to compute the sample moments.

$$m_1 = w_0 \tag{20}$$

$$m_2 = 2w_1 - w_0 \tag{21}$$

$$m_3 = 6w_2 - 6w_1 + w_0 \tag{22}$$

The location (μ), scale (δ), and shape (ξ) of the GEV parameters are calculated as follows:

$$\xi = 2.9554rc^2 + 7.8590c \tag{23}$$

$$c = \frac{2}{3+\frac{\text{m3}}{\text{m2}}} - \frac{\text{mn}(2)}{\text{mn}(3)} \tag{24}$$

$$\delta = \frac{\text{m}2\xi}{(1-2^{-\xi}).\Gamma(1+\xi)} \tag{25}$$

$$\mu = \text{m}1 - \delta \frac{((1-\Gamma(1+\xi))}{\xi} \tag{26}$$

Where $\Gamma(.)$ the gamma function m1, m2, m3 are the first third moments and location (μ), scale (δ), and shape (ξ) are parameters of the GEV distribution.

2.6. Checking Climate Trend Tests in Rainfall Data

Mann-Kendall Trend Test

The alternative hypothesis (Ha) and the null hypothesis (Ho) are the foundations of the MK-test, which is used to perform statistically significant rising or falling trends in long span temporal data. Whereas Ha indicates if there is a rising or decreasing trend in the rainfall data, Ho displays the absence of any trend [10, 14, 17, 18].

The following formula is given as:

$$S = \sum_{i=1}^{n-1} \sum_{k=i+1}^{n} sign(Xj - Xi) \tag{27}$$

Where Xj and Xi represent the rainfall values in years J and I, and n denotes the number of data points so that J>1 $sign(Xj - Xi)$ is calculated by the equation under here.

$$sign(Xj - Xi) = -1 \; for (Xj - Xi) < 0,$$

$$= 0 \; for \; (Xj - Xi) = 0,$$

$$= 1 \; for \; (Xj - Xi) > 0$$

2.7. Generalized Extreme Value Distribution (GEV)

In extreme value analysis, the Generalized Extreme Value Distribution (GEV) is a continuous probability distribution function that is commonly used. The distribution of extreme values, such as the highest or lowest value within a set of data, is modeled using this approach [12, 13]. The probability density function (PDF) of the GEV distribution is shown in the equation below.

$$f(x) = \frac{1}{\sigma}\left[1 + \xi((\frac{x-\mu}{\sigma}))\right]^{((-\frac{1}{\xi})-1)} * \exp[-[1 + \xi((\frac{x-\mu}{\sigma})]^{\left(-\frac{1}{\xi}\right)}] \quad (28)$$

The Generalized Extreme value of the distribution is composed of continuous probability distributions and is based on the limit theorems for blocking minimal or annual maximum [27]. Generalized extreme value distribution (GEV) is the term used to describe the combining of these three distributions, such as Gumbel, Frechet, and Weibull, into a single family. The General extreme value cumulative distribution function F(x) is given by the following equations.

$$\mathrm{F(X)} = exp\{-[1 + \frac{\xi(X-\mu)}{\delta}]^{-\left(\frac{1}{\xi}\right)}\}, \text{ for } \delta > \; 0.1 + \frac{\xi(X-\mu)}{\delta}\} \; \xi \neq 0 \quad (29)$$

$$F(x) = \exp\{-\exp[-(\frac{X-\mu}{\delta})]\}, \delta > 0, \xi = 0) \quad (30)$$

The shape parameter is represented by ξ, the mean by μ, the standard deviation by σ, the cumulative distribution function by F(x), and the annual extreme value of rainfall by X in this case. The maximum likelihood estimator is the statistical technique used to estimate the distribution parameters since it can be extended to non-stationary evaluation. The extreme value theory allows for the incorporation of non-stationary behavior into the general extreme value model by specifying one or more of the parameters as functions of time as a covariate. Empirical study suggests that it is preferable to express the non-stationary model both in terms of location and scale factors. Attempting to model ξ as a smooth function of time is unrealistic since it is often hard to estimate the shape parameter correctly [36].

The Generalized Extreme Value Distribution is flexible for modeling different characters of extremes with three distribution parameters location parameter (μ), which species the center of the distribution; the scale parameter (σ) indicates the size of deviation around the location parameter; and the shape parameter (ξ) governs the tail behavior of the Generalized extreme value distribution. The shape parameter selects the appropriate distribution type among the three GEV distributions. A value of ξ→0 indicates the Gumbel distribution, a value of ξ<0 indicates the Weibull distribution, and a value of ν>0 indicates the Frechet distribution [6, 7, 12, 13].

2.8. Non-Stationary Generalized Extreme Value Models

The parameters of the GEV are stated as a function of covariates inside the extreme value modeling formats. Extreme rainfall behavior described in terms of many variables, often known as covariates. When one or more of the GEV distribution's parameters are expressed as a function of time, it is considered non-stationary [24]. Non-stationary models better fit data sequences when working with a single model that has a well-defined functional relation between the length of the rainfall and the return period [2, 7]. The distribution's properties exhibit time-varying behavior due to the time dependence of the underlying distribution function's parameters. The location and/or scale parameter are thought of as linear, quadratic, or exponential functions of time if the shape parameters remain constant [25-27]. The maximum likelihood estimator approach can be used to describe the location, scale, and shape of the GEV parameters as a linear or quadratic approximation of the time constraints. The fundamental distribution function's parameters in a non-stationary process have time-varying characteristics and are reliant on time. The location and scale partners are considered to be functions of time in order to account for non-stationary, while the shape parameter is kept constant, in order to reflect a dynamic distribution [7].

$$\mu\,(t) \;=\; \mu 1t + \mu 0 \quad (31)$$

$$\sigma\,(t) \;=\; \sigma 1t + \sigma 0 \quad (32)$$

The process uses a log function since the scale parameter stays positive.

$$\ln \sigma\,(t) \;=\; \sigma 1t + \sigma o \quad (33)$$

$$\text{That is, } \sigma\,(t) \;=\; \mathrm{Exp}\,(\sigma 1t + \sigma o) \quad (34)$$

Here, ν, σ1, σo, ε is the regression parameter and t is the time in years. Given the conditions, the following is the log likelihood function for the stationary scenario that was derived:

$$Log\; L(\mu,\sigma,\xi|X) = -n * log\sigma - \left[1 + \frac{1}{\xi}\right]\sum_{i=1}^{n}\Big(\log(1 + \xi(\frac{xi-\mu}{\sigma})\Big) - [\textstyle\sum_{i=1}^{n} 1 + \xi(\frac{(xi-\mu)}{\sigma}^{-\frac{1}{\xi}}] \quad (35)$$

For $\xi \neq 0$ and $1+\xi\frac{(xi-\mu)}{\sigma}>0$

In the non-stationary case, this formula can be extended to the universal extreme value distribution whose parameters depend on time. The maximum likelihood estimator uses the minimization of the negative log-likelihood function as an alternative to the direct maximization method. Based on the non-stationary setting that meets the predetermined conditions, the non-stationary situations, scale, and location parameters in the previously described equations are replaced. R-studio was used to fit general extreme parameters to the data based on the maximum likelihood estimator for both the stationary and non-stationary models because the models equations are complex. The function has to be solved by iterative numerical procedures. One may efficiently choose the best general extreme value model and construct the rainfall quintile by using the maximum likelihood estimator approach.

The general extreme values and the parameters of the extreme distribution will be obtained by an iterative numerical approach by minimizing the negative log-likelihood function.

Table 1. *Examined GEV Non-stationary Parameter Models.*

Model Type	**Parameter Combination**	**Remark**
GEV Type -0	$\mu(t) = \mu, \sigma(t) = \sigma, \xi(t) = \xi_0$	Model with stationary parameters
GEV Type-	$\mu(t) = \mu_{0+}\ \mu_1 t, \sigma(t) = \sigma_0, \xi(t)= \xi_0$	Model with non-stationary parameters
GEV Type-∏	$\mu(t) = \mu_{0,}\ \sigma(t) = \sigma_{0+}\ \sigma_{1t}, \xi(t)= \xi_0$	Model with non-stationary parameters
GEV Type-∏	$\mu(t) = \mu_{0+}\ \mu_1 t, \sigma(t) = \sigma_{0+}\ \sigma_{1t}, \xi(t)= \xi_0$	Model with non-stationary parameters
GEV Type-IV	$\mu(t)= \mu0+ \mu1t, \sigma(t)= e^{(\sigma0+ \sigma1t)}, \xi(t)= \xi_0$	Model with non-stationary parameters
GEV Type-V	$\mu = \mu_0 + \mu_1(t) + \mu_2(t^2), \sigma = \sigma_0, \xi(t)= \xi_0$	Model with non-stationary parameters

2.9. Selection of Best GEV Distribution Non-Stationary Parameter Models

After the non-stationary model is developed, a critical step is selecting the model that most accurately depicts the original data. Adding new criterion to Akaike's information criteria, such AICC was done to choose the best GEV model among all options. It penalizes the minimized negative log-likelihood function (-log L) for each estimated model parameter. Akaike's Information Criterion is influenced by the relationship between the sample size (n) and the number of parameters (k) in a practical application. To avoid over fitting of the data, the Corrected Akaike's Information Criterion (AICC) is suggested when $\frac{n}{k}$ >40. When n values are greater, AIC_C converges to AIC [36].

