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Evaluation of Extreme flow Quantiles estimated from Global Reanalysis runoff data: A case study of Blue Nile River Basin

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CERTIFICATION

I, the undersigned, certify that I read and hereby recommend for the acceptance by the Addis Ababa University a Thesis entitled**: Evaluation of Extreme flow Quantiles estimated from Global Reanalysis runoff data** in partial fulfillment of a degree of Masters of Science in Hydraulics Engineering.

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LIST OF ABBREVIATIONS AND ACRONYMS

AD	Anderson Darling
AM	Annual Maximum
ARBIDMPP	Abbay River Basin Development Integrated Master Plan Project
BCEOM	French Consultants Company
BNRB	Blue Nile River Basin
CDF	Cumulative Distribution Function
CESR	Center for Environmental System Research
CRU	Climatic Research Unit
DEM	Digital Elevation Model
ECDF	Empirical Cumulative Distribution Function
ECMWF	European Center for Medium range Weather Forecast
ERA	European Re-Analysis
EU WATCH	European Union Water and global Change
EV1	Extreme value type 1 distribution
EV2	Extreme value type 2 distribution
EXP	Exponential distribution
FFA	Flood Frequency Analysis
G2 (Gamm2)	Gamma with two parameter distribution
GCS	Geographic Coordinate System
GEV	Generalized Extreme Value
GLg	Generalized logistic distribution
GPar	Generalized Pareto distribution
HTESSEL	Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land
ICDF	Inverse Cumulative Distribution Function
KS	Kolmogorov-Smirnov
LN3	Lognormal with three parameter distribution
LN	Lognormal distribution
LN2	Lognormal with two parameter distribution
LP3 (LP-III)	Log-Pearson type three distribution
LSE	Least Squares Estimates

ML	Maximum Likelihood
MLM	Maximum Likelihood Method
MOM	Method of Moment
MoWR	Ministry of Water Resources
N	Number of record year
netCDF	Network common data form
NSE	Nash-Sutcliffe Efficiency
P3 (P-III)	Pearson type three distribution
PBIAS	Percentage of bias
PD	Partial Duration
POT	Peak over a threshold
PWM	Probability Weighted Moment
Q	Flow magnitude
$Q_{observed}$	Observed annual maximum discharge
$Q_{reanalysis}$	Reanalysis annual maximum discharge
Q_T	Flow quantiles corresponding to the return period
R^2	Coefficient of determination
RivOut	River discharge
r_1	Lag 1 serial autocorrelation coefficient
SQRT	square root
T	Return period or Recurrence interval
THREDDS	Thematic Real-time Environmental Distributed Data Services
UNIVK	University of Kassel
USWRC	United State Water Resources Council
WGS	World Geographic System
WMO	World Meteorological Organization
WAK4	Four parameter wake by distribution
WAK5	Five parameter wake by distribution
WAPCOS	Water and Power Consultancy Services
WaterGAP3	Water Global Assessment and Prognosis
X_T	Value of X for return period T

ABSTRUCT

Stream discharge data have long been measured and used by engineers in the design of hydraulic structures and flood protection works, and in planning for flood plain use. A flood frequency analysis is the basis for the engineering design of many projects and economic analysis of flood control projects. The study was to evaluate the performance of earth2observe global reanalysis runoff products obtained from ECMWF and UNIVK reanalysis in reproducing the peak discharges for potential use in the planning and design of water resources structures. The daily peak discharge data from 5 stations; Gilgel Abbay, Kessie, Bahirdar, Main Beles and Border in the Blue Nile basin were used for the evaluation. The stations were selected based on independence and randomness tests, recorded length of data and catchment area of the station. The reanalysis and observed AM discharge were analyzed from daily flow for estimation of extreme flow quantiles at a return period, using at-site flood frequency analysis. The widely used distributions; GEV, LN3, LP3 and EV1 were used to estimate flow quantiles. For selection of best-fit distributions, method of parameters estimation and parameter estimation Easy-Fit statistical software was employed. Goodness of-fit-test; Chi-square, Kolmogorov-smirnov and Coefficient of determination were used for selection of best fit distributions. The results indicate that the reanalysis runoff products (ECMWF and UNIVK) have limitation in reproducing the peak discharges. The ECMWF reanalysis AM discharge was overestimated for Kessie, Gilgel Abbay and Border stations by PBIAS of -4.43, -22.30 and -131.41% respectively and underestimated for Main Beles and Bahirdar stations by PBIAS of 30.08 and 39.9% respectively. The UNIVK reanalysis AM discharge was overestimated for Bahirdar, Gilgel Abbay and Border stations by PBIAS of -10.65, -28.90 and -68.30% and underestimated for Main Beles and Kessie by PBIAS of 28.71 and 4.28% respectively. The annual maximum discharges extracted from both ECMWF and UNIVK runoff products were not found reliable to estimate flood quantiles for design purposes. Therefore, both data have severe limitation in reproducing the peak discharges and estimation of flood quantiles and can't be used for design purpose before major correction is done.

Keywords: Global reanalysis runoff, ECMWF and UNIVK reanalysis, Flow quantiles, Earth2Observe, Blue Nile

1. INTRODUCTION

1.1 Background

Stream discharge have long been measured/observed and used by engineers in the design of hydraulic structures and flood protection works, and in planning for flood plain use. A flood frequency analysis is the basis for the engineering design of many projects and economic analysis of flood control projects. A flood frequency analysis consists of study of past records of flow discharge and an estimate of frequencies of future floods. The primary objective of analysis is to relate the flow quantiles of these extreme events to their frequency occurrence through the use of probability distributions (Chow et al, 1988). The resulting relationship between magnitude and return period is referred to as the Q-T relationship. Return period, T, may be defined as the time interval for which a particular flood having magnitude QT (also known as quantiles) is expected to be exceeded (Admasu 1989). Extreme flow quantiles are a critical issue to design any hydraulic structures for many countries in the developed and developing country. Estimation of extreme flow quantiles using statistical distribution from runoff dataset provides vital information for engineering design of any hydraulic structure such as culvert, bridge, reservoir, spillway and water resources planning and development projects. Identification of the true statistical distributions for the various hydrologic and meteorological datasets continues to be major challenges facing engineers and hydrologists (Crichley and Siegert, 1991).

The global reanalysis runoff data as an alternative to in-situ observation runoff data is developed by earth2observe and the accurate mapping and estimation of global water resources requires: the use of many sources of earth observations (such as satellite and ground-based remote sensing, in-situ measurements, vertical profiles), combined with state-of-art earth system modeling components that are developed for hydro-meteorological and environmental applications. The earth2observe developed a global water resources reanalysis based on state-of-the art meteorological reanalysis, earth observations and extended with output from hydrological and land surface models to construct a consistent global water resources reanalysis (wrr) dataset of sufficient length (at least 30 years) (more information at http:/www.earth2observe.eu).

Multi-model reanalysis of the state of the surface water storage and fluxes provide an ensemble that is not dependent on a single model. This is generally superior to the results of any individual model, and as good as or better than the best model at each point and time (Dirmeyer et al. 2006). Considering the significant uncertainties in modeling the different components of the surface water cycle a multi model approach can consider the inter-model uncertainties that can be used in downstream applications of water resources. Earth2Observe generate a first version of global water resource reanalysis (wrr1). This first version is based on a set of different land surface and hydrological models simulations with their current modeling system with a controlled modeling protocol. For the meteorological forcing, it was decided to use a recent state-of-the-art dataset: the WATCH Forcing Dataset ERA-Interim (hereafter WFDEI, Weedon et al. 2014). WFDEI is a follow up dataset of the EU WATCH project (Harding et al. 2011). WFDEI is based on the ECMWF ERA-Interim reanalysis (Dee et al. 2011) with a spatial resolution of 0.5°× 0.5°, and temporal frequency of 3 hours for the period 1979-2012 with several bias corrections using gridded observations. WFDEI provides two sets of precipitation based on different observational datasets corrections, and it was decided to use the CRU (Climatic Research Unit) based dataset that is available for the period 1979-2012.

Data generated or extracted at the station over an extended period of time from global reanalysis runoff dataset are analyzed in frequency analysis for estimation of extreme flow quantiles, instead of the in-situ observation/measured runoff data and the reliability of the estimated flow quantiles from global reanalysis runoff data is evaluated for design of hydraulic structures. The data are assumed to be independent and identically distributed. Further, it is assumed that the flood have not been affected by natural or man-made changes in the hydrological regime in the system (Rao, 2000). Estimation of reliable extreme flow quantiles with various risks of exceedance are needed for a wide range of engineering problems: Examples in design of any hydraulic structure such as culvert, bridge, reservoir, spillway and construction in major project. In order to be able to plan and design these projects such as hydraulic or water resources projects, continuous hydrological data, for example, river flow data is necessary. With the help of the data, flow pattern or trend can be determined to make sure the design and planning can be done accordingly with a reliable and good estimation of extreme flow quantile.

However, to select a reliable design quantile, which has affect on design, operation, management and maintenance of hydraulic structure depends on statistical methods used in parameter estimation belonging to probability distribution (Hosking and Wallis, 1993). Probability for future events can be predicted by fitting past observations to selected probability distributions.

The purpose of this paper is to evaluate extreme flow quantiles estimated from global reanalysis runoff data with the flow quantiles estimated from the in-situ observation runoff data on Blue Nile River Basin. The basin is found in the northwestern part of Ethiopia between $7^0$45' and $12^0$45'N latitude, and $34^0$05'and 39^0 45' E longitudes. It has an average annual runoff about 54.80 billion cubic meters [Abbay River Basin Development Integrated Master Plan Project (ARBIDMPP), 1999]. It covers an area of approximately 199,812km^2 with a total perimeter of 2440km.

1.2 Statement of Problem

Blue Nile River Basins have sparse network of observation sites with short record length of observed flow that makes the use of single site analysis to estimate design parameters at many potential project sites unreliable due to lack of fund and qualified person, density of gauging station is low, and the operation and maintenance of stream gauging networks are difficult, so reliable estimation of the flow quantile is difficult for design of hydraulic structures such as culvert, spillway, bridge, reservoir and dikes and for integrated water resources management such as water supply, irrigation and hydropower and reducing flood induced losses.

Instead of gauging; global runoff reanalysis datasets have the potential to allow us to progress towards global scale flow quantiles estimation systems. However, these datasets need to be validated with in-situ observational data. So, evaluation of extreme flow quantiles estimated from global reanalysis dataset with in-situ observation data will occur for the check of flow quantiles accuracy to make safe design of hydraulic structures, integrated water resources management and flood induced losses.

1.3 Objective of the Research

1.3.1 Main objective

The main objective of the thesis is to evaluate application of the global re-analysis runoff products for determination of flood quantiles to be used in the design of water resources projects in data scarce areas in the Blue Nile Basin.

1.3.2 Specific objectives

The thesis will achieve the following specific objectives:

- Extract and compare the Annual Maximum (AM) daily discharges from the in-situ observational runoff data and the global re-analysis products.
- Develop a statistical procedure to estimate flood quantiles of the stations
- Estimate flood quantiles from both in-situ observational data and global reanalysis runoff data sets using the established procedure
- Undertake graphical and statistical comparison of the estimated quantiles obtained from global reanalysis datasets and in-situ observation data

1.4 Research question

- What is the performance of the extracted annual maximum (AM) discharges against the in-situ observational data?
- Is the global reanalysis peak discharges reasonably accurately captured?
- Are the global reanalysis data sets useful to estimate flood quantiles at many of the data scarce locations in the Blue Nile Basin?

1.5 Thesis Outline

This thesis contains seven chapters organized as follows: Chapter one gives a general introduction to the study with its background, statement of the problem, objectives and research questions, as well as the overall thesis outline. Chapter two describes the reviewed literature related to the study. Chapter three describes methodology with its brief description of the study area, checking data quality, data collection and analysis, selection of global reanalysis runoff dataset, global reanalysis runoff data extraction, selection of flood frequency distribution, parameter and quantile estimation and evaluation of global reanalysis runoff data. Chapter four discusses the results and discussions of the study. Finally, in chapter five conclusion and recommendations are given. In chapter six references which are used for this study are listed. In chapter seven appendixes which are used for more information are shown.

2. LITERATURE REVIEW

2.1 Introduction

Extreme flow quantiles estimated from global reanalysis runoff data provides vital information for engineering design of any project and economic appraisal of a variety of engineering and water resources planning and development projects, when there is sparse of observed flow data. Extreme flow quantiles are estimated from reanalysis and observed flow data using flood frequency analysis. Flood frequency analysis is a hydrologic field dealing with estimation of a flood magnitude corresponding to any required return period of occurrence.

2.2 Reanalysis dataset description

The reanalysis data-sets are technology based which are used for data generation instead of observed data, when there is sparse of observed data. There are different type of dataset based on their area of application such as: Snow Cover (SC) used to generate the snow cover data, Global Runoff Data Centre (GRDC) for River mean daily Discharge Data, ECMWF Forcing for meteorological data, European Center for Medium-Range Weather Forecast (ECMWF) and University of Kassel (UNIVK) datasets for monthly and daily river discharge data extraction and etc. Each of the dataset including the datasets which are not explained are used as input and output data instead of observed data, when full and enough record length of observed data are not available. All of the datasets are available on the threads server and can be explored from https://wci.earth2observe.eu/thredds/catalog.html.

2.3 Global reanalysis runoff dataset

Global runoff reanalysis are used to extract/generate a river discharge as an alternative to the observed river discharge. When there is sparse of observed discharge data in record length due to lack of fund and qualified person, density of gauging station is low, and the operation and maintenance of river gauging networks are difficult, so reliable estimation of the flow quantiles using the sparse observed data is difficult for design of hydraulic structures such as culvert, spillway, bridge, reservoir and dikes and for integrated water resources management such as water supply, irrigation and hydropower and reducing flood induced losses.

To generate daily/monthly full and enough record length of river discharge data ECMWF and UNIVK reanalysis are more specifically applied. The two reanalysis provide the "best" estimate of RivOut (River discharge) in each grid box at each observation time.

2.3.1 ECMWF reanalysis dataset

ECMWF reanalysis is the Earth2Observe water resources reanalysis version 1 produced by European Center for Medium-Range Weather Forecast (ECMWF) institution. Water resources reanalysis version 1 performed by ECMWF land surface scheme forced by the WDFEI CRU dataset and developed by HTESSEL model.

The land surface model HTESSEL (Hydrology Tiled ECMWF Scheme for Surface Exchanges over Land) computes the land surface response to atmospheric conditions, and estimates the surface water and energy fluxes and the temporal evolution of soil temperature, soil moisture content, vegetation interception and snowpack conditions. These are computed for each grid-point independently, i.e. there is no horizontal interaction between each surface/soil column. At the interface to the atmosphere each grid box is divided into fractions (tiles), with up to six fractions over land (bare ground, low and high vegetation, intercepted water and shaded and exposed snow).

Vegetation types and cover fractions are derived from an external climate database, based on the Global Land Cover Characteristic (Loveland et al. 2000). The grid box surface fluxes are calculated separately for each tile, leading to a separate solution of the surface energy balance equation and skin temperature. The interception reservoir is a thin layer on top of soil/vegetation, collecting liquid water by the interception of rain and the collection of dew, and evaporating at the potential rate. The maximum capacity of this reservoir is a function of the grid-box leaf area index. The snow represents an additional layer on top of the upper soil layer, with independent prognostic, thermal and mass contents (Dutra et al. 2010).

The snowpack is represented by a single layer with an evolution of snow temperature, snow mass, snow density, snow albedo, and a diagnostic formulation for the snow liquid water content. Below the surface, the soil is discretized in four layers (0.07, 0.21, 0.72 and 1.89 m) for the water and energy transfer. Soil heat transfer follows a Fourier law of diffusion, modified to take into account soil water freezing/melting (Viterbo et al. 1999).

The ECMWF reanalysis extract monthly and daily river discharge for a year of 1979 to 2012. ECMWF reanalysis begins 1 January 1979 and ends 31st December 2012. Such reanalysis dataset has temporal coverage (from 1979-01-01 12:00:00 pm to 2012-12-31 12:00:00 pm) and geographic coverage (latitude: 90°S-90°N and longitude: 180°W-180°E) with 720 columns and 360 rows to cover the globe. The distribution of the river discharge within each cell is described using a cumulative function of the 50 × 50km. For water resources reanalysis version 1 of Earth2Observe, the reanalysis is carried out at 0.5° × 0.5° spatial and monthly or daily temporal resolution. The data access to the project THREDDS (Thematic Real-time Environmental Distributed Data Services) catalogue for ECMWF Reanalysis is available at https://wci.earth2observe.eu/thredds/catalog/ecmwf/wrr1/catalog.html and dataset of ECMWF Water Resource Reanalysis v1/e2o_ecmwf_wrr1_glob30_day_RivOut_1979-2012.nc. The Table 2.1 shows description of ECMWF reanalysis dataset.

