JIMMA UNIVERSITY

SCHOOL OF POSTGRADUATE STUDIES

INSTITUTE OF TECHNOLOGY

FACULTY OF CIVIL AND ENVIRONMENTAL ENGINEERING

CHAIR OF HYDROLOGY AND HYDRAULICS ENGINEERING

M.SC. PROGRAM IN HYDRAULICS ENGINEERING

Regional Flood Frequency Analysis; A case of Genale Sub-Basin, Genale Dawa River Basin, Ethiopia

A thesis submitted to the School of Post Graduate Studies of Jimma University in Partial Fulfillment of the Requirements for the Degree of Master of Science in Hydraulic Engineering.

By: Seid Abas

June, 2022

Jimma, Ethiopia

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By: Seid Abas

Advisor: Mamuye Busier (Ass. Prof.)
Co-advisor: Natnael Sitota (MSc)

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Declaration

I hereby declare that the thesis entitled **"Regional Flood Frequency Analysis; A Case of Genale Sub-Basin, Genale Dawa River Basin, Ethiopia"** was the original work that I submitted for Partial Fulfillment of the Requirements for the Degree of Masters of Science in Hydraulic Engineering to the school of post-graduate studies. The thesis was conducted under the guidance of Mamuye Busier (Ass. Prof) and Natnael Sitota (MSc).

Student name	Signature	Date
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Co-advisor	Signature	Date

Approval

As members of the graduate faculty members of M.Sc, we certify that this student has successfully presented the necessary written final thesis and oral presentation for partial fulfillment of the thesis requirements for the degree of Master of Science in Hydraulic Engineering.

External Examiner	Signature	Date
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Internal Examiner	Signature	Date
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Abstract

Floods are common natural hazards, and they cause great economic damage and a great loss of human life. The design of hydraulic structures requires the estimation of flood quantiles. However, the quantification of these quantiles in data-scarce regions has been a continuing challenge in hydrologic design. In many developing countries, records of flood data are rarely available. Regionalization techniques are essential to overcome the scarcity of hydrological data and provide regional flood information. The overall goal of this study is to develop a regional flood frequency analysis for the Genale Sub-Basin. The Index flood method based on the L-moment was chosen for this study. The annual maximum series of 5 gauging stations were selected to conduct regional flood frequency analysis. The collected data was evaluated and tested for data sufficiency, stationary, independence, homogeneity, randomness, and outliers. This test revealed that the data met the basic assumptions of hydrological data. The identification of homogeneous regions was performed based on flood statics. The region has shown satisfactory results in spatial homogeneity tests. Several candidate probability distributions have been applied. The parameters obtained from the Kolmogorov–Smirnov and chi-square tests using HEC-SSP helped to select the best distribution. The result shows that the Gumbel distribution was identified as a robust regional probability distribution for the study area. From the probability-probability and discharge-discharge plots, the plot points tend to lie reasonably along and close to a straight line, and this provides validation of Gumbel's distribution for accurately estimating flood flow for different return periods. The flood discharge of specific recurrence intervals was computed, and regional growth curves were developed for the regions by using the L-moment parameter estimation method. The standardize flood corresponding to return period such as 2, 2.33, 5, 10, 20, 50, 100,200,500,1000,5000 and10,000 were 0.964,1.000,1.155,1.281,1.402,1.558,1.675,1.792,1.946, 2.063, 2.333 and 2.450 respectively. Lastly, the index flood estimation model $Q2.33=0.521A^{0.6819}$ *was developed for the region by regression analysis with a coefficient of determination of 0.9557 for the estimation of index flood from the ungagged watershed. The parameters that affect the catchment features of the basin have to be integrated using multiple integration techniques to obtain a better estimation of the index flood of the ungauged catchment.*

Keywords: *Genale Sub-Basin, Index-flood, L-moments, Quantiles, Regional Flood Frequency Analysis, Regionalization*

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Abbreviations and Acronyms

AMS………………Annual Maximum Series

CC………………...Combined Coefficient

CDF………………Cumulative Distribution Function

CFA………………Consolidated Frequency Analysis

C-S………………..Chi-Squared

CV………………...Coefficient of Variance

DEM………………Digital Elevation Model

FFA………………..Flood Frequency Analysis

GIS………………..Geographic Information System

GSB………………Genale Sub-Basin

K–S………………..Kolmogorov–Smirnov

LCk………………..L-Moment Coefficient of Kurtosis

LCL………………..Lower Confidence Limit

LCv………………..L-Moment Coefficient of Variance

LM………………...L-Moments

MSL……………….Mean Sea Level

MCMC…………….Markov Chain Monte Carlo

MK………………...Mann-Kendall

MLM………………Maximum Likelihood Method

MOM………………Method of Moment

MoWE……………..Ministry of Water and Energy Ethiopia

POT………………..Peak-Overthreshold

P-P…………………Probability-Probability

PWM………………Probability Weighted Moment

Q-Q………………..Quantile-Quantile

RFFA……………...Regional Flood Frequency Analysis

SNHT……………...Standard Normal Homogeneity Test

SROSCC…………..Spearman Rank-Order Serial Correlation Coefficient

UCL……………….Upper Confidence Limits

1 Introduction

1.1 Back Ground of Study Area

Floods are one of the most common natural hazards, and they are causing great economic damage and a great loss of human life (Igor Lescesen et al., 2019). Flood incidents are sometimes extremely complex natural events. They are the results of several parameters. Therefore, it is difficult to model floods analytically due to the contribution uncertainty. For example, catchment floods depend on the catchment characteristics, rainfall, land use, land cover, other catchment characteristics, and other antecedent conditions. In turn, each of these factors depends on a host of constituent parameters (Subramanya, 1984). The estimation of flood peaks is a complex problem, leading to a different approach (Yayneshet, 2020). Besides the rational method, unit hydrograph method, and rainfall-runoff model method, frequency analysis was one of the main techniques used to define the relationship between the magnitude of an event and the frequency with which that event is exceeded (Bhagat, 2017). Flood frequency analysis (FFA) is the estimation of how often a specific event occurs (Pradesh et al., 2017).

Precise estimates of flood quantiles are needed to efficiently design hydraulic structures (Tegegne & Kim, 2020). Also, in extreme floods, emergency evacuation of people can be carried out well in advance (Bhagat, 2017). In developing countries, annual flood series are too short to allow a reliable estimation of extreme events, or no flow record is available at the site of interest (Mosaffaie, 2015). The use of regional information to estimate flood magnitudes at sites with little or no observed data has become increasingly important because many projects which require design flood information are located in areas where observed flood data are either missing or inadequate (Yirefu, 2010). The Genale River sustains the livelihoods of millions of people across this river. The river requires new approaches for ensuring the ongoing security of the water supply for drinking purposes, hydropower, and agricultural production. In this direction, the Ministry of Water and Energy of Ethiopia has been conducting several high-level feasibility studies for hydraulic construction structures.

Some of those studies were completed and are currently at the implementation stage, while others are ongoing (Amiin & Wiliq, 2018). Therefore, developing the regional flood frequency analysis improved the design reliability of various water resources projects in the study area.

1.2 Statement of Problem

The design of hydraulic structures and the assessment of flood control measures required the estimation of flood quantiles (Do-Hun Lee 1, 2019). However, the quantification of these quantiles in data-scarce regions has been a continuing challenge in hydrologic design (Tegegne & Kim, 2020). In many developing countries, records of flood data are rarely available (Obinna & Ekwueme, 2020). Most of Ethiopia's river basins have a small hydrological gauge station with a short length of the record. Also, the existing gauged stations face problems, such as incomplete and missing data records (Eregno, 2014).

The Genale river overflows frequently during the rainy season and is one of the flood-prone areas. Besides, A lot of hydraulic structures for hydropower, water supply, and other irrigation structures have been constructed in many areas of this catchment. However, there were a few sources of design parameters corresponding to the recurrence interval that was used for designing hydraulic structures, early flood warning activities, or any other related tasks. Currently, ongoing hydrological research is providing adequate techniques to fill these gaps. Therefore, this study is intended to solve the above problems of the catchment using regional flood frequency analysis.

1.3 Objectives of the Study

1.3.1 General Objective

The general objective of this study is to develop the regional flood frequency analysis for the Genale Sub-Basin.

1.3.2 Specific Objectives

- To identify the hydrological homogeneous region of the Genale Sub-Basin
- To identify the best regional probability distribution and corresponding parameters for the Genale Sub-Basin
- To develop a dimensionless regional growth curve for the research area
- To derive a relationship between index floods and drainage area that can be used for estimation of quantiles in the un-gauged watershed within the region

1.4 Research Questions

- Is it Genale Sub-Basin hydrological homogeneous regions?
- What are the best regional probability distribution and corresponding parameters in the Genale Sub-Basin?
- What does it seem the dimensionless regional flood frequency curve of the research area?
- What are the best models that could be used for ungagged watersheds in the Genale Sub-Basin?

1.5 Significance of the study

If any design flood data is required in these regions, it would be easy to read the value with the corresponding return period from the regional growth curve. The results from the analysis can be used for the proper planning, design, management, and operation of water resources projects and some other related tasks for which flood quantiles are important in the basin. In addition, the study can be used as a point of reference for policy and decision-makers and any further investigation can be carried out on the Genale Sub-Basin.

1.6 Scope of Study

The study was mainly focused on conducting regional flood frequency analysis (RFFA) based on available streamflow data records of the Genale Sub-Basin and was trying to establish a regional growth curve and index flood model for ungagged sites using a linear regression model.

Besides, the study includes: checking the basic assumption of hydrological data; identification of a homogeneous region; selection of the best fit regional probability distribution with its corresponding method of parameter estimation; quantile estimation; and estimation of index flood for standardization.

1.7 Limitation of the study

Using long-term streamflow for flood frequency analysis brings in the question of flood stationary (distribution parameters are constant in time). Climatic change, land-use conditions, and other factors in the hydrological cycle can affect the relevance of past flooding as a predictor of future flooding. Thus, the assumption of stationary in hydrology should no longer serve as a central and default assumption in water resources design and planning. The stationary models do not indicate the existence of periods in which flood frequency experienced significant variability (decreases and increases).

1.8 Research Composition

The whole theme of the paper was trying to be compiled into five chapters. The first chapter deals with the background of the study area, and also states the objective, research questions, statement of problems, significance of the study, the scope of the study, and limitations of the study. Then, the second chapter would try to review the literature on regional flood frequency analysis. The third chapter deals with the description of the study area; materials and methodology of the study area; data collection; data screening; filling and extension of missing data; data quality checking; and estimation of flood statistics of the study area. Chapter four presents the identification of homogenous regions by conducting various tests of homogeneity, fitting a parent distribution to the region, estimating the parameters, regional quantile estimation, and derivation of the regional growth curve, and would develop an index flood regression model. Finally, the last chapter would try to provide some conclusions and recommendations.

2 Literature Review

2.1 Flood

A flood is an unusually high stage in a river, normally the level at which the river overflows its banks and inundates the adjoining area. The damage caused by floods in terms of loss of life, property, and economic loss due to disruption of activity is all too well known (K Subramanya, 1984). Estimation of floods arises in hydrology for forecasting and prediction purposes. Problems of forecasting approach for flood estimation arise most directly in the operation of hydrological controls in the broadest sense, including flood warnings. While the predictions approach, issues are associated with the designs rather than the operation of such controls (Younis, 2020). Peak or flood flow is an important hydrologic parameter in the determination of flood risk, water resources management, and the design of hydraulic structures such as dams, spillways, culverts, and irrigation ditches (Abida & Ellouze, 2008). The estimate of the design event must be fairly accurate to avoid excessive costs in the case of overestimation of the flood magnitude or excessive damage and even loss of human lives while under-estimating the flood potential (Abida & Ellouze, 2008). Flood frequency analysis of streamflow data aims to associate the magnitude of extreme events with their frequency of occurrence using the probability distributions function (Ahuchaogu, et al 2021). The streamflow data may be limited or, in other cases, not be available for a proposed site. A hydrologically homogeneous region can overcome this challenge by conducting RFFA (Obinna & Ekwueme, 2020). In the past, RFFA methods have been applied to estimate the flood quantiles in ungauged or poorly gauged basins (J. L. Salinas et al, 2013).

2.2 Regional Flood Frequency Analysis

Engineers and planners are frequently interested in determining the magnitude and frequency of peak discharge at project areas when planning and designing water resources projects (Bhagat, 2017). Flood frequency analysis is performed either for a single site when extensive historic peak flow data are available, or on a regional data basis, when there is little or no historic streamflow data at a particular site (Abida & Ellouze, 2008). In this latter case, hydrologically homogeneous regions from the statistical point of view were considered. Available streamflow data from neighboring watersheds were tested for spatial homogeneity and groups of stations satisfying the test were identified.

This group of stations constitutes a region, and all the gauge stations of these regions are pooled and analyzed as a group to find the regional flood frequency characteristics of the region (Subramanya, 1984).

Furthermore, RFFA, an important tool for estimating design flows in ungauged basins, can add information to the existing time series in gauged sites and transfer them to the ungauged catchment (Cassalho et al., 2017). RFFA uses the spatial coherence of hydrological variables to provide regional estimates of flood quantiles, which are superior to at-site estimates even in the presence of moderate heterogeneity (Komi et al., 2016). Generally, the use of regional information allows a reduction of sampling uncertainty by introducing more data as well as a reduction of model uncertainty by facilitating a better choice of distribution. Recently, research efforts have focused more on regional rather than conventional at-site flood frequency analysis.

2.3 Flood Frequency Models

In FFA, the objective is to determine a Q-T relationship at any required site along a river. Two methods are generally used for FFA: annual maximum series (AMS) and peak-over threshold (POT). The AMS method uses one maximum event per year, while the POT method uses every peak above the selected threshold level (Ologhadien, 2021). The AMS is a widely and commonly used model by different researchers for FFA. However, using an AM series may involve some loss of information due to generalization. For example, the second, third, or four peaks within a year are possibly greater than the peak streamflow in other years, yet they are ignored. In this approach, there is no certain fixed value above which the peaks should be considered. This scenario is avoided in the peaks over a threshold (POT) models where all peaks above a certain selected base value are considered. The base is usually selected low enough to include one prominent event each year. However, the POT model approach is limited by the fact that observations may not be independent. Thus, to avoid the problem of dependency on data, the AMS model was selected in this study.

2.4 Regionalization

Regionalization is a way of grouping river basins into homogeneous regions. In other words, regionalization means the identification of homogeneous regions, that contain stations with similar flood-producing features (Ase et al., 2018). In the context of RFFA, regionalization refers to identifying homogeneous regions through a homogeneity test and selecting a suitable probability distribution for the identified stations and regions (Mengistu, 2008). The term "regionalization" is based on the assumption that the standardized variable has a similar probability distribution at every site in the region under consideration (Damtie, 2020).

Regionalization serves two purposes. For sites where data are not available, the analysis is based on regional data. For sites with available data, the joint use of data measured at a site and regional data from several stations in a region provides adequate information to use probability distribution with greater reliability (Cunnane, 1988). Therefore, regionalization techniques are essential to overcome the scarcity of streamflow data and regional flood information (Rezende et al., 2021).

2.4.1 Identify Hydrological Homogeneous Regions

The most important step in RFFA was the formulation of homogeneous regions of selected sites. A region was considered to be homogeneous if the sites included in the region had some common characteristics (Ahmad et al., 2017). Homogeneity implies that regions have similar flood-generating mechanisms. The specific definition of a homogeneous region is a region that consists of sites having the same standardized probability distribution form and parameter. Such a region must be geographically continuous and it forms a basic unit for carrying out regional flood frequency analysis for estimation of quantile for water resources design and planning projects (Ase et al., 2018).

Preliminary identification of groups of stations into a certain category (regions) was achieved by looking at catchment characteristics (Hussen & Wagesho, 2016). First, some of the parameters that affect flow conditions like soil type, elevation, land use, land cover, and slope of the sub-basin with similar flood-producing characteristics were examined. Then, those stations with nearly the same physiographic and climatic characteristics are grouped.

In this study, L-moment statistics are used to group stations into regions (i.e., sets of gauging sites whose flood-producing behavior is homogeneous) in terms of geographical proximity and continuity of gauging stations. Finally, by considering the boundaries of each sub-catchment, the delineation of homogeneous regions was carried out, and for each region, the homogeneous test was performed to confirm that the delineated regions are statistically homogeneous (Yayneshet, 2020).

2.4.2 Homogeneous Tests

A test of regional homogeneity is needed for the regional flood frequency analysis to evaluate whether a proposed region might be regarded as a homogeneous region (Do-Hun Lee 1, 2019). The homogeneity test aims to estimate the degree of homogeneity in a group of sites (Mosaffaie, 2015). Homogeneity of the region is done based on the conventional moment and L-moment. The fundamental advantage of the L-moment approach over the standard moment method is that it can characterize a wider range of distributions, is less prone to estimate bias, and is more robust because it is unaffected by the presence of outliers in the data (Hosking & Wallis, 1997).

2.5 Choice of Probability Distribution Functions

After the successful formulation of homogeneous regions, the next step was the selection of a robust and appropriate statistical model. The best fit probability distribution to the selected region provided accurate quantile estimates for different recurrence intervals (Ahmad et al., 2017). The probability distribution helps to relate the magnitude of the flood to its number of occurrences with time (Alam & Khan, 2015). Different frequency distribution techniques have been developed for the determination of FFA (Hanwat et al., 2020). However, no single distribution method can be accepted as the universal distribution for describing the flood frequency for any gauging site. Therefore, the proper choice of a statistical distribution that best fits the AMS data is essential to analyzing flood frequency for the study area (Hasan, 2020). The choice of distribution is influenced by many factors, such as the method of discrimination between distributions, the method of parameter estimation, and the availability of data. The method of parameter estimation goes in parallel with distribution selection (Cunnane, 1988).

In many countries, the selection of probability distribution is not made in any objective manner and the selection of distribution is argued in a general manner, as follows: The chosen distribution was: widely accepted, simple and convenient to apply; consistent, flexible, or robust (low sensibility to outliers); theoretically well based, and documented in the Guide (WMO, 1983) and elsewhere (WMO, 1989).

2.6 The goodness- of- Fit Tests

(Asnake,2018) explains that goodness-of-fit tests can be used to compare fitted distributions, select a model, and determine how well the distribution was fitted to the data. The Anderson–Darling, Kolmogorov–Smirnov, and Chi-Squared statistical tests are commonly used to check the adequacy of the probability distribution functions for FFA (Tegegne & Kim, 2020). Therefore, this study considered the Kolmogorov–Smirnov, Chi-Squared goodness of fit tests method, to investigate the robust probability distribution function for RFFA in the Genale Sub-Basin.

2.6.1 Kolmogorov–Smirnov Test (K–S)

The K–S test determines the greatest statistical distance between the CDF F(x) and the theoretical function F(x). The K-S test was distribution-free; the critical values do not depend on the specific distribution being tested.

The test statistic D is rejected if it exceeds the tabulated critical value or when the p-value is lower than the significance level (Malaysiana et al., 2021). The KS test is also appropriate for a small sample size. However, to utilize this test, the location, shape, and scale parameters have to be specified since they cannot be estimated directly from the data (Malaysiana et al., 2021).

2.6.2 Chi-Squared Test (C–S)

In the C–S goodness of- fit- test, sample data is divided into intervals. Then the numbers of points that fall into the interval are compared with the expected numbers of points in each interval (Gooch, 2011).