The expressions for AIC and AICC are as follows:

$$\mathrm{AIC} = -2logL + 2K \tag{36}$$

$$\mathrm{AICc} = \mathrm{AIC(k)} + \frac{\mathrm{2k(k+1)}}{n-k-1} \tag{37}$$

$$BIC = K * \ln(n) - 2 * \ln(L) \tag{38}$$

The influence of the number of parameters, k, on AICc is higher than that on its rescaling form. The sample size determines the change in Δi, which is used to rank the GEV model.

$$\Delta \mathrm{i} = \mathrm{AICc} - \min(\mathrm{AICc}) \tag{39}$$

Where: min(AICc) is the smallest model value from all models of values. The model with Δi zero value is best model and the model which has $\Delta i \leq 2$ is considered as good choice [7].

By contrasting the p-values of the non-stationary model with the chi square distribution, one can determine the statistical significance of the model [31]. If the p-value, or 95% confidence level, is less than 0.05, the best non-stationary model is considered statistically significant when compared to the stationary model.

2.10. Development of GEV Intensity Duration Frequency Curves

In this work, rainfall intensity duration frequency curves were created using R-studio software. The model parameters are used to estimate precipitation intensities based on the GEV distribution return periods and return levels of extremes, as well as the formulation of the function of return level as the return period.

$$\mathrm{T} = \frac{1}{1-P} \tag{40}$$

In the stationary model, p represents the non-exceedance probability of occurrence in a given year since it is regarded as constant. The intensity of the stationary rainfall extreme value is computed using the following formula [36]

$$X_T = \mu - \frac{\sigma}{\xi}[1 - \{-\ln\left(1 - \frac{1}{T}\right)\}^{-\xi}] \text{ for } \xi \neq 0 \quad (41)$$

Since it is thought to be constant, p in the stationary model stands for the non-exceedance probability of occurrence in a specific year. The following formula is utilized to calculate the intensity of the stationary rainfall extreme value [7, 27]

$$XT = \bar{\mu} + \frac{\sigma}{\xi}[(-\frac{1}{\ln p})^{\xi} - 1], \xi \neq 0 \quad (42)$$

$$\bar{\mu} = Qk(\mu t1, \mu t2, \mu t3 \ldots . \mu tm), (\mu(t) = \mu 1t + \mu o) \quad (43)$$

In this case, Qk is the parameter's k^{th} quantile, T is the return time, and X_T is the rainfall intensity exceedance value.

3. Results and Discussion

3.1. Disaggregation of Daily Rainfall Data into Shorter Durations

In order to adjust with observed rainfall data and take into account short duration rainfall intensity based infrastructures, Debre Tabor's 35 years of annual maximum daily rainfall data series were also downscaled into shorter durations of 10 minutes15 minutes, 30 minutes, 45 minutes, 60 minutes, 120 minutes, and 180 minutes. The formula below, which was originally intended by the Indian Methodological Department, was used to reduce the sorted annual maximum daily rainfall values with minute's interval into time scales of 24 hours and shorter durations. After calibration, the modified Chodhury Indian Methodological Department equation was used.

$$Rt = R24(\frac{t}{24})^n \quad (44)$$

The original Indian weather equation, Where n= $\frac{1}{3}$

Rt = The required rainfall in millimeters less than a day

t= required time in hours

R24 = The modified Chodhury Indian methodological department, the amount of rainfall per day in millimeters the first equation was followed by another equation.

$$Rt = R24(\frac{t}{24})^n + C \quad (45)$$

The amount of rainfall in millimeters per day on the modified Chodhury Indian Methodological Department There was an additional equation after the first one [7].

In this study C=10 and n= $\frac{1}{9}$

Table 2. *Disaggregated Rainfall Values.*

Year	ANMS	10 Min	15 Min	30 Min	45 Min	1 hr	2 hr	3hr
1988	60.60	39.14	40.47	42.91	44.43	45.55	48.39	50.16
1989	57.00	37.06	38.30	40.57	41.98	43.02	45.66	47.30
1990	43.13	29.08	29.95	31.55	32.54	33.28	35.14	36.30
1991	40.90	27.79	28.61	30.10	31.02	31.71	33.44	34.53
1992	55.10	35.97	37.16	39.33	40.69	41.68	44.22	45.80
1993	55.10	35.97	37.16	39.33	40.69	41.68	44.22	45.80
1994	79.90	50.25	52.09	55.46	57.56	59.10	63.04	65.48
1995	67.40	43.05	44.57	47.33	49.05	50.32	53.55	55.56
1996	54.60	35.68	36.86	39.01	40.35	41.33	43.84	45.40
1997	114.30	70.06	72.81	77.84	80.97	83.27	89.14	92.78
1998	77.70	48.98	50.77	54.03	56.06	57.56	61.37	63.73
1999	65.50	41.96	43.42	46.10	47.76	48.99	52.11	54.05
2000	57.30	37.24	38.48	40.76	42.18	43.23	45.89	47.54
2001	72.70	46.10	47.76	50.78	52.66	54.05	57.57	59.77
2002	91.30	56.81	58.96	62.88	65.32	67.11	71.69	74.53
2003	90.60	56.41	58.54	62.42	64.84	66.62	71.15	73.97

Year	ANMS	10 Min	15 Min	30 Min	45 Min	1 hr	2 hr	3hr
2004	52.00	34.18	35.29	37.32	38.58	39.50	41.87	43.34
2005	79.40	49.96	51.79	55.14	57.22	58.75	62.66	65.08
2006	70.00	44.55	46.13	49.03	50.82	52.15	55.52	57.62
2007	65.50	41.96	43.42	46.10	47.76	48.99	52.11	54.05
2008	69.50	44.26	45.83	48.70	50.48	51.80	55.14	57.23
2009	59.40	38.44	39.75	42.13	43.61	44.70	47.48	49.21
2010	52.00	34.18	35.29	37.32	38.58	39.50	41.87	43.34
2011	70.20	44.66	46.25	49.16	50.96	52.29	55.68	57.78
2012	54.20	35.45	36.62	38.75	40.07	41.05	43.54	45.08
2013	85.60	53.53	55.53	59.17	61.44	63.11	67.36	70.00
2014	76.20	48.12	49.87	53.06	55.04	56.51	60.23	62.54
2015	51.30	33.78	34.87	36.86	38.10	39.01	41.34	42.78
2016	54.70	35.74	36.92	39.07	40.41	41.40	43.92	45.48
2017	157.10	94.70	98.59	105.68	110.09	113.34	121.61	126.75
2018	85.20	53.30	55.29	58.91	61.17	62.83	67.06	69.69
2019	97.90	60.61	62.93	67.17	69.81	71.75	76.69	79.77
2020	42.35	28.63	29.48	31.04	32.01	32.73	34.55	35.68
2021	64.60	41.44	42.88	45.51	47.15	48.36	51.43	53.34
2022	73.60	46.62	48.30	51.37	53.27	54.68	58.26	60.48

3.2. Different Tests on Rainfall Data

In order to ensure the quality and completeness including its representativeness of the rainfall data in the advance of the subsequent steps necessary to construct IDF curves, a number of tests were carried out after the rainfall data was collected, estimation of missing values was made, maximum annual daily rainfall data series was extracted to the corresponding years, Disaggregation of annual maximum daily rainfall values to smaller durations was done, and then rainfall data quality check was performed using various methods.

3.2.1. Von-Neumann's Independent Test

If the series X_1, X_2….X_n are independent and normally distributed the value of the function P(x) will be two [14].

$$P(x) = \frac{\sum_{i=1}^{n-1}(Xi+1-Xi)^2}{\sum_{i=1}^{n}(Xi-Xavg)^2}=2$$

Where X_{avg}=average value of the series X_i…X

Table 3. Von-Neumann's Independent Test.