Table 2.1: Description of ECMWF reanalysis dataset

Dataset Description	Earth2Observe water resources reanalysis version 1 produced by ECMWF
Provider	European Centre for Medium Range Weather Forecasting (ECMWF)
Status/Available	https://wci.earth2observe.eu/thredds/catalog/ecmwf/wrr1/catalog.html
Creator name	Emanuel Dutra
Publisher name	Emanuel Dutra
Variables	RivOut (River discharge) in m^3/sec
Data type	NetCDF
Period	1979-2012
Temporal resolution	Daily and monthly
Spatial resolution	0.5° x 0.5° (Pixel size 50km x 50km)
Coverage	Global
Data licensing	Free for research users

Network Common Data Form (netCDF) is a file format for storing multidimensional scientific data (variables) such as temperature, humidity, pressure, wind speed, direction and river discharge.

The netCDF file for ECMWF reanalysis is e2o_ecmwf_wrr1_glob30_day_RivOut_1979-2012.nc, which is used for storing daily river discharge data from 1979 to 2012 year. The image of the ECMWF reanalysis daily high and low RivOut (River discharge) on 1 January 1979 and daily river discharge for the year of 1979 to 2012 are shown in Figure 2.1.

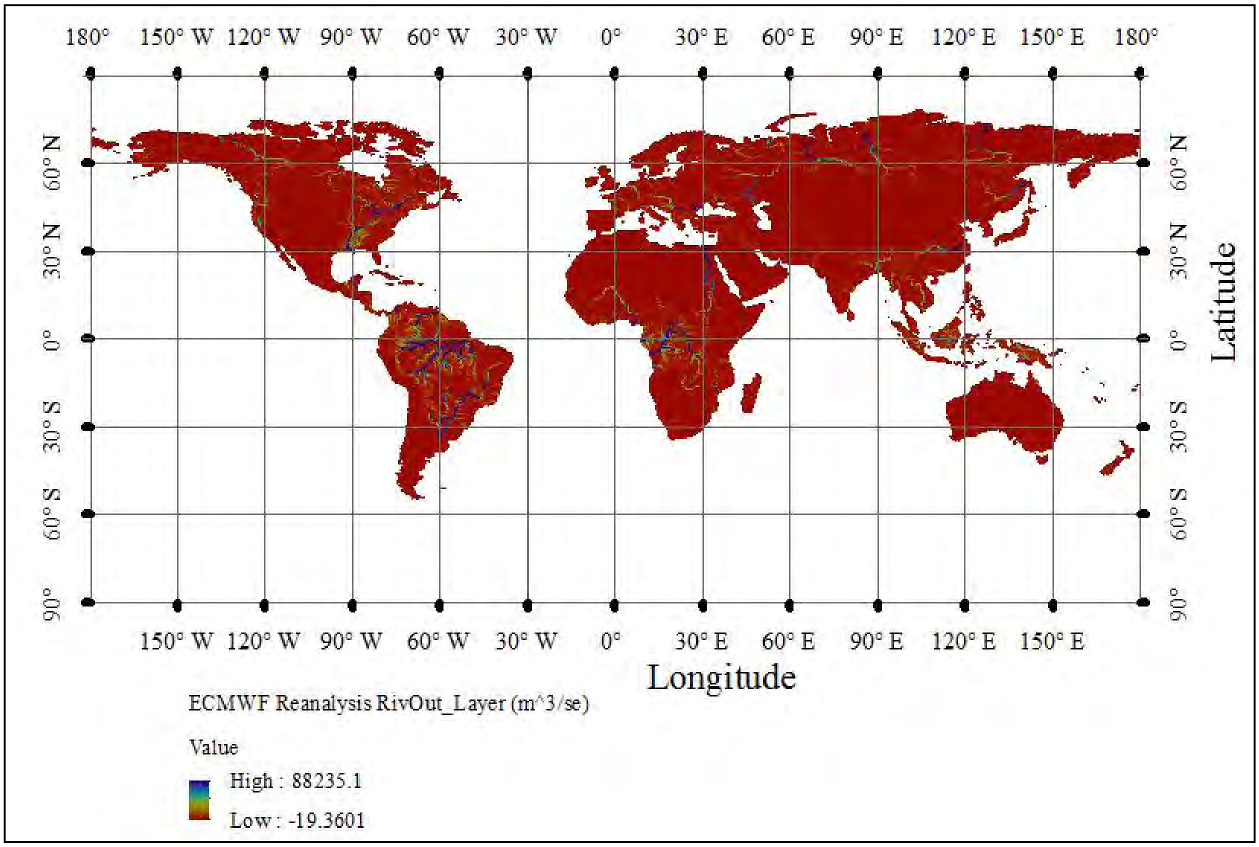


Figure 2.1: Image of the ECMWF reanalysis daily high and low river discharge on 1 January 1979 and Daily River discharge for the year of 1979 to 2012

2.3.2 UNIVK reanalysis dataset

The UNIVK reanalysis is the Earth2Observe water resources reanalysis version 1 produced by University of Kassel institution, Center for Environmental System Research (CESR). Water resources reanalysis version 1 is performed by WaterGAP3 forced by the Water and global change Data Forcing ERA Interim (WDFEI) CRU dataset. The global water model WaterGAP3 (Water Global Assessment and Prognosis) is a grid-based, integrative assessment tool to examine the state of global freshwater resources. The model framework consists of a spatially-distributed rainfall-runoff model. The global hydrological model simulates the terrestrial part of the global hydrological cycle by a sequence of storage equations for the most relevant continental storage compartments: canopy, snowpack, soil, renewable groundwater, and surface water bodies.

The model requires daily fields of precipitation, near-surface air temperature, downwelling short wave and long wave radiation as external meteorological forcing. Potential evapotranspiration is estimated according to the Priestley Taylor approach with surface net radiation calculated on the basis of land-cover dependent albedo and emissivity values. Surface and subsurface runoff generated in each grid cell and inflow from upstream cells is transported through a series of linear and nonlinear retention storages representing lakes, reservoirs, and wetlands before contributing to stream flow. Flow velocity in the river segment is calculated as a function of river bed roughness, river bed slope and hydraulic radius of the channel according to the Manning-Strickler equation (Verzano et al. 2012). Lateral flow, i.e. between grid cells, is assumed to occur as stream flow only.

The reanalysis is used to extract the monthly and daily river discharge (m^3/sec) for a year of 1979 to 2012. The UNIVK reanalysis begins 1 January 1979 and ends 31st December 2012. UNIVK reanalysis dataset has temporal coverage (from 1979-01-01 00:00:00 to 2012-12-31 00:00:00) and geographic coverage (latitude: 90°S-90°N and longitude: 180°W-180°E) with 720 columns and 360 rows to cover the globe. The distribution of the river discharge within each cell is described using a cumulative function of the 50km × 50 km. For water resources reanalysis version 1 of Earth2Observe, the UNIVK reanalysis is carried out at 0.5° × 0.5° spatial and monthly or daily temporal resolution. The access to the project THREDDS (Thematic Real-time Environmental Distributed Data Services) catalogue for UNIVK Reanalysis is available at https://wci.earth2observe.eu/thredds/catalog/univk/wrr1/catalog.html and dataset of UNIVK Water Resource Reanalysis v1/e2o_univk_wrr1_glob30_day_RivOut_1979-2012.nc. The Table 2.2 shows description of UNIVK reanalysis dataset.

Table 2.2: Description of UNIVK reanalysis dataset

Dataset Description	Earth2Observe water resources reanalysis version 1 produced by University of Kassel, CESR
Provider	Center for Environmental Systems Research CESR, University of Kassel
Status/Available	https://wci.earth2observe.eu/thredds/catalog/univk/wrr1/catalog.html
Creator name	Gabriel Fink
Publisher name	Center for Environmental Systems Research CESR, University of Kassel
Variables	RivOut (River discharge) in m^3/sec
Data type	NetCDF
Period	1979-2012
Temporal resolution	Daily and monthly
Spatial resolution	0.5° x 0.5° (Pixel size 50 km x 50 km)
Coverage	Global
Data licensing	Free for research users

The netCDF file for UNIVK reanalysis is e2o_univk_wrr1_glob30_day_RivOut_1979-2012.nc, which is used for storing daily river discharge data from 1979 to 2012 year.

The image of the UNIVK reanalysis daily high and low RivOut (River discharge) on 1 January 1979 and daily river discharge for the year of 1979 to 2012 are shown in Figure 2.2.

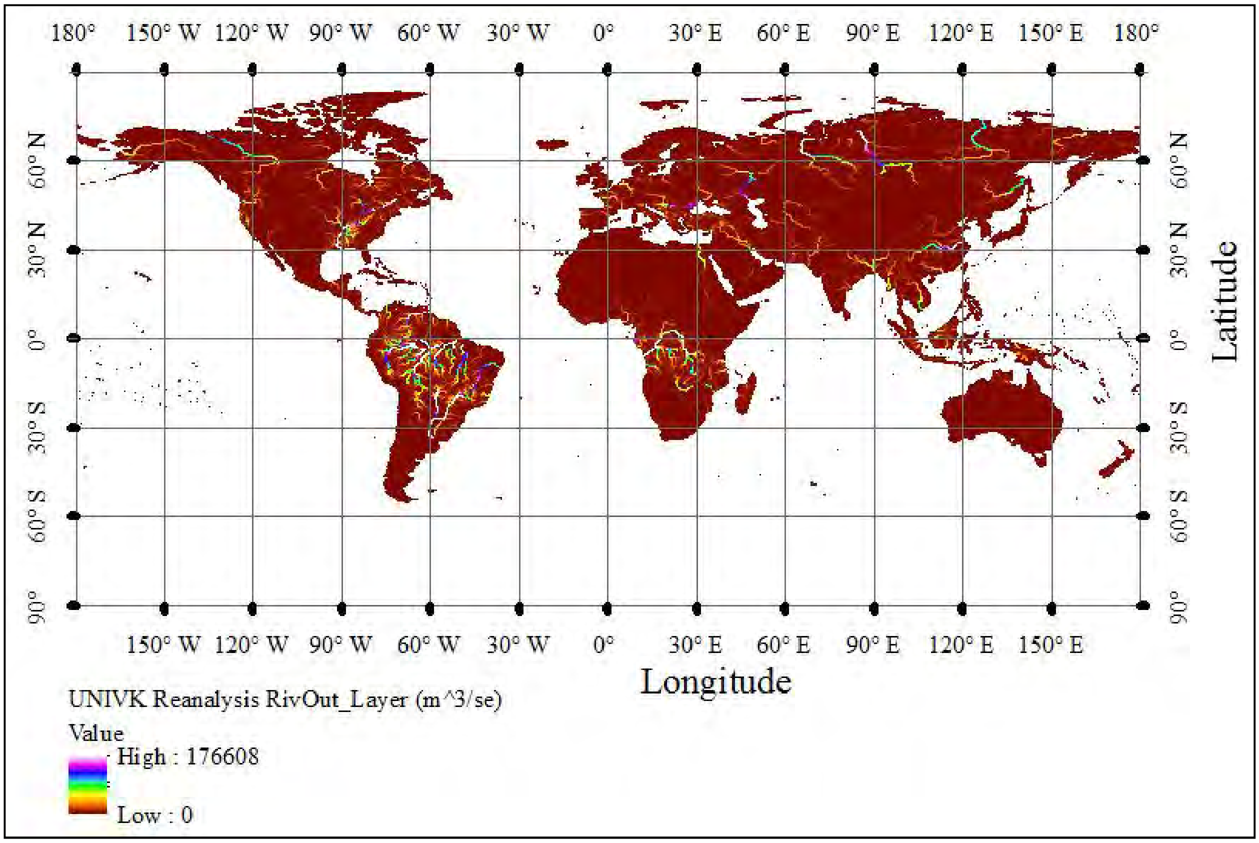


Figure 2.2: Image of the UNIVK reanalysis daily high and low river discharge on 1 January 1979 and Daily River discharge for the year of 1979 to 2012

2.4 Extreme flow quantiles estimation

Extreme flow quantiles estimation is estimating a future high and low flow magnitude from the available gauged flow data or from the available reanalysis flow data. They are essential for the efficient operation of water infrastructure, the mitigation of natural disasters such as floods and droughts and design of hydraulic structure such as culvert, spillway, and bridge. In addition, they are becoming increasingly important in supporting integrated water resources management and reducing flood induced losses. Estimates of flow having given recurrence intervals or probabilities of exceedance are needed for design of hydraulic structures and flood plain management.

2.5 Global survey distributions to estimate flow quantiles

Many statistical distributions for flood-frequency analysis have been investigated in hydrology. Annual maximum flow series were found to be often skewed, which led to the development and use of many skewed distributions, with the most commonly applied distributions now being the Gumbel (EV1), the Generalized Extreme Value (GEV), the Log Pearson Type III (LP3), and the 3 parameter Lognormal (LN3) (Pilon and Harvey, 1994). The proponents of each distribution have been able to show some degree of confirmation for their particular distribution by comparing theoretical results and measured values.

2.6 Standard distributions adopted by national institutions in the world

A number of methodologies to quantify flood with certain return period and probability exist, but none has been accepted universally or not uniformly standardized, for similar discussion see also for instance Gebeyehu (1989), H.Abida and M.Ellouze (2008). There are a number of articles published on journals, conference proceeding, etc., offering different approaches on the methods of estimation of extreme flow quantiles and its return periods.

More recently, a worldwide survey of flood frequency methods, prepared for the World Meteorological Organization in 1984 and involving 55 agencies from 28 countries, reported the use of six distributions namely EV1, EV2, GEV, LN2, P3, and LP3. The survey, which was summarized by Cunnane (1989), revealed that EV1, LN2, P3, and LP3 were the most common distributions while only one country used the GEV distribution in spite of its recent popularity.
Selection of the most appropriate distribution for annual maximum (AM) Discharge series has received widespread attention.

Others are the Gamma and log-logistic distributions, among others, including some relatively new distributions such as the Walter Boughton, the log-Walter Boughton, Wakeby and the log-Wakeby distributions. The distributions can be used to fit the probability of occurrence of flood series.

Details of these distributions are available in many references including Cunnane (1989) among others. The following distributions were considered for the current study:

Extreme value type 1 (EV1)	(Gumbel, 1941)
General Extreme Value (GEV)	(Jenkinson, 1955, 1969)
Lognormal (LN)	(Hazen, 1914)
Two-parameter Gamma (G2)	(Moran, 1957)
Pearson type 3 (P3)	(Foster, 1924)
Log Pearson type 3 (LP3)	(USWRC, 1967)

2.7 Flood frequency model

In flood frequency analysis the objective is to determine a Q-T relationship at any required site along a river discharge. At any river site it is usually assumed that nature provides a unique Q-T relationship and that Q is a monotonically increasing function of T. In order to estimate this natural Q-T relation from a good quality continuous hydrometric record of N year's duration, it is necessary to resort to a statistical or stochastic model of the continuous hydrograph, which retains information in the hydrograph relevant to the Q-T relation, and discard the rest.

Two such models are:

- Annual maximum series model, AM
- Partial duration series model, PD

In flood frequency modeling the problems related to the following points have to be solved (Cunnane 1989);

- Choice of model type (AM, or PD)
- Choice of distribution to be used in the chosen model
- Choice of method of parameter

It should be noted that two separate aspects of such choice are important. These are the descriptive and predictive properties of the chosen method. The descriptive property relates to the requirements that the chosen distribution shape resembles the observed sample distribution of floods and that random samples drawn from the chosen model distribution must be statistically similar to the properties of real flood series, the predictive properties relates to the requirement that quantile estimates are robust with small bias and standard error (Cunnane, 1989).

2.7.1 Relative advantage of the two models

a) Annual maximum (AM) series model

Cunnane, 1989 has stated that a series of annual maximum flood is assumed to form a random sample from stationary population in which Q is a random variable with distribution PR $(Q<q) = F(q)$. The variate values with exceedance probability 1/T is said to have return period T.

Denoting this value

Q_T, it is such that: $1-F(Q_T) = 1/T$

In the annual maximum (AM) flow series, only the peak flow in each year of record is considered, that may involve some loss of information.

b) Partial duration (PD) series model

In this model most of the flow hydrograph is disregarded and the hydrograph is viewed as a series of randomly spaced flood peaks of random magnitude. For case of statistical modeling and also for case of identification of the values, which form the series, only the series of peak exceeding an arbitrary threshold q_o are considered. In particular, each of these showed that if the number of flood peaks exceeding some value q_o (a threshold value) in some interval of time such as a year has a poisson distribution with parameter λ, the number of events exceeding a great value $\bar{q}$ also poisson distributed with parameter $\bar{\lambda} = \lambda p$. Here p is a conditional probability, being the proportion of all peaks exceeding q_o which also exceeds $\bar{q}$ (Cunnane, 1989). In partial duration series all peaks above a certain base value are considered. The base is usually selected low enough to include at least one event in each year (Rao and hammed, 2000).