2.6.3 Anderson–Darling Test (A-D)

The A-D test is an upgraded version of the KS test that considers the tail of a distribution. This test can overcome the limitations of K-S, although it can only be used for certain distributions. AD is more sensitive to the distribution's tail. The disadvantage of this test is that critical values must be calculated for each distribution.

The critical values of A-D depend on the specific distribution that is being tested. The test is a one-sided test and the hypothesis that the distribution is rejected if the test statistics are greater than the critical value.

2.7 Method of Parameter Estimation

After the best fit distribution was selected to fit the data, its parameters were estimated. The estimate parameters were to calculate the quantile for different recurrence intervals or, conversely, to calculate the recurrence interval for a given flood magnitude. The most common and important reason for possible errors in modeling annual maxima series is the methods used in parameter estimation. The accuracy of the estimation of parameters decides the accuracy of quantile estimation of any distribution (Alam & Khan, 2015).

There are several methods available for parameter estimation of a distribution. The method of moments (MOM), probability-weighted moments (PWM), maximum likelihood method (MLM), and L-Moments (LM) method are the most commonly used methods in hydrology for parameter estimation (Kousar & Raza, 2020). The location parameter of the distribution indicates where the distribution lies along the x-axis. The scale parameter of distribution determines the degree of spread in a distribution. The shape parameter of the distribution allows the distribution to take different shapes (Malaysiana et al., 2021).

2.7.1 Method of Moments (MOM)

In MOM, the estimators of the population moments must be equal to the sample moments. MOM is best implemented when moments are available. The principle behind the moment method is to equate the moments of the probability density function about the origin to the corresponding moments of the sample data (Malaysiana et al., 2021). This is relatively easy, but less efficient and biased for the three-parameter distribution and preferable for the two-parameter distribution.

2.7.2 Method of Maximum Likelihood (MLM)

MLM maximizes the likelihood, or joint probability of occurrence, of the observed sample. However, MLM is not suitable for implementation in a small sample size (Malaysiana et al., 2021). This strategy entails selecting parameter estimates that produce the highest chance of the observations occurring (Damtie, 2008).

It provides the smallest sampling variance of the estimated parameters; it is considered the most efficient method even though it provides a biased estimator, which can be corrected and requires higher computational effort.

2.7.3 Method of Probability Weighted Moments (PWM)

PWMs (probability-weighted moments) is useful for generating expressions for the parameters of precisely defined distributions. The moment of the distribution is equated with the relevant sample moment of observed data in this approach of parameter estimation. The first sample moments are set equal to the corresponding population moments in a parameterized distribution. The unknown parameters are then solved simultaneously for the resulting equation. PWM is a relatively recent method of parameter estimate that is as simple to use as ordinary moments. It is usually unbiased and almost as efficient as MML. Indeed, in small samples, PWM may be as efficient as MML; given the right distribution, PWM can help with robustness assessment (Cunnane, 1988).

2.7.4 L-Moments

L-Moment was a newer method of parameter estimation. Sample estimators of L-moments are linear combinations of the ranked observations, so they do not involve "powering" (squaring, cubing, etc.) of observations, like the MOM method. (Alam & Khan, 2015) show that L-moment ratio estimators of location, scale, and shape are nearly unbiased, not depending on which probability distribution is used, from which the observations arise. Therefore, the method of L-moments presents almost unbiased and efficient estimates relative to the other estimation methods (Ahmad et al., 2017). Due to the complexity of parameter estimation methods, the use of statistical software packages was recommended.

2.8 Quantile Estimation

The quantile (QT) that corresponds to different return periods was computed after the distribution parameters were estimated. The term "return period" is used to denote the reciprocal of the probability of exceedance. Plotting Position formulas are used to calculate the probability of being equaled or exceeded at least once. The plotting formula holds good for smaller values of the return period. When a larger extrapolation of the return period is involved, a frequency distribution has to be used (Alam & Khan, 2015).

Several plotting position formulas were developed, some of which are California, Hazen, Weibull, Chegodayev, and Blom. The Weibull formula is the most commonly used plotting formula.

Table 2.1: Plotting position formula

Method	Probability of exceedance(p)
California	$\frac{m}{N}$
Hazen	$\frac{m-0.5}{N}$
Weibull	$\frac{m}{N+1}$
Chegodayev	$\frac{m-0.3}{N+4}$
Blom	$\frac{m-0.44}{N+0.12}$

Flow discharge was calculated through confidence limits (up to 95%). Confidence limits can be used to measure the uncertainty of the estimated exceedance probability of a select discharge or a measure of the uncertainty of the discharge at a select exceedance probability.

2.9 Estimation of Index Flood for Standardization

Dalrymple (1960) introduced the index flood method. The underlying assumption was that flood data within a homogeneous region is drawn from the same frequency distribution, apart from a scaling factor (Crochet, 2015).

This method calculates a dimensionless flood variable that allows for estimating a regional growth curve (Rezende et al., 2021). Many types of regionalization procedures are available. One of the most (Cunnane, 1988) straightforward procedures used for a long time is the index flood method. The index-flood method is most appropriate for frequency estimation at ungauged sites or sites with insufficiently long series (Igor Lescesen et al., 2019). Index-flood estimation methods depend on whether the site of interest is gauged or ungauged. For gauged sites, the estimation methods are usually called the direct methods and use the information from AMS at the site of interest.

In this approach, the mean of the observed sample is used as an estimator of the index flood (Younis, 2020). For the ungauged site in a hydrologic homogeneous region, the index-flood estimation method may be called an indirect method and uses the information on regional basins related to the flood values and the corresponding physiographic/climatic properties (Younis, 2020).

2.10 Derivation of the Regional Growth Curve

A regional growth curve was developed for each region after quantile estimation. The regional growth curve is the dimensionless frequency distribution common to all sites within a hydrologically homogeneous region (Do-Hun Lee 1, 2019). The flow quantile for the ungauged catchment within that region can be easily computed from the regional curve development.

2.11 Design Flood for the Ungauged Catchment

At ungauged sites, the index flood is determined by relating the average AMS to explanatory variables of the monitored catchments in a region. The explanatory variables to describe this relationship could be the drainage area, drainage density, length and steepness of the main river, average annual rainfall, landcover, and so on (Rezende et al., 2021). The index flood of the ungauged watershed was a function of the catchment area (A). An equation of mean annual discharge with the watershed area has been developed using the regression method (Alam & Khan, 2015).

3 Materials and Methods

3.1 Description of the Study Area

3.1.1 Location of the Study Area

The Genale Sub-Basin, which is the study area, is situated in the south-eastern part of Ethiopia. Its origin is in the mountains east of Aleta Wendo. The Sidama and Bale highlands provide the vast majority of their water (Bastian, 2015). The Genale has a total length of 858 km. It is geographically located between 4° 0’0"N and 8° 0’0"N latitude and 38° 0’0"E to 42° 0’0"E longitude.

The watershed gets its first maximum rainfall during spring (March to May) and its second maximum rainfall during autumn (September to November). The yearly average precipitation experienced in the study area was about 810 mm, and the rainfall distribution in a watershed ranges from 300 to 1302 mm per year. The Genale River joins the Dawa River at the Dolo Ado border, which then forms the Genale-Dawa River Basin. The monthly temperature ranges from 14.5° C to 24.6° C, with an average of 19.5° C (Negewo, 2021).

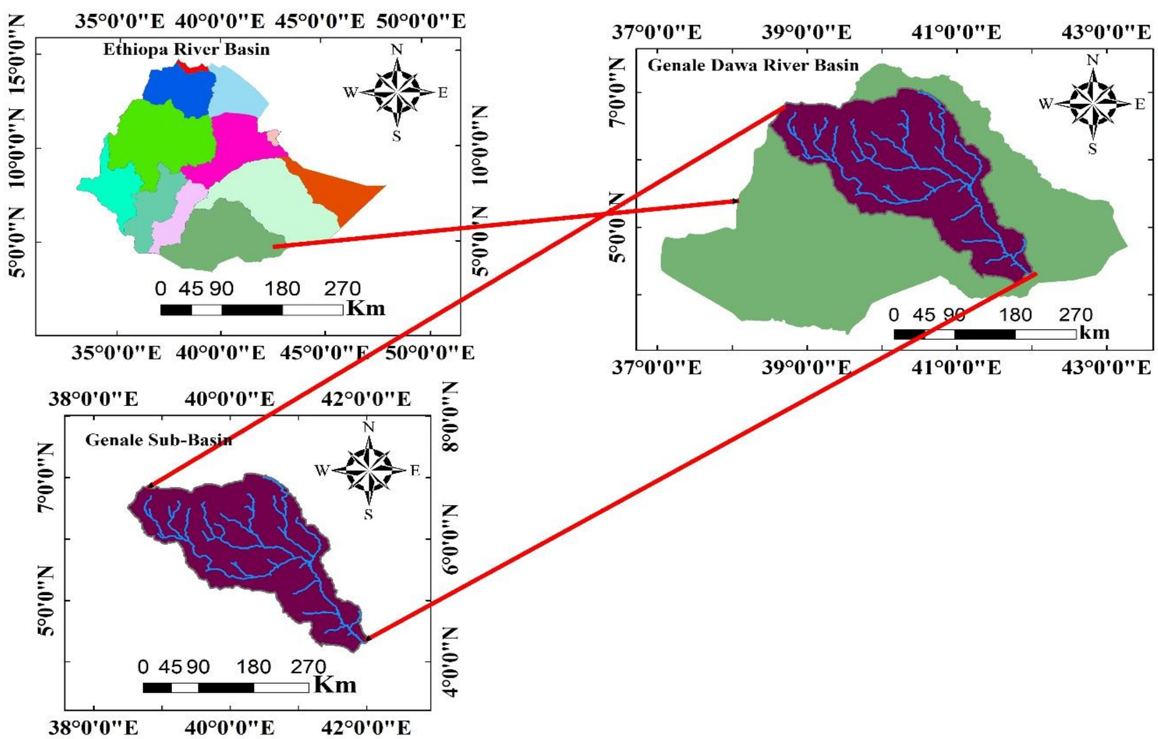

Figure 3.1: Location of GSB

3.1.2 Topography of Genale Sub-Basin

The Genale Sub-Basin is characterized by great geographical diversity, with flat-topped plateaus, highlands, deep gorges, and river valleys. The highest and lowest elevations of the basin were 4288 m and 185 m, respectively, above mean sea level. The basin can be defined in terms of four major landforms: Highlands and plateaus; steep sloping escarpments; gently sloping lowlands; and lowlands and flood plain basins.

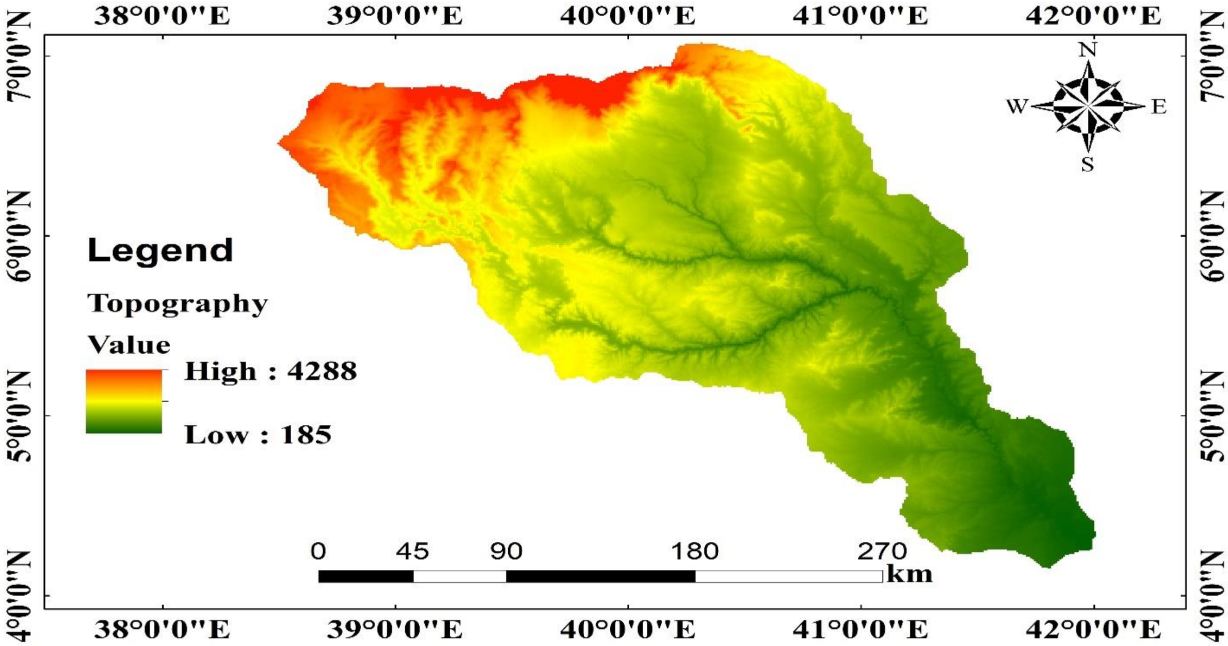

Figure 3.2: Topography of GSB

3.1.3 Land Use Land Cover of Genale Sub-Basin

The analysis of LULC change patterns for the study area over 24 years showed that most 17 parts of the green forest, barren land, and range shrubs were changed into agriculture, built up, wetlands, and water bodies with an increase of agriculture by 60%, built up by 68%, pasture 37%, range shrubs 9%, and water body 57% over 19 (1990 to 2013), which increased surface runoff, water yield, and sediment yield in the watershed (Negewo, 2021).

3.1.4 Soil Type of Genale Sub-Basin

The soil of the study area can be classified based on FAO soil classification. The following were the types of soil in the study area: Eutric Cambisols, Plinthic Ferralsols, Eutric Nitosols, Calcaric Regosols, Eutric Regosols, Haplic Xerosols, and Haplic Yermosols.

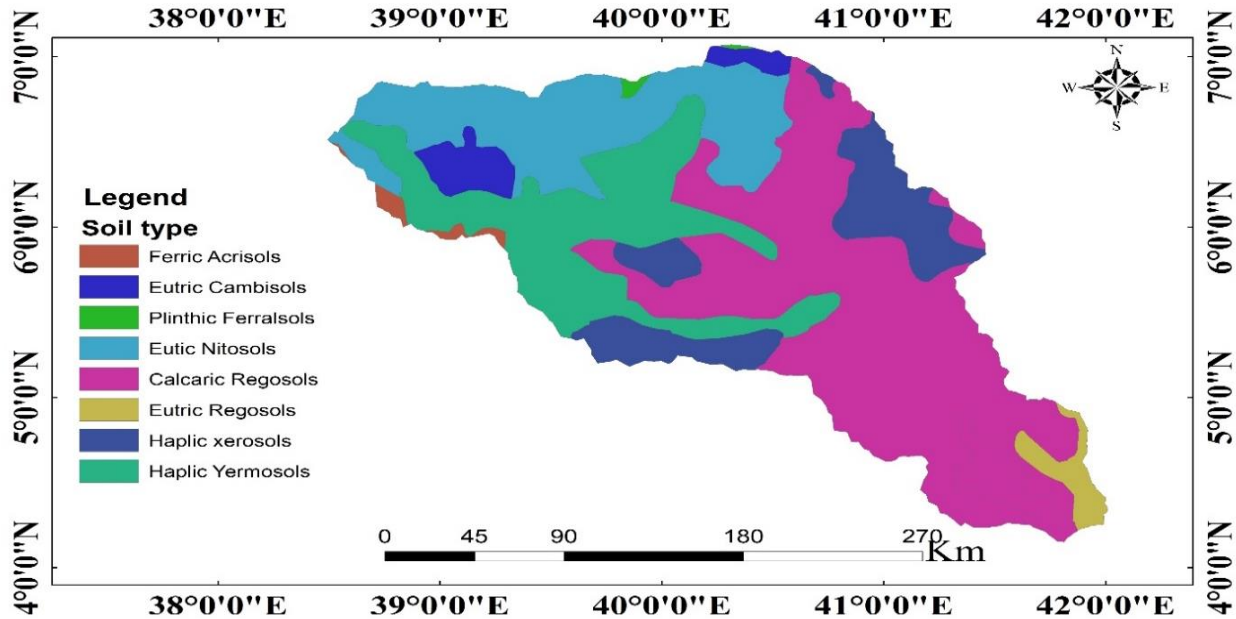

Figure 3.3: Soil types of GSB

3.1.5 The slope of Genale Sub-Basin

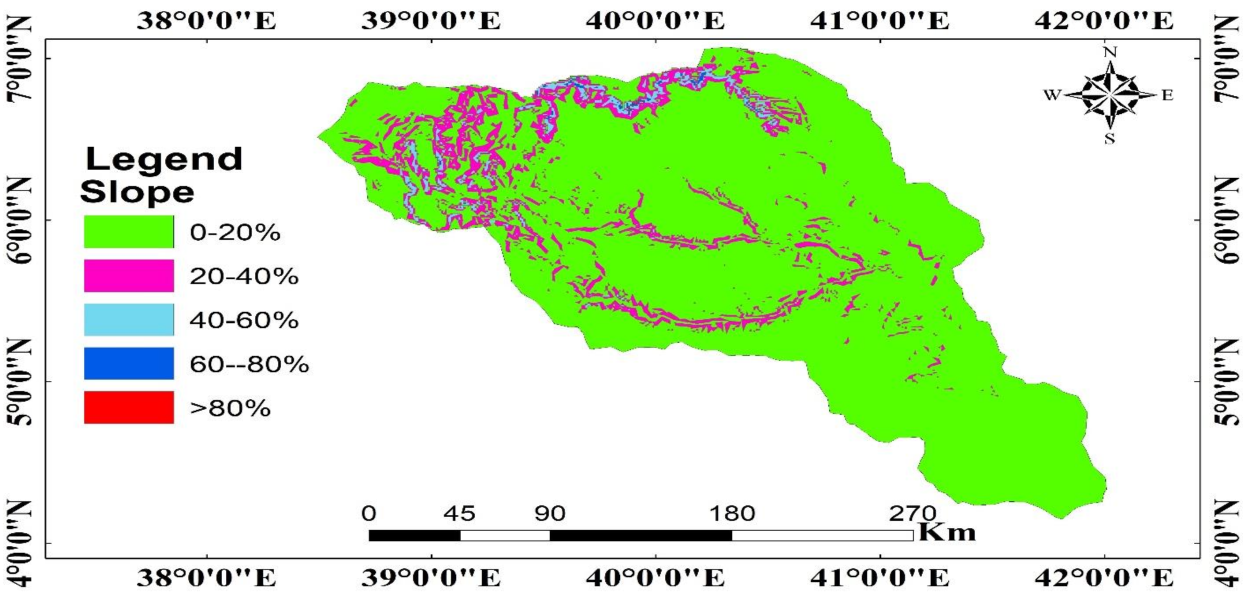

Figure 3.4: Slope of GSB

3.1.6 Watershed and Stream Network Delineation

A watershed has five components: a watershed boundary, sub-basin, drainage divides, stream network, and outlets. Watershed delineation is part of the process known as watershed segmentation to analyze watershed behavior.