Year	Max RF	Arithmetic Mean	$(X_i-X_{avg})^2$	$(X_{i+1}-X_i)^2$
1988	60.6	69.83	85.2	12.96
1989	57	69.83	164.61	192.38
1990	43.13	69.83	712.89	4.97
1991	40.9	69.83	836.95	201.64
1992	55.1	69.83	216.97	0
1993	55.1	69.83	216.97	615.04
1994	79.9	69.83	101.41	156.25
1995	67.4	69.83	5.91	163.84
1996	54.6	69.83	231.95	3564.09
1997	114.3	69.83	1977.58	1339.56
1998	77.7	69.83	61.94	148.84
1999	65.5	69.83	18.75	67.24
2000	57.3	69.83	157.00	237.16
2001	72.7	69.83	8.24	345.96
2002	91.3	69.83	460.96	0.49

Year	Max RF	Arithmetic Mean	$(X_i-X_{avg})^2$	$(X_{i+1}-X_i)^2$
2003	90.6	69.83	431.39	1489.96
2004	52	69.83	317.91	750.76
2005	79.4	69.83	91.59	88.36
2006	70	69.83	0.03	20.25
2007	65.5	69.83	18.75	16
2008	69.5	69.83	0.11	102.01
2009	59.4	69.83	108.79	54.76
2010	52	69.83	317.92	331.24
2011	*70.2*	*69.83*	*0.14*	*256*
2012	54.2	69.83	244.30	985.96
2013	85.6	69.83	248.69	88.36
2014	76.2	69.83	40.58	620.01
2015	51.3	69.83	343.36	11.56
2016	54.7	69.83	228.92	10485.76
2017	157.1	69.83	7616.05	5169.61
2018	85.2	69.83	236.24	161.29
2019	97.9	69.83	787.93	3085.80
2020	42.35	69.83	755.15	495.06
2021	64.6	69.83	27.35	81
2022	73.6	69.83	14.21	5416.96
Sum			17086.69	36761.16

$P(x) = \frac{\sum_{i=1}^{n-1}(\text{Xi+1}-\text{Xi})^2}{\sum_{i=1}^{n}(\text{Xi}-\text{Xavg})^2} = \frac{36761.1348}{17086.6901}$ =2 the result shows that according to Von-Neumann's criteria the rainfall data are independent.

3.2.2. Mann-Whitney's Homogeneity Test Method

This method is used to verify whether every component of the data series is derived from the same population and can follows the same probability distribution.

Table 4. *Mann-Whitney's Homogeneity Test Method.*

P	Annual Max daily RF	q	Annual Max daily RF	N=P+q	Annual Max daily RF
1	60.6	1	79.4	1	40.9
2	57	2	70	2	42.35
3	43.13	3	65.5	3	43.13
4	40.9	4	69.5	4	51.3
5	55.1	5	59.4	5	52
6	55.1	6	52	6	52
7	79.9	7	70.2	7	54.2
8	67.4	8	54.2	8	54.6
9	54.6	9	85.6	9	54.7
10	114.3	10	76.2	10	55.1
11	77.7	11	51.3	11	55.1
12	65.5	12	54.7	12	57
13	57.3	13	157.1	13	57.3
14	72.7	14	85.2	14	59.4
15	91.3	15	97.9	15	60.6
16	90.6	16	42.35	16	64.6
17	52	17	64.6	17	65.5
		18	73.6	18	65.5
				19	67.4

P	Annual Max daily RF	q	Annual Max daily RF	N=P+q	Annual Max daily RF
				20	69.5
				21	70
				22	70.2
				23	72.7
				24	73.6
				25	76.2
				26	77.7
				27	79.4
				28	79.9
				29	85.2
				30	85.6
				31	90.6
				32	91.3
				33	97.9
				34	114.5
				35	157.1

After arranging the data series into two ranked portions as p=17 and q=18 and sorting the total series in descending orders the value of S was calculating as follow as:

$$S = 1 + 3 + 5 + 10 + 11 + 12 + 15 + 17 + 18 + 19 + 23 + 26 + 28 + 31 + 32 + 34 = 286$$

S =Sum of ranks that are common for both the total series (N) and the first group ranks (p) that are represented by N=P+q.

The value of V and W are competed as follow as

$$V = S - \frac{P*(P+1)}{2}$$

$$V = 285 - \frac{17*(17+1)}{2} = 285 - 153 = 132$$

And the value of W calculated by the formula:

$$W = q * p - V$$

$$W = 17 * 18 - 153 = 306 - 153 = 153$$

The smaller of V or W is the value of U.
U=132

$$\bar{U} = \frac{p*q}{2} = \frac{17*18}{2} = 153$$

$$\mathrm{Var(U)} = \left[\frac{P*q}{N*(N-1)}\right]\left[\frac{N^3-N}{12}\right] + \sum_{I=0}^{n} \mathrm{T}$$

Where T, refers ties in the groups

In Mann-Whitney U test, ties refer to situations where two or more observations from different groups have the same value. When encountering ties; the average rank is assigned to each tied observation. The presence of ties affects the calculation of the expected value and variance of U. Special formulas are used to account for ties in these calculations. But in in this research case the number is from one group and $\sum_{I=1}^{43}$ T=0, $\mathrm{Var(U)} = \left[\frac{17*18}{35*(35-1)}\right]\left[\frac{35^3-35}{12}\right] + \sum_{I=1}^{35} 0$

$$\mathrm{Var(U)} = 0.257 * 3570 + \sum_{I=1}^{n} 0 = 918$$

$$\mathrm{Var(U)} = 918$$

Finally the parameter, u is commuted using the formal

$$u = \frac{\mathrm{U} - \bar{\mathrm{U}}}{\mathrm{var(U)}(\frac{1}{2})}$$

$$u = \frac{132-153}{(918)(\frac{1}{2})} = -0.693$$

Since at 5 % level of significance $P_{critical}$ is 1.96

$$|u|=|-0.693| \leq 1.96$$

The result verify that the calculated value is less than the critical value indicating that annual daily maximum rainfall is homogeneous at 5 % level of significance.

3.2.3. Outliers Tests

Grubbs-Beck (G-B) Test

The following formulas are used to determine the upper outlier and X_H and lower outlier X_L values.

$$XH = EXP(\bar{X} + KN * S)$$

$$XL = EXP(\bar{X} - KN * S)$$

$$K_N = -3.62201 + 6.28446N^{1/4} - 2.49835N^{1/2} + 0.491436N^{3/4} - 0.037911N$$

Where N=Sample size and 5≤N≤150 in this research case N=35

$$KN = -3.62201 + 6.28446 * 35^{\frac{1}{4}} - 2.49835 * 35^{\frac{1}{2}} + 0.491436 * 35^{\frac{3}{4}} - 0.037911 * 35 = 2.63$$

$$K_N=2.63$$

Table 5. *Grubbs-Beck (G-B) Outlier Test method calculations for Debre Tabor Town Station Rainfall.*

Year	P=Max Annual Daily RF	lnP	Mean of lnP	St. deviation lnP
1988	60.6	4.10	4.20	0.28
1989	57	4.04	4.20	0.28
1990	43.13	3.76	4.20	0.28
1991	40.9	3.71	4.20	0.28
1992	55.1	4.01	4.20	0.28
1993	55.1	4.01	4.20	0.28
1994	79.9	4.38	4.20	0.28
1995	67.4	4.21	4.20	0.28
1996	54.6	4.00	4.20	0.28
1997	114.3	4.74	4.20	0.28
1998	77.7	4.35	4.20	0.28
1999	65.5	4.18	4.20	0.28
2000	57.3	4.05	4.20	0.28
2001	72.7	4.29	4.20	0.28
2002	91.3	4.51	4.20	0.28
2003	90.6	4.51	4.20	0.28
2004	52	3.95	4.20	0.28
2005	79.4	4.37	4.20	0.28
2006	70	4.25	4.20	0.28
2007	65.5	4.18	4.20	0.28
2008	69.5	4.24	4.20	0.28
2009	59.4	4.08	4.20	0.28
2010	52	3.95	4.20	0.28
2011	70.2	4.25	4.20	0.28
2012	54.2	3.99	4.20	0.28
2013	85.6	4.45	4.20	0.28
2014	76.2	4.33	4.20	0.28
2015	51.3	3.94	4.20	0.28
2016	54.7	4.00	4.20	0.28
2017	157.1	5.06	4.20	0.28
2018	85.2	4.45	4.20	0.28
2019	97.9	4.58	4.20	0.28
2020	42.35	3.75	4.20	0.28
2021	64.6	4.17	4.20	0.28
2022	73.6	4.30	4.20	0.28