In the annual maximum (AM) flow series, only the peak flow in each year of record is considered. However, the use of an AM series may involve some loss of information. For example, the second or third peak within a year may be greater than the maximum flow in other years, and yet they are ignored. This situation is avoided in the partial duration (PD) or peak over a threshold (POT) model where all peaks above a certain base value are considered. The base is usually selected low enough to include at least one event in each year (Rao & Hamed, 2000).

Statistical efficiency of estimates of Q_T by each model

Denoting the estimates of Q_T obtained by AM method as Q_T and that obtained from the same hydrometric record by the PD method as $\bar{Q}_T$ it is usually observed that these two estimates are unequal. Furthermore the sampling variance of Q_T is not equal to that of $\bar{Q}_T$. i.e. Var (Q_T) ≠ Var ($\bar{Q}_T$). From a statistical point of view that method which has the smallest sampling variance enjoys an advantage. Under certain common assumption Cunnane (1989) examined the relative values of Var ($\bar{Q}_T$ and Var (Q_T) and found that Var (Q_T) < Var ($\bar{Q}_T$ provided λ is less than 1.65 where λ is the mean number of peaks per years included in the PD series. Where λ is greater than 1.65 the opposite was true. This $\bar{Q}_T$ shows that the AM method is statistically more efficient than the PD method when λ is small but less efficient when λ is large. In many practical situations the assumptions of the PD model may not be valid if λ is increased to too high a level, certain if λ is greater than 3 (Cunnane 1989).

Therefore, to avoid the problem of dependency on data, annual maximum (AM) series model has been selected. In addition to this, AM series is widely and commonly used model by different researchers for the purpose of flood frequency analysis (Cunnane, 1989).

The PD or POT model, however, is limited by the fact that observations may not be independent which violets the assumption of independence of flood peaks for statistical analysis. According to Cunnane (1989), the AM model is statistically more efficient than PD model when λ is small (λ is less than 1.65), where λ is the mean number of peaks per year included in the PD series. When λ value is greater than 1.65 the opposite was true.

2.8 Method of parameter estimation

In the past only the ordinary methods of moments (MOM) was mentioned for parameter estimation. It should be noted that MOM and PWM are the most efficient method of parameter estimation available. There are no other available methods of parameter estimation, which yield parameter, and quantile estimates, which have smaller error than those of MOM and PWM estimates (Cunnane, 1989). Some of parameter estimation methods are discussed as follow:

A. Method of Moments (MOM)

It is one of the most commonly used methods of estimating parameters of a probability distribution. The estimates of the parameters of a probability distribution function are obtained by equating the moments of the sample with the moments of the probability distribution function. Parameter estimation by MOM is known to be biased and inefficient especially with three parameter distributions. Method of moments (MOM) is a relatively easy parameter estimation method. Unfortunately, MOM estimates are usually inferior in quality and generally not as efficient as the MLM estimates especially in the case where the distributions have a large number of parameters. This is due to the fact that higher order moments are more likely to be highly biased in relatively small samples.

B. Maximum Likelihood Method (MLM)

The maximum likelihood method (MLM) is often regarded as the most efficient method. This is because it provides the smallest sampling variance of the estimated parameters which leads to the smallest sampling variance of the estimated quantiles compared to other methods. MLM has disadvantages in some particular cases, such as the Pearson type III distribution where the optimality of the MLM is only asymptotic and small sample estimates may lead to estimates of inferior quality (Bobée et al., 1993). Another disadvantage is that MLM often gives biased estimates. However, these biased estimates can be corrected. Furthermore, MLM might be hard to compute especially if the number of parameters is large. This will in turn make it hard and might also be impossible to obtain MLM estimates of small samples.

Estimation by the Maximum Likelihood Method (MLM) involves the choice of parameter estimates that produce a maximum probability of occurrence of the observations. The parameter estimates that maximize the likelihood function are computed by partial differentiation with respect to each parameters and setting these partial derivatives equal to zero and finally solve the resulting set of equations simultaneously. The equations are usually complex that can only be solved by numerical techniques. As a result of this difficulty, the solution set may not properly found. (Rao & Hamed, 2000)

C. Method of probability weighted moments (PWM)

The probability weighted moments (PWM) method (Hosking, 1986) gives parameter estimates comparable to the MLM estimates. In fact, in some cases the estimation procedures are much less complex and thus less complicated since the computations are simpler than that of MLM estimates. Parameter estimates are obtained in this method, as in the case of MOM, by equating moments of the distributions with the corresponding sample moments of observed data. For a distribution with k parameters, the first k sample moments are set equal to the corresponding population moments.

The resulting equations are then solved simultaneously for the unknown parameters. Parameter estimation by PWM, which is relatively new, is as easy to apply as ordinary moments (MOM), is usually unbiased and is almost as efficient as MLM. Indeed in small samples PWM may be as efficient as MLM. With a suitable choice of distribution PWM estimation also contributes to robustness and is attractive from that point of view. Another attraction of the PWM method is that it can be easily used in regional estimation schemes (Roa & Hamed, 2000).

D. L-Moment method (LMM)

L-Moments are analogous to method of moments but are estimated by linear combinations of an ordered data set, namely L-statistics. (Roa & Hamed, 2000)

The following are advantage of L-moments: (Cunnane, 1989)

- Compared to method of moments, L-moments can characterize a wide range of distributions
- Sample estimates of L-moments are so robust that they are not affected by the presence of outlier in the dataset and are less subjected to bias in estimation

L-moments yield more accurate estimates of the parameters of a fitted distribution. Even some times parameter estimated form samples are more accurate than maximum likelihood.

The following L-Moments are defined in (Cunnane, 1989):

$\lambda 1 = L1 = M100$

$\lambda 2 = L2 = 2M110 - M100$

$\lambda 3 = L3 = 6M120 - 6M110 + M100$

$\lambda 4 = L4 = 20M130 - 30M120 + 12M110 - M100$

The 4 L-Moments ($\lambda 1$, $\lambda 2$, $\lambda 3$, $\lambda 4$) are all derived using the 4 PWMs. Other useful ratios are L-CV ($\tau 2$), L-Skewness ($\tau 3$) and L-Kurtosis ($\tau 4$).

L-CV is similar to the normal coefficient of variation (CV). The standard equation for CV = standard deviation/mean, and shows how the data set varies. The larger the CV value, the larger the variation of the data set from the mean. For example, in arid regions that receive few storm events, the variation will be large, as one storm will deviate greatly from the low mean.

$\tau 2 = L2/L1$ (L-CV)

L-Skewness is a measure of the lack of symmetry in a distribution. If the value is negative, the left tail is long compared with the right tail, and if the value is positive, the right tail is longer.

For GEV frequency analysis, a positive L-Skewness value is desired, as we are interested in the extreme events that occur in the right side tail of the distribution.

$\tau 3 = L3/L2$ (L-Skewness)

L-Kurtosis is difficult to interpret, however is often described as the measure of "peakedness" of the distribution (Hosking, 1997). L-kurtosis is much less biased than ordinary kurtosis.

$\tau 4 = L4/L2$ (L-Kurtosis)

Where, L1 = measure of location

$\tau 2$ = measure of scale and dispersion (LCv)

$\tau 3$ = measure of skewness (LCs)

$\tau 4$ = measure of kurtosis (LCk)

2.8.1 Comparison and Selection

In general, the L-Moment and the MOM are better for estimating the parameters for three and two parameter distributions respectively of the underlying distribution from which the data are sampled. They are less sensitive than others to sampling variability or measurement errors in the extreme data value (outliers), and therefore, they yield more accurate and robust estimates of the characteristics or parameters of the underlying probability distribution.

The selection of a distribution for flood frequency analysis goes with the selection of the method of parameter estimation. Parameters estimated by any of the above methods are subject to sampling errors. While a method may be efficient for one distribution it is not necessarily efficient for other distributions.

2.9 Selection of probability distributions

Many flood frequency distributions have been suggested for modeling flood flows, but none has been accepted universally. Cunnane (1989) has listed the commonly used type of statistical distributions in choice of distribution for AM series has received wide spread attention.

The choice of distribution is influenced by many factors, such as methods of discrimination between distributions, methods of estimation parameters, the availability of data, etc. Normally, there is no general global agreement as to a preferable technique of model choice and no single one distribution accepted universally.

Generally the chosen distribution should be (Cunnane, 1989) widely accepted, simple and convenient to apply, consistent, flexible or robust (low sensibility to outliers, theoretically well based (established) and documented in the guide World Meteorological Organization (WMO).

It is already mentioned that many distributions have been proposed for flood frequency analysis as a result of considerable research work carried out by scientists worldwide. Current research in the area of flood frequency analysis is on the selection of a suitable probability distribution coupled with the choice of a parameter estimation procedure. The main question of concern is which distribution is most suitable for generating a given particular annual maximum discharge series.

The choice of an appropriate flood frequency procedure to model flood flows for a particular site by applying a series of tests. These tests on the ability of the flood frequency model to describe the underlying empirical sample are classified into two broad categories such as goodness of fit test and analysis of tail behavior test.

2.9.1 Goodness of-fit-tests

The choice of distribution to be used in flood frequency analysis has been a topic of interest for a long time (Rao and Hamed, 2000). Chi-Squared (x^2) test and Kolmogorov-Smirnov (KS) test have been typically used to identify the stream flow distributions for flood frequency analysis. The Anderson-Darling (AD), Kolmogorov-Smirnov (KS), and Chi-Squared (x^2) tests are used for the goodness of fit tests. All test statistics are defined in (Solaiman, 2011).

The goodness of fit tests was executed in the downloadable software Easy-Fit, available at http://www.mathwave.com/easyfit-distribution-fitting.html. All test values and statistics were produced from this program.

2.10 Previous Study of the Area

In the earlier time, flood frequency analysis has been done on North-western highlands of Ethiopian's basins (such as Abbay basin, parts of Gibe-Omo and Awash basins together) by Admasu, 1989.

The Earth2observe monthly River out flow products was evaluated by (Fitsume et al, 2015) and the ECMWF river outflow discharge is found to be better than the other Earth2Observe river outflow products. The Earth2Observe ECMWF better estimated the Blue Nile flow both at Kessie (PBIAS of -7.889%) and Border (PBIAS of 0.67%). The Earth2Observe UNVIK also better estimated the Blue Nile flow at Kessie (PBIAS = -18%) and Border (PBIAS = 23%) than the other products. The study shows that these two products better estimate the Blue Nile flow than the other products. Therefore these two products are evaluated for extreme flow quantiles from Earth2Observe datasets and intensive investigation is made in this study related to evaluation of extreme flow quantile estimated from global reanalysis runoff data with the flow quantile obtained from in-situ observed runoff data.

3. METHODOLOGY

For this research, identifying clear and efficient methodology used is crucial for the effectiveness of the study not only from time budget point of view, but also from the quality of the research result. As it was indicated in the first chapter the main objective of this research is to estimate the extreme flow quantiles from global reanalysis runoff data and to evaluate the validity of flow quantiles with a flow quantiles obtained from in-situ observation data in the area of Blue Nile River Basin. In this study the flood frequency analysis method was used, which consists of data preparation, selection of frequency distribution, method of parameter estimation and finally estimation of extreme flow quantiles for the global reanalysis runoff data and observed data. The ECMWF and UNIVK water resources reanalysis version 1 (wrr1) were used to extract daily river discharge data.

Figure 3.1 the flow chart below shows the general methodology/conceptual framework of the study adopted in this thesis work.

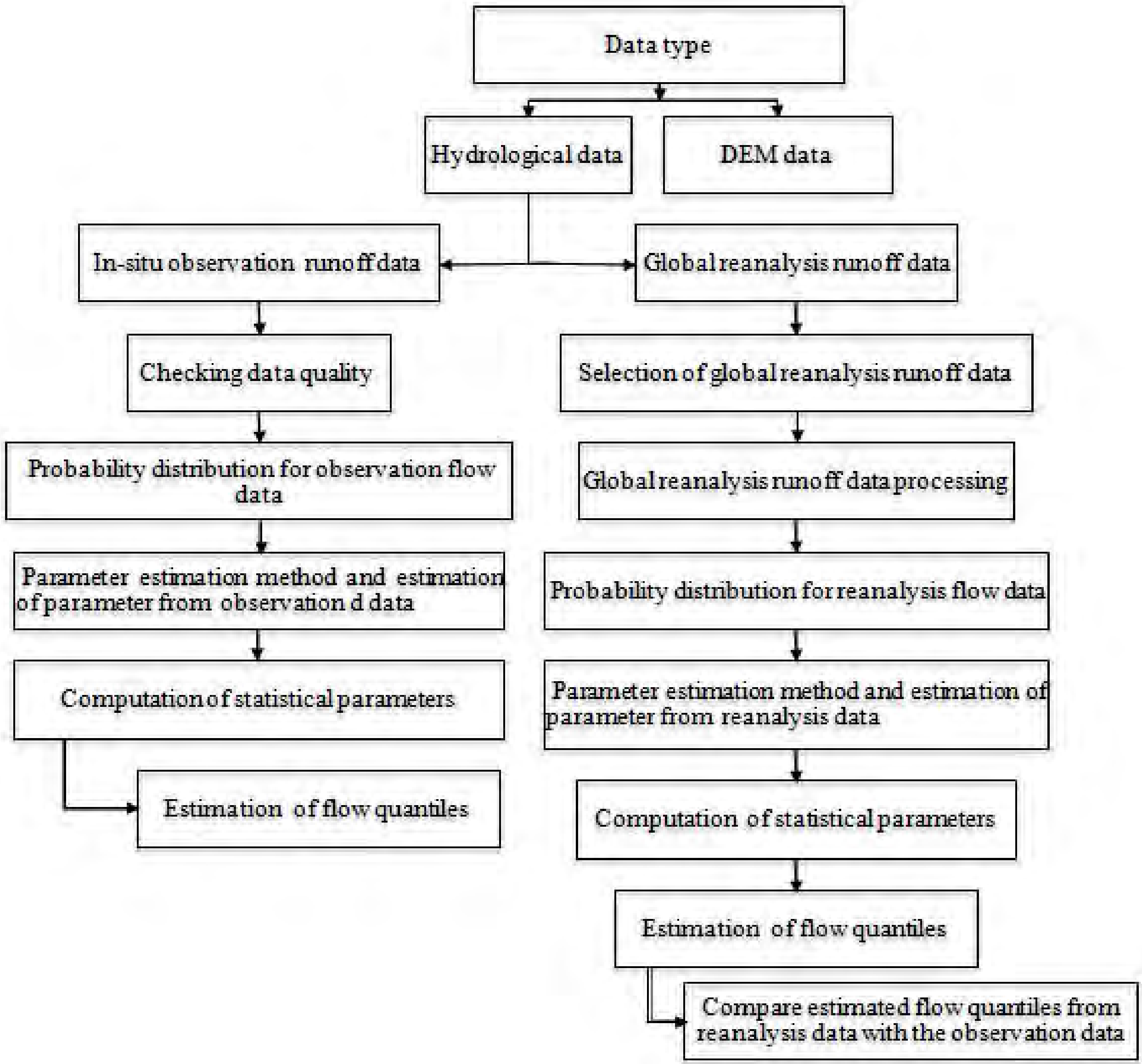


Figure 3.1: Conceptual frame works for the Study

3.1 Description of Study Area

3.1.1 Location

The study area, Blue Nile River Basin, which is found in the northwestern part of Ethiopia between $7^0 45'$ and $12^0 45'$N latitude, and $34^0 05'$and 39^0 45'E longitude. It has an average annual runoff about 54.80 billion cubic meters [Abbay River Basin Development Integrated Master Plan Project (ARBIDMPP), 1999]. It covers an area of approximately 199,812km^2 with a total perimeter of 2440km.It shares a boundary with the Tekeze basin to the north, Awash basin to east and south east, the Omo-Gibe basin to the south, and the Baro Akobo basin to the south west. The basin accounts for major share of the countries irrigation and hydropower generation potential. Estimated energy potential of the basin is about 98,831Giga watt hour per year (WAPCOS, 1990). The development of the sector is 218.4Mega watt (1004Giga watt hour per year) from Tis-Abbay and Fincha plants which account less than 1% of the potential.