The delineation of watersheds was an essential step in the hydrologic analysis. The outlet point placement is an important step in the process of watershed delineation that should exist within an area of high flow accumulation (Ali & Ali, 2018).

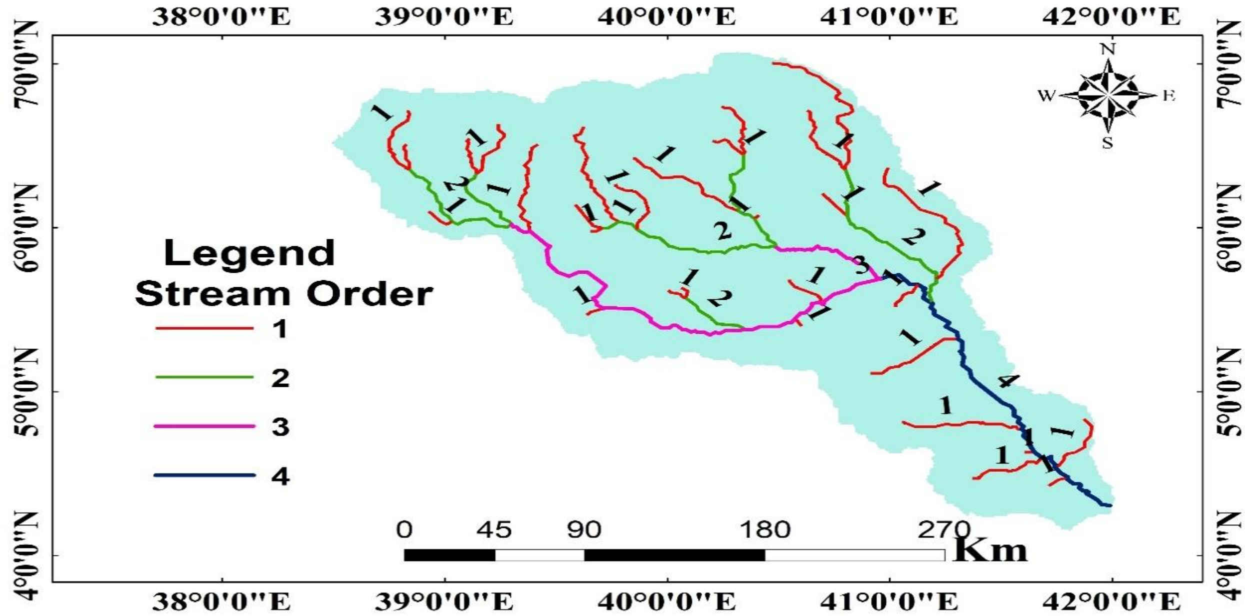

Figure 3.5: Stream order of GSB

3.2 Materials

The materials were used for this study:

a) **Arc GIS**: Arc GIS was used for the delineation of the study area and as a representation gauge station for Genale Sub Basin.

b) **XLSTAT 2018 software**: XLSTAT was used for organizing raw data, filling in missing data, and plotting regional growth curves.

c) **HEC-SSP Version 2.2 Software**: Hydrologic Engineering Center's (HEC) Statistical Software Package (HEC-SSP) was used to analyze statistical hydrologic data, fitting probability distributions to sample data, select a suitable probability distribution and parameter estimation, and quantile estimation.

d) **Consolidated Frequency Analysis (CFA) Version 3.1**

The programming language of this software was Fortran 77**.** The CFA was a hydrologic program used to perform statistical tests such as independence, trend, homogeneity, and randomness.

e) **DOSBox:** DOSBox is a free and open-source emulator that runs software for MS-DOS compatible disk operating systems. The Mac OSX 0.74-3-3 version of DOSBox was used to operate the CFA software.

f) **Rainbow version 2.2:** It is used to test the homogeneity of hydrological data.

3.3 Methodology

There are a lot of approaches developed by different researchers, but the index flood method is nowadays the best and most commonly recommended approach (Damtie, 2008). The methodology chosen in this study was the index flood method based on L-moments for regional flood frequency analysis. The flow chart of the research methodology in this study was as indicated in figure 3.6:

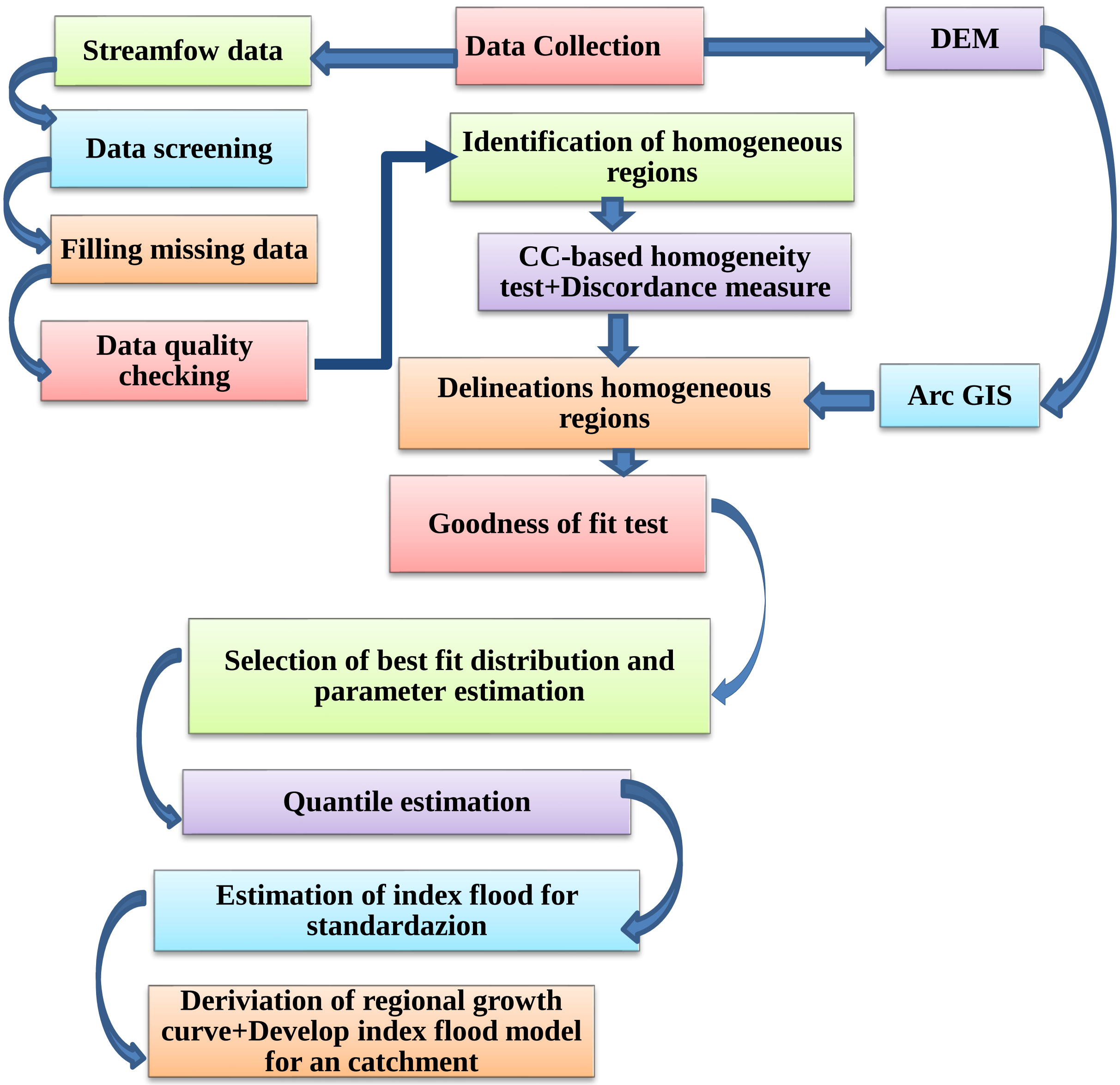

Figure 3.6: Flow chart of research methodology

3.4 Data Collection

The availability of data for analysis determines the outcome of any research work. In this study, the following data were used: Hydrological data and spatial data (DEM).

3.4.1 Hydrological Data

Streamflow data for more than ten years with good quality was required for RFFA. The long-time series provides an accurate and reliable prediction. The study was conducted using AMS.

The AMS method is more widely used; because it provides statistical independence of data (Saf, 2009). The time-series data were obtained from the Ministry of Water and Energy of Ethiopia (MoWE) to analyze the magnitude and frequency of the study area. The length of historical streamflow records varies from 18 years to 21 years.

3.4.2 Spatial Data

A DEM of 30mx30m resolution was used for study area delineation; specifying the location of the gauging stations in the river basin; describing the site characteristics of the study area, such as topography and LULC. The DEM data for the study area was obtained from the MoWE GIS department.

Table 3.1: Site characteristics of study of stations

S. No	River	Gauging Station Location	Coordinate		Area Coverage Km^2	Record Period	Sample size
			Latitude	Longitude			
1	Genale	@Halowey	4°26′	41°50′	54093	1995-2013	19
2	Genale	@Chenemasa	5°31′	39°41′	10574.0	1995-2015	21
3	Genale	@Kole Bridge	4°32′	41°45′	83219.0	1998-2015	18
4	Mana	Near Goro	7°01′	40°22′	485.0	1995-2015	21
5	Shawe	@Mrslo Project	6°26′	39°41′	340.0	1995-2015	21
6	Yadot	Near Dello Mena	6°25′	39°51′	531.0	1990-2008	19
7	Halgol	Gom-Goma	6°20′	39°50′	164.0	1995-2012	18
8	Welmel	@Melka Amana	6°14′	39°46′	3048.0	1995-2015	21

3.5 Data Screening

Checking that the data is relevant to the analysis is the first step in every statistical analysis. The data gathered at the location for flood frequency analysis must be a true representative of the quantity measured and drawn from the same frequency distribution. The screening should try to ensure these standards. Data screening is the process of ensuring your data is clean before conducting further statistical analyses. After data screening was done, the total stations which were used for further analysis became 5, and 3 of the stations (Genale at Kole Bridge; Shawe at Mrslo project; and Mena near Goro) were rejected due to their poor data quality.

The five streamflow gauge stations were selected for analysis based on the length and quality of the data they have.

3.6 Filling Missing Data

For accurate flood analysis, reliable, long, and continuous-time series are necessary. Due to technical or maintenance issues, long-term hydrological data production and management are difficult tasks. These missing intervals in the time series represent a loss of information and cause unreliable analysis. Consequently, to obtain reliable and accurate information from the data, these gaps must be filled (Tencaliec et al., 2016). Most XLSTAT functions include options to handle missing data. This tool allows you to complete your dataset using advanced missing value treatment methods. For this study, Markov Chain Monte Carlo (MCMC), a multiple imputation algorithm, was selected for filling and extending missing data by using XLSTAT 2018 software.

3.7 Data Quality Assessment

The hydrological data for water-management studies should be stationary (without trends), homogeneous, independent, and random when they are used in FFA (Abida & Ellouze, 2008). The data quality was checked using six tests: data adequacy, stationary, independence, homogeneity, randomness, and outliers.

3.7.1 Data Adequacy and Reliability

The data was checked for its adequacy and reliability. Adequacy and reliability were checked and defined (McCuen, 1998**)** using the equation:

$$De=\frac{Cv}{N^{0.5}} \qquad [3.1]$$

Where De denotes standard error

Cv=Coefficient of variation is the ratio of the standard deviation to the mean.

N denotes the number of yearly data points in the series.

Adequacy and reliability of data were checked, and the data series could be regarded as reliable and adequate if De was less than 10% significance.

Table 1.2: Data adequacy and reliability

Station	Parameters				Remark
	Mean (μ)	Standard deviation (σ)	Coefficient of variation (Cv)	Standard error (De) %	
Genale @ Halowey	592.605	178.115	0.301	6.895	<10%
Genale @ Chenemasa	440.357	149.023	0.338	7.385	<10%
Yadot near Dello mena	43.781	18.022	0.412	9.444	<10%
Halgol Gom- goma	12.354	4.766	0.387	9.112	<10%
Welmel@Melka Amana	138.641	57.804	0.417	9.098	<10%

Therefore, the data for all stations was found to be accurate, adequate, and reliable as the De value for all stations was less than 10% standard error.

3.7.2 Independence Test

An independent data series means the data was not correlated with adjacent observations.

The time series independence can be measured by the correlation coefficient. In this study, the serial-correlation coefficient and the nonparametric Spearman rank-order serial correlation were used to verify the independence of a time series.

a) Serial-Correlation Coefficient

The lag-1 serial correlation coefficient, R1, is defined as follows:

$$R1=\frac{\sum_{i}^{n-1}(X\,i-Xm)(Xi+1-Xm)}{\sum_{1}^{n}(Xi-Xm)^{2}} \qquad [3.2]$$

Xi is an observation, Xi+1 is the following observation, Xm is the mean of the time series, and n is the number of observations in a sample.

After computing R1, the test hypothesis is that H0: R1 = zero (that there is no correlation between two consecutive observations) against the alternative hypothesis, H1: R1 <> 0.

Anderson (1942) defines the critical region, R1 at the 5% level of significance as (1, (LCL) R1 (UCL), 1).

The upper confidence limit, UCL, for R1 as:

$$UCL(R1)=\frac{-1+1.96*(N-2)^{0.5}}{N-1} \qquad [3.3]$$

The lower confidence limit, LCL, for R1 as:

$$LCL(R1)=\frac{-1-1.96*(N-2)^{0.5}}{N-1} \quad [3.4]$$

To accept hypothesisH0: R1 = 0, the value of R1 should fall between the UCL and LCL.

According to equation 3.2-3.5, the independence test of hydrological data was done and it is tabulated as shown in the following table 3.3.

Table 3.3: Result of Serial-correlation coefficient for independence test

S.No	Station Name	LCL(R1) value	R1	UCL(R1) value
1	Genale @ Halowey	-0.5	0.346	0.39
2	Genale @ Chenemasa	-0.48	0.098	0.38
3	Yadot near Dello mena	-0.5	0.109	0.39
4	Halgol Gom- goma	-0.52	0.046	0.4
5	Welmel @ Melka Amana	-0.48	-0.086	0.38

Applying this condition to the time series: LCL (R1) R1 UCL (R1) is satisfied for all stations. Therefore, no correlation exists between successive observations for all stations. The data are independent, and the time series show no persistence.

b) Spearman Rank-order Serial Correlation coefficient (SROSCC) for Independence

The series of data was put in chronological order. The series was analyzed to determine the longest sequence of consecutive observations. The longest consecutive data was then denoted as Qi, with i ranging from 1 to n. Two sequences are created and ranked within the series.

Q1, Q2, QN-1 Where x_i is the rank of the series Qi, i = 1 to n-1 and

Q2, Q3, Q_{N-1} Where y_i is the rank of the series Qi, i = 2 to n

Then the Spearman rank-order serial correlation coefficient is:

$$S_1=\frac{1}{2}(\sum xi^2+\sum yi^2-\sum di^2)\ (\sum xi^2 \sum yi^2)^{-1/2} \quad [3.5]$$

$$\text{Where } \sum xi^2=(m^3-m)/12-\sum Tx \quad [3.6]$$

$$\sum yi^2==(m^3-m)/12-\sum Ty \quad [3.7]$$

M=N-1,

di is the difference in rank between xi and yi the summations are over the m pairs of xi and yi.

Table 3.4: Result of Spearman test for independence

Station	Parameters					Remark
	SROSCC	DFT	Corresponds to students T	Critical T @ 5%	Critical T @ 1%	
Genale @ Halowey	0.352	16	1.504	1.746	2.583	Independent
Genale @ Chenemasa	0.066	18	0.282	1.734	2.552	Independent
Yadot near Dello mena	0.166	16	0.674	1.746	2.583	Independent
Halgol Gom- goma	0.047	15	0.181	1.753	2.602	Independent
Welmel@MelkaAmana	-0.059	18	-0.249	1.734	2.552	Independent

The null hypothesis was that there was a zero correlation. At the 5% level of significance, the correlation was not significantly different from zero. That is, the data does not display significant serial dependence for all gauge stations.

3.7.3 Randomness Test

In a hydrologic context, randomness means that the fluctuations of the variable arise from natural causes and that the data series is not the result of human intervention. The test was based on the number of runs that a sample exhibited. A "run" was defined as a succession of identical symbols that are followed and preceded by different symbols or by no symbol at all (Harvey, K.David 1993).

Table 3.5: Result of run test for general Randomness

Station	Parameters				Remark
	RUNAB	N1	N2	Rang @ 5% level of significance	
Genale @ Halowey	6	9	9	6 to 14	Random
Genale @ Chenemasa	12	10	10	7 to 15	Random
Yadot near Dello mena	6	9	9	6 to 14	Random
Halgol Gom- goma	10	9	9	6 to 14	Random
Welmel@MelkaAmana Amana	12	10	10	7 to 15	Random

The data are random, according to the null hypothesis. At the 5% level of significance, the null hypothesis cannot be rejected. That is, the sample was significantly random for all gauge stations.

3.7.4 Trend Test

For this study, stationarity can be verified through the Mann-Kendall test and Spearman rank-order correlation coefficient test. This test to Check whether AMS is stationary or not.

a) Mann Kendall Test (MK)

The MK test was a non-parametric test for the detection of trends in hydro-climatic variables. This test has the advantage over parametric methods in that it is less sensitive to outliers (W. Wang,& Faculty, 2005). using the MK test. The null hypothesis, Ho_t, is that there is no trend in the time series; and the alternative hypothesis, Ha_t, is that there is a trend in the time series for a given significance level(Belete, Ermias Teferi, 2018). Nonparametric Sen slope quantifies existing increasing or decreasing statistical trends (Duguma et al., 2021). The MK test positive slope indicated increasing and the negative slope indicated decreasing. The statistics of the MK test (S) and its variance are given by:

$$S=\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \mathrm{sgn}(xj - xi) \qquad [3.8]$$

$$\mathrm{sgn}(xj\text{-}xi) = \begin{cases} 1, \text{if } (xj - xi) > 0 \\ 0, \text{if } (xj - xi) = 0 \\ -1, \text{if } (xj - xi) < 0 \end{cases} \qquad [3.9]$$

Under the null hypothesis, the statistical S is approximately normally distributed with zero mean and its variance is given by:

$$\mathrm{Var}(S) = \frac{n(n-1)*(2n+5)}{18} \qquad [3.10]$$

n is the number of observations and xi (i = 1... n) is the independent observations without tie values.

Table 3.6: Results of the Mann-Kendall test

MK test	Streamflow station				
	Genale @ Halowey	Genale @ Chenemasa	Yadot near Dello Mena	Halgol Gom- goma	Welmel@Melka Amana
Kendall's tau	-0.135	-0.129	-0.205	-0.059	0.171
S	-23.000	-27.000	-35.000	-9.000	36.000
Var(S)	817.000	1095.667	817.000	697.000	1096.667
p-value	**0.441***	**0.432***	**0.234***	**0.762***	**0.291***
alpha	0.05	0.05	0.05	0.05	0.05
Sen's slope	-6.400	-5.607	-1.107	-0.069	2.142

*As the computed P-value is greater than the significance level alpha = 0.05, one cannot reject the hypothesis HO_t. As presented in table 3.6 results of the Mann-Kendall test, the streamflow pattern in the study area of all stations has no specific trend (p-value > 0.05). Thus, the series almost have the same variation pattern around the average and are indicating a stationary state (trend-free) for all stations in the study area.

b) **Spearman Rank-order Correlation Coefficient Test for Trend**

If the series Qi with i=1 to N was put in chronological order and ranks were assigned to the series, Q1, Q2..........QN by yi, the rank of Qi.