Where: lnP and St.deviation.S are the sample's natural logarithms of annual maximum daily disaggregated rainfall data and the standard deviations of the natural logarithms of annual maximum daily disaggregated rainfall data respectively. Mean lnP also represents the arithmetic mean of natural logarithms of annual maximum daily disaggregated rainfall data. Mean lnR=4.2; St. Deviation. S=0.28

After computing statistical parameters the other steps is determining upper and lower limits. K_N=2.63

Upper Limit

$$X_H = EXP(\bar{X} + KN * S)$$

$$X_H = EXP(4.2 + 2.63 * 0.28)$$

$$X_H = EXP(4.936) = 139.27 \text{ mm}$$

Lower

$$X_L = EXP(\bar{X} - KN * S)$$

$$X_L = EXP(4.2 - 2.63 * 0.28)$$

$$X_L = EXP(3.464) = 31.93\text{mm}$$

The results show that for annual maximum daily rainfall data 31.53 mm is the smallest and 139.27 mm is the largest value, which indicate that there was upper outlier in the year 2017 with the rainfall value amount 157.1 mm but there was no lower outlier. The upper outlier value indicate that unusual value was observed from other years of rainfall values verifying that there was flooding or highest rainfall in the year 2017which should need further investigation.

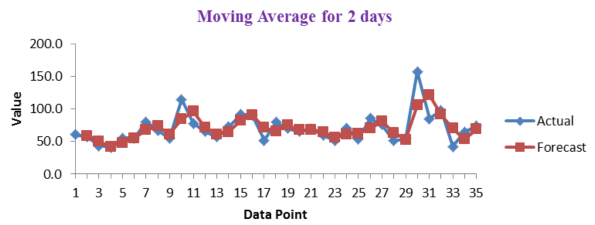
3.3. Deriving Two, Three and Five Days Rainfall from Annual Maximum Daily Rainfall

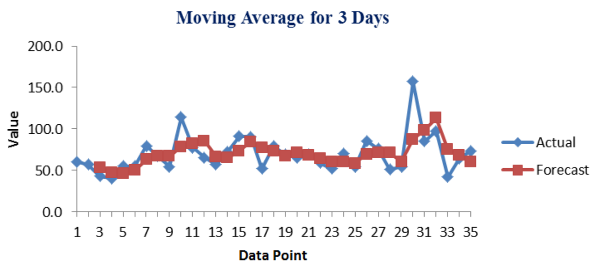
It should be required to drive rainfall from the previous day for each day in order to create IDF curves for two, three, and five days. There are several techniques, such rolling aggregation and moving average methods, to estimate data for use in the future from the historical data. Because the moving average method is simple to use, effective at handling outliers, and allows for the calculation of future values from prior values, it was employed to extract rainfall data for two, three, and five days from daily rainfall data. It calculates the unknown values by taking sum of two, three and five day's consecutive values and divide the sum by Two, Three, and five respectively.

Table 6. *Deriving Two, Three, and Five Day Rainfall from Annual Maximum Daily Rainfall.*

Year	1 Day	2 Days	3 Days	5 Days
1988	60.6	#N/A	#N/A	#N/A
1989	57.0	58.8	#N/A	#N/A
1990	43.1	50.1	53.6	#N/A
1991	40.9	42.0	47.0	#N/A
1992	55.1	48.0	46.4	51.3
1993	55.1	55.1	50.4	50.2
1994	79.9	67.5	63.4	54.8
1995	67.4	73.7	67.5	59.7
1996	54.6	61.0	67.3	62.4
1997	114.3	84.5	78.8	74.3
1998	77.7	96.0	82.2	78.8
1999	65.5	71.6	85.8	75.9
2000	57.3	61.4	66.8	73.9
2001	72.7	65.0	65.2	77.5
2002	91.3	82.0	73.8	72.9
2003	90.6	91.0	84.9	75.5
2004	52.0	71.3	78.0	72.8
2005	79.4	65.7	74.0	77.2
2006	70.0	74.7	67.1	76.7
2007	65.5	67.8	71.6	71.5
2008	69.5	67.5	68.3	67.3
2009	59.4	64.5	64.8	68.8
2010	52.0	55.7	60.3	63.3
2011	70.2	61.1	60.5	63.3
2012	54.2	62.2	58.8	61.1
2013	85.6	69.9	70.0	64.3
2014	76.2	80.9	72.0	67.6
2015	51.3	63.8	71.0	67.5
2016	54.7	53.0	60.7	64.4
2017	157.1	105.9	87.7	85.0
2018	85.2	121.2	99.0	84.9
2019	97.9	91.6	113.4	89.2
2020	42.4	70.1	75.2	87.5
2021	64.6	53.5	68.3	89.4
2022	73.6	69.1	60.2	72.7

The two and three-day moving averages are more accurate at predicting future values because, as the plot illustrates, they vary more quickly depending on past days than the five-day morning average, which is smoother and didn't fluctuate as much. The standard errors of the two- and three-day moving averages are less than those of the five-day moving average.





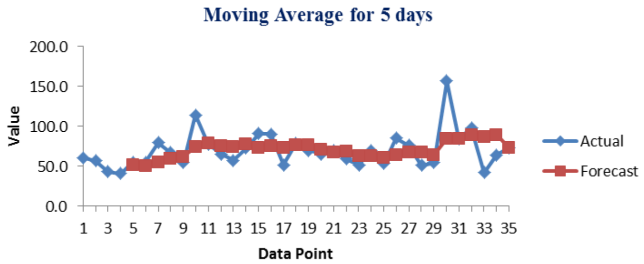


Figure 3. *Moving Average Plots for Different Days.*

3.4. Evaluation of Parameter Model Comparing Criteria

The statistical technique used to calculate the distribution parameters is called the maximum likelihood estimator. Next, one or more GEV distribution parameters are expressed as a function of time in order to indicate the non-stationarity. The R-Studio program was used to estimate a variety of parameters by merging pertinent functions with corresponding packages. The maximum likelihood estimator approach was utilized to estimate the parameters of the GEV distribution. While the parameters of non-stationary models exhibit time-varying properties, the parameters of stationary models remain unaffected by time. It is therefore easy to deduce from the above table that all MO models are stationary because they are all utilized to calculate their respective return levels, and that all other models are non-stationary because all of their parameters vary on time.

Table 7. *Assessing GEV Parameter Models using Two Criterion.*

Duration (min)	Model Type	AIC	AICC
10	MO	268.98	269.76
	MI	270.09	270.87
	MII	270.92	271.69
	MIII	270.22	270.99
	MIV	269.98	270.75
	MV	269.53	270.30
15	MO	272.12	272.90
	MI	273.23	274.01
	MII	274.05	274.83
	MIII	273.36	274.13
	MIV	273.12	273.89
	MV	272.66	273.44
30	MO	277.51	278.29
	MI	278.62	279.40
	MII	279.44	280.22
	MIII	278.75	279.52
	MIV	278.51	279.28
	MV	278.06	278.83
45	MO	280.67	281.44
	MI	281.78	282.55
	MII	282.60	283.37
	MIII	281.90	282.67
	MIV	281.66	282.43
	MV	281.21	281.98
60	MO	282.90	283.68
	MI	284.01	284.79
	MII	284.84	285.61
	MIII	284.14	284.91
	MIV	283.90	284.67
	MV	283.45	284.22
120	MO	288.29	289.07
	MI	289.41	290.18
	MII	290.23	291.00
	MIII	289.53	290.30
	MIV	289.29	290.06
	MV	288.84	289.61
180	MO	296.84	297.61
	MI	297.95	298.72
	MII	298.77	299.55
	MIII	298.07	298.85
	MIV	297.83	298.61
	MV	297.38	298.16
Considered Days			
1 day	MO	307.62	308.40
	MI	308.73	309.51
	MII	309.55	310.33
	MIII	308.86	309.63
	MIV	308.62	309.39
	MV	308.16	308.94
2 days	MO	286.41	287.18
	MI	284.28	285.06
	MII	287.96	288.74
	MIII	285.44	286.22
	MIV	285.29	286.07

Duration (min)	Model Type	AIC	AICC
3 day	MV	281.41	282.18
	MO	269.26	270.04
	MI	263.65	264.42
	MII	269.60	270.37
	MIII	265.41	266.19
	MIV	265.35	266.13
	MV	261.36	262.14

Because they have the minimum AIC and AICC values, the shaded numbers are R-studio outputs, which indicate the best parameters model for all durations. The best models were chosen after evaluating smaller numbers in the above table and making a judgment based on criteria for GEV models. Apart from AIC, the optimal model was ascertained by employing a statistical method called the corrected Akaike's information criterion. The following formulas were used in the process:

$$\mathrm{AIC} = -2logL + 2K$$

$$\mathrm{AICc} = \mathrm{AIC(k)} + \frac{2\mathrm{k(k+1)}}{n-k-1}$$

In a given mode, k represents the total number of parameters [36].