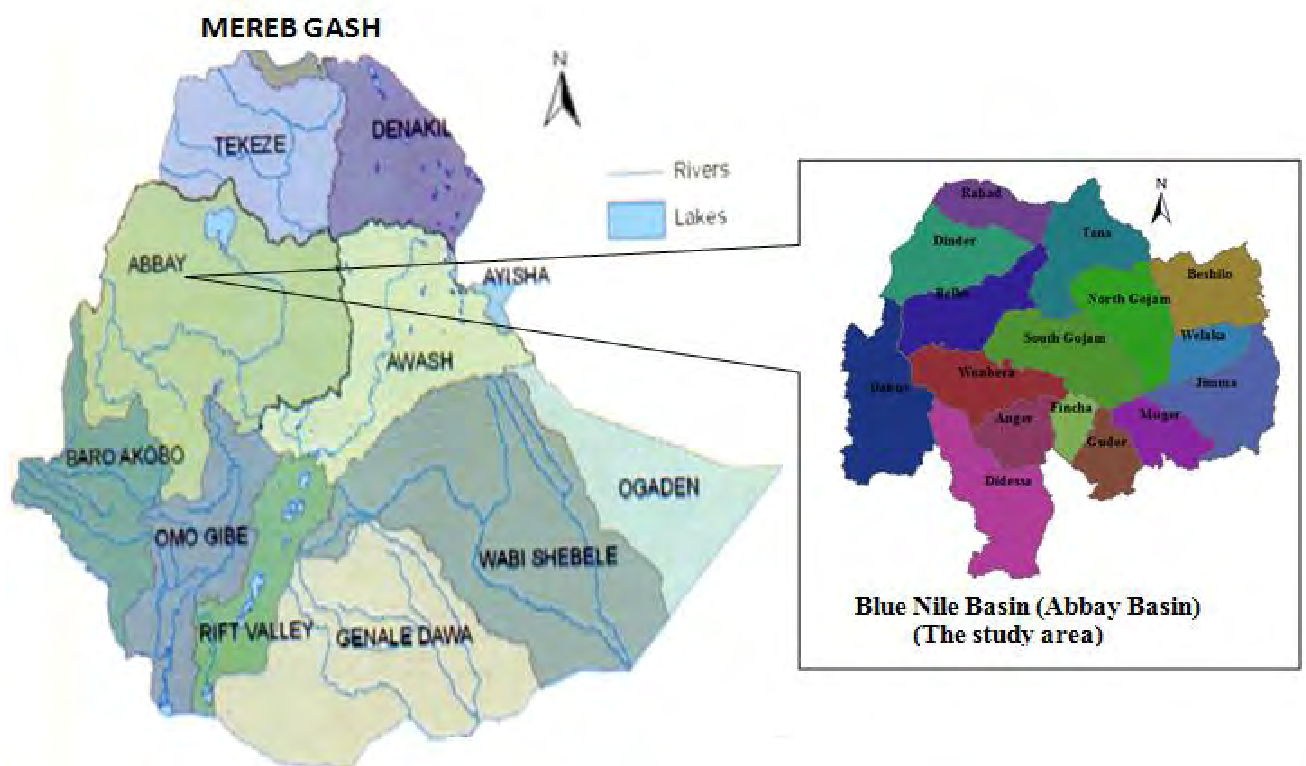


Figure 3.2: Location and basin map of the study area

3.1.2 Topography and Slope

Most of the Blue Nile River Basin areas are hilly and relatively flat near the border of Sudan. The highland areas of the country are cut by deep narrow valley with steep sided in which the river flows. In some place, the river flows in a channel that is about 1200m.a.s.l below the level of country on either side. The drop of the plateau to the reservoirs plain, in most places is, steep. Much of the upper part of the basin comprises the highland plateau with elevation generally exceeding 2000m. The plateau exhibits extensive level areas with intensive agriculture divided by incised valleys. The Blue Nile flows generally within a deeply incised gorge which has a relatively gentle gradient falling some 645m over 600km from an elevation of El.1030m at Kessie Bridge to El. 485m at the Sudan Border on main stream. The headwaters of the Blue Nile River are in the mountains surrounding Lake Tana. Lake Tana, at an elevation of approximately EL. 1785m provides significant regulation of the natural river flow in the upper reaches of the Blue Nile. The Didessa, Dabus and Beles rivers are the main tributaries which join the Abbay in the reach between Lake Tana and the Border dam site (Source: Pre-feasibility).

3.1.3 Climate

Climate in the Ethiopian highlands is strongly influenced by the effects of elevation, which gives rise to distinct zones and characteristics. The climate of Blue Nile Basin is dominated by an altitude ranging from 590m to more than 4000m. The influence of this factor determines the rich variety of local climates ranging from hot to desert-like climate along the Sudan-border to moderate on the high plateau and cold on the mountain peaks. The climate of Ethiopia is mainly controlled by the seasonal variation of the Inter-tropical Convergence Zone and an associated atmospheric circulation as well as by their complex topography of the country. It has a diversified climate range from semiarid desert type in the lowlands to humid and temperate type in the southwest. The climate of the study area varies from humid to semi-arid.

3.1.4 Rainfall

Based on the rainfall pattern, the year is divided in to two seasons: a rainy season of Blue Nile Basin, mainly from June to September, and a dry season from October to March. The annual rainfall varies between about 800mm to 2,220 mm with a mean of about 1420mm (Master Plan of Blue Nile River Basin (BNRB) – Main Report). The rainfall pattern is almost uni-modal (BCEOM, 1999).

3.1.5 Temperature

The highest temperature observed is in the north western part of the basin. The mean temperature of the coldest month above 18.5^{o}C, to temperate on the high plateau, and cold on the mountain peaks, with mean temperature of the warmest month below 11.4^{o}C.

3.1.6 Soil and Geology

The river channel of the Nile at the dam site comprises massive exposures of granite with Quartz intrusions with several deep and sharply defined narrow channels through which the river passes at low flows. Large exposures of granite bedrock were observed on the abutments. The Abbay River cuts deep into the Precambrian basement rocks, forming an 800m deep V-shaped valley. In the project area, the river flows nearly east-west and is flanked on both sides by steep slopes. The asymmetric valley has steeper slopes on the southern than the northern flanks. The steep slopes are largely covered by collu-vial/talus material. The area is largely covered by elephant grass and scattered trees that survived wild fires (Source: pre –feasibility). The major dominant soil types in the basin are mostly covered by Eutric leptosols, Cambisols (sandy loam soil), Fluvisols and Haplic Alisols, Nitisols (clay and clay loam), and Arcisols.

3.1.7 Land Use/Land Cover

The main land covers in the Abbay catchment are agro-pastoral, agriculture, marshland, urban, cultivated land, forest and grassland with frequent patches of shrubs, woods, trees and water.

3.1.8 Drainage sub-basins of Blue Nile River Basin

The Abbay (Blue Nile) River basin has about 14 major drainage sub-basins as listed in Table 3.1.

Table 3.1: Drainage sub-basins of Blue Nile River Basin

	Name of sub basin	Area (km^2)
1	Beles	13271
2	Bijena-Beshilo	12060
3	Bir-Temcha	6020
4	Dabus	14668
5	Didessa -Anger	27814
6	Dinder	11503
7	Fincha	3478
8	Guder-kale	6695
9	Jema-Wenchit	14770
10	Mugar-Urga'A	7786
11	Tana	14897
12	Shinfa – Rahad	9710
13	Weleka- Beto	4896
14	Main Abbay (North & South Gojam)	51734

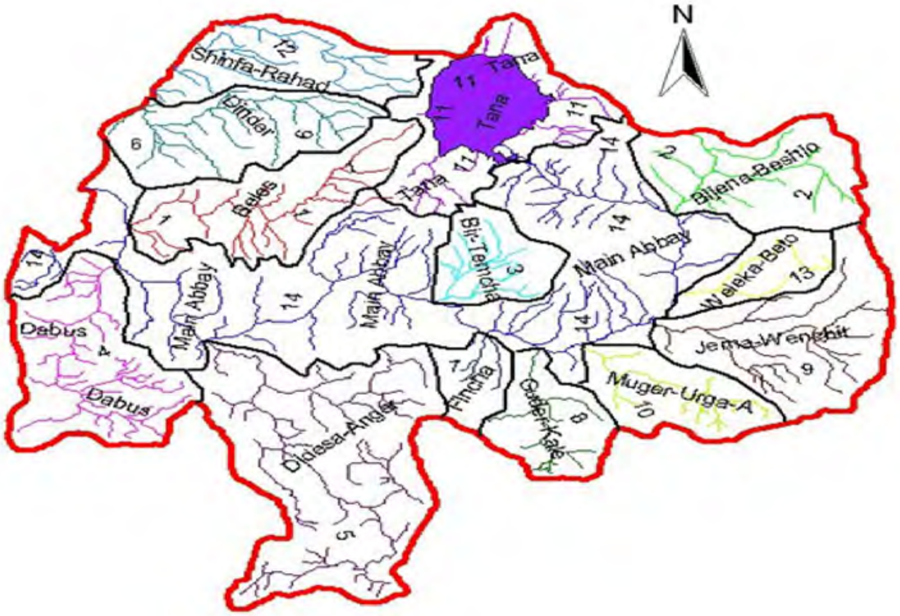


Figure 3.3: Blue Nile river system and sub-basins derived from DEM

In this study 78 stations were considered for the analysis. The distribution of the stations within the basin is high at the central, northern and southern part of the basin. Whereas, the north-west part of the basin does not have sufficient stations. Generally the distributions of the observed stations used in this study are shown in Figure 3.4.

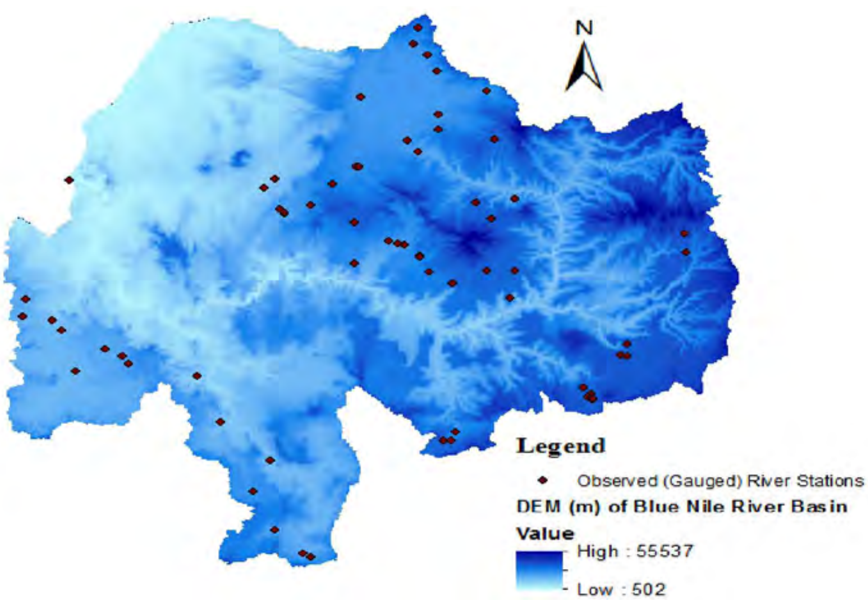


Figure 3.4: Distribution of observed flow stations with in Blue Nile River Basin

3.2 Checking Data Quality

Hydrological data for flood water management studies should be independent, random, stationary and consistent or homogenous when they are used in flood frequency analysis.

3.2.1 Test for Consistency

According to Chang and Lee (1974), a time series of hydrological data is relatively consistent if the periodic data are proportional to an appropriate simultaneous time series (as cited in Dahmen and hall, 1990). In other words, relative consistency means mechanism that generated similar or related data at other stations.

3.2.2 Test for Randomness

Time series data used for statistical distribution analysis should be random. To test whether or not the data order is random, the Run test applied to the data using mintab software. The normal approximation for run test is given by:

Z = $\mathrm{Observed} - \mathrm{Expected}/\mathrm{SQRT}(\mathrm{Vriance})$...Eqn.3.1

Where, observed = the number of runs in the sample

Expected = $1 + (2 * A * \frac{B}{N})$...Eqn.3.2

Variance = 2*A*B (2*A*B-N/N2 (N-1)...Eqn.3.3

A = the number of data above k

B = the number of data below or equal to k

N = the number of data

P-values are the probability of observing the absolute value of a standard normal variable greater than the absolute value of Z. The hypothesis is that if the value of p less than alpha value, then the data is not random.

3.2.3 Test for independency and stationary

It is usually assumed that all peak magnitude in annual maximum series is usually mutually independent in the statistical sense. Notable exceptions are time series of data from river with considerable carryover of ground water flow from one year to the next and those of data from rivers whose catchment includes large lakes.

In these cases, one will want to test time series for independence. Non independent of the events in the data series may bias the result of frequency analysis.

Serial-correlation coefficient is work to verify the independence of the data of the selected hydrological stations. If the time series is completely random, the population autocorrelation function will be zero for all lags other than zero (when its value is unity), because all data sets are perfectly correlated with themselves and the sample serial-correlation coefficients will deviate slightly from zero only because of sampling effects. For this purposes, it is usually sufficient to compute the lag 1 serial-correction coefficient, i.e. the correlation between adjacent observations in a time series. According to box and Jenkins (1970), the lag 1 serial-correlation coefficient, r_1, defined as follows (as cited in Dahmen and Hall, 1990).

$$r_1 = \frac{\sum_{i=1}^{n-1} (Xi-Xaverage)*(Xi+1-Xaverage)}{\sum_{i=1}^{n}(Xi-Xaverage)} \text{...Eqn.3.4}$$

Where x_i is an observation, x_{i+1} is the following observation and n is the number of data. After computing r_1, the test hypothesis is that H_o : r_1 = zero (that there is no correlation between two consecutive observations) against the alternate hypothesis, $H_1 : r_1 <> 0$.

The other is the results of autocorrelation test which is that the autocorrelation coefficients of lag-1, for annual maximum series of each site are smaller than $1.96/n^{0.5}$, where n is the recorded extent of data. Hence, the observations in that series can be accepted as being independent at the 5% significance level. Therefore, all series can be accepted as being stationary and without serial correlation. It means that the flood frequency analysis can be applied to the hydrological series for all sites.

3.2.4 Check for outliers

Flood frequency analysis is one of the investigations of extreme events. In any time series data, outliers may or may not exist. These outliers may come due to personal error during recording and inadequacy of measuring device or really due to very extreme condition of natural phenomenon that is important information for flood frequency analysis.

Therefore, unless the source of the outliers clearly identified, it is difficult to remove outliers completely from analysis. Outliers can be excluded from the estimation procedure only if it is certain that annual maximum (AM) flow can be adequately modeled by a single known distributional form. (Cunnane, 1989)

As a result outliers test was not done in this study. However, to avoid the effect of outliers an efficient method of parameter estimation like L-Moment was used. Even if retained in analysis, outliers have only a small effect if an efficient method of parameter estimation (MLM or MOM) is used. (Cunnane, 1989)

3.2.5 Check for Missing Records

Observed flow data frequently contain gaps for a variety of reasons including the malfunction of recording equipment. Stream flow data from nearby catchments may indicate the likelihood of a large flow having occurred during the gap. A regression may be able to be derived to enable a missing flow data to be estimated, but the degree of correlation is often insufficient for a quantitative estimate. For annual series the missing record period is of no consequence and can be included in the period of record if it can be determined that the largest flow for the year occurred outside the gap. However the flow on nearby catchments might indicate that a large flow could have occurred during the period of missing record. If a regression with good correlation can be derived from concurrent records, the missing flow can be estimated and used as the annual flow for the year. If the flow cannot be estimated with reasonable certainty, the whole year should be excluded from the analysis.

3.3 Data Collection and Analysis

To achieve the goal of the research various data have been collected from different agencies, which include time series data and digitized map of the study area.

3.3.1 Time Series Data

The hydrological time series data were collected for the purpose of this study. Seventy eight (78) stream flow gauging stations are available in the Blue Nile River Basin. The instantaneous daily flow was collected from Ministry of Water resource of Hydrology department.

The annual maximum discharge series data were analyzed and used for estimation of extreme flow quantiles using flood frequency analysis.

3.3.2 Observed Discharge Data

For flood frequency analysis, systematic stream gauging records of sufficient length (at least 15 years) are required to warrant statistical parameters as the basis for determination (Guidelines for FFA, USWRC). For flood frequency, annual maximum discharge series have to be used for analysis. (Guidelines for FFA, USWRC)

But in this study for the evaluation extreme flow quantiles estimated from the reanalysis data, the record length of the observed discharge data time series of at least 24 recorded length of year are considered. Blue Nile River Basin has 78 stream flow gauging stations which are operated by Hydrology Department of ministry of Water Resources (MoWR). Out of 78 stream flow gauging stations only six stations are selected by considering a record length of year greater than or equal to 24 years and removing station of very small catchment area or almost less than 2500km^2. For evaluation of extreme flow quantiles estimated from reanalysis AM discharge data, a minimum of 24 recorded year of stream gauging length are used for this study in order to match the record length of observed discharge data with the record length of reanalysis discharge data.