And 1, 2,... N by xi, the sequential order of Qi; then the Spearman Rank Order Correlation Coefficient r_s is calculated.

$$r_s=\frac{1}{2}(\sum xi^2+\sum yi^2-\sum di^2(\sum xi^2 \sum yi^2)^{-1/2} \quad [3.11]$$

Where $\sum xi^2=(m^3-m)/12-\sum Tx$ [3.12]

$\sum yi^2==(m^3-m)/12-\sum Ty$ [3.13]

M = N, Tx = 0, and the summations are taken over the N pairs of xi, Yi.

Table 3.7: Result of Spearman test for trend

Station	Parameters					Remark
	SROSCC	DFT	Corresponds to students T	Critical T @ 5%	Critical T @ 1%	
Genale @ Halowey	0 .153	17	0 .637	2.110	2.898	No trend
Genale @ Chenemasa	0.173	19	0.765	2.093	2.861	No trend
Yadot near Dello Mena	0.311	17	1.347	2.110	2.898	No trend
Halgol Gom- goma	0.179	16	0.726	2.120	2.921	No trend
Welmel@MelkaAmana Amana	-0.275	19	-1.248	-2.093	-2.861	No trend

The null hypothesis is that the serial (lag-one) correlation is zero. At the 5% level of significance, the correlation was not significantly different from zero. That is, the data does not display a significant trend for all gauge stations.

3.7.5 Homogeneity Test

A homogenous data series are identically distributed and comes from the same population. A time series was called time-homogeneous (also known as stationary) if identical events under consideration in the time series were likely to occur at all times. The homogeneity test is used to understand the consistency of the data of stations (Duguma et al., 2021). In statistical hypothesis testing, the data is tested against the null hypothesis that the data is homogenous. If the P-value is greater than the 0.05 significance level, the data is homogeneous; if the P-value is less than the 0.05 significance level, the data is non-homogeneous (Shan et al., 2018). For this study, homogeneity tests, namely Pettitt's, SNH, Buishand’s, von Neumann's test, and Mann-Whitney split sample test, were used for performing the homogeneity test of the time series.

a) Pettitt's Test

Pettitt's test was an adaptation of the rank-based Mann-Whitney test that allowed identifying the time at which the break occurs. This test was a nonparametric rank test and requires no assumptions about the data distribution(Elzeiny et al., 2019).To compute, the ranks r1... rn of xi..., xn are used.

$$Y(k)=2\sum_{i}^{k} r_i - k(n+1) \quad k=1\ldots, n \qquad [3.14]$$

The break occurs at a k observation where Y (k) was maximum or minimum.

b) Standard Normal Homogeneity Test (SNHT)

The SNHT was developed by Alexanderson (1986) to detect a variation in a time series of rainfall data. The SNH test is based on the T (k) statistic that compares the mean of the first k observations with the mean of the remaining n-k observations.

$T(k)=kz1^2+(n-k)\ z1^2\ \ k=1,\ldots,n$ [3.15]

Where $z1=\frac{1}{k}\sum_{i=1}^{k}\frac{xi-\mu x}{\sigma X}$ [3.16]

$Z2=\frac{1}{n-k}\sum_{i=k+1}^{k}\frac{xi-\mu x}{\sigma X}$ [3.17]

c) Buishand's Range Test

The Buishand range test was a parametric test that assumes that test values are independent and identically normally distributed. The alternative hypothesis assumes that the series contains a jump-like shift (break.) The Buishand test can be applied to variables following any type of distribution (Elzeiny et al., 2019). Buishand test statistics S is defined as

$S(k)=2\sum_{i}^{k}(xi-\mu x)\ \ k=1\ldots,n$ [3.18]

d) Von Neumann's Test

The Von Neumann ratio test was a nonparametric test with the null hypothesis that the data are independent and identically distributed random values. The test was very powerful at all times but does not allow detection of the time of the change. The variable N of the Von Neumann ratio test is defined as the ratio of the mean square successive difference and the time-series variance (Vezzoli et al., 2013).

$N=\frac{\sum_{i}^{n-1}(xi-xi+1)^2}{\sum_{i}^{n}(xi-\mu x)^2}$ [3.19]

Table 3.8: Result of homogeneity test

Homogeneity Test	Streamflow station					
		Genale @ Halowey	Genale @ Chenemasa	Yadot near Dello Mena	Halgol Gom-goma	Welmel@ MelkaAmana
Pettitt's test	k	40	46	54	38	54
	t	4	6	9	8	11
	p-value	**0.638**	**0.694**	**0.158**	**0.590**	**0.358**
SNHT test	T0	4.213	3.560	4.608	2.441	4.664
	t	4	4	9	12	15
	p-value	**0.233**	**0.407**	**0.184**	**0.634**	**0.204**
Buishand's test	Q	3.747	3.687	4.800	3.216	5.059
	t	4	6	9	12	11
	p-value	**0.307**	**0.386**	**0.104**	**0.443**	**0.114**
von Neumann's test	N	1.283	1.697	1.719	1.872	2.150
	p-value	**0.054**	**0.242**	**0.269**	**0.378**	**0.629**

Test interpretation:

$H0_h$: The data is homogeneous.

Ha_h: There was a date at which there was a change in the data.

As the computed p-value (bold value) for all stations was greater than the significance level alpha=0.05, one cannot reject the null hypothesis $H0_h$. As a result, the AMS was consistent across all stations.

e) Mann-Whitney Split Sample Test for Homogeneity

The sample was split into two subsamples and ranks were assigned. The Mann-Whitney U statistic was then defined as the lesser of:

$U_1=n_1n_2+n_1(n_1+1)/2-R_1$ [3.20]

Or $U_2= n_1n_2-U_1$ [3.21]

Where n1 denoted the size of the smaller subsample.

The larger subsample's size was n2.

The sum of the ranks in subsample n1 was R1

Table 3.9: Result of Mann-Whitney Split Sample test for homogeneity

Station	Parameters				
	SS1	SS 2	U	Critical U @ 5% significance level	Critical U @ 1% significance level
	N	N			
Genale @ Halowey	9	10	27.0	24.0	16.0
Genale @ Chenemasa	10	11	50.5	31.0	22.0
Yadot near Dello Mena	M	10	19	24	16
Halgol Gom- goma	9	9	27.0	21.0	14.0
Welmel@MelkaAmana Amana	10	11	34.0	31.0	22.0

The null hypothesis is that there is no location difference between the two samples. At the 5% level of significance, there was no significant location difference between the two samples; that is, they appeared to be from the same population for the 4-gauge station; but, for Yadot near Dello Mena station, at the 5% level of significance, there was a significant difference in location, but not so at the 1% level. That was, the location difference was significant but not highly so.

3.7.6 Test for Outliers

Outliers are data points that depart significantly from the trend of the remaining data; which may be due to errors in data collection, and recording or due to natural causes, which may slightly deviate from assumed homogeneous values. The presence of outliers in a data sample can lead to problems in formulating a probabilistic model (Plavsic et al., 2014). Outliers (extreme points) often distort the results of an analysis. Therefore, a careful review of the extreme values in the record before proceeding to RFFA was essential. The retention or deletion of these outliers can significantly affect the magnitude of statistical parameters computed from the data, especially for small samples. For this study, the L-moment parameter estimation technique was employed. Because L-moment was more robust and they were not affected by the presence of outliers in the data (Hosking & Wallis, 1997).

The hypothesis is tested by the Grubbs test.

HO: There is no outlier in the data.

The minimum or maximum value is an outlier.

The Grubbs' test statistic is defined as:

$$G=\frac{\max(X-\mu)}{s} \qquad [3.22]$$

with μ and **s** denoting the sample mean and standard deviation, respectively.

The Grubbs' test can also be defined as one of the following one-sided tests:

Test whether the minimum value is an outlier

$$G=\frac{X-Xmin}{s} \qquad [3.23]$$

x_{min} denotes the minimum value.

Test whether the maximum value is an outlier.

$$G=\frac{XMax-X}{s} \qquad [3.24]$$

with x_{max} denoting the maximum value.

The critical value of the test is

$$Gcrit=\frac{(n-1)tcrit}{\sqrt{n(n-2+t^2crit)}} \qquad [3.25]$$

Table 3.10: Result of Grubs test for detecting outliers

Outliers Test	Streamflow station				
	Genale @ Halowey	Genale @ Chenemasa	Yadot near Dello mena	Halgol Gom-goma	Welmel @ Melka Amana
G (Observed value)	1.543	1.893	1.630	2.251	1.736
G (Critical value)	2.681	2.734	2.681	2.652	2.734
p-value (Two-tailed)	**1.000***	**1.000***	**1.000***	**0.274***	**1.000***

*As the computed P-value is greater than the significance level alpha=0.05, one cannot reject the hypothesis HO.

Also, the following techniques are used for detecting outliers: Boxplot, scatter plots, Z-score, and Inter Quantile Range.

The Z score is given by $Z=\frac{X-\mu}{\sigma}$ [3.26]

Where X=Observation,μ=Mean,σ =Standard Deviation

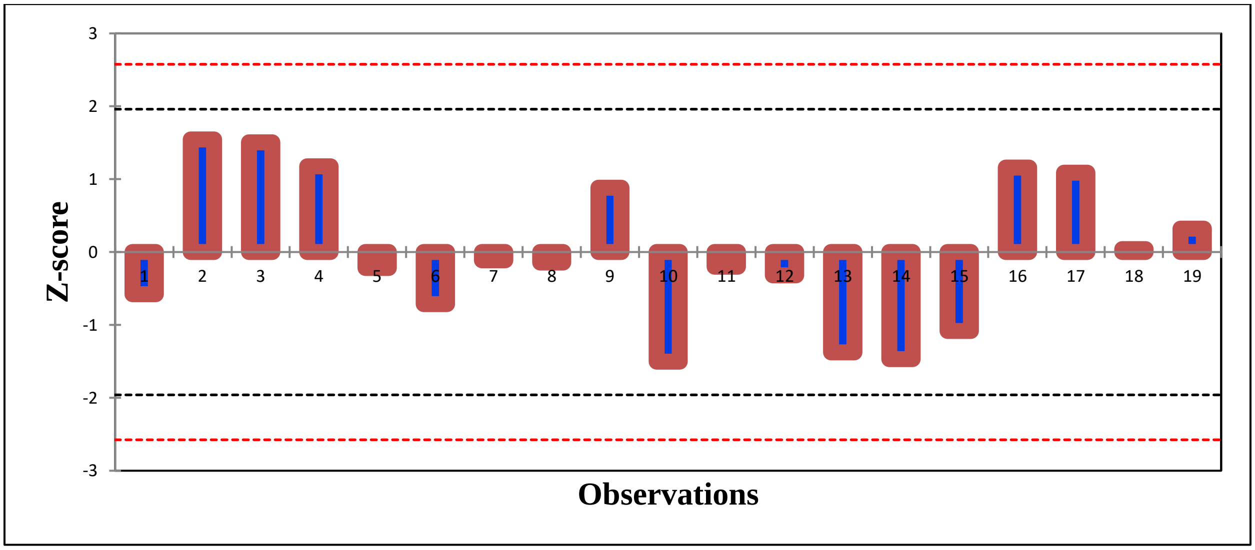

Figure 3.7: Z-Score of Genale @Halowey station

3.8 Identification of Homogeneous Regions

The identification of hydrologically homogenous regions was usually the most difficult stage and required the greatest amount of subjective judgment. The aim was to form a group of sites that satisfied the homogeneity condition. Preliminary identification of groups of stations into a certain group was achieved by looking at the catchment characteristics of the study area. After processing a preliminary region, the next step was identifying stations having the same parent distribution using flood statistics of the sub-basin (Hosking & Wallis, 1997). Flood statistics for Genale Sub-Basin stations were computed using conventional moment and L-moment methods.

3.9 Flood Statics of Study Area

Flood statistics for Genale Sub-Basin basin stations were computed using both conventional moment and L-moment methods. The L-moment was a powerful and efficient method to compute any statistical parameter. Generally, the statistical parameters computed include: mean, standard deviation, coefficient of variation, coefficient of skewness, and coefficient of kurtosis. These parameters, later on, are basic input for regionalization and selection of robust distribution.

Table 3.11: Result of flood statics based on the Conventional moment

Station	Flood statics based on Conventional moment					
	Mean (μ)	Variance(s^2)	(σ)	Cv	Cs	Ck
Genale @ Halowey	592.605	31724.9	178.115	0.301	0.076	-1.116
Genale @ Chenemasa	440.357	22207.72	149.023	0.338	0.315	-0.533
Yadot near Dello Mena	43.781	324.789	18.022	0.412	-0.089	-1.487
Halgol Gom- goma	12.354	22.812	4.776	0.387	0.971	0.404
Welmel@Melka Amana	138.641	3341.285	57.804	0.417	0.696	-0.860

Table 3.12: Result of flood statics on L-moment

Station	Flood statics based on L-moment			
	L-Mean	LCv	LCs	LCk
Genale @ Halowey	592.605	0.176	0.021	0.024
Genale @ Chenemasa	440.357	0.196	0.068	0.105
Yadot near Dello mena	43.781	0.241	-0.025	-0.074
Halgol Gom- goma	12.354	0.217	0.229	0.131
Welmel@ Melka Amana	138.641	0.237	0.206	-0.0001

3.10 Regional Homogeneity Tests

The regional homogeneity test was used to determine the relevance of the streamflow data for RFFA. Some of the most commonly used statistical homogeneity tests are the CC-the-based homogeneity test and the discordance measure test. In this study, both these homogeneity tests were verified to check the regional homogeneity of the proposed stations in the Genale Sub-Basin.

3.10.1 Conventional Homogeneity Test

The mean annual maximum series of the station was calculated as follows:

$$Q_m=\frac{1}{n}\sum_{i}^{n} Qi \qquad [3.27]$$

where Qi was the flow rate (m3/s), Qm was the mean flow rate (m3/s), and n was the number of the record year.

A Sample Moment is defined as:

Variance (μ_2) $=\sum_i^n \frac{(Qi-Qm)^2}{n-1}$ [3.28]

The standard deviation of the AMS of the station:

$s=\sqrt{\sum_i^n \frac{(Qi-Qm)^2}{n-1}}$ [3.29]

Third moment (μ_3) $=\frac{n\sum_i^n (Qi-Qm)^3}{(n-1)(n-2)s^3}$ [3.30]

Fourth moment (μ_4) $=\frac{n^2\sum_i^n (Qi-Qm)^4}{(n-1)(n-2)(n-3)s^4}$ [3.31]

The conventional moment ratios are defined:

The coefficient of variation (Cv)$=\frac{s}{\mu}$ [3.32]

Coefficient of skew-ness (Cs)$=\frac{\mu 3}{\mu 2^{\frac{3}{2}}}$ [3.33]

Coefficient of Kurtosis (C_K)$=\frac{\mu 4}{\mu 2^2}$ [3.34]

The corresponding CC value is calculated for each region using the following relationships:

The regional mean coefficient of variation

$Cvi=\frac{1}{N}\sum_i^n Cv$ [3.35]

Standard deviation by region

$\delta Cv=\sqrt{\sum_i^N \frac{(Cv-Cvi)^2}{N-1}}$ [3.36]

CC, is defined as follows:

$CC=\frac{\delta Cv}{Cvi}<0.3$ [3.37]

where N is the number of sites in a region.

3.10.2 L-Moment Homogeneity Test

The criterion to check for regional homogeneity is based on the value of CC. This method is used for the determination of regional homogeneity and regional distribution. The L-moment-based homogeneity testing was a more accurate and effective way of testing the homogeneity of the site. The L-Moments procedures test is described below:

$\beta_0=\frac{1}{n}\sum_i^n Qi$ [3.38]

$\beta_1=\sum_i^{n-1}\frac{(j-1)*Qi}{n(n-1)}$ [3.39]

$\beta_2=\sum_i^{n-2}\frac{(j-1)(j-2)*Qi}{n(n-1)(n-2)}$ [3.40]

$\beta_3=\sum_i^{n-3}\frac{(j-1)(j-2)(j-3)*Qi}{n(n-1)(n-2)(n-3)}$ [3.41]

Where Qi=AMS (m^3/s) from station data series; n=Number of years; b0, b1, b_2, and b_3 are L-moment estimators. (Hosking & Wallis, 1997) the first four L-moments that are expressed as linear combinations of PWMs are:

$\lambda_1=\beta_0$ [3.42]

$\lambda_2=2\beta_1-\beta_0$ [3.43]

$\lambda_3=6\beta_2-6\beta_1+\beta_0$ [3.44]

$\lambda_4=20\beta_3-30\beta_2+12\beta_1-\beta_0$ [3.45]

λ_1=First L-moment as a measure of central tendency; λ_2=Second L-moment as a measure of dispersion; λ_3 =Third L-moment as a measure of skewness; and λ_4=Fourth L-moment as a measure of kurtosis. The ratio of L-moments is calculated as follows:

Location=λ_1 [3.46]

The measure of scale and dispersion: $L\text{-}C_v=\tau_2=\frac{\lambda 2}{\lambda 1}$ [3.47]

Skewness: $LC_s=\tau_3=\frac{\lambda 3}{\lambda 2}$ [3.48]

Kurtosis: $LC_k=\tau_4=\frac{\lambda 4}{\lambda 2}$ [3.49]

Application of L-moments for FFA includes four steps which go as follows: screening of the data; the identification of homogeneous regions, choice of regional frequency distribution, and parameter estimation of the frequency distribution (Hosking & Wallis, 1997). CC is computed for each region using the following relation:

$LCv(mean)=\sum_i^N\frac{LCv}{N}$ [3.50]

$\sigma LCv = \sqrt{\sum_i^N\frac{(LCv-LCv(mean))2}{N-1}}$ [3.51]

$CC=\frac{\sigma LCv}{LCv(mean)}$ [3.52]

The regions are assumed to be homogeneous if $CC < 0.3$

3.10.3 Discordancy Measure Regions.

The discordancy measure is used for screening the data in RFFA and the process is called the discordancy test(Alam & Khan, 2015). A discordancy measure can check that the data is valid for the regional frequency analysis. In addition, it allows one to detect discordant sites within the group as a whole(Do-Hun Lee 1, 2019)). If computed discordancy values are less than the critical value, no sites are discordant with the group(Do-Hun Lee 1, 2019). Discordancy is measured using the L-moment of the sites' data. (Hosking & Wallis, 1997) defined the discordancy measure for a site as:

$$Di=\frac{N}{3}(Ui-Um)^{T} * S^{-1} * (Ui-Um) \qquad [3.53]$$

S is the covariance matrix of Ui, and calculated as follows:

The criterion for discordancy should, to some extent, be a function of the number of sites in each region.

$$S=\sum_{i}^{N}(Ui-Um)(Ui-Um)^{T} \qquad [3.54]$$

where N is the number of sites; $Ui = [\_\tau^{i},\tau3^{i},\tau4^{i}]^{T}$, T is the transpose of the vector Ui; Um is the regional average of Ui and Di=discordancy index. The critical values for Discordancy Statistic were dependent on the number of sites included in the study at the initial stage(Ahmad et al., 2017). Sites are discordant if Di is larger than or equal to 3, according to Hosking and Wallis (1993), however, this is inadequate for small regions.