In this study using the previously indicated equations, computations were performed for all model duration. For fifteen minutes, for instance, the non-stationary GEV model type-MV computation was completed as blow. Analogous work was completed for other non-stationary GEV model types, and provisions were made for stationary models. The outcomes were then summed up in the ways listed below. With R-Studio, the previous table shows us

AIC=261.36

K=3

n=35

$$\mathrm{AICc} = \mathrm{AIC(k)} + \frac{2\mathrm{k(k+1)}}{n-k-1}$$

$$\mathrm{AICc} = 261.36 + \frac{2*3*(3+1)}{35-3-1} = 261.36 + 0.774 = 262.13$$

Five different candidate models were considered for consideration in the computation, as the aforementioned tables showed. To determine which model was the winner, the AIC and AICC values were compared with the corresponding values for the same duration. The winner would be the model with the lowest value as determined by the updated Akaike's information criteria. This logic indicates that the GEV Type-MV is the best model for all durations since, for the same length, its AIC and AICC are the lowest of all the models. It was surprising to find that the GEV model Type MV is the best model for all non-stationary models because all AIC and AICC values are the lowest. But in the case of the stationary model, it became necessary to use the representative of all durations to compute return levels for all stationary models. In contrast to stationary models, non-stationary models utilized a single optimal model selected for all duration to determine return levels for all duration. The GEV non-stationary model is ranked using the change (Δi).

$$\Delta \mathrm{i} = \mathrm{AICc} - \min(\mathrm{AICc})$$

Given that min (AICc) = 256.26, the remaining values of Δi are calculated using the formula Δi=AICc-262.14. To obtain the matching AICC value, replace the corresponding row value of AIC. The ideal model is one with Δi = 0, and choosing a value less than 2 is recommended. It was determined that GEV Type-MV is the best model and a wise choice among the models based on this criterion and the information in the above table. The following phase involves utilizing RStudio software to determine rainfall intensity or return levels based on the stationary and non-stationary model formula.

3.5. Goodness of Fit Test

In order to determine which GEV distribution model best fits the sample rainfall data, a graphic diagnostic test was employed. The distribution can be fitted using a variety of graphical and numerical techniques; the degree to which the fitted model fits the sample data should be assessed based on the models and functions that were employed.

If every scatter follows the 1-1 axis, a better match is assured, as indicated by the graphical diagnosis plotted above. To assess the quality of the model fitting, the Q-Q plot of the models was also utilized. In all models, the scatters fall between the upper and lower bounds of the 95% conference band, but in models M-I and MV, the scatters appear to follow the 1-1 line quite well. There is also a closer relationship between the regression line and the 1-1 line. However, out of all the model types, the MV model turned out to be the best one due to its smaller AIC and AICC information criterion. The return levels for each time frame of the return periods of 2, 5, 10, 25, 50, and 100 years were predicted using the parameters of the best-fit GEV model. The projected return levels were compared as percentages of variances across the six time periods in order to monitor trends in extreme events. The greatest yearly rainfall from the best appropriate model was determined using its exceedance probability because non-stationary models have fluctuating return levels over time. The highest rainfall in each fit was determined using the 95% exceedance of the return level.