Stream flow gauging stations with catchment area of very less than 2500km^2 are removed from the study, because of the spatial resolution or pixel size of the reanalysis (ECMWF and UNIVK) dataset is 50km x 50km. It doesn't give sense to consider the comparisons of flow generated from very less area than 2500km^2 with flow generated from a pixel size of 2500km^2. Six stream flow gauging stations are passed for primary screening, while the other seventy two stations are not passed for primary screening because of unfavorable factors, such as lack of stations coordinates, short record length, small catchment area and influence of human interfere etc.

The detail of six stations, which were passed for primary screening for this study and their record extent of the station considered for evaluation of reanalysis (ECMWF and UNIVK) data are shown in the Table 3.2 and 3.3 respectively.

The hydrological data i.e. annual maximum flow series are analyzed from instantaneous daily flow were collected from Hydrology Department of Ministry of Water Resources (MoWR).

Table 3.2: List of stations for the study

No	River name	Site	Coordinates		Area (km^2)	Record Extent	N
			Latitude	Longitude			
1	Gilgel Abbay	Near Marawi	$11^0 22'$ N	$37^0 2'$ E	1664	1973-2002	30
2	Abbay	Near Kessie	$11^0 4'$ N	$38^0 11'$ E	65784	1975-2002	28
3	Abbay	At Bahirdar	$11^0 36'$ N	$37^0 24'$ E	15321	1973-2002	30
4	Didessa	Near Arjo	$8^0 41'$ N	$36^0 25'$ E	9981	1960-2002	43
5	Main Beles	At Bridge	$11^0 15'$ N	$36^0 27'$ E	3431	1962-2002	41
6	Abbay	At Border	$11^0 14'$ N	$34^0 59'$ E	172254	1964-2009	46

Table 3.3: Record extent of year for selected stations considered for evaluation of re-analysis

No	River name	Site	Coordinates		Area (km^2)	Record Extent	Number of AM flow data
			Latitude	Longitude			
1	Gilgel Abbay	Near Marawi	$11^0 22'$ N	$37^0 2'$ E	1664	1979-2002	24
2	Abbay	Near Kessie	$11^0 4'$ N	$38^0 11'$ E	65784	1979-2002	22
3	Abbay	At Bahirdar	$11^0 36'$ N	$37^0 24'$ E	15321	1979-2002	24
4	Didessa	Near Arjo	$8^0 41'$ N	$36^0 25'$ E	9981	1979-2002	24
5	Main Beles	At Bridge	$11^0 15'$ N	$36^0 27'$ E	3431	1979-2002	21
6	Abbay	At Border	$11^0 14'$ N	$34^0 59'$ E	172254	1979-2009	31

3.3.3 Data quality check for the sub-basin hydrological data

3.3.3.1 Test for independency and stationary

The autocorrelation coefficient of lag-1 test was used to verify the independence of the data of the selected hydrological stations. The autocorrelation coefficients of lag-1 test for annual maximum series of each site are smaller than $1.96/n^{0.5}$. Hence, the observations in that series can be accepted as being independent at the 5% significance level. Therefore, all series can be accepted as being stationary and without serial correlation. It means that the flood frequency analysis can be applied to the hydrological series for all sites. The summarized result of the test for annual maximum flow series are given in Table 3.4.

Table 3.4: Result of independence test for annual maximum flow series using autocorrelation coefficients of lag-1 test

No	Name of stations	Number of data (n_i)	Test Result		Remark
			Autocorrelation Coefficient Lag-1 (r_1)	Critical Value (D_i)	
1	Gilgel Abbay near Marawi	24	-0.14	0.4	Independent
2	Abbay near Kessie	22	0.36	0.42	Independent
3	Abbay at Bahirdar	24	0.03	0.4	Independent
4	Didessa near Arjo	24	0.25	0.4	Independent
5	Main Beles at Bridge	21	-0.42	0.43	Independent
6	Abbay at Border	31	-0.18	0.35	Independent

The results shows that the annual maximum flow series for all stations are independent

3.3.3.2 Test for randomness

The result of Run test shows that only Didessa near Arjo is not random. As a result Didessa near Arjo station is rejected from further analysis. The detail of the test results for a recorded year (1979-2002) and (1979-2009) are given in Table 3.5.

Table 3.5: Result of the randomness for the observed annual maximum flow data series by Run test

No	Name of stations	P-Value	Alpha Level	Remark
1	Gilgel Abbay near Marawi	0.877	0.05	Random
2	Abbay near Kessie	0.076	0.05	Random
3	Abbay at Bahirdar	0.352	0.05	Random
4	Didessa near Arjo	0.028	0.05	Not Random
5	Main Beles at Bridge	0.063	0.05	Random
6	Abbay at Border	0.07	0.05	Random

3.3.3.3 Observed daily discharge data missing analysis

Only five (5) stations, out of six (6) stations are passed for further analysis, because of their randomness, independence and stationary of the annual maximum discharge data. The time series of instantaneous daily flow observed data have some missing value for some of the stations. The percentage of missing for a time series instantaneous daily flow recorded data of 1979-2002 for Gilgel Abbay, Kessie, Bahirdar and Main Beles stations and 1979-2009 for a Border station are shown in Table 3.6.

Table 3.6: Percentage of missing data for a daily flow time series of selected stations

No	River Name	Site	Coordinates		Area (km^2)	Record Extent	Missing data (%)
			Latitude	Longitude			
1	Gilgel Abbay	Near Marawi	$11^0$22' N	37^0 2' E	1664	1979-2002	0.46
2	Abbay	Near Kessie	11^0 4' N	$38^0$11' E	65784	1979-2002	9.22
3	Abbay	At Bahirdar	$11^0$36' N	$37^0$24' E	15321	1979-2002	1.72
4	Main Beles	At Bridge	$11^0$15' N	$36^0$27' E	3431	1979-2002	17.16
5	Abbay	At Border	$11^0$14' N	$34^0$59' E	172254	1979-2009	No

3.4 Selection of Global reanalysis runoff data

In flood frequency analysis, global reanalysis runoff data and ground based measurement (gauge, radar etc.) data are the main input variable for extreme flow quantiles estimation. The ground based measurement are supposed to be reliable and although they have poor spatial coverage in most part of the world. Currently there are a number of global reanalysis data, such as: Global Runoff Data Centre (GRDC) for generation of mean daily River Discharge Data, ECMWF Forcing for meteorological data, Snow Cover (SC) for snow cover data, ECMWF and UNIVK reanalysis for daily river discharge data and etc, but this study was focus on annual maximum discharge data for estimation of extreme flow quantiles and annual maximum discharge data are analyzed from extracted daily discharge data.

In this study, two reanalysis datasets such as ECMWF and UNIVK water resources reanalysis version 1 (wrr1) were used, which are comparable with the ground-based measurements of river discharge data. The two global reanalysis runoff datasets are notably European Center for Medium range Weather Forecast (ECMWF) and University of Kassel (UNIVK) are used for evaluation of extreme flow quantiles. Two global reanalysis runoff datasets were downloaded for the study. https://wci.earth2observe.eu/thredds/catalog.html link is used to download the two reanalysis datasets. To download ECMWF and UNIVK water resources reanalysis version 1 (wrr1), the links https://wci.earth2observe.eu/thredds/catalog/ecmwf/wrr1/catalog.html and https://wci.earth2observe.eu/thredds/catalog/univk/wrr1/catalog.html are used respectively.

The two reanalysis are selected for the study, the reanalysis have daily and monthly temporal resolution, which mean both reanalysis extract or generate mean monthly and daily river flow data. The mean daily and monthly flow hydrograph (flow versus time) and annual maximum flow are the output of the reanalysis dataset. The reanalysis are simulated model, which extract the river discharge at-site stations. The monthly hydrograph of the reanalysis by using earth2observe ECMWF and UNIVK reanalysis runoff product was evaluated on Blue Nile by (Fitsume et al, 2015). For this study annual maximum flow are analyzed from daily mean flow of reanalysis data-sets and extreme flow quantile are estimated and compared with the quantiles of in-situ observed data. The reanalysis annual maximum (AM) flows are basic data for evaluation and estimation of extreme flow quantiles.

3.5 Global reanalysis (ECMWF and UNIVK) runoff data extraction

The purpose of dataset extraction is to evaluate its performance with the observed flow data. The ECMWF and UNIVK reanalysis data-sets are accessed from the respective web sites were processed with set of ArcGIS tools. Once Export_Output and RivOut (River discharge) _layer were created, and then daily flow data was extracted from the ECMWF and UNIVK reanalysis datasets. The steps used in reanalysis (ECMWF and UNIVK) data generation or extraction, comprises the following three steps:

I. Export_Output

The Export_Output for a gauged flow stations was created using the following steps:
After installing ArcGIS 10.2 open ArcMap 10.2, go to file, add data, add x-y data, give x equal to longitude and y equal to latitude of stations, edit coordinate system (Geographic coordinate system (GCS), world, WGS-1984), export data, save the data and then add the exported data to the map as a layer and finally the next step was exporting output map of flow stations. Figure 3.5 show Exported_Output map for observed (gauged) flow stations of study area.

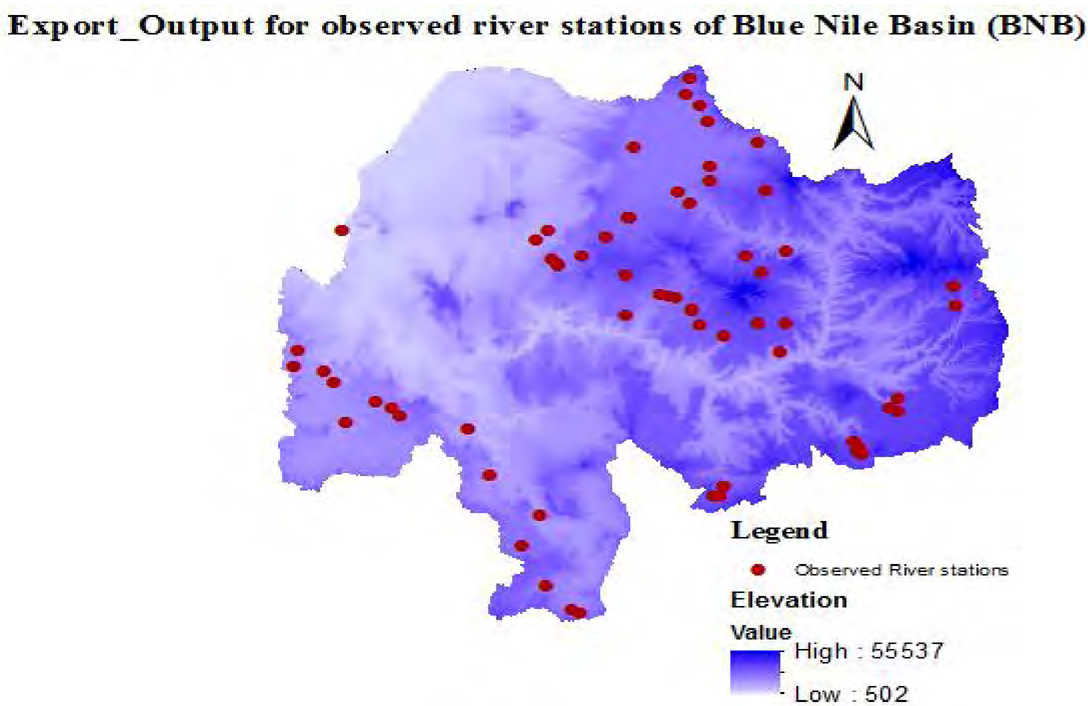


Figure 3.5: Exported_Output map for observed flow stations of Blue Nile River Basin

ii. RivOut (River discharge) _layer

The RivOut (River discharge) _layer for a gauged flow stations was done using the following steps:

After exporting the output of flow stations, insert search from ArcMap 10.2, enter netCDF, make netCDF raster layer, input netCDF file (Use e2o_ecmwf_wrr1_glob30_day_RivOut_1979-2012.nc file for ECMWF water resources reanalysis version 1 dataset and e2o_univk_wrr1_glob30_day_RivOut_1979-2012.nc file for UNIVK water resources reanalysis version 1 dataset), enter RivOut as a variable, enter longitude as x dimension and latitude as y dimension, then RivOut_layer as output raster layer and finally the RivOut_layer of observed stations were configured. Figure 3.6 and 3.7 shows RivOut (River discharge) _layer for observed flow stations of study area using ECMWF and UNIVK reanalysis datasets respectively.

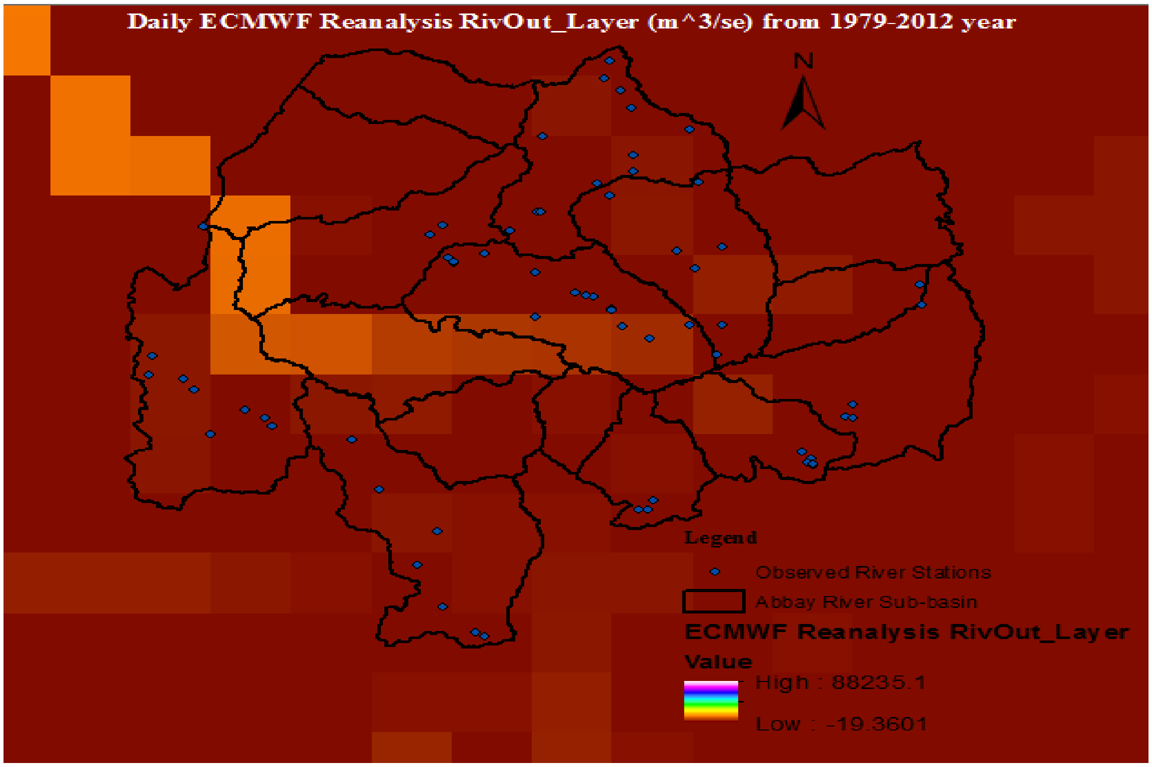


Figure 3.6: ECMWF reanalysis RivOut (River discharge) _layer for observed flow stations