Di fulfills the algebraic bound:

$$Di \leq \frac{N-1}{3} \qquad [3.55]$$

Only areas with 11 or more sites can have a Di value greater than three. The criterion for discordancy should, to some extent, be a function of the number of sites in each region.

The static Di isn't very useful in extremely small regions. The matrix S is unique when N is less than three, and Di cannot be determined. Each Di value is one when N equals four. The critical value is found in the table when N is equal to or larger than five.

(Hosking & Wallis, 1997) tabulated critical values of the discordancy statistic Di for various numbers of sites in a region at a significance level of 10%. These were used to assess each of the study sites and identify whether they should be analyzed further to ensure homogeneity.

Table 3.13: Critical value for the Discordancy static (Di)

Critical Value for the Discordancy Static (Di) Number of the site in the region	Critical value	Number of the site in the region	Critical value
5	1.33	10	2.491
6	1.648	11	2.632
7	1.917	12	2.757
8	2.14	13	2.869
9	2.329	14	2.971
		>=15	3

Source: (Hosking & Wallis, 1997)

3.11 Selection of Best Fit Probability Distribution

After the study region is confirmed to be homogeneous, a suitable distribution needs to be selected for the RFFA. The suitable distribution is selected by the goodness-of-fit test. Distribution Fitting Analysis is a component of HEC-SSP software that provides a tool for fitting multiple different analytical distributions using two possible fitting methods. This tool allows the user to assess the uncertainty in their distribution/fitting method choice for their data set.

The candidate distributions were Log-Logistic, Ln-Normal, Log10-Normal, Gumbel, Triangular, Gamma, Log-Pearson III, Generalized Extreme Value, Pearson III, Shifted Gamma, Generalized Logistic, Logistic, Generalized Pareto, Normal, Uniform, Shifted Exponential, Exponential, Beta, and 4 Parameter Beta. The model parameters established can then be used to predict the flood events of a large return period (Bhagat, 2017).

3.12 Parameter Estimation

The commonly used methods are considered here, namely, the method of moments (MOM), and L-moment. After the best-fit distribution has been selected from candidate distributions, the parameters must be estimated.

3.13 Regional Quantile Estimation

A single flood data series obtained at a specific hydrometric station can be fitted to a set of probability density functions, and an at-site quantile estimation can be quickly generated. However, the difficulty in regional flood frequency analysis is figuring out how to fit a candidate distribution to flood data series collected at multiple stations within a homogeneous region and generate a regional growth curve that can be used for both site and regional quantile estimates.

RFFA is used to estimate the quantile for the region with inadequate streamflow data or no data (Eregno, 2014). The quantile, which corresponds to different return periods, is computed after the parameters of the distribution are estimated(Yayneshet, 2020). The quantile of different return periods was determined by using HEC-SSP software for this study.

3.14 Estimation of Index Flood for Standardization

(Younis, 2020) verified that the index-flood method was found to have slightly better prediction accuracy than the direct-regression method. There are two major parts to the index-flood method. The first is the development of a basic dimensionless frequency curve representing the ratio of the flood of any frequency to an index flood (Q2.33). The second is the development of relations between the characteristics of drainage areas and the Q2.33 by which to predict the mean annual flood at any point within the region. Index flood estimation relationships were derived using simple and multiple regression analysis. A drainage area is considered important in governing the magnitude of a flood. In addition, data on the drainage area of the study basins can be easily collected. In simple regression, the mean annual floods are plotted against the corresponding basin area to establish an index–flood relationship. The derivation of the index-flood relationships started with simple regression. The simple regression technique was applied to the region, using the drainage area (A) as an independent variable (Mishra et al., 2009).

3.15 Derivation of Regional Flood Frequency Curve

The ratio of the peak flow for a given return period to the index flood gave a dimensionless growth curve. Thus, the dimensionless regional growth curve was generated by correlating the dimensionless flood variables with their return periods. The basic relationship for estimating design flood QT of recurrence interval T at site i in index-flood is based on the analysis of regional flood frequency, which is expressed as equation 3.56:

$$Q(T)=\mu q_T \qquad [3.56]$$

$$q_T=\frac{Qp}{Q2.33} \qquad [3.57]$$

$$Q2.33=\frac{1}{N}\sum_j^N Qi \qquad [3.58]$$

Q(T)= estimated flood peak discharge during T-year for an ungauged catchment **i**

m = Catchment Flood Index, zT =Dimensionless regional growth curve (zT)

Qp = peak flow for a given return period during the year j for gauged I, Q2.33= mean annual peak flood

3.16 Index Flood Regression Model for an Ungagged Catchment

If the catchment has no records of flow, an index flood for the ungauged catchment must be estimated from a relation between Q2.33 and catchment characteristics, which are calibrated from gauged catchments in the region. Finally, the growth factor was used to get the final estimate of quantile on the ungauged sites (Hussen & Wagesho, 2016). Hence, due to the lack of densely gauged stations in the sub-basin and also because the available gauged stations have poor data quality, it needs to transfer data from the gauged site to the un-gauged site. Index-flood at any location is mainly governed by its drainage area, A, which is usually available for most watersheds. In this study, drainage area only was used for the regression model as a predictor variable to estimate the index flood for an un-gauged watershed. The regional flood-frequency relationship is a power function and can be expressed as:

$$Q2.33=\alpha A^{\beta} \qquad [3.59]$$

Where Q2.33 is the index flood for the un-gauged watershed and A is the watershed area.

The α and β are regression parameters, estimated based on linear regression analysis.

4 Results and Discussions

At-site data must be given special consideration in the analysis because they are the primary input for regional data analysis. After the screening of the data and checking the basic assumptions of hydrological data, RFFA procedures were performed. Initially, the study area was considered one region.

4.1 Identification of a Homogeneous Region

The most difficult part of flood analysis is identifying homogeneous regions, which requires the most subjective judgment. The goal is to create a cluster of sites that satisfy the homogeneity criteria. The homogeneous region satisfies the condition that all sites within the region can be described by one probability distribution having common distribution parameters. Regions are formed depending on site characteristics and statistics. In this study, hydrologically, the homogeneous region from the statistical point of view was considered for the regionalized Genale Sub-Basin with similar flood-producing characteristics. Available streamflow data is tested for spatial homogeneity of the proposed region, and a group of gauge stations satisfying the test are identified.

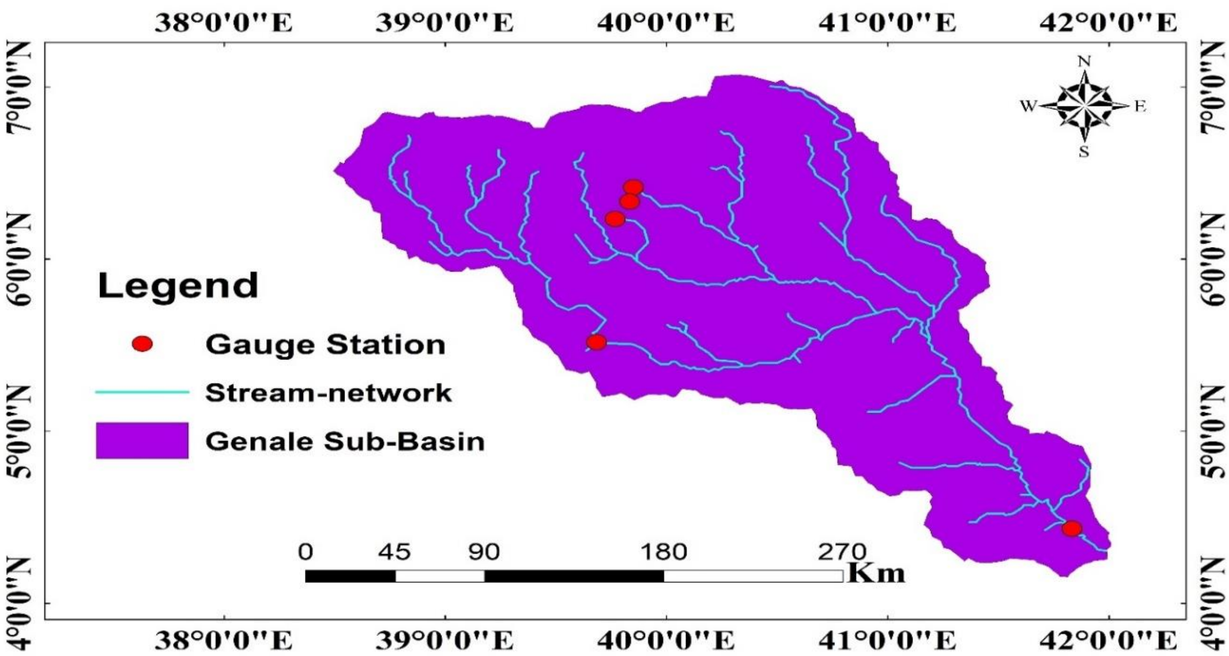

Figure 4.1: The Distributions of hydrological gauging stations of GSB

4.1.1 Results of CC–Based Homogeneity Test

In this study, the combined coefficient of variation (site-to-site coefficient of variation of the coefficient of variation) was calculated by using conventional moment and L-moment statistical values were applied to verify the acceptability of clustering techniques. The combined coefficient of variation (CC) for both conventional moment and L-moment flood statistics for all stations, as shown in table 4.1, was less than 0.3. The region was confirmed to be homogeneous as one region; since CC for both criteria of the homogeneity test were satisfied.

Table 4.1:CC values for both Conventional and L-moment

Station name	Conventional Moment-Based homogeneity test			L- moment Based homogeneity test		
	Cv	Cs	Ck	LCv	LCs	LCk
Genale @ Halowey	0.301	0.076	-1.116	0.176	0.021	0.024
Genale@Chenemasa	0.338	0.315	-0.533	0.196	0.068	0.105
Yadot near Dello Mena	0.412	-0.089	-1.487	0.241	-0.025	-0.074
Halgol Gom-Goma	0.387	0.971	0.404	0.217	0.229	0.131
Welmel Melka Amana	0.417	0.696	-0.860	0.237	0.206	-0.0001
CC	0.135<0.3			0.129<0.3		

4.1.2 Discordance Measure

In the process of grouping sites for screening of the data and proposed homogeneous regions, it is standard practice to compute a discordancy measure (Di) for each site. The discordancy measure identifies unusual sites that are grossly discordant with the group as a whole and eliminates grossly discordant stations from the analysis. Values of the discordancy measure are computed in terms of the L-moments. Using equation [3.53], a Discordancy Index of regional data was calculated for five gauging stations. The computed discordancy values in the region range from -0.865 to 0.722, as shown in table 4.2 below. The critical value of the discordancy index Di for various numbers of sites in a region at a significance level of 10% was obtained from table 3.13.

Because the computed discordancy values in table 4.2 were less than 1.33 (Di≤ $\frac{N-1}{3}$,) no sites were discordant with the group, implying that the regions are homogeneous and data from all gauging sites are suitable for regional flood frequency analysis.

Table 4.2: The Result of the Discordancy measure for the GSB region

Name of station	LCv	τ_3	τ_4	Di	Remark
Genale @ Halowey	0.176	0.021	0.024	0.722	Homogenous
Genale @ Chenemasa	0.196	0.068	0.105	0.524	Homogenous
Yadot near Dello Mena	0.241	-0.025	-0.074	0.721	Homogenous
Halgol Gom- Goma	0.217	0.229	0.131	-0.865	Homogenous
Welmel Melka Amana	0.237	0.206	-0.0001	-1.102	Homogenous

Generally, the region satisfies the criteria of homogeneity test for CC-based homogeneity test and discordance measure. No further division of the region into individual sites would improve the accuracy of flood estimates. Because all gauge stations meet the spatial homogeneity test criteria, this group of stations constitutes a region, and all station data in this region are pooled and analyzed as a group to determine the region's RFFA. Therefore, the L-moment method was suitable for regional flood frequency analysis of the study area. After confirmation of the homogeneity of the region, the next step was the delineation of the study area. Since Genale Sub-Basin was homogeneous as one region, no delineation was required for the study area.

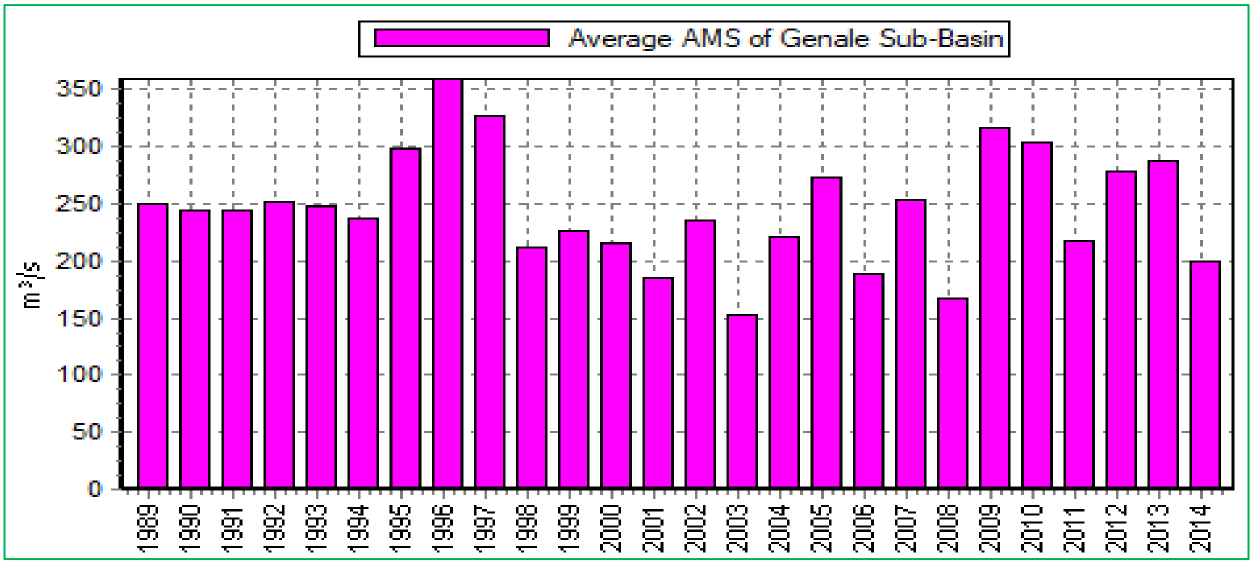

Figure 4.2:Average annual maximum series of GSB

4.2 The Goodness of Fit Test

The performance of the candidate probability distributions was assessed using goodness-of-fit test statistics to investigate the robust probability distribution for FFA. In this study, the best fit distribution from the candidate was selected by using HEC-SSP software. Within this software, all goodness of fit tests such as Kolmogorov Smirnov and Chi-Square common tests were done for the yearly average peak discharge data of Genale Sub-Basin, and the most likely fit distribution from the candidate distribution was displayed automatically. Using the Kolmogorov-Smirnov test (D), it was observed that the Log-Logistic distribution provides a good fit to the yearly average peak discharge data of the Genale Sub-Basin. Using the Chi-squared test (X^2) has been applied to test the goodness-of-fit, and it has been shown that the Gumbel distribution provides a good fit. The best-fit distribution was taken as the distribution with the lowest sum of the two test statistics. By comparing two goodness-of-fit tests, it has been observed that the Gumbel distribution provides a good fit for the Genale Sub-Basin.

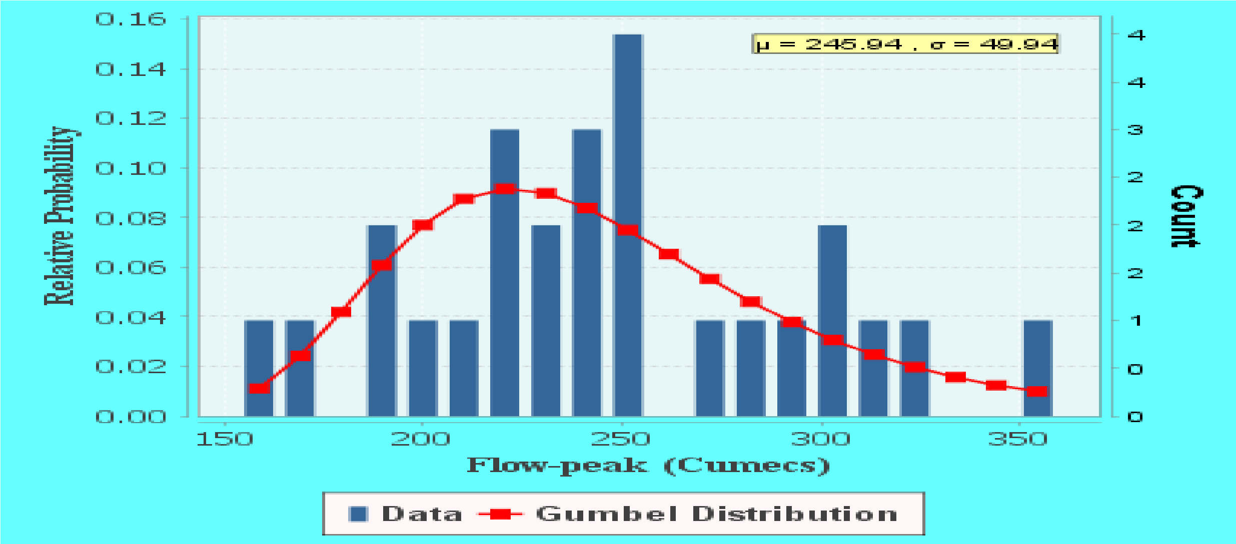

Figure 4.3:PDF plot of Gumbel distribution

4.3 Selection of Regional Best Fit Distribution

The validity of the best-fit regional probability distribution was checked by using the probability-probability (P-P) and discharge-discharge (Q-Q) plots. The P-P and Q-Q were visualization techniques for selected distributions through the visual assessment of the linearity of the pattern of points on the plot. As we can see from Figures 4.4 (P-P plot) and 4.5 (Q-Q plot), the plot points tend to lie reasonably along and close to a straight line, and this provides validation of Gumbel's distribution to regional data for accurately estimating flood flow for different return periods in the Genale Sub-Basin.