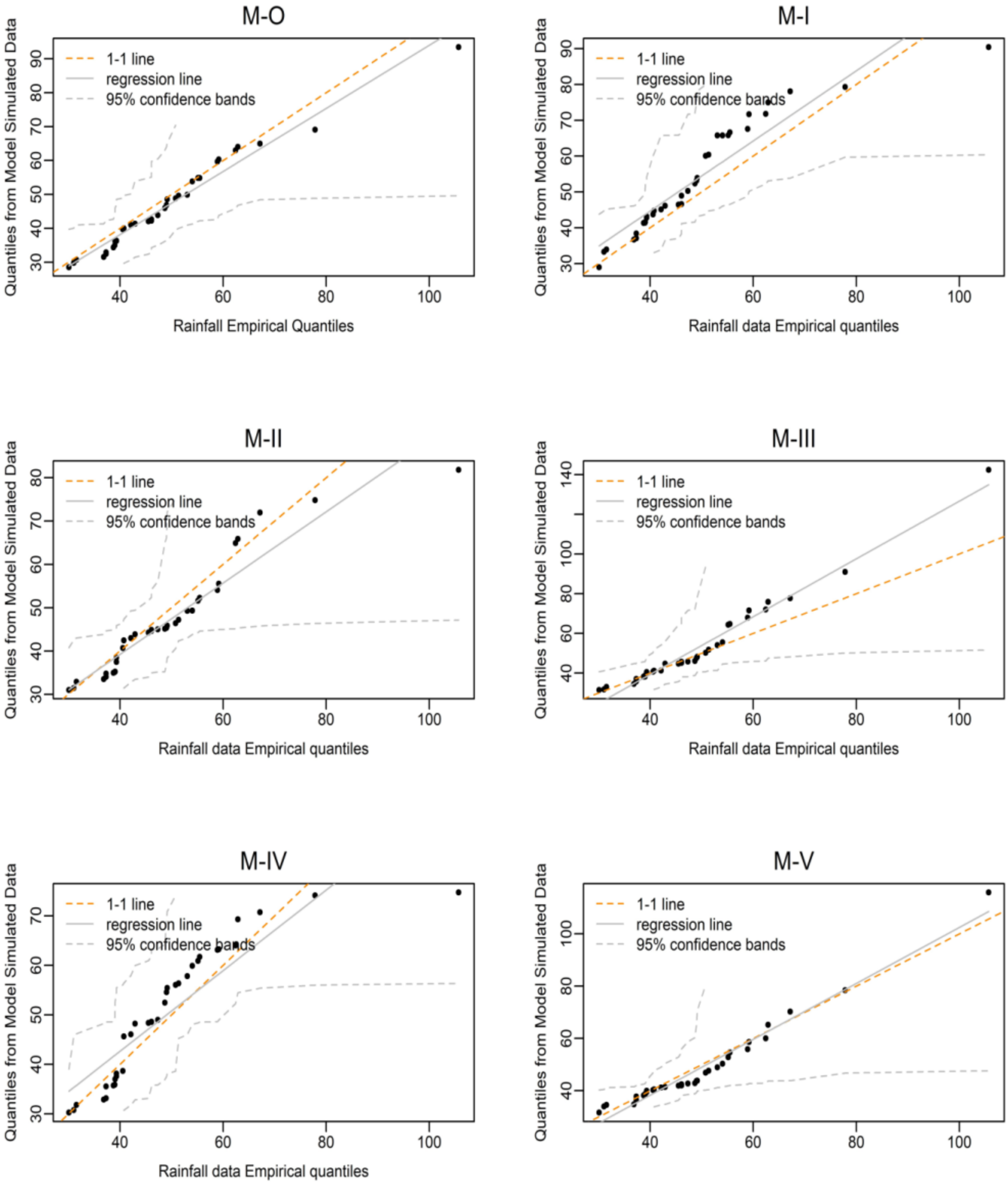


Figure 4. *Rainfall Quantile Plots at Debre Tabor Station for Various Models.*

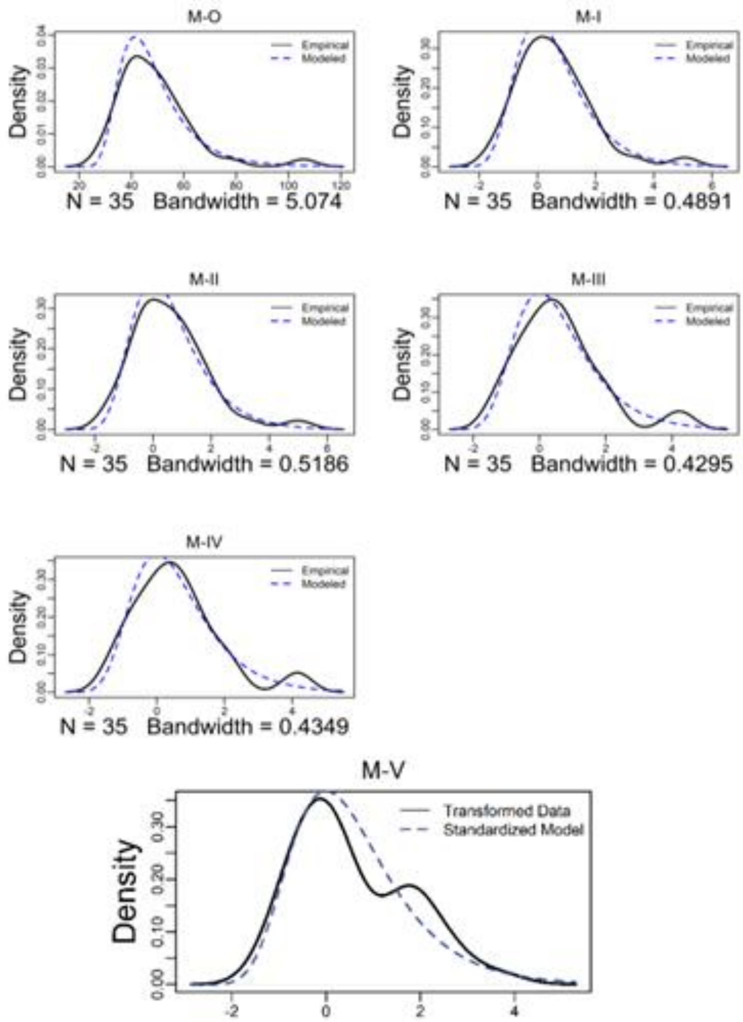


Figure 5. *Density Plot of Debre Tabor Station for Fit and Simulated Rainfall Data.*

Because of these factors, M-Ⅴ is the best fit model, and M-I, M-II, M-II, and M-IV are also eliminated by the AIC and AICC criteria. The M-□ model is primarily similar in shape to the fitted sample rainfall data, and the regression line of M-Ⅴ converged to the 1-1 line of the quantile plot of the model. As can be seen from the density plot figure above, M-0 is eliminated from the best fitting models since it is over fit and the simulated model's shape differs from the shape of the observed rainfall data. As a result, model M-Ⅴ has surpassed all other models as the best density plot model.

3.6. Development of GEV Models IDF Curves

Statistical modeling, rigorous data analysis, and consideration of the changing characteristics of rainfall events over time were all necessary for the development of GEV-based IDF curves, whether for stationary or non-stationary models The highest daily rainfall data for various years were retrieved and broken down to smeller durations from the rainfall data records that were gathered for Debre Tabor town over suitably long periods of time. By applying a statistical technique known as maximum likelihood estimation, the GEV distribution was fitted to the annual maximum rainfall data. The required GEV distribution parameters, such as μ, σ, and ξ that best characterized the extreme rainfall events seen in the sample data were estimated using the fitted procedure. Using the estimated GEV values, rainfall intensities were calculated for different durations and return times. The average recurrence interval of an event of a given amount is described by the return period. The return periods used in this research are 2-years, 5-years, 10-years, 25-years, 50-years, and 100 years. The GEV stationary IDF curves display the computed rainfall intensities plotted on the x-y axis for various durations and return times. The duration of the rainfall, given in time units like minutes or hours, is depicted on the x-axis, while the corresponding intensity of the rainfall, expressed in millimeters per hour, is represented on the y-axis. The IDF curves provide an example of how rainfall intensity, duration, and return periods are correlated.

Table 8. GEV Fitted Stationary Rainfall Intensity (mm/hr).

Duration (min)	Return Periods					
	2 years	5 years	10 years	25 years	50 years	100years
15	100.68	144.45	176.73	221.70	258.36	297.83
30	55.65	79.29	96.72	121.01	140.81	162.12
45	39.30	55.79	67.94	84.88	98.69	113.55
60	30.69	43.46	52.87	66.00	76.68	88.19
120	16.90	23.79	28.87	35.96	41.73	47.95
180	11.91	16.71	20.26	25.20	29.23	33.56

Considered Days	Return Periods					
	2 years	5 years	10 years	25 years	50 years	100years
1	2.71	3.47	4.027	4.80	5.44	6.12
2	1.40	1.70	1.90	2.15	2.34	2.52
3	0.95	1.12	1.23	1.35	1.44	1.52

For all the considered portion of durations in minutes the rainfall intensity show an increasing value as the length of return periods increase and show decreasing value while the length of duration increase.

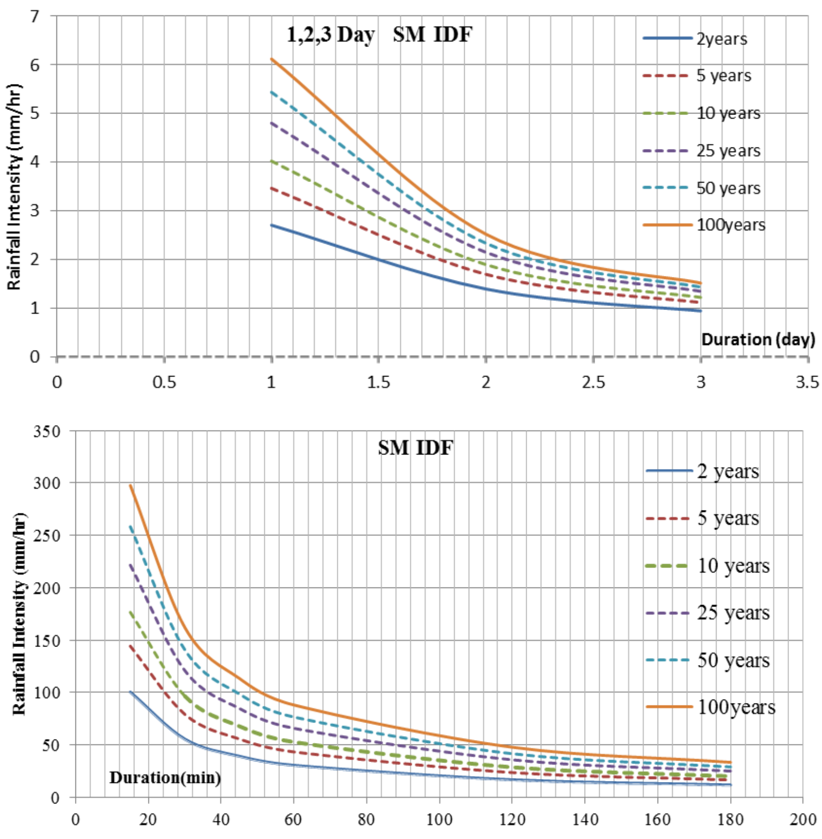


Figure 6. GEV Distribution Fitted Stationary IDF Curves for Debre Tabor Station.

The two IDF figures above revealed that the curves get closer as durations increase and the gaps between the curves get increased as the durations get a decreased. The curve for 2 years of return period is at lowest position and the curve for 100 years of return period is the top most position.

Table 9. GEV Fitted Non-stationary Rainfall Intensity (mm/hr).

Duration (min)	Return Periods					
	2 years	5 years	10 years	25 years	50 years	100 years
15	110.26	182.00	240.36	329.34	408.45	480.09
30	60.81	99.48	130.96	178.95	221.61	261.04
45	42.89	69.86	91.80	125.25	155.00	182.80
60	33.48	54.36	71.35	97.27	120.31	147.01
120	18.40	29.69	38.88	52.90	65.37	88.82
180	12.96	20.84	27.25	37.02	45.71	55.77

Considered Days	Return Periods					
	2 years	5 years	10 years	25 years	50 years	100 years
1	2.88	4.12	5.13	6.67	8.04	9.62
2	1.53	2.12	2.56	3.16	3.65	4.18
3	1.02	1.32	1.52	1.77	1.95	2.13