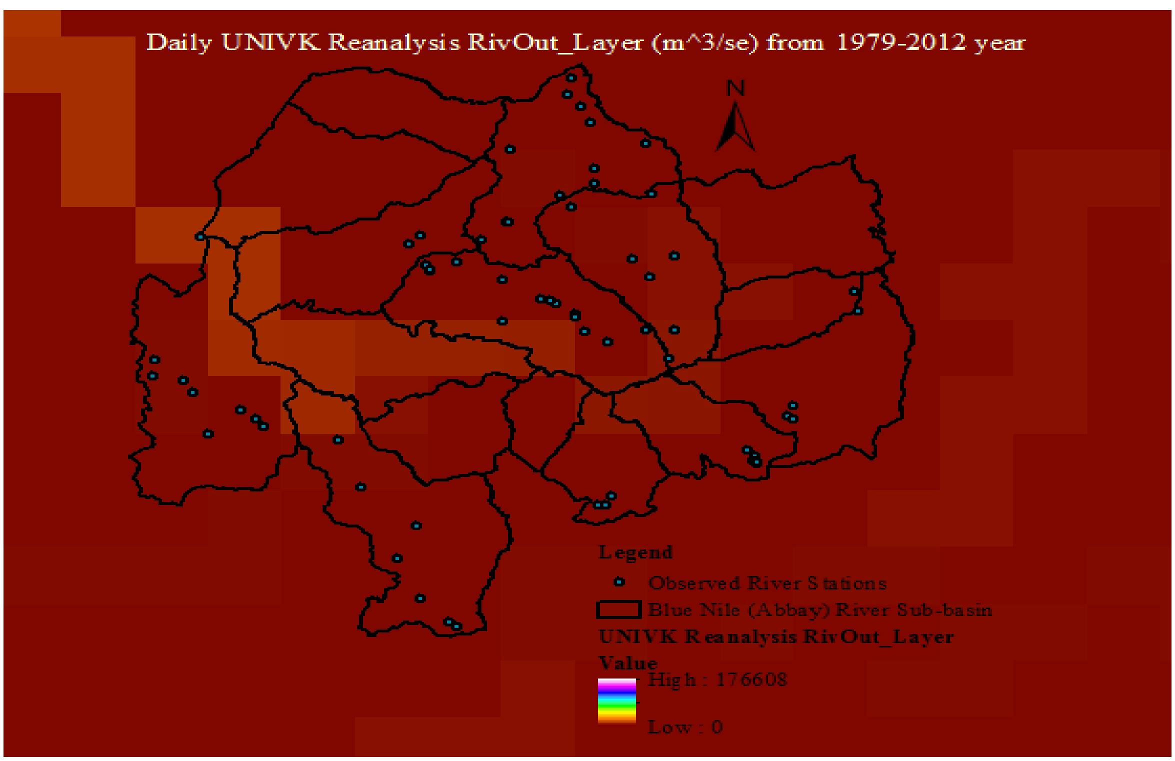


Figure 3.7: UNIVK Reanalysis RivOut (River discharge) _layer for observed flow stations

iii. Extraction of Global reanalysis data

This is a final step for extracting the reanalysis flow data after creating RivOut_layer of observed stations. Extraction of reanalysis (ECMWF and UNIVK) flow data was done using the following steps:

Insert search from ArcMap 10.2, then enter netCDF, make netCDF label view, input netCDF file (use e2o_ecmwf_wrr1_glob30_day_RivOut_1979-2012.nc file for ECMWF reanalysis dataset and e2o_univk_wrr1_glob30_day_RivOut_1979-2012.nc file for UNIVK reanalysis dataset), enter RivOut as variable, time as row dimension and latitude and longitude of observed flow stations as the dimension value then open e20_univk_wrr1_glob30_day_RivOut_1979-2012.nc for UNIVK reanalysis and e20_ecmwf_wrr1_glob30_day_RivOut_1979-2012.nc for ECMWF reanalysis data and finally extracted daily flow data were exported in dBase files. Both ECMWF and UNIVK reanalysis datasets extracts daily flow distribution in m^3/s for a year 1979 to 2012.

3.6 Selection of flood frequency distribution

An important problem in hydrology is the estimation of flood magnitudes, especially because planning and design of water resource projects and flood plain management depend on the frequency and magnitude of peak discharges. A flood event can be described as a multivariate event whose main characteristics can be summarized by its peak, volume, and duration, which may be correlated. However, flood frequency analysis has often concentrated on the analysis of flood peaks. Several summaries, discussions and extensive reviews of the field of flood frequency analysis are given by different authors.

In the statistical analysis of floods extreme value probability distribution are fitted to observed peak flows and reanalysis (ECMWF and UNIVK) peak flow. As discussed in chapter three, many flood frequency distributions have been suggested for flood modeling, but none has been accepted universally. This is because the choice of distribution is influenced by many factors such as method of discrimination between distributions, method of parameters estimation, the availability of data etc.

Cunnane (1989) proposed the following criteria for selection of appropriate distributions:

- Widely accepted
- Simple and convenient to apply
- Consistent, flexible or robust (low sensible to outliers)
- Theoretically well based
- Documented in the guide

The objective of this study is to evaluate extreme flow quantiles estimated from Global reanalysis runoff data at site of in-situ observed flow stations for a comparative analysis, and determining the best distribution for the station is needed. Many statistical distributions for flood-frequency analysis have been investigated in hydrology.

Annual maximum flow series were found to be often skewed, which led to the development and use of many skewed distributions, with the most commonly applied distributions now being the Gumbel (EV1), the Generalized Extreme Value (GEV), the Log Pearson Type III (LP3), and the 3 parameter Lognormal (LN3) (Pilon and Harvey, 1994). In this study, according to (Pilon and Harvey, 1994) the candidate probability distributions are Lognormal III (LN3), Generalized extreme value (GEV), Extreme value I (EV1) and Log -Pearson Type III (LP3) are used. The detail descriptions of the candidate probability distribution were given in Appendix-B.

The choice of distribution to be used in flood frequency analysis has been a topic of interest for a long time (Rao and Hamed, 2000). When a theoretical distribution has been assumed, the validity of the assumed distribution may be verified or disproved statistically by goodness-of-test (Ang and Tang, 1975a). The results of the goodness-of-fit tests are used to select a distribution for reanalysis and observed flow at site of a stations. The method of moments (MOM), maximum likelihood method (MLM) and L-moments method (LMM) are used for parameter estimation (using Easy-fit computer software). These parameters are used to calculate the quantiles corresponding to return periods of T years. Distributions fitted by using these methods are tested by using the Chi-Square (χ^2), Kolmogorov-smirnov (KS) and Coefficient of determination (R^2) tests. The Chi-square test, Kolmogorov-smirnov test and Coefficient of determination tests are discussed below.

A. Kolmogorov-Smirnov Test

Kolmogorov-Smirnov (KS) test is another widely used goodness-of-fit besides Chi-square test. KS test is based on the deviation of the sample distribution function from the specified continuous hypothetical distribution function, providing a comparison of a fitted distribution with the empirical distribution.

The Kolmogorov-Smirnov test statistic is based on the greatest vertical distance from the empirical and theoretical CDFs. The most important test alternatives to chi-square (χ^2), is the Kolmogorov statistic (D). This test is used to decide if a sample comes from a hypothesized continuous distribution. It is based on the empirical cumulative distribution function (ECDF).

Definition

The Kolmogorov-Smirnov statistic (D) is based on the largest vertical difference between the theoretical and the empirical cumulative distribution function: The test statistic D is defined in equation 3.5.

$$D = \max_{1 \le i \le n} |F_n(x_i) - F_0(x_i)| \qquad \text{Eqn.3.5}$$

Where, i = rank of data and n = number of the sample data

The values of $F_n(x_i)$ are estimated as n_i/n where n_i is the cumulative number of sample events in class interval I. $F_0(x_i)$ is then 1/k, 2/k…..etc. The value of D must be less than a tabulated value of D at the specified confidence level for the distribution to be accepted.

Hypothesis Testing

The null and the alternative hypotheses are:

- H_o: the data follow the specified distribution;
- H_A: the data do not follow the specified distribution.

The hypothesis regarding the distributional form is rejected at the chosen significance level (α) if the test statistic, D, is greater than the critical value obtained from a table.

The fixed values of α (0.01, 0.05 etc.) are generally used to evaluate the null hypotheses (H_o) at various significance levels. A value of 0.05 is typically used for most applications. The standard tables of critical values used for this test are only valid when testing whether a data set is from a completely specified distribution.

If one or more distribution parameters are estimated, the results will be conservative: the actual significance level will be smaller than that given by the standard tables and probability that the fit will be rejected in error will be lower.

P-value

The p-value, in contrast to fixed alpha values, is calculated based on the test statistic, and denotes the threshold value of the significance level in the sense that the null hypothesis (H_o) will be accepted for all values of alpha less than the p-vale.

For example, if P = 0.025, the null hypothesis will be accepted at all significance levels than p (i.e. 0.01 and 0.02), and rejected at higher levels, including 0.05 and 0.1. The p-value can be useful; in particular, when the null hypothesis is rejected at all predefined significance levels, and you need to know at which level it could be accepted.

In the proposed approach of identification of distribution, the assumed distribution is required to be appraised by both chi-square test and KS test.

B. Chi-Squared Test

In Chi-square test, the observed and reanalysis data values of the relative frequency or the cumulative frequency function are compared with the corresponding value of the assumed theoretical distribution to test the goodness of fit of a probability. In the test, the data are divided into k class intervals (k is recommended to be more than 5).

The Chi-Squared test is used to determine if a sample comes from a given distribution. It should be noted that this is not considered a high power statistical test and is not very useful (Cunnane, 1989).

The test is based on binned data, and the number of bins (k) is determined by:

$k = 1+\log_2 n$...Eqn.3.6

In which n = sample size

The test statistic (χ^2) is:

$\chi^2 = \sum_{i=1}^{k} \frac{(Oi - E_i)}{Ei}$...Eqn.3.7

Where,

In equation 3.7, Oi is the observed and re-analysis (ECMWF and UNIVK) runoff number of events in the class interval I, Ei is the number of events that would be expected from the theoretical distribution, and k is the number of classes to which the in-situ observed and re-analysis runoff data are sorted.

If the class intervals are chosen such that each interval corresponds to an equal probability, then Ei = n/k where n is the sample size and k is the number of class intervals and, equation 3.7 reduces to equation 3.8.

$\chi^2 = \frac{k}{n} \sum_{i=1}^{k} O_i^{\,2} - n$ Eqn.3.8

Class intervals can be computed by using the inverse of the distribution function corresponding to different values probability F, Similar to estimation quantiles.

Hypothesis testing

The null hypotheses are:

- H_o: the data follow the specified distribution;
- H_A: the data do not follow the specified distribution.

The hypothesis regarding the distributional form is rejected at the chosen significance level (α) if the test statistic is greater than the critical value defined as $x^2{}_{1-\alpha k-1,}$ meaning the Chi -squared inverse CDF with k-1 degree of freedom and significance level of alpha (α). Though the number of degree of freedom can be calculated as k-c-1 (where c is the number of estimated parameters).

C. Coefficient of determination (R^2)

The goodness-of-fit was also further tested applying Coefficient of determination (R^2) test on the fitted distribution to select the best fit distribution. The R^2 test is a commonly used and powerful goodness-of-fit test based on statistics. It assesses the correlation between the ordered data and the corresponding fitted quintiles of the distribution and therefore measures the linearity of a probability and quantiles plot. The fitted quantiles are based on Hazen plotting position formula using Easy-Fit computer software and select the best fit distribution to the observed and reanalysis (ECMWF and UNIVK) peak flows.

$$R^2 = \frac{\left(\sum_{i=1}^{n}(x_i-\bar{x}_i)(Q_i-\bar{Q}_i)\right)^2}{\sum_{i=1}^{n}(x_i-\bar{x}_i)^2\sum_{i=1}^{n}(Q_i-\bar{Q}_i)^2} \quad \text{……………………………………………………Eqn.3.9}$$

Where, n is number of recorded data, i is rank of data and fitted quantile in ascending order, x_i is the AM discharge data, $\bar{x}_i$ is the mean of AM discharge data, Q_i is the fitted quantiles and $\bar{Q}_i$ is the mean of the fitted quantiles by the distribution to the AM discharge data.

The probability-probability (P-P) plot

It is the graph of the Empirical Cumulative Distribution Function (ECDF) values plotted against the theoretical CDF values. It is used to determine how well a specific distribution fits to the observed and reanalysis (ECMWF and UNIVK) data. This plot will be approximately linear if the specified theoretical distribution is the correct model.

The probability-probability plot of reanalysis and observed AM discharge with the distribution were developed as the following steps:

Step 1: Sort the n values from the smallest to the largest

Step 2: For each of the N data points, compute an empirical (observed) cumulative probability as: $F_n(x_i) = \frac{i}{n}$, for i= 1, 2, ..., n. This simple formula works well in Easy-Fit software cases, for computing the empirical cumulative probability for use in probability plots.

Step 3: Then compute the theoretical (fitted) cumulative distribution function

Step 4: Finally plot the graph of empirical cumulative probability on abscissa and cumulative distribution function on ordinates. The P-P plot for Kessie station is shown in Figure 3.8 and Figure 3.9 as below.

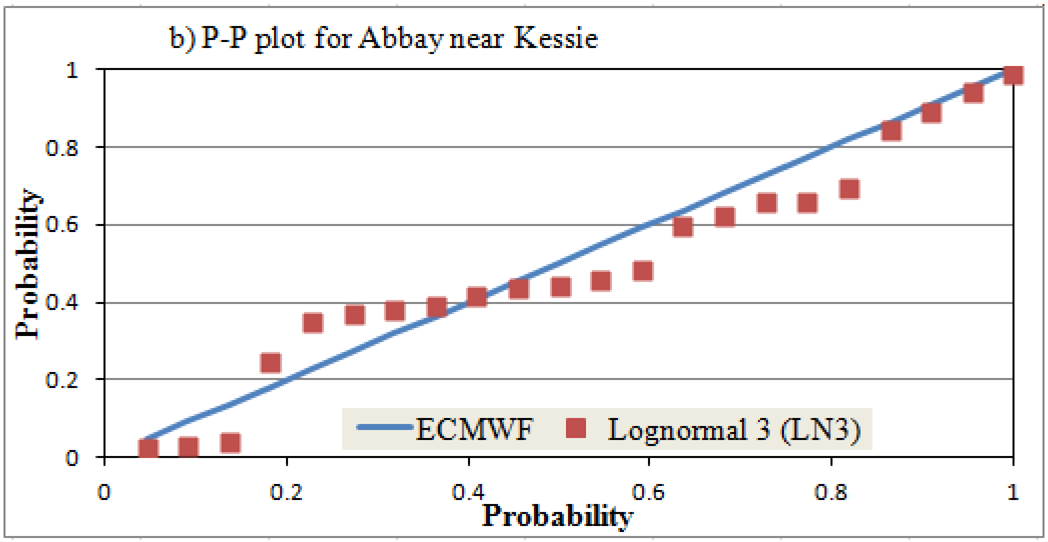


Figure 3.8: P-P plot ECMWF cumulative probability and cumulative distribution function for Kessie station

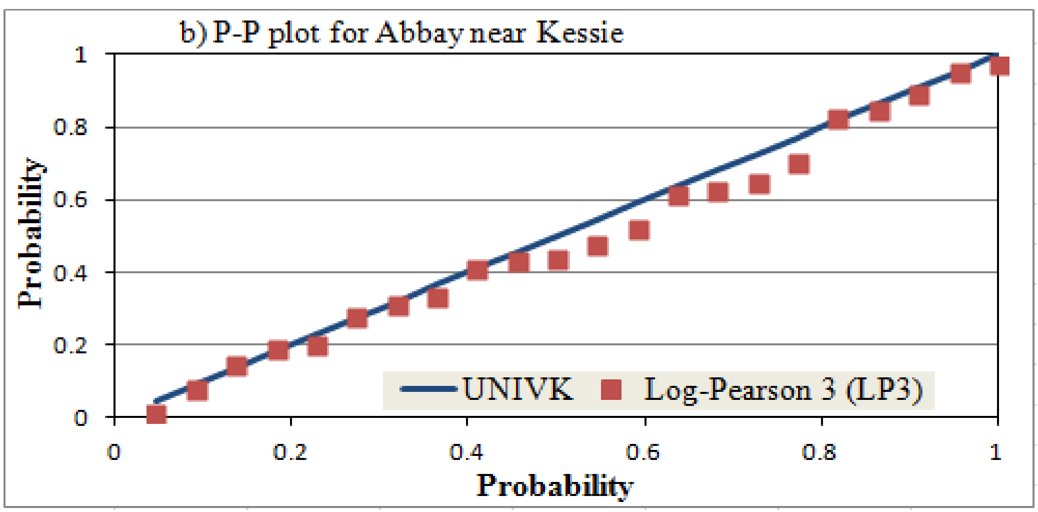


Figure 3.9: P-P plot of UNIVK cumulative probability and cumulative distribution function for Kessie station

The quantile-quantile (Q-Q) plot

It is the graph of the input (observed and reanalysis) data values plotted against their theoretical (fitted) distribution quintiles. The quantile-quantile graph are produced by plotting the data value $x_i(i = 1,.. n)$ against the X-axis, and the following values against the Y- axis:

$F^{-1}\left(F_n(x_i) - \frac{05}{n}\right) = F^{-1}(\frac{i-05}{n})$ (Hazen plotting position).......................................Eqn.3.10

Where, F^{-1} = is the inverse cumulative distribution function (ICDF) using Hazen plotting position
F_n = Empirical CDF
n = sample size

The Q-Q plot will be approximately linear if the specified theoretical distribution is the correct model. The type of plot utilized for distribution fit and assessment is the quantile–quantile plot, where each ordered data point x(i) is plotted against the inverse of the chosen probability distribution for the empirical plotting position corresponding to that data point. On the quantile–quantile plot, perfect matching of the data along a 45° line on this type plot would suggest a "perfect" fit.