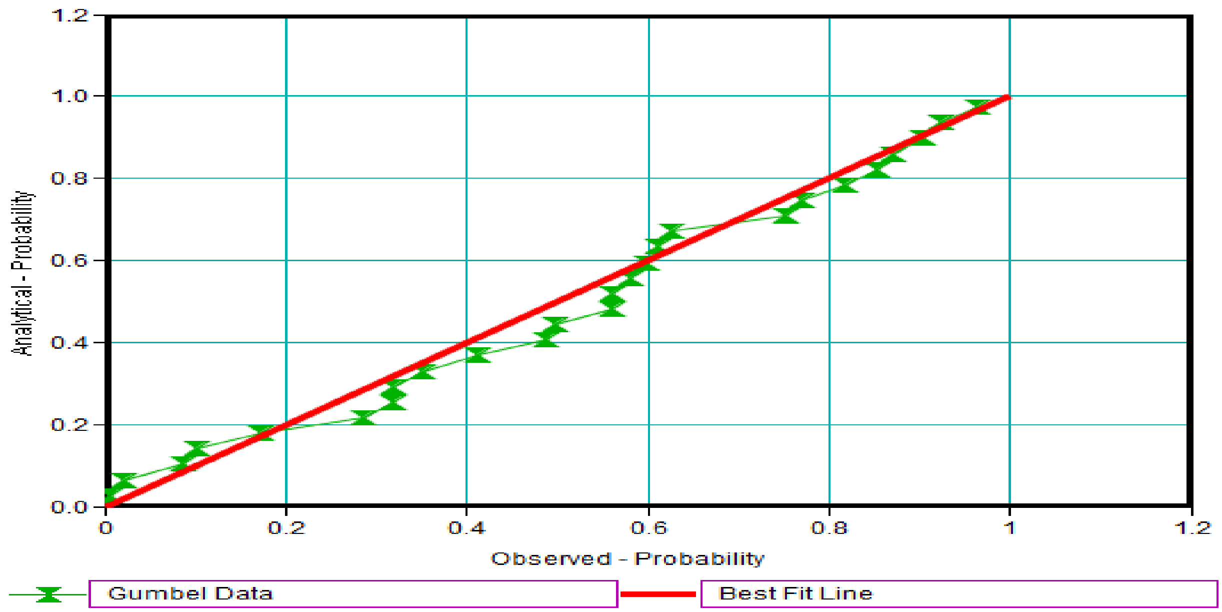

Figure 4.4:P-P plot for best-fit distribution

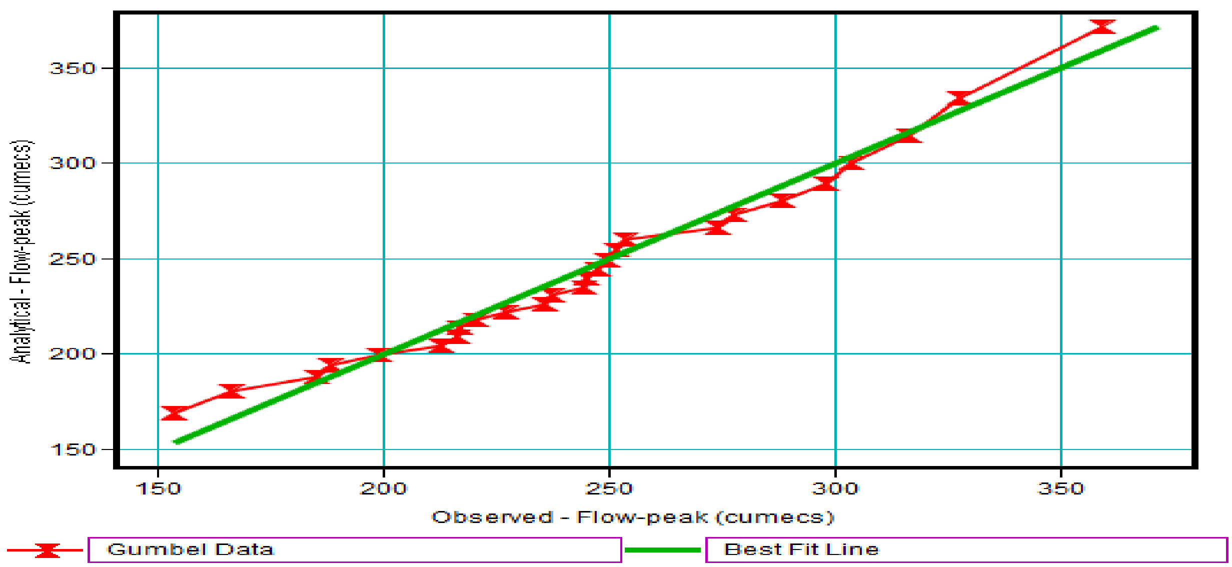

Figure 4.5: Q-Q plot for best-fit distribution

4.4 Parameter Estimation

The estimates of the regional parameters for Gumbel distribution were: the location parameter and the scale parameter. The methods used for parameter estimation in this study are the method of moment (MOM) and L-Moment. The summary of parameter estimation for the best regional distribution of region using both methods of the moment (MOM) and L-Moment (L-M) is shown in table 4.3.

Table 4.3: Best regional distribution and parameters selection for the GSB

Best regional distribution	Parameter	
	MOM	L-moment
Gumbel distribution	Location 223.470, Scale 38.940	Location (222.094, Scale 41.317

4.5 Regional Quantile Estimation

The best methods of quantile estimation were selected based on the goodness-of-fit test. Thus, the best fit distribution for Genale Sub-Basin was the Gumbel distribution. It was widely used in probability distribution functions for extreme values in hydrological studies or prediction of flood peaks, maximum rainfall, etc. Due to outliers, the use of conventional moments would either over or underestimate the T-year flood event. Therefore, in this case, it is more rational to use a method that is less sensitive to outliers in the data, such as L-moments, which provide undeniable advantages over conventional moments in using FFA for the estimation of flood quantiles. The discharges for return periods such as 2, 2.33, 5, 10, 20, 50, 100, 200, 500, 1000, 5000, and 10,000 years were predicted using the L-moment method.

Table 4.4: Estimated quantile of GSB Region

Percent chance exceedance	Return period(T) in year	Computed flow in m^3/s	Confidence limits in m^3/s	
			0.05(UCL)	0.95(LCL)
50.0	2	237.24	253.86	222.11
42.918	2.33	246.00	263.67	229.50
20.0	5	284.07	311.22	259.88
10.0	10	315.07	351.77	283.49
5.0	20	344.81	390.07	305.64
2.0	50	383.31	439.99	334.10
1.0	100	412.16	478.72	355.27
0.5	200	440.90	516.16	376.30
0.2	500	478.82	565.53	404.04
0.1	1000	507.48	604.38	424.88
0.02	5000	573.99	690.69	473.41
0.01	10,000	602.63	729.92	493.86

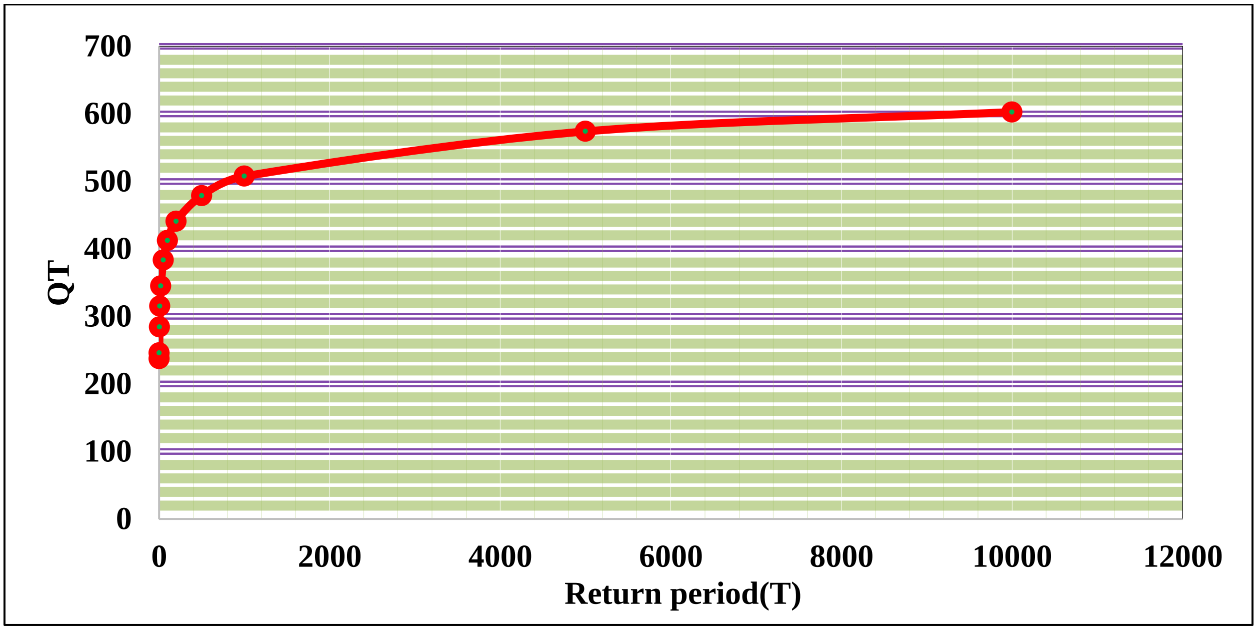

Figure 4.6: Regional quantile versus return period of GSB

4.6 Estimation of Index Flood for Standardization

The index-flood method was based on the hypothesis that floods from different catchments within a region are normalized by their mean annual flood coming from a single distribution. The dimensionless index flood was used for the transfer of the flood frequency curve (FFC) among stream gauging sites in a hydrologically homogeneous region. The mean annual maximum discharge series, which corresponds to a recurrence interval of 2.33 years, was used as the index flood. Table 4.5 shows the standardized flood (QT/Qm) of Genale Sub-Basin with their corresponding return period.

Table 4.5: Computed standardized flood corresponding to return period

Percent chance exceedance(P)	Return period(T)	Gumbel reduced Variate $-(\ln\times\ln(\frac{T}{T-1}))$	QT/Qm
50.0	2	0.367	0.964
42.918	2.33	0.579	1.000
20.0	5	1.500	1.155
10.0	10	2.250	1.281
5.0	20	2.970	1.402
2.0	50	3.902	1.558
1.0	100	4.600	1.675
0.5	200	5.296	1.792
0.2	500	6.214	1.946
0.1	1000	6.907	2.063
0.02	5000	8.517	2.333
0.01	10,000	9.210	2.450

4.7 Derivation of the Regional Growth Curve

After the region had been accepted as spatially homogeneous and suitable probability distributions were identified for the regions, the quantile of the regions and the index of food for standardization were estimated, and then the regional growth curve was developed for the region. Dimensionless regional growth curves were generated by plotting QT/Qm versus return period (T) or QT/Qm versus Gumbel reduced variate $(-\ln(\ln(\frac{T}{T-1})))$. The curve was drawn for 2–10,000 years of recurrence intervals.

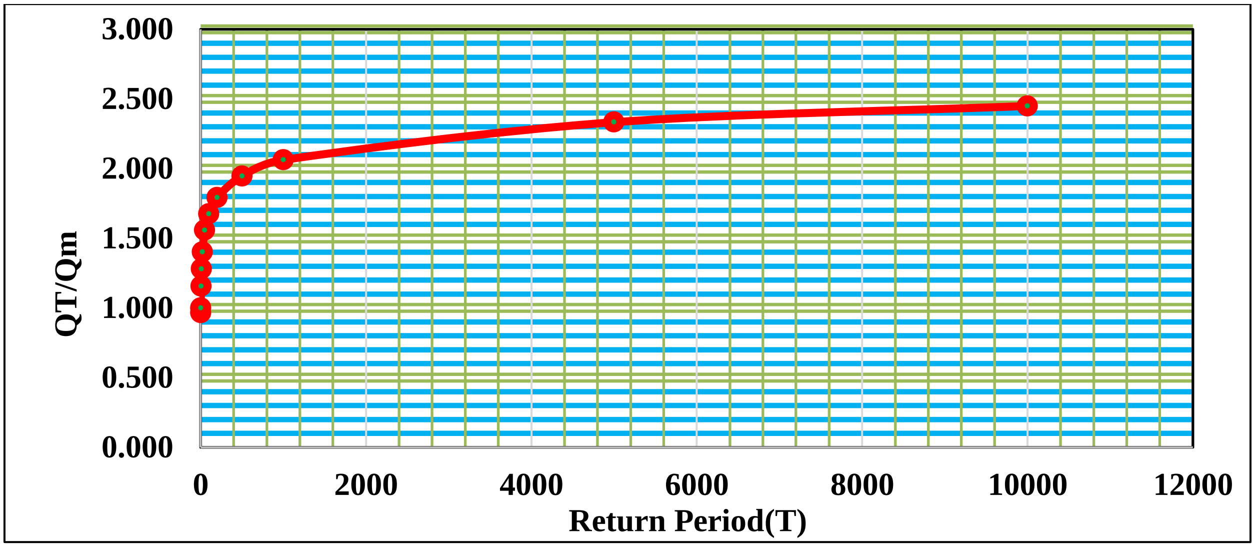

Figure 4.7: Regional growth curve (QT/Qm versus T) of GSB

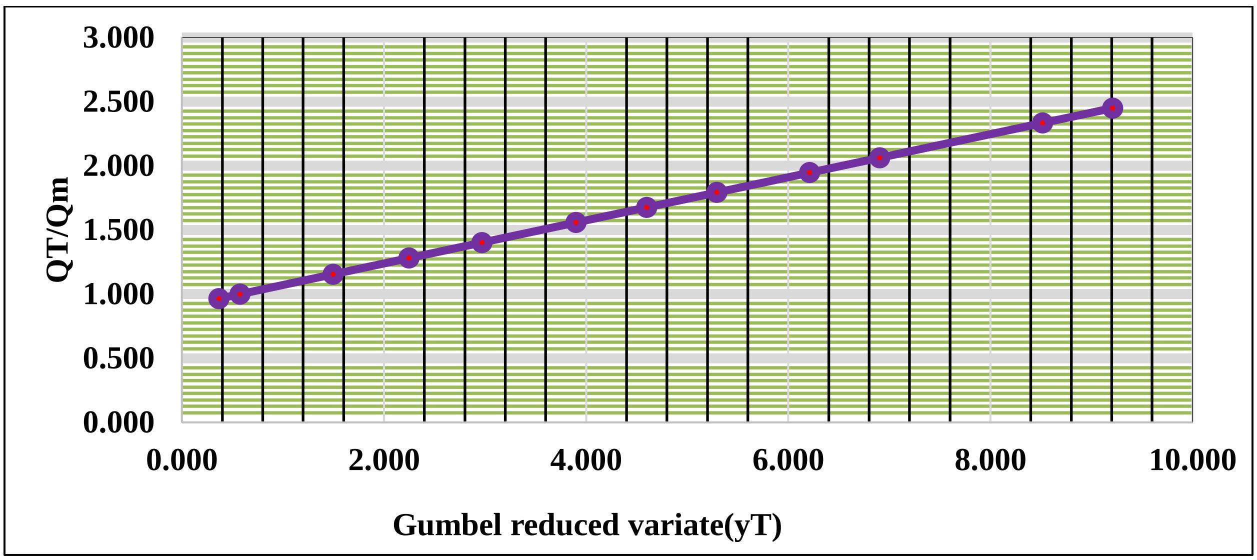

Figure 4.8: Regional growth curve (QT/Qm versus yT) of GSB

4.8 Index Flood Regression Model for an Ungagged Catchment

The watershed was the principal variable for predicting the index flood. A scatter plot of each possible variable with the Q2.33 for each station in the region was used to develop the index flood estimation equation. An index-flood relationship has been established by computing the mean annual maximum discharge values at all the stations that are averaged together to give an observed index-flood.

Annual extreme floods from five selected gauging sites located in Genale Sub-Basin were used to demonstrate that the developed index flood model estimated flood quartiles in an ungauged site of the basin.

Table 4.6: Index flood and area of gauge station

Station	Station No	Q2.33	Area of gauge Station
Genale Halowey Station	072001	594.14	54093
Genale @ Chenemasa	072002	440.506	10574
Yadot Near Dello Mena	072005	43.981	531
Halgol Gom-Goma	072006	12.481	164
Welmel	073008	138.605	3048

The equation which describes this relationship between Q2.33 and the catchment area was selected as the best index flood estimation equation (model) as shown in figure 4.9. The correlation coefficient of this equation was 0.9557. Equation 4.9 shows that the exponent and the coefficient of the catchment area obtained by linear regression were 0.6819 and 0.521 respectively.

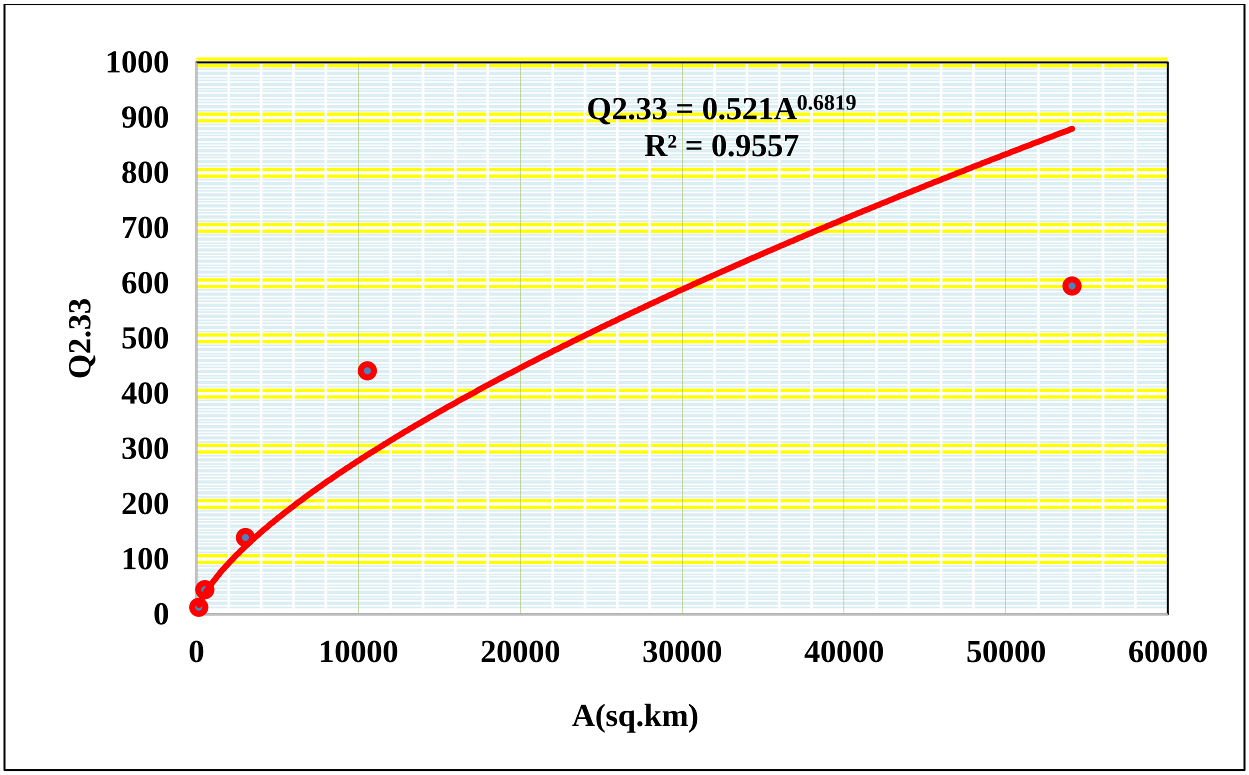

Figure 4.9: Index flood estimation equation for GSB

The model validity was further confirmed by calculating the coefficient of determination R^2. If the R^2 was very high (0.95-1), the index flood model was the best model for estimating the index flood of the ungauged catchment. Thus, the R^2 was high for the regions; this indicates that the index flood estimation model was suitable for estimating the index flood for the ungauged catchment.

5 Conclusions and Recommendations

5.1 Conclusions

From the above findings of RFFA in the Genale Sub-Basin, the following conclusions were withdrawn. The time-series data was obtained from Ethiopia's Ministry of Water and Energy (MoWE). After data screening was done, the total number of stations that were used for further analysis became 5, and 3 of the stations were rejected due to their poor data quality. The data quality was checked after data filling and the extension of missing data. They have fulfilled the basic assumption of hydrological data and RFFA procedures were performed.