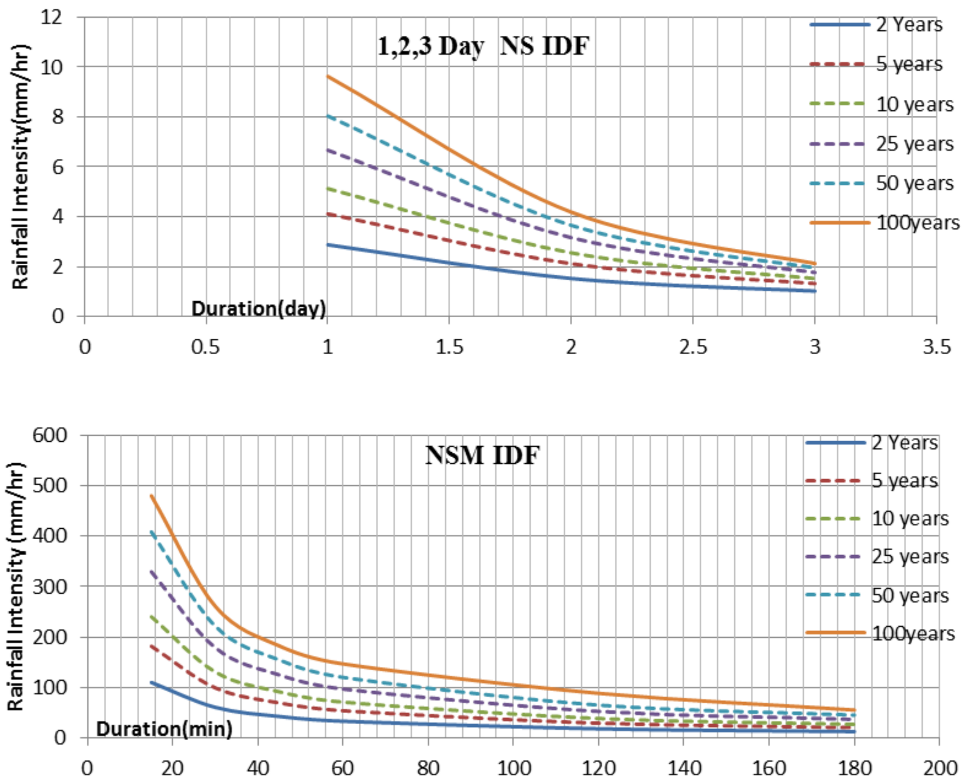
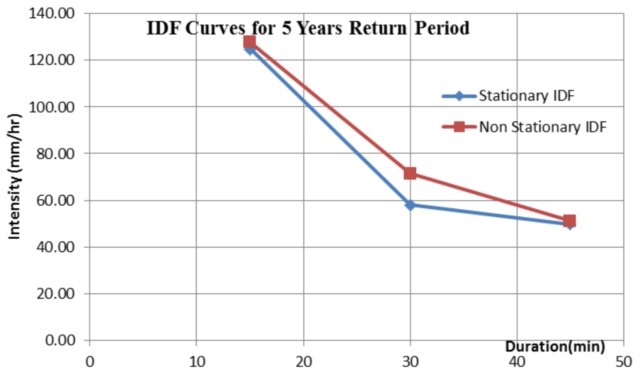


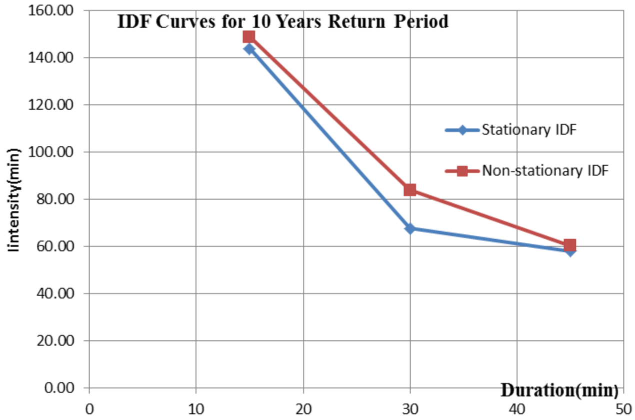
Figure 7. GEV Distribution Fitted Non-stationary IDF Curves for Debre Tabor Station.

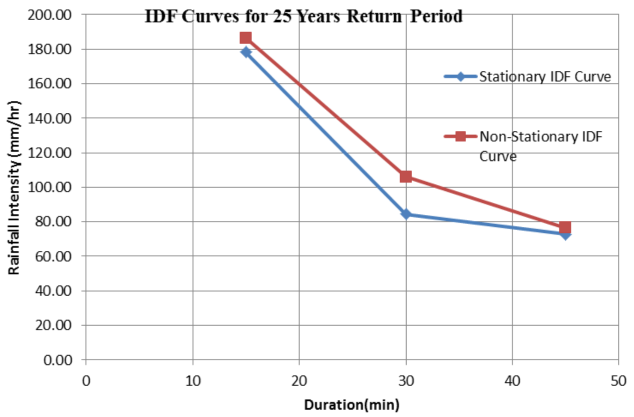
The rainfall intensity for non-stationary model show similar characteristics even though shows greater values than stationary model. As comparison the highest rainfall intensity value for stationary model is 297.83 mm/hr while that of non-stationary model is 480.09 mm/hr.

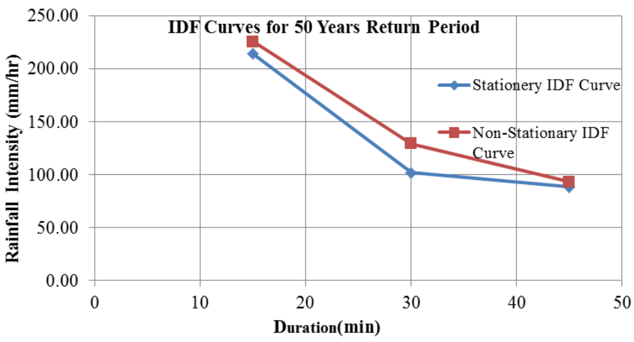
3.7. Comparing Stationary and Non-Stationary Models IDF Intensities

A detailed analysis of the GEV fitted distributions of rainfall intensities in Debre Tabor Station above and a visual inspection of graphical plots of the rainfall intensity against duration and return period also show a significant difference between stationary and non-stationary model intensities at each plotting point. The rainfall intensity values calculated for both stationary and non-stationary distributions were plotted against different durations for predetermined return periods on the same regular graph paper, as can be seen in the graphs below. As reported in numerous recent publications, it was verified that the stationary model generates IDF curves that understate exceptional occurrences. Compared to the stationary rainfall intensity distribution, the non-stationary rainfall intensity distribution produced higher values. Using stationary IDF curve values would not ensure that the hydraulic and hydrologic structural design of such facilities is safe against more hydraulic extreme occurrences projected by non-stationary approach for any given return period. For example, a 15-minute downpour with a 25-year return period resulted in non-stationary rainfall intensity of 329.34 mm/hr; yet, the same rainstorm length and return period also produced stationary rainfall intensity of 221.70 mm/hr. This means that the intensity difference between the two events was 107.64 mm/hr. A 30-minute rainstorm, again for a 100-year return period, produced a non-stationary rainfall intensity of 261.04 mm/hr and a stationary rainfall intensity of 162.12 mm/hr. This difference in rainfall intensity amounts to 98.92 mm/hr, or 61.02 percent, of the rainfall intensity calculated using the stationary method. Additionally, over a longer length of time the 60-minute rainstorm produced a rainfall intensity of 120.31 mm/hr using a non-stationary technique, and 76.68 mm/hr using a stationary method during the 50-year rerun period. There is a slight variation in the rainfall intensity between them of 43.63 mm/hr, or 56.90 percent, compared to the rainfall intensity determined using a stationary approach. This indicates that longer duration rainfall events have not altered considerably over the course of succeeding years, in contrast to shorter duration rainfall events, which intensified more with the corresponding return time. Further research showed that during shorter intervals, there was a greater disparity in rainfall intensities between non-stationary and stationary situations. The disparity narrows to 5.9 mm/hr rainfall intensity. For example, at a 5-year return time, a 2-hour rainfall storm produced 29.69 mm/hr rainfall intensity in the non-stationary technique and 23.79 mm/hr rainfall intensity in the stationary model.









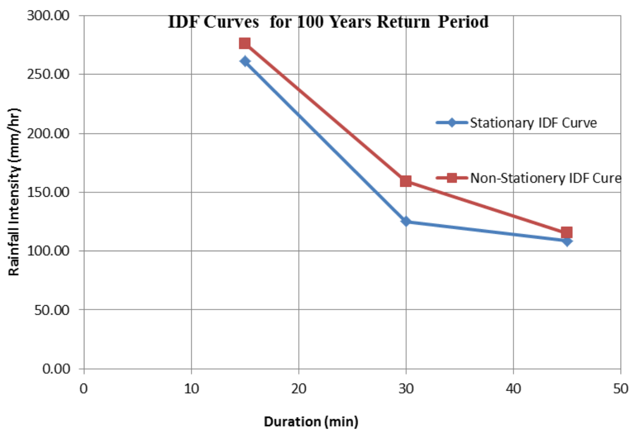


Figure 8. GEV Distribution Fitted Stationary against Non-Stationary IDF Curves.