The quantile-quantile plot of reanalysis and observed AM discharge with the distribution were developed as the following steps:
Step 1: Sort the n values from the smallest to the largest, so that $x_1 \leq x_2 \leq .... < x_n$. This presentation allows for sometimes among the n values.
Step 2: Then compute the inverse cumulative distribution function using $F^{-1}(F_n(x_i) - \frac{05}{n})$
Step 3: Finally plot the graph of the input (observed) data values plotted against the theoretical (fitted) distribution quantiles. The Figure 3.10 and 3.11 shows the Q-Q plot of Kessie station as below.

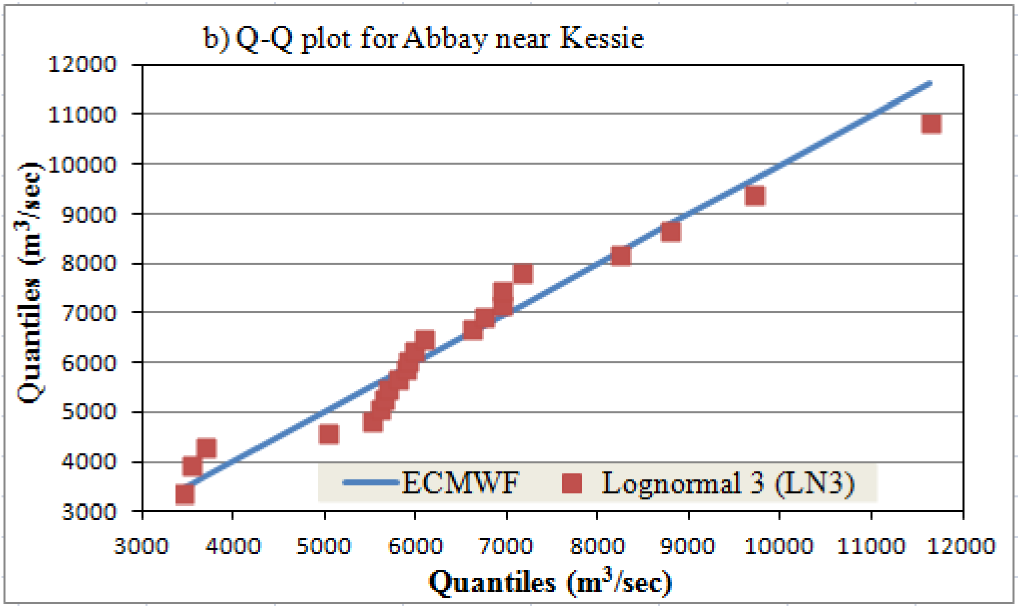


Figure 3.10: Q-Q plot of ECMWF reanalysis data and fitted distribution for Kessie station

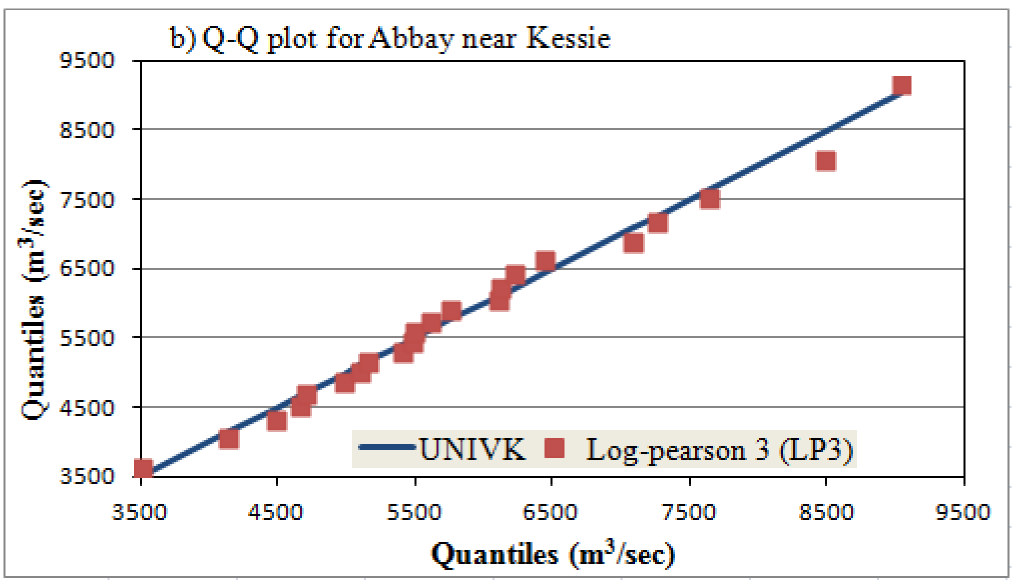


Figure 3.11: Q-Q plot of UNIVK reanalysis data and fitted distribution for Kessie

3.7 Parameter and Quantile Estimation

In flood frequency analysis, an assumed probability distribution is fitted to the available data to estimate the flood magnitude for a specified return period. The choice of an appropriate probability distribution is quite arbitrary, as no physical basis is available to rationalize the use of any particular distribution. The first of error which is associated with wrong assumption of a particular distribution for the given data can be checked to a certain extent by using goodness-of-fit tests. These are statistical tests which provide a probabilistic framework to evaluate the adequacy of a distribution.

Even if an acceptable distribution is selected, proper estimation of parameters is important. Some of the parameter estimation methods may not yield good estimates, or even converge. Therefore, some guidance is needed about the parameter estimation methods. In this study the parameters estimation is done using the Easy-Fit statistical computer software with proper parameter estimation method suitable for each distribution within the interface.

3.7.1 Parameter Estimation

Several methods can be used for parameter estimation. In this study, the method of moments (MOM), the maximum likelihood method (MLM) and the L-moment method (LMM) are used for parameter estimation with the statistical computer software (Easy-Fit). The maximum likelihood method (MLM) is considered to be the most accurate method, especially for large data sets since it leads to efficient parameter estimators with Gaussian asymptotic distributions. It provides the smallest variance of the estimated parameters, and hence of the estimated quintiles, compared to other methods. However, with small samples the results may not converge.

The method of moments (MOM) is relatively easy and is more commonly used. It can also be used to obtain starting values for numerical procedures involved in MLM estimation. However, MOM estimates are generally not as efficient as the MLM estimates, especially for distributions with large number of parameters, because higher order moments are more likely to be used to obtain starting values for numerical procedure involved in MLM estimation.

However, MOM estimates are generally not as efficient as the MLM estimate especially for distribution with large number of parameters, because higher order moments are more likely to be highly biased for relatively small samples.

Easy-Fit software uses the least computationally intensive methods. Thus, it employs the method of moments for those distributions whose moment estimates are available for all possible parameter values, and do not involve the use of iterative numerical methods. For many distributions, Easy-Fit uses the MLM involving the maximization of the log-likelihood function. For some distributions, such as the 2-parameter Exponential and the 2 parameter Weibull, a closed form solution of this problem exists.

For other distributions, Easy-Fit implements the numerical method for multi-dimensional function minimization. Given the initial parameter estimates vector, this method tries to improve it using subsequent iteration. The algorithm terminates when the stopping criteria is satisfied (the specified accuracy of the estimation is reached, or the number of iterations reaches the specified maximum). The advanced continuous distributions are fitted using the ML estimates, the modified least square estimates (LSE), and the L-moments methods. In this study Easy-Fit statistical computer software were used for parameter estimation of selected distributions. Easy-Fit software use MLM for Lognormal with three parameter (LN3), MOM for Extreme Value type 1 (EV1) and Log-pearson with three parameters (LP3) and LMM for Generalized Extreme Value (GEV) distributions.

For the convenience of application, the most applied distributions and the associated parameter and method of parameter estimation selected using Easy-Fit software are listed in Appendix C.

3.7.2 Quantile Estimation

After selection of best-fit distribution, the desired extreme flow quantile estimates (X_T) which correspond to different return periods (T) are then computed from the statistics of the adopted distribution.

The return period is related to the probability of non-exceedence (F) by the relation,

$F = 1-1/T$..Eqn.3.11

Where $F = F(X_T)$ is the probability of having a flood of magnitude equal or less than X_T. The problem then reduces to evaluating X_T for a given value of F. In practice, two types of distribution functions are encountered. The first type is that which can be expressed in the inverse form $X_T = \phi^{-1}(F)$. In this case, X_T is evaluated by replacing $\phi^{-1}(F)$ by its value from above equation.

In the second type the distribution cannot be expressed directly in the inverse form $X_T = \phi^{-1}(F)$. In this case numerical methods are used to evaluate X_T corresponding to a given value of $\phi^{-1}(F)$.

3.8 Evaluation of global reanalysis runoff data

In this study, performance of the global reanalysis (ECMWF and UNIVK) runoff data is evaluated by comparing the reanalysis annual maximum (AM) discharge with the observed annual maximum (AM) discharge. Global reanalysis runoff data also evaluated by comparing the extreme flow quantile estimated from the reanalysis AM discharge data with the extreme flow quantiles estimated from the observed AM discharge data. The statistical tools such as Nash-Sutcliffe Efficiency (NSE), Coefficient of determination (R^2), and percent of bias (PBIAS) are used to measure performance global reanalysis runoff data outputs.

A. Nash-Sutcliffe Efficiency (NSE)

The Nash and Sutcliffe coefficient (NSE) is a measure of efficiency that relates the goodness-of-fit of the global reanalysis (ECMWF and UNIVK) annual maximum (AM) discharge to the variance from observed AM discharge. NSE can range from $-\infty$ to 1 and an efficiency of 1 indicates a perfect match between observed AM discharge and reanalysis AM discharge.

The efficiency, E proposed by Nash and Sutcliffe (Nash, 1970) is defined as one minus the sum of the absolute squared differences between reanalysis and observed AM discharge normalized by the variance of the observed AM discharge during the period under investigation.

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{n}\left(Q_{\text{observed}} - Q_{\text{reanalysis}}\right)^2}{\sum_{i=1}^{n}\left(Q_{\text{observed}} - \overline{Q}_{\text{observed}}\right)^2} \text{...Eqn.3.12}$$

NSE is Nash-Sutcliffe Efficiency, Q_{observed} is observed AM discharge, $Q_{\text{reanalysis}}$ is reanalysis AM discharge and $\overline{Q}_{\text{observed}}$ is average observed AM discharge.

B. Coefficient of determination

Another widely used statistical measure is Coefficient of determination (R^2). The coefficient of determination R^2 is defined as the squared value of the coefficient of correlation. It is estimated as:

$$R^2 = \frac{\left(\sum_{i=1}^{n}\left(Q_{\text{observed}} - \overline{Q}_{\text{observed}}\right)\left(Q_{\text{reanalysis}} - \overline{Q}_{\text{reanalysis}}\right)\right)^2}{\sum_{i=1}^{n}\left(Q_{\text{observed}} - \overline{Q}_{\text{observed}}\right)^2 \sum_{i=1}^{n}\left(Q_{\text{reanalysis}} - \overline{Q}_{\text{reanalysis}}\right)^2} \text{................Eqn.3.13}$$

Where,

Q_{observed} and $Q_{\text{reanalysis}}$ are observed and reanalysis AM discharge respectively; $\overline{Q}_{\text{observed}}$ and $\overline{Q}_{\text{reanalysis}}$ are average observed and average reanalysis AM discharge respectively. Coefficient of determination varies from 0 to 1 where higher value denotes better fit of the regression line between observed AM discharge data and reanalysis AM discharge data. When global reanalysis AM discharge data and observed AM discharge data exactly match each other, a value of 1 is obtained.

C. Percent bias (PBIAS)

Percent bias is a volume balance, which can be called as Percent volume error. The PBIAS compares the average tendency of the reanalysis annual peak discharge corresponding observed annual peak discharge. The optimal value of PBIAS is 0. A positive value indicates that the reanalysis runoff has underestimation and a negative value indicates overestimation (Gupta et al., 1999). PBIAS is computed with Equation 3.14.

$$\text{PBIAS} = \frac{\sum_{i=1}^{n}\left(Q_{\text{observed}} - Q_{\text{reanalysis}}\right)}{\sum_{i=1}^{n} Q_{\text{observed}}} \text{...Eqn.3.14}$$

4. RESULTS AND DISCUSSIONS

4.1 Reanalysis AM Discharge data and comparison

The earth2observe global reanalysis (ECMWF and UNIVK) annual maximum (AM) discharge data since (1979-2012) were retrieved from RivOut (River discharge) _Layer and compared with the available in-situ observed annual maximum discharge data using statistical comparison. The abilities of AM discharge retrieved from the RivOut_layer of ECMWF and UNIVK Reanalysis to capture the annual maximum variability of observed discharge are presented in this section for five stations. The RivOut_Layer of ECMWF and UNIVK reanalysis were created using the procedures indicated in section 3.5. Figure 4.1 and 4.2 shows the daily RivOut_Layer of the ECMWF and UNIVK reanalysis datasets respectively.