Initially, the study area was considered one region. From the statistical point of view, it was considered for the regionalized Genale Sub-Basin. The homogeneity of the region is verified through a CC-based homogeneity test and a discordance measure. Since all gauge stations satisfy the criteria of the spatial homogeneity test, this group of stations constitutes a region. The study area was homogeneous as one region; no delineation was required. The goodness of fit tests was verified by the Kolmogorov Smirnov and Chi-Square tests with the help of HEC-SSP. The best-fit statistical distribution for the study area was the Gumbel distribution.

The performance of the best fit regional probability distribution was checked by using the P-P and Q-Q plots. The methods used for parameter estimation in this study are the method of MOM and L-Moment. The quantiles for return periods such as 2, 2.33, 5, 10, 20, 50, 100, 200, 500, 1000, 5000, and 10,000 years were predicted using the L-moment method. The mean annual maximum discharge series, which corresponds to a recurrence interval of 2.33 years, was used as the index flood. Dimensionless regional growth curves were generated for 2–10,000 years of recurrence intervals. An index flood estimation equation was developed for ungauged basins by linear regression between the Q2.33 values and drainage areas. From the regression analysis equation, the R^2 gives a value of 0.9557 and is high for the regions. This indicates that the index flood estimation model was suitable for estimating the index flood for the ungauged catchment. The regional growth curve for the region will support the decision-makers in the proper planning, design, operation, and management of hydraulic structures.

5.2 Recommendations

Based on the findings of this study on Genale Sub-Basin, the following points were recommended to different stakeholders.

The density of hydrological gauging stations in river basins should be increased and the concerned bodies should give maintenance and operation to existing gauge networks for accurate estimation of quartiles of extreme floods for planning, design, and management of hydraulic structures.

The parameters that affect catchment features such as drainage area, rainfall, soil type, land use, land cover, drainage slope, and elevation of the basin have to be integrated using multiple integration techniques to obtain a better estimation of the index flood of the ungauged catchment.

Stationary regional flood frequency analyses are suitable for climates that are uniform from year to year. However, the assumption of stationary was no longer valid because the magnitude of the peak discharge would be affected by gradual land-use changes, human intervention in nature, and climate change. Ignoring a trend in the hydrological regime can lead to an under or overestimation of flood quantile. Thus, the other researcher considers non-stationary assumptions.

Naturally, nature is dynamic with time. The parameters that we get today will change over days, so researchers should conduct research periodically to get updated information on the flood frequency analysis from time to time to design hydraulic structures and reduce the impact of flooding.

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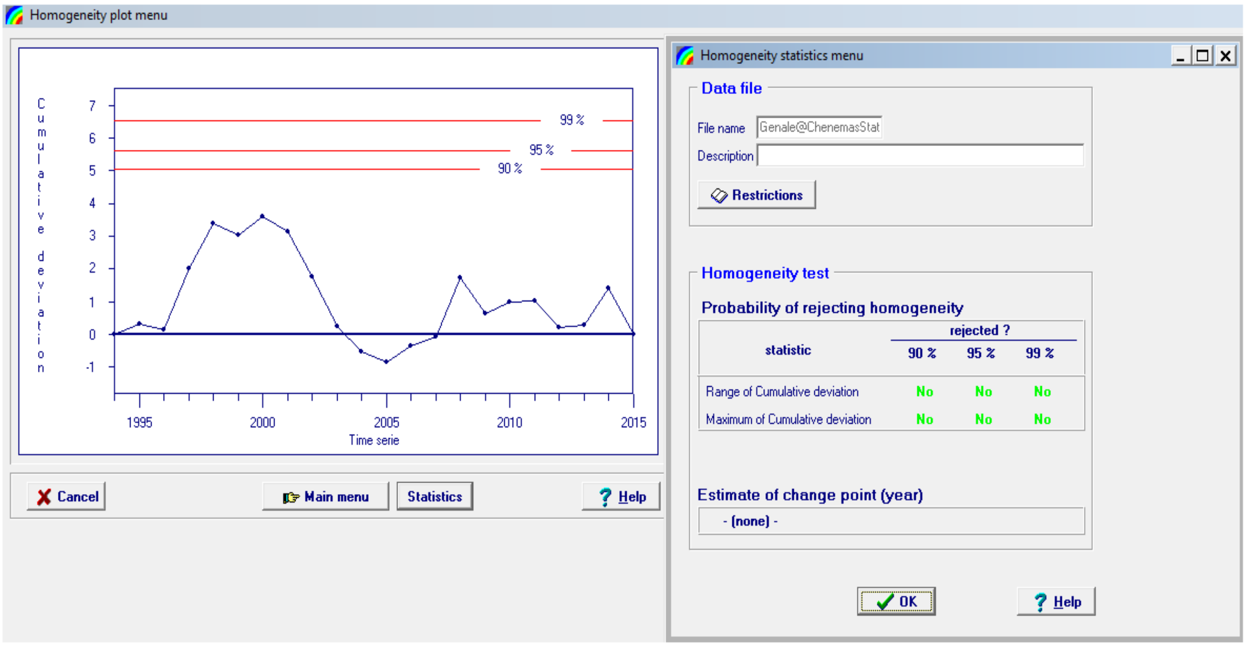
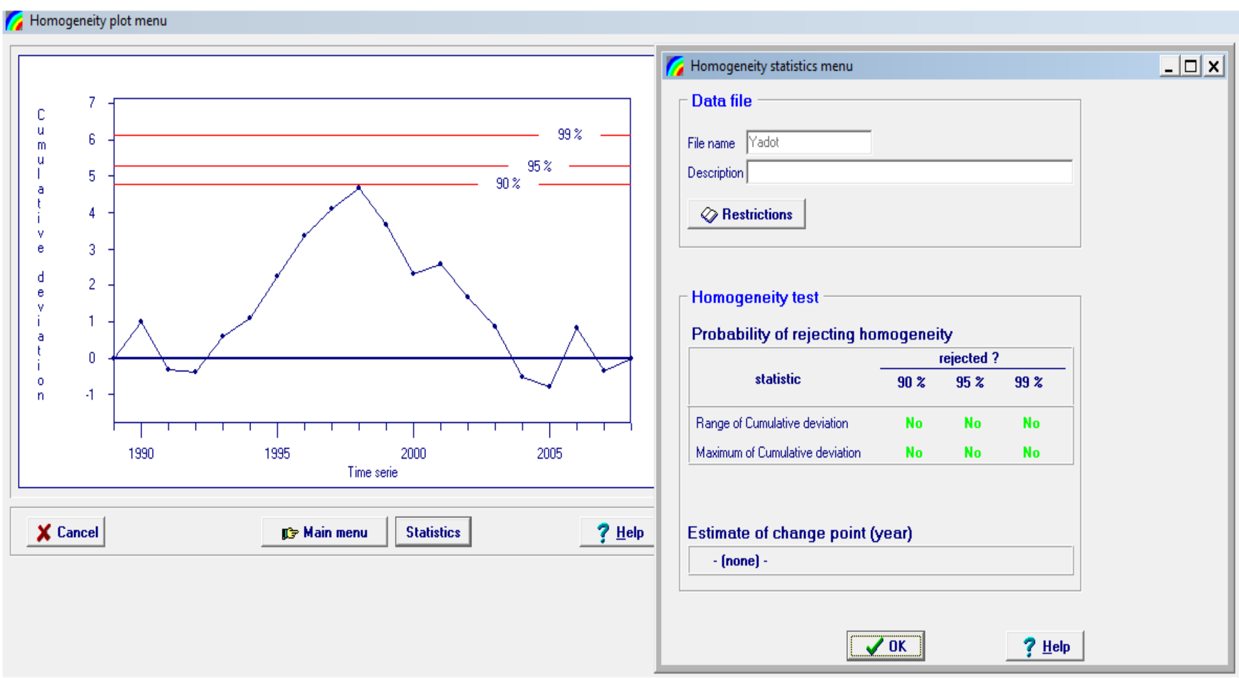
Appendixes

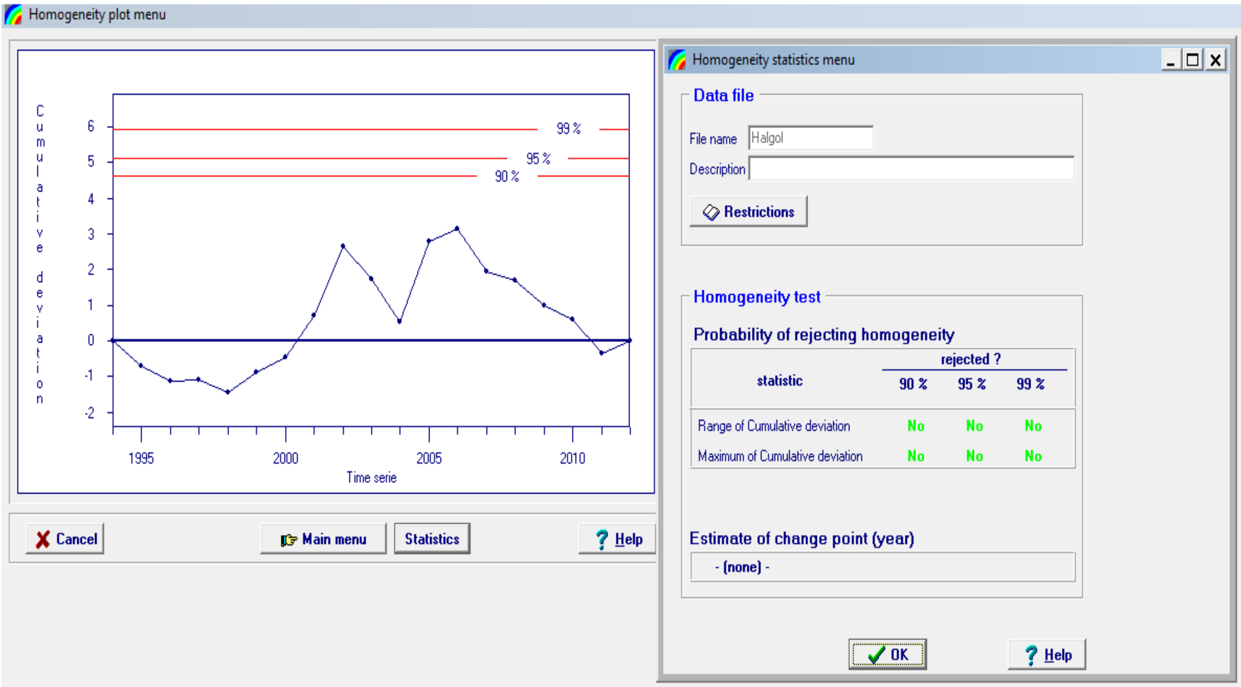
Appendix A: Homogeneity Test of Genale@Chenemasa Station by Rainbow Software



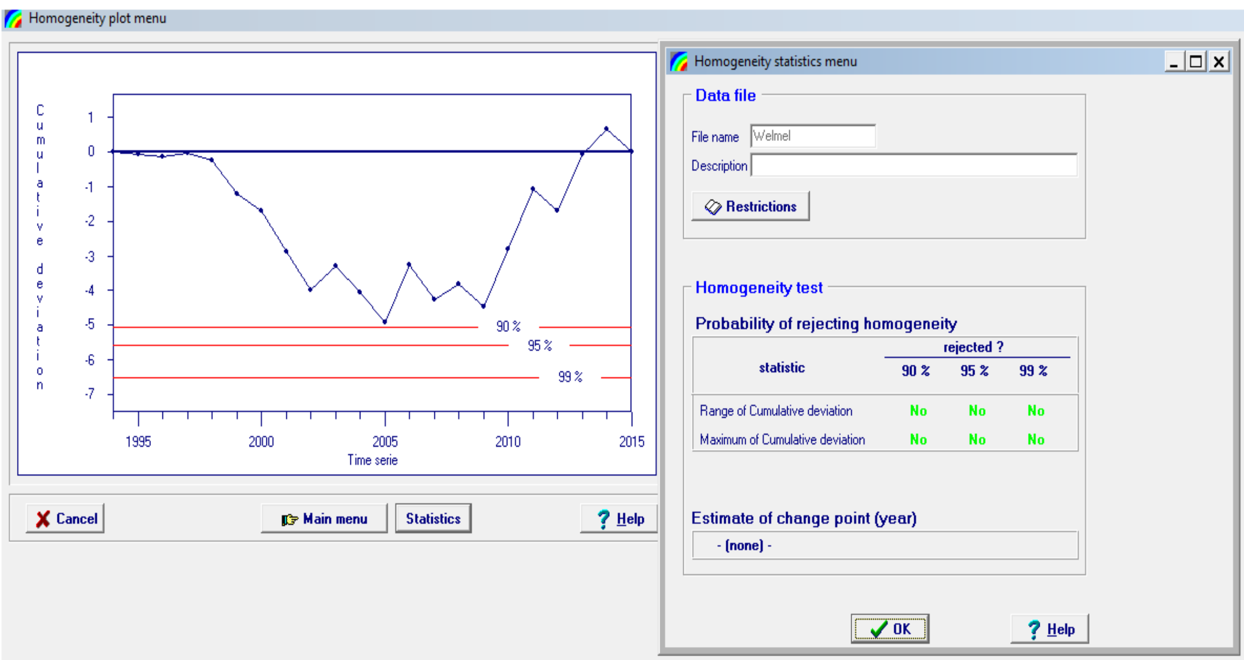
Appendix B: Homogeneity Test of Yadot Near Dello Mena Station



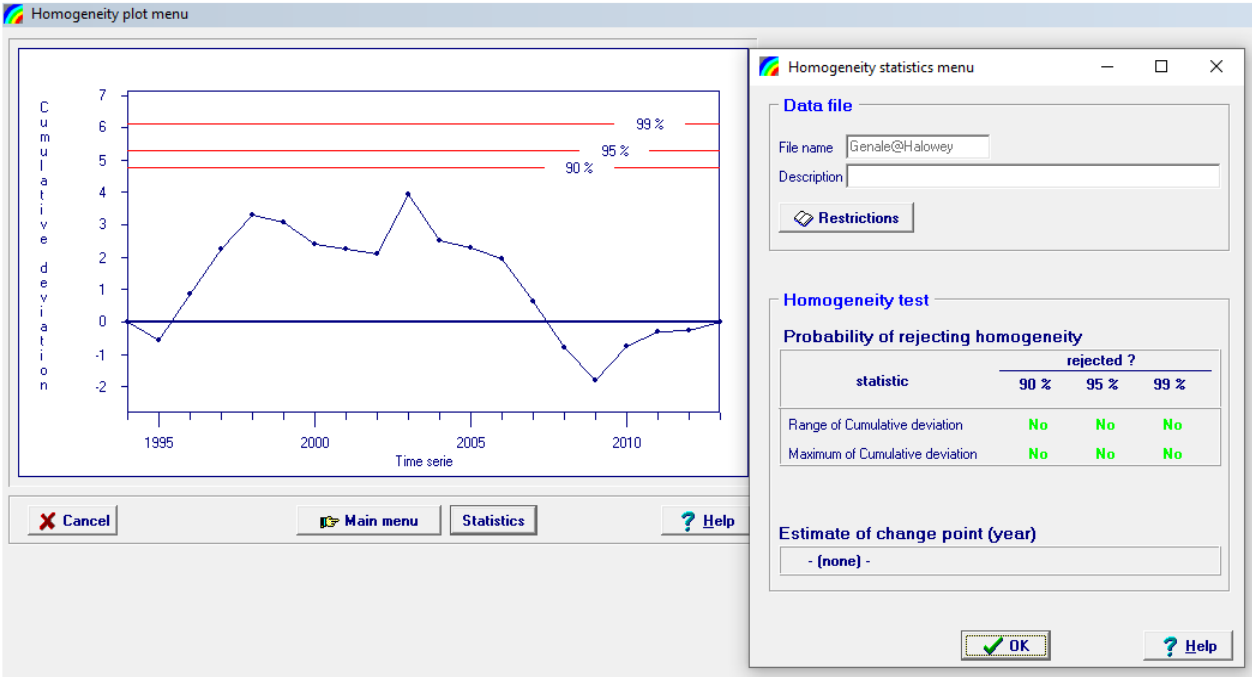
Appendix C: Homogeneity Test of Halgol Gom-Goma Station



Appendix D: Homogeneity Test of Welmel @ Melka Amana Station



Appendix E: Homogeneity Test of Genale @ Halowey Station



Appendix F: Result of Spearman Test for Independence of Genale @ Halowey Station

```
       --- SPEARMAN TEST FOR INDEPENDENCE ---

    072001        Genale@Halowey
ANNUAL MAXIMUM DAILY FLOW SERIES   1995 TO 2013  DRAINAGE AREA =   54093.00

SPEARMAN RANK ORDER SERIAL CORRELATION COEFF =   .352     D.F.= 16
                   CORRESPONDS TO STUDENTS T = 1.504
                CRITICAL T VALUE AT 5% LEVEL = 1.746     NOT SIGNIFICANT
                    -    -    -    -   1%    -   = 2.583     NOT SIGNIFICANT

Interpretation: The null hypothesis is that the correlation is zero.

At the 5% level of significance, the correlation is not significantly
different from zero.  That is, the data do not display significant
serial dependence.

Press <RETURN> to continue , <CTRL> P to obtain hard copy_
```

Appendix G: Result of Spearman Test for Trend of Genale @ Halowey Station

```
      --- SPEARMAN TEST FOR TREND ---

   072001       Genale@Halowey
ANNUAL MAXIMUM DAILY FLOW SERIES  1995 TO 2013  DRAINAGE AREA =  54093.00

SPEARMAN RANK ORDER CORRELATION COEFF =  .153    D.F.= 17
            CORRESPONDS TO STUDENTS T =  .637
         CRITICAL T VALUE AT 5% LEVEL = 2.110    NOT SIGNIFICANT
             -    -   -   -  1%   -   = 2.898    NOT SIGNIFICANT

Interpretation: The null hypothesis is that the serial(lag-one) correlation
                is zero.

At the 5% level of significance, the correlation is not significantly
different from zero. That is, the data do not display significant
trend.

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```

Appendix H: Result of Run Test for General Randomness of Genale @ Halowey Station

```
      --- RUN TEST FOR GENERAL RANDOMNESS ---

   072001       Genale@Halowey
ANNUAL MAXIMUM DAILY FLOW SERIES  1995 TO 2013  DRAINAGE AREA =  54093.00

THE NUMBER OF RUNS ABOVE AND BELOW THE MEDIAN (RUNAB) =  6
      THE NUMBER OF OBSERVATIONS ABOVE THE MEDIAN(N1) =  9
      THE NUMBER OF OBSERVATIONS BELOW THE MEDIAN(N2) =  9
Range at 5% level of significance:  6. to 14.    NOT SIGNIFICANT

Interpretation: The null hypothesis is that the data are random.

At the 5% level of significance, the null hypothesis cannot be
rejected. That is, the sample is significantly random.