3.8. Validation for Rainfall Intensity

When rainfall intensities calculated from observed rainfall are compared to projected rainfall intensities, this process is known as intensity validation. Various approaches to validation can be taken, depending on the particular situation, the data at hand, and the intended use of rainfall intensity estimations. The validation procedure requires specialized knowledge and comprehension in order to express the results and analyze the overall reliability of rainfall intensity estimates.

Table 10. Rainfall Intensity (mm/hr) derived using Hazen standard formula.

Duration (minutes)	1.2 Years Return Period	2 Years Return Period	6 Years Return Period
15	61.2	64	75.2
30	34	48	53.2
45	24.53	40.53	42.40
60	19.6	32.5	33.7

The rainfall intensity for table 10 is obtained by using Hazen method of estimating probability of exceedance. The formula used was

$$\frac{r-0.5}{n} * 100 \tag{46}$$

Where n is number of observations and r is rank [37].

Table 11. GEV Fitted Non-Stationary Disaggregated Rainfall Intensity (mm/hr).

Duration (min)	1.2 Years Return period	2 Years Return period	6 Years Return period
15	95.12	105.64	131.64
30	52.16	58.4	74.42
45	36.84	41.41	53.19
60	28.82	32.5	41.96

The aforementioned tables demonstrate that, for a 1.2 year return period and 15-minute duration, observed rainfall produced an intensity of 61.2 mm/hr. In contrast, the non-stationary method produced an intensity of 95.12 mm/hr during the same return period and duration. This indicates a positive difference and shows that the non-stationary method did not underestimate the rainfall intensity compared to the benchmark of observed rainfall intensity.

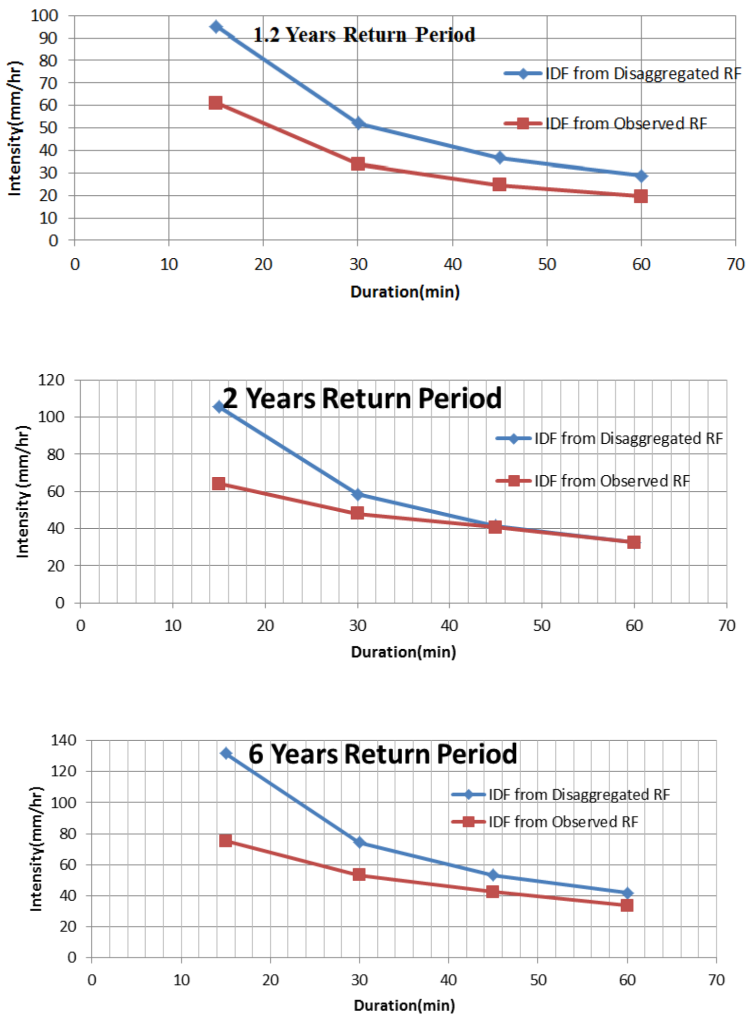


Figure 9. *Comparing the Disaggregate and Observed IDF Curves on the Same Plots.*

3.9. Conclusion and Discussion

The development of intensity-duration -frequency curves is very important task in hydrology for the prediction of design rainfall extreme events. IDF curves have historically been using stationary models, which makes the assumption those statistical characteristics of precipitation data remains constant throughout the time. However, there is growing understanding that climate change and other causes may introduce non-stationarity in precipitation patterns, necessitating the use of non-stationary models. In order to develop intensity-duration-frequency curves for Debre Tabor town using generalized extreme value distribution models, Debre Tabor station of annual maximum of daily rainfall of 35 years, and 6 years of maximum sub-daily annual (hourly) data on rainfall were utilized. Excel software was used to apply logical codes to modify the automatically recorded rainfall data with the relevant metrological data. The annual maximum daily rainfall data is founded generally homogeneous, non-stationary, independent and no outliers found. In addition to these data tests, the Mann-Kendall test using R studio for data trend test analysis was employed to find trends in the rainfall data. The generalized extreme value distribution function was used to fit the best fitting model of the annual maximum daily rainfall data; R-Studio software was used to analyze the model fitting processes. Five expected parameter models integrating time as a covariate was compared in order to estimate rainfall intensity for the non-stationary intensity-duration-frequency models. The predicted rainfall intensities for both the stationary and non-stationary models showed that the non-stationary intensities yielded values greater than the stationary intensities, suggesting that the stationary method underestimates the occurrence of intense rainfall occurrences. IDF curves were plotted for both stationary and non-stationary model intensities. Precipitation intensities shown different behavior over the two time intervals that are [15 minutes, 60 minutes) and [1 hour, 3 hours], where the values of the rainfall intensity were higher for shorter durations of time than longer ones. Practically in the rainfall intensity computation the non-stationary models produced greater values than stationary models, for example for 25 years return period, 15 minutes duration rainstorm produced the non-stationary rainfall intensity of 329.34

mm/hr, while the same return period and duration produced stationary intensity of 221.28 mm/hr. A variation of 107.64 mm/hr rainfall intensity is observed over this event. Once more, over 100 years return period, the 30 minute rain storm produced a non-stationary rainfall intensity of 261.04 mm/hr, while stationary rainfall intensity produced is 161.12 mm/hr. This difference in rainfall intensity amounts to 99.92mm. Additionally in a different analysis that was presented for a longer length, during a 50-year return period, a downpour lasting 1 hour yielded rainfall intensity of 76.68 mm/hr for stationary approach and 120.31 mm/hr for the non-stationary method.. A variation in rainfall intensity of 43.63 mm/hr, as such, the intensity of the rainfall, particularly for shorter durations, may cause the stationary IDF models highly under estimate the peak flood. It was verified that for periods ranging from 15 minutes to 30 minutes, the difference in rainfall intensities between stationary and non-stationary elements showed a discernible rise. However, the values of intensity of rainfall decreased with increasing durations, indicating that events with shorter durations became more intense with time, but events with longer durations did not very much. Because shorter-storms are producing higher intensities and sign of a greater difference in the extreme values, which could increase the risk of flooding and lead to hydraulic and hydrologic infrastructures failure, analysis on these storms should be focused on shorter durations for design purposes of different structures. Generally, the research work shows how important and useful GEV distribution models both stationary and non-stationary are for comprehending exceptional occurrence. These models help in improved risk management and decision making across a range of industries by offering insightful information on the behavior of catastrophic occurrence.

Abbreviations

RF	Rainfall
IDF	Intensity Duration Curves
AMS	Annual Maximum Series
MK	Mann-Kendall
EVT	Extreme Value Theory
GEV	General Extreme Value
GEV1	General Extreme Value Type-I
GEV2	General Extreme Value Type-II
GEV3	General Extreme Value Type-III
CDF	Cumulative Distribution Function
PDF	Probability Density Function
NAMA	National Meteorological Agency
SM	Stationary Model
NS	Non-Stationary
AIC	Akaike's Information Criteria
AICC	Corrected Akaike's Information Criteria
WMO	World Meteorological Organization
EMA	Ethiopian Meteorological Agency
ERA	Ethiopian Roads Authority

Author Contributions

Tebikew Dereje Alemu: Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

Temesgen Zelalem Addis: Conceptualization, Software, Visualization, Writing – review & editing

Yenesew Mengiste Yihun: Supervision, Visualization, Writing – review & editing

Conflicts of Interest

The authors declare no conflicts of interest.

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