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Appendix I: Mann-Whitney Split Sample Test for Homogeneity of Genale @ Halowey Station

```
  --- MANN-WHITNEY SPLIT SAMPLE TEST FOR HOMOGENEITY ---

    072001        Genale@Halowey
ANNUAL MAXIMUM FLOW SERIES  1995 TO 2013   DRAINAGE AREA=  54093.00

SPLIT BY TIME SPAN, SUBSAMPLE 1 SAMPLE SIZE=  9
                    SUBSAMPLE 2 SAMPLE SIZE= 10

                                MANN-WHITNEY U =  27.0
     CRITICAL U VALUE AT 5% SIGNIFICANT LEVEL =  24.0    NOT SIGNIFICANT
      -   -   -   -   -  1%       -         -  =  16.0    NOT SIGNIFICANT

Interpretation: The null hypothesis is that there is no
                location difference between the two samples.

At the 5% level of significance, there is no significant
location difference between the two samples. That is, they
appear to be from the same population.

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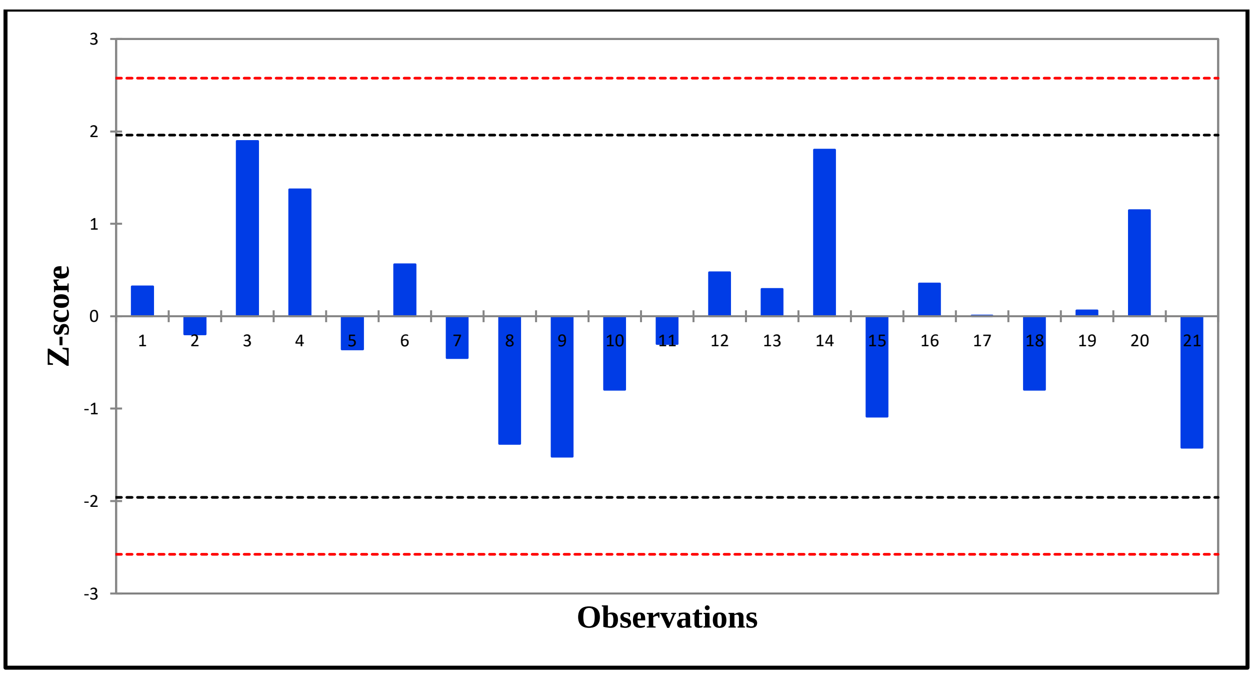
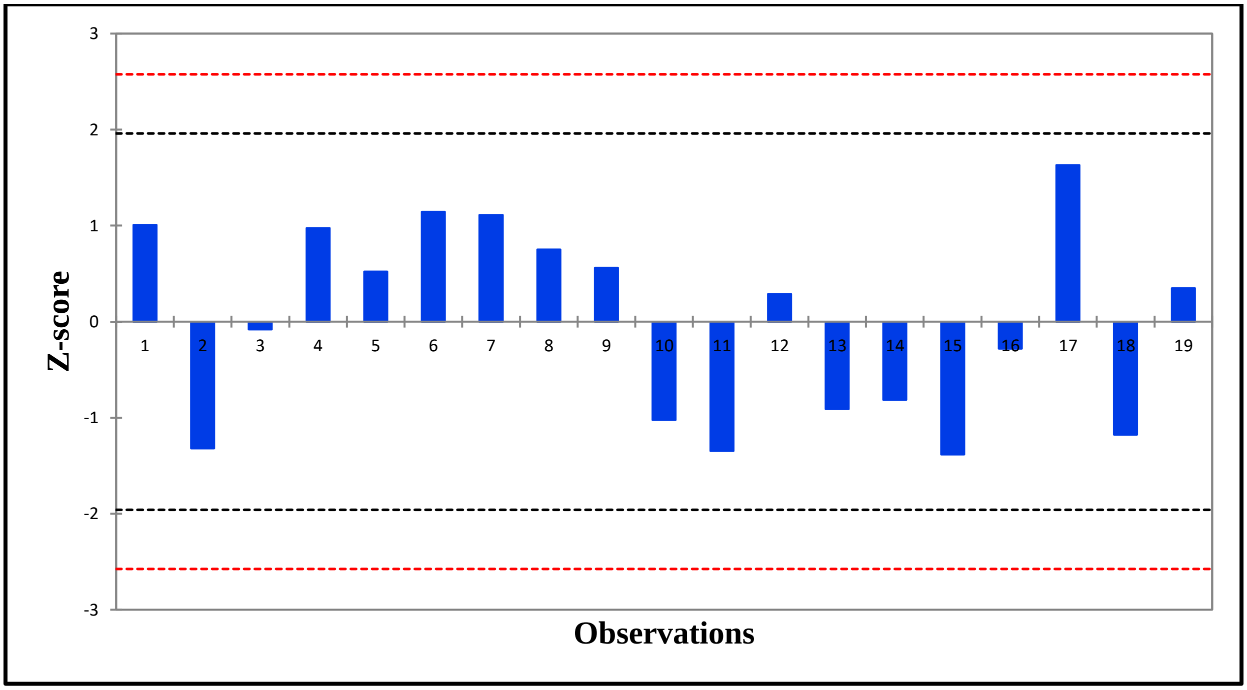
```

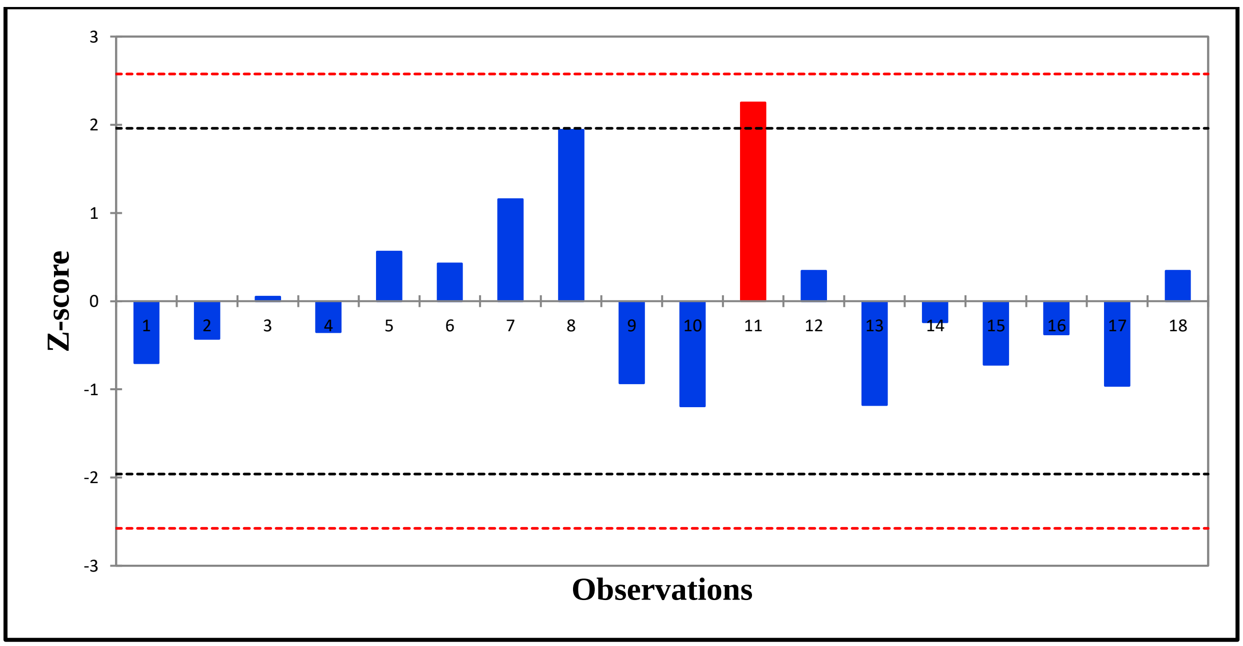
Appendix J: Z-score of Genale @ Chenemasa Station



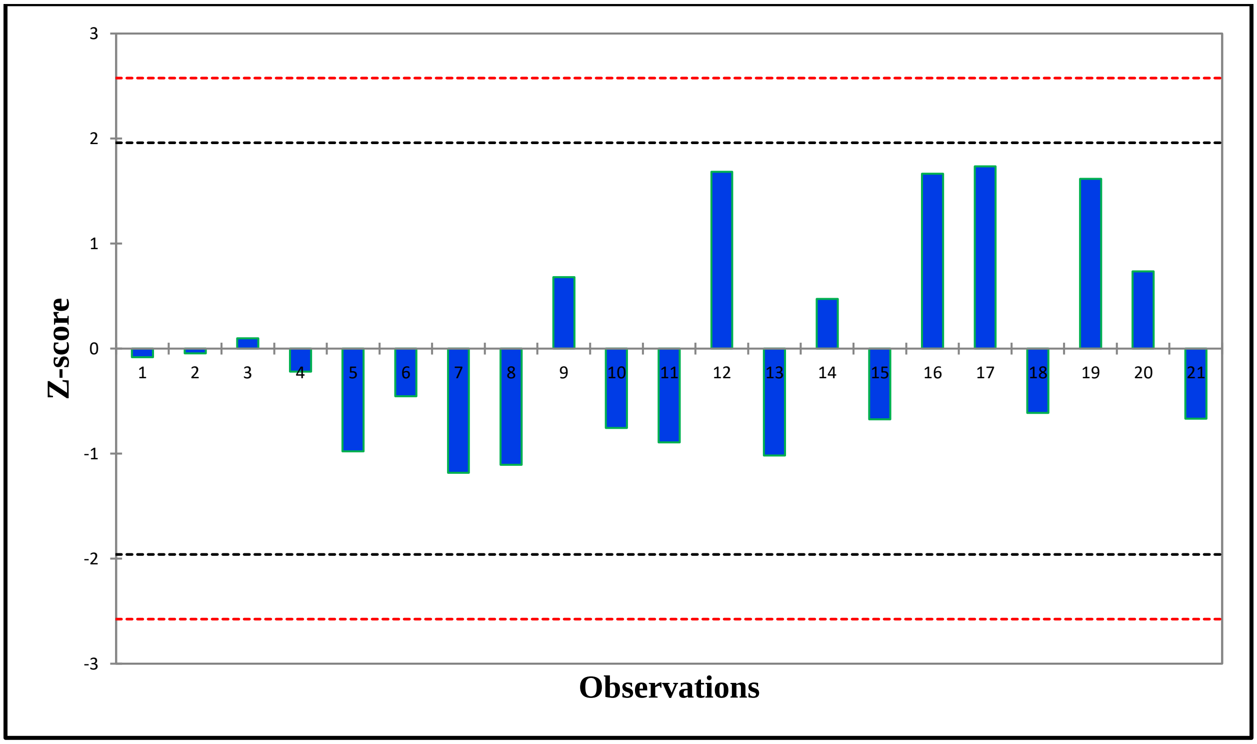
Appendix K: Z-score of Yadot Near Dello Mena Station



Appendix L: Z-score of Halgol Gom-Goma Station



Appendix M: Z-score of Welmel Melka Amana Station



Appendix N: Result of Discordance Measure of GSB

Name of station	τ	τ_3	τ_4	Ui		
Genale @ Halowey	0.176	0.021	0.024	U1		
Genale @ Chenemasa	0.196	0.068	0.105	U2		
Yadot near Dello mena	0.241	-0.025	-0.074	U3		
Halgol Gom- goma	0.217	0.229	0.131	U4		
Welmel@Melka Amana	0.237	0.206	-0.0001	U5		
Genale Sub Basin as one Region						
U1	U2	U3	U4	U5	∑Ui	Um
0.176	0.196	0.241	0.217	0.237	1.067	0.2134
0.021	0.068	-0.025	0.229	0.206	0.499	0.0998
0.024	0.105	-0.074	0.131	-0.0001	0.1859	0.03718

Ui-Um				
U1-Um	U2-Um	U3-Um	U4-Um	U5-Um
-0.037	-0.017	0.028	0.004	0.024
-0.079	-0.032	-0.125	0.129	0.106
-0.013	0.068	-0.111	0.094	-0.037

$(Ui-Um)^T$			
$(U1-Um)^T$	-0.037	-0.079	-0.013
$(U2-Um)^T$	-0.017	-0.032	0.068
$(U3-Um)^T$	0.028	-0.125	-0.111
$(U4-Um)^T$	0.004	0.129	0.094
$(U5-Um)^T$	0.24	0.106	-0.037

$(U1-Um) * (U1-Um)^T$	0.0014	0.0029	0.0005
	0.0029	0.0062	0.0010
	0.0005	0.0010	0.0002
$(U2-Um) * (U2-Um)^T$	0.0003	0.0006	-0.0012
	0.0006	0.0010	-0.0022
	-0.0012	-0.0022	0.0046
$(U3-Um) * (U3-Um)^T$	0.0008	-0.0034	-0.0031
	-0.0034	0.0156	0.0139
	-0.0031	0.0139	0.0124
$(U4-Um) * (U4-Um)^T$	0.00001	0.00047	0.00034
	0.00047	0.01669	0.01212
	0.00034	0.01212	0.00880
$(U5-Um) *(U5-Um)^T$	0.0006	0.0025	-0.0009
	0.0025	0.0113	-0.0040
	-0.0009	-0.0040	0.0014
S	0.003	0.003	-0.004
	0.003	0.051	0.021
	-0.004	0.021	0.027
S^{-1}	827.268	-150.389	245.240
	-150.389	56.115	-66.611
	245.240	-66.611	126.159

$$\frac{N}{3}(Ui-Um)^{T} * S^{-1} *(Ui-Um)$$

1.241	-0.094	-0.425	-0.559	-0.163
-0.094	0.716	-0.098	0.250	-0.774
-0.425	-0.098	1.243	-0.556	-0.165

Appendix O: Fitting Method: Standard Product Moments

Distributions	Parameter
Log-Logistic	Scale=241.049, Shape=8.807
Ln-Normal	MeanLn=5.485, StDvLn=0.206
Log10-Normal	MeanLog=2.382, StDvLog=0.089
Gumbel	Loctn=223.465, Scale=38.941
Triangular	Left=139.485, Peak=218.758, Right=379.585
Gamma	Shape=24.250, Scale=10.142
Log-Pearson III	MeanLog=2.382, StDvLog=0.089, Skew=-0.214
Generalized Extreme Value	Loctn=226.192, Scale=46.935, Shape=0.184
Pearson III	Mean=245.943, StDv=49.944, Skew=0.310
Shifted Gamma	Shape=41.500, Scale=7.753, Shift=-75.798
Generalized Logistic	Loctn=244.718, Scale=27.454, Shape=-0.027
Logistic	Loctn=245.943, Scale=27.535
Generalized Pareto	Loctn=168.863, Scale=130.337, Shape=0.691
Normal	Mean=245.943, StDv=49.944
Uniform	Left=159.438, Right=332.448
Shifted Exponential	Scale=49.944, Shift=195.999
Exponential	Scale=245.943
Beta	shape0 =NaN, shape1=NaN
4 Parameter Beta	shape0 =NaN, shape1=NaN,Left=NaN,Right=NaN

Appendix P: Fitting Method L-Moment

Distributions	Parameter
Log-Logistic	Scale=241.049, Shape=8.462
Ln-Normal	MeanLn=5.485, StDvLn=0.209
Log10-Normal	MeanLog=2.382, StDvLog=0.091
Gumbel	Loctn=222.094, Scale=41.317
Triangular	Left=137.355, Peak=220.957, Right=379.515
Gamma	Shape=23.224, Scale=10.590
Log-Pearson III	MeanLog=2.382, StDvLog=NaN, Skew=NaN
Generalized Extreme Value	Loctn=225.507, Scale=47.181, Shape=0.167
Pearson III	Mean=245.943, StDv=NaN, Skew=NaN
Shifted Gamma	Shape=NaN, Scale=NaN, Shift=NaN
Generalized Logistic	Loctn=242.805, Scale=28.429, Shape=-0.067
Logistic	Loctn=245.943, Scale=28.639
Generalized Pareto	Loctn=167.195, Scale=137.782, Shape=0.750
Normal	Mean=245.943, StDv=50.761
Uniform	Left=160.027, Right=331.859
Shifted Exponential	Scale=57.277, Shift=188.665
Exponential	Scale=245.943
Beta	shape0 =NaN, shape1=NaN
4 Parameter Beta	shape0=NaN, shape1=NaN,Left=NaN,Right=NaN

Appendix Q: The Goodness of Fit Test Based on MOM

Distributions	Kolmogorov-Smirnov (Ks)	Chi-Square(X^{2})
Log-Logistic	0.084	1.692
Ln-Normal	0.096	3.615
Log10-Normal	0.096	3.615
Gumbel	**0.099**	**1.308**
Triangular	0.105	2.462
Gamma	0.107	3.615
Log-Pearson III	0.110	3.615
Generalized Extreme Value	0.111	3.615
Pearson III	0.113	3.615
Shifted Gamma	0.113	3.615
Generalized Logistic	0.114	3.615
Logistic	0.125	3.615
Generalized Pareto	0.126	4.000
Normal	0.133	3.615
Uniform	0.149	2.462
Shifted Exponential	0.165	2.462
Exponential	0.464	45.154
Beta	NaN	NaN
4 Parameter Beta	NaN	NaN

Note: Bold value test statistics is the best-fit PD according to the Goodness of fit test

Appendix R: Goodness of Fit Test Based on L-Moment

Distributions	Kolmogorov-Smirnov (Ks)	Chi-Square(X^2)
Log-Logistic	0.088	1.692
Ln-Normal	0.098	3.615
Log10-Normal	0.098	3.615
Gumbel	**0.104**	**1.308**
Triangular	0.107	2.462
Gamma	0.108	3.615
Log-Pearson III	NaN	NaN
Generalized Extreme Value	0.108	3.615
Pearson III	NaN	NaN
Shifted Gamma	NaN	NaN
Generalized Logistic	0.101	3.615
Logistic	0.128	3.615
Generalized Pareto	0.123	4.000
Normal	0.134	2.462
Uniform	0.149	2.846
Shifted Exponential	0.177	2.846
Exponential	0.464	45.154
Beta	NaN	NaN
4 Parameter Beta	NaN	NaN

Note: Bold value test statistics is the best-fit PD according to the goodness of fit tests.