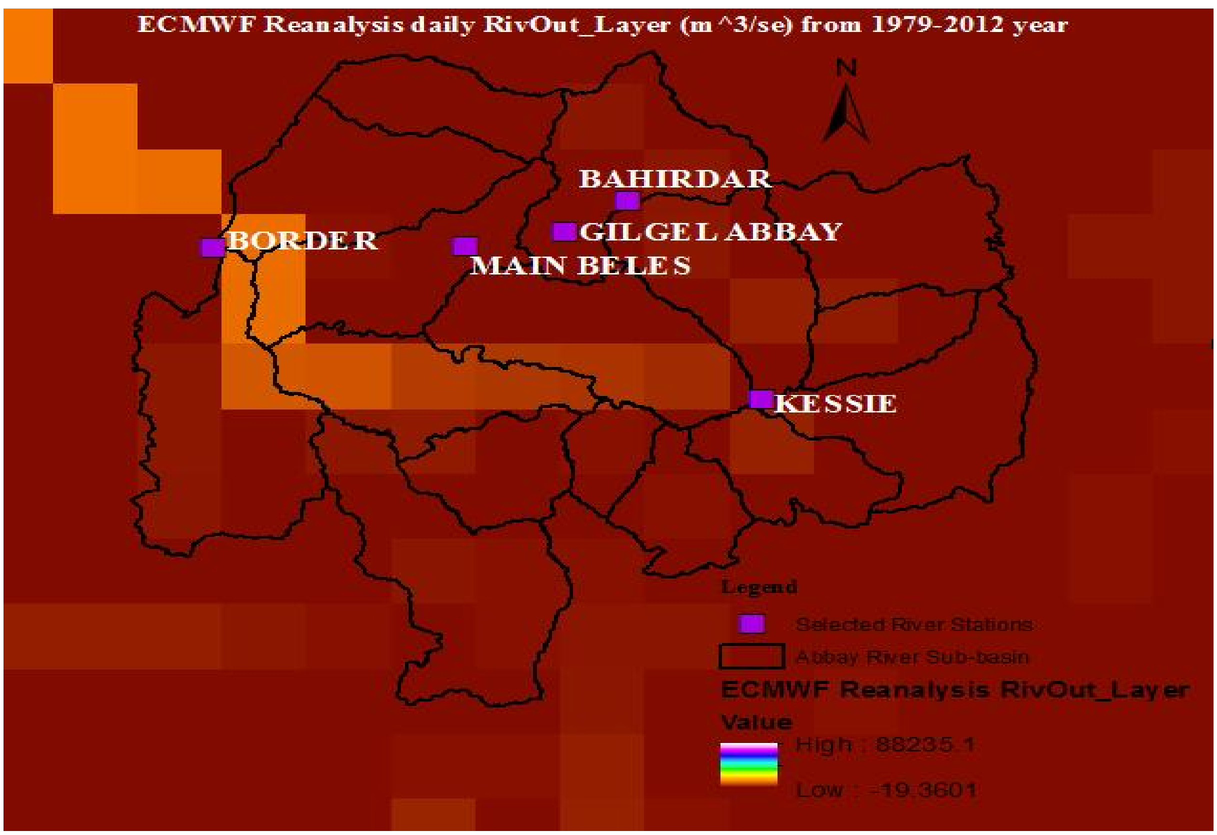


Figure 4.1: Daily ECMWF Reanalysis RivOut_layer for five observed flow stations

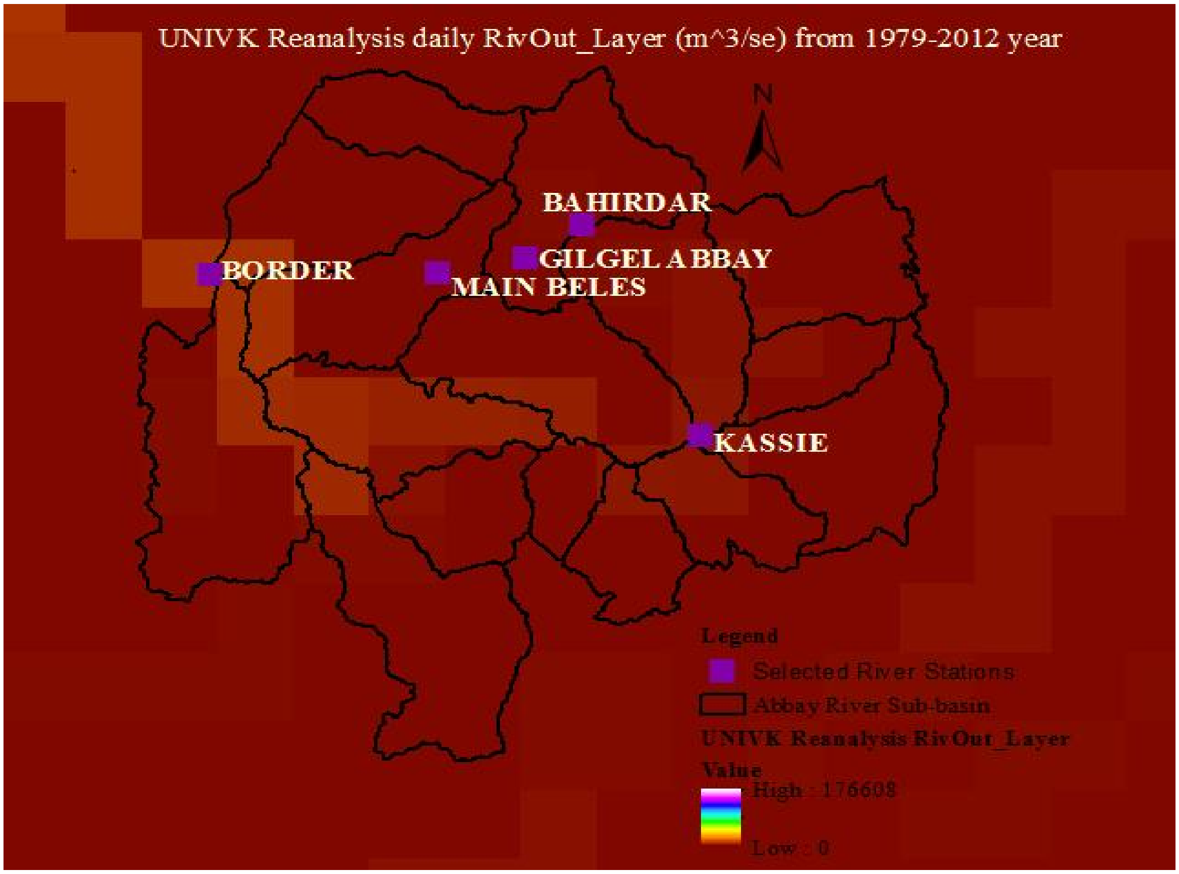


Figure 4.2: Daily UNIVK Reanalysis RivOut_layer for five observed flow stations

The goal of the comparison was to evaluate how global reanalysis annual maximum discharge are reliable as compared with the in-situ observed annual maximum discharge, to estimate extreme flow quantiles at certain return period (T) for water management problems. Measures of global reanalysis performance using NSE (Nash, 1970) and PBIAS (Gupta et al, 1999) values are listed in Table 4.1. See the result of reanalysis (ECMWF and UNIVK) annual maximum discharge for five selected stations in Appendix-A

Table 4.1: Comparison of global reanalysis (ECMWF and UNIVK) and observed AM discharge

Name of stations	PBIAS (%)		NSE	
	UNIVK	ECMWF	UNIVK	ECMWF
Gilgel Abbay near Marawi	-28.90	-22.30	-3.20	-3.55
Abbay near Kessie	4.28	-4.43	0.06	0.15
Abbay at Bahirdar	-10.65	39.90	-1.32	-0.65
Main Beles at Bridge	28.71	30.08	-0.26	-0.98
Abbay at Border	-68.30	-131.41	-12.30	-50.10

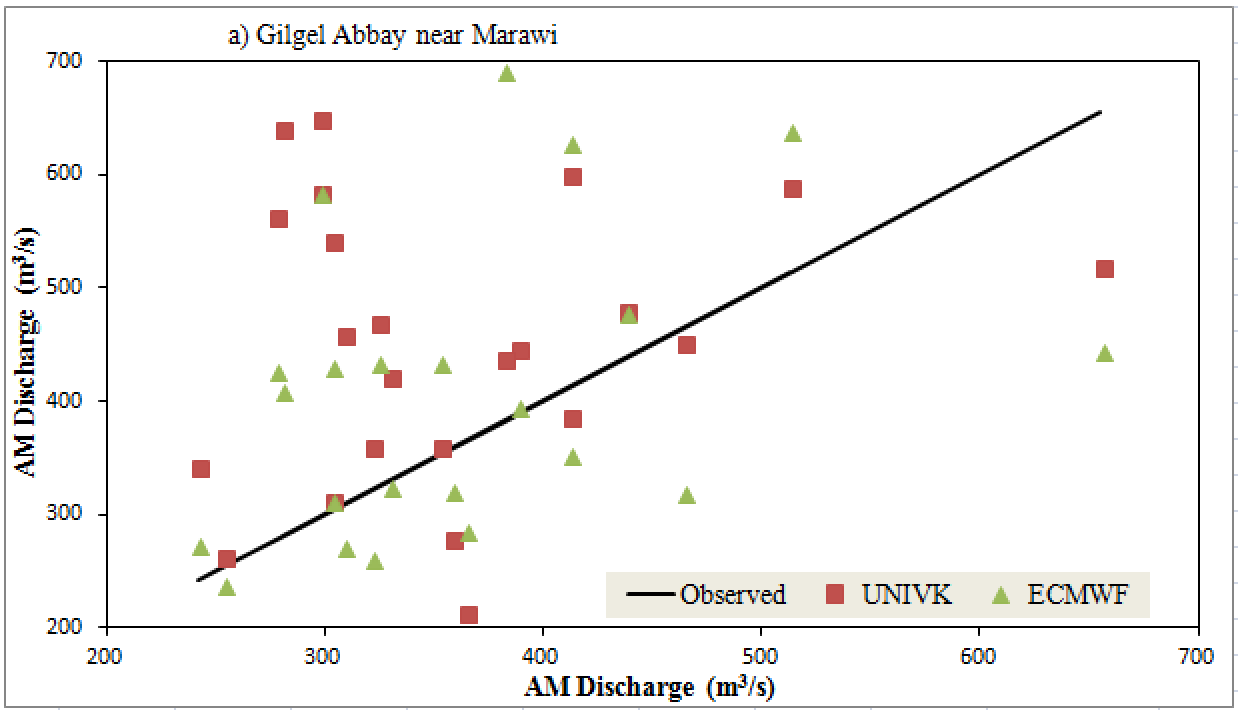
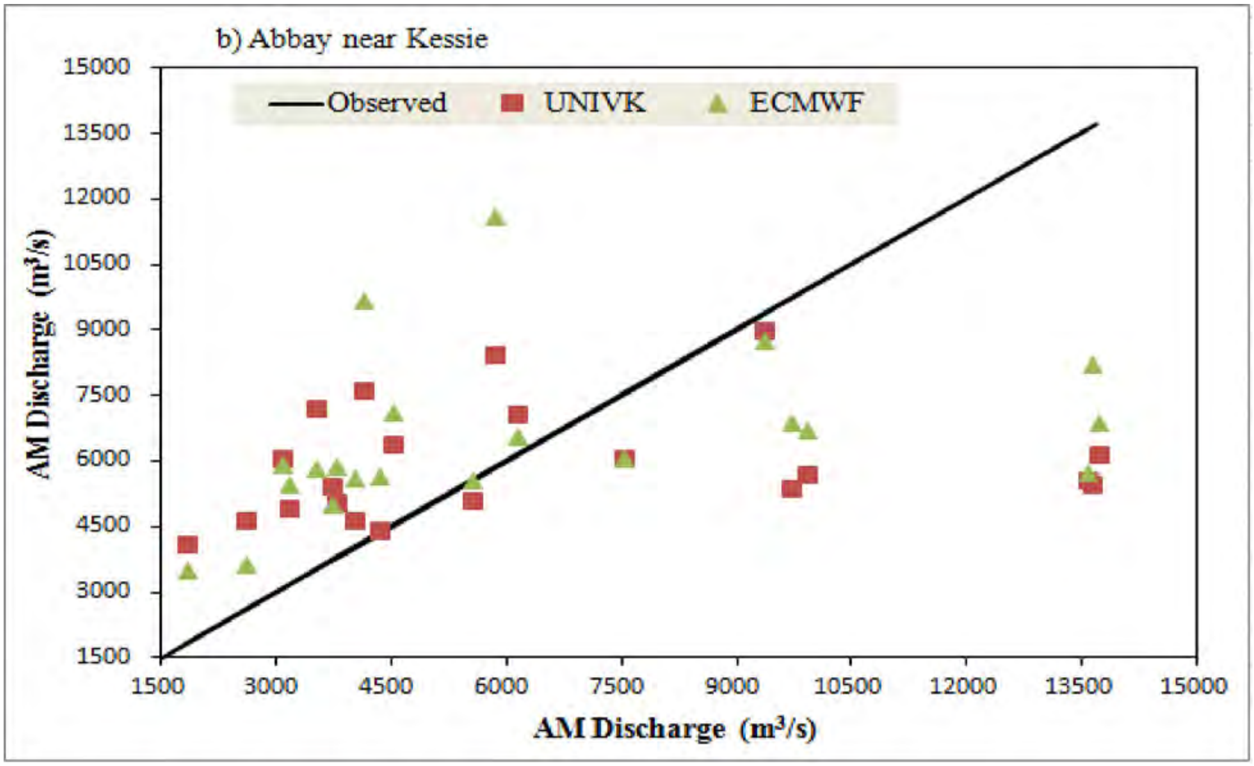


Figure 4.3: Scatter diagram for comparison of the two reanalysis and observed AM discharge



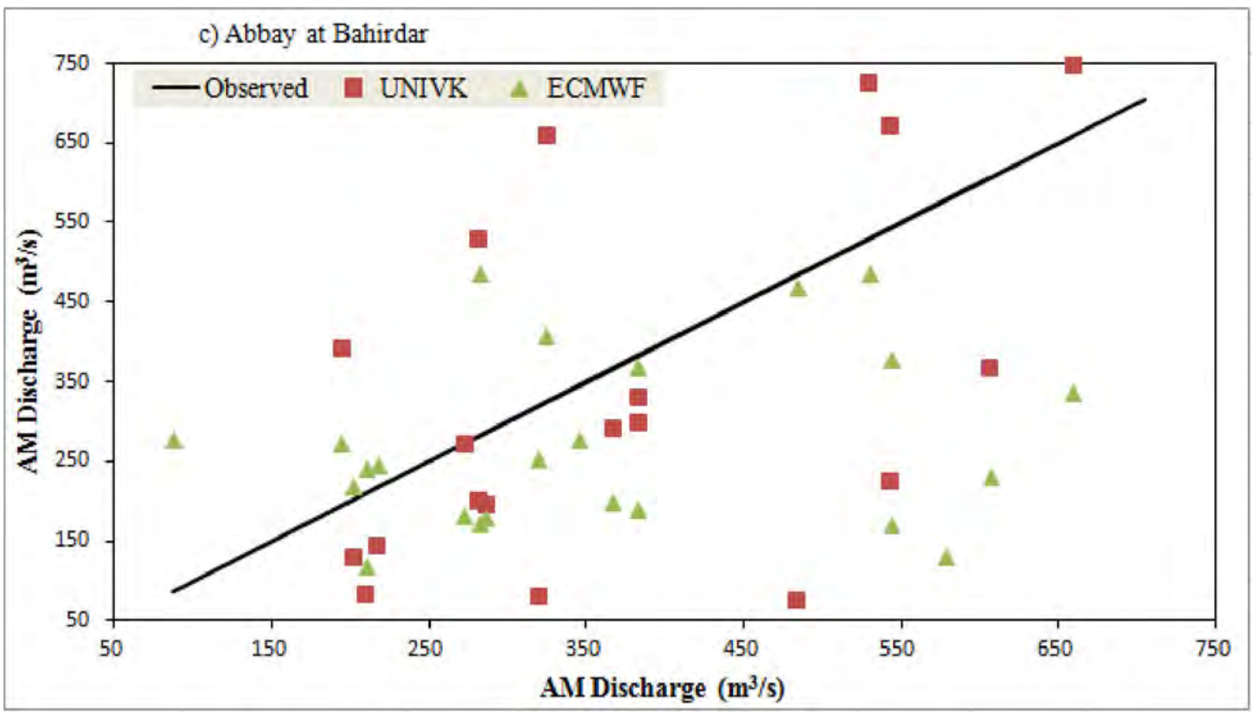
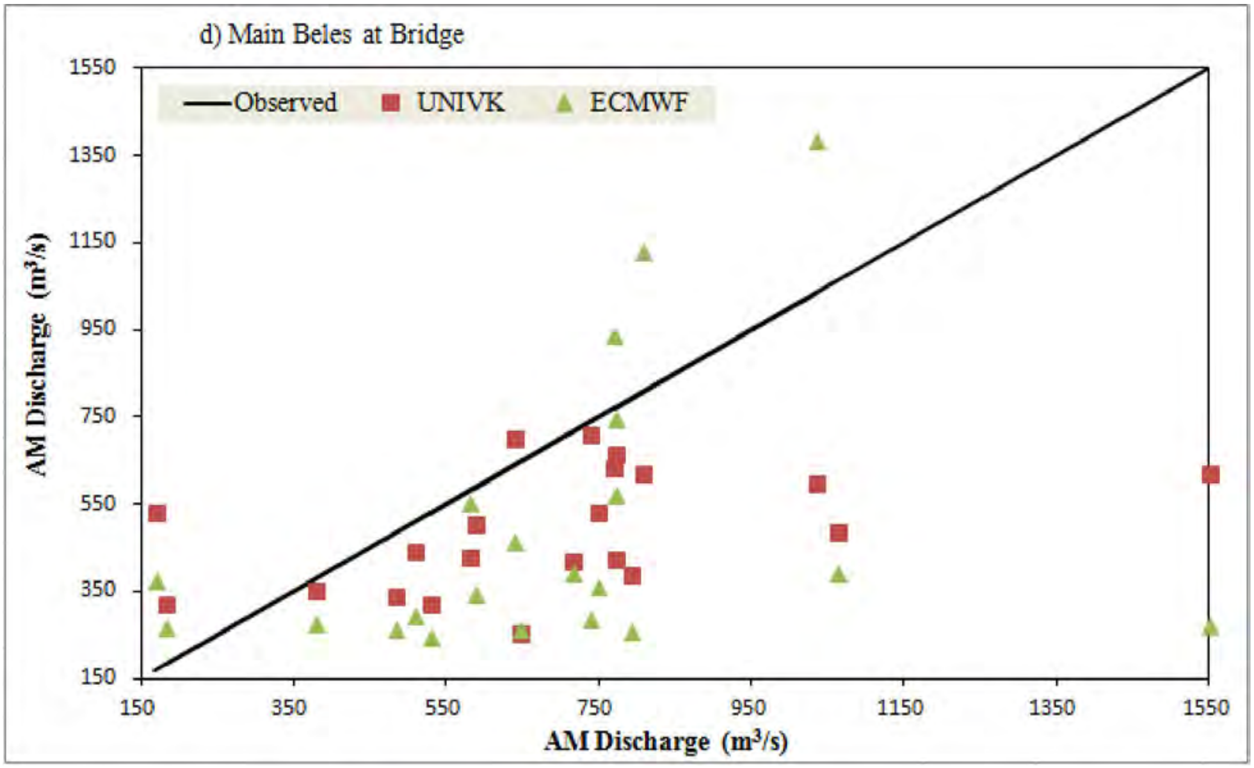


Figure 4.3: Scatter diagram for comparison of the two global reanalysis and observed AM discharge (continued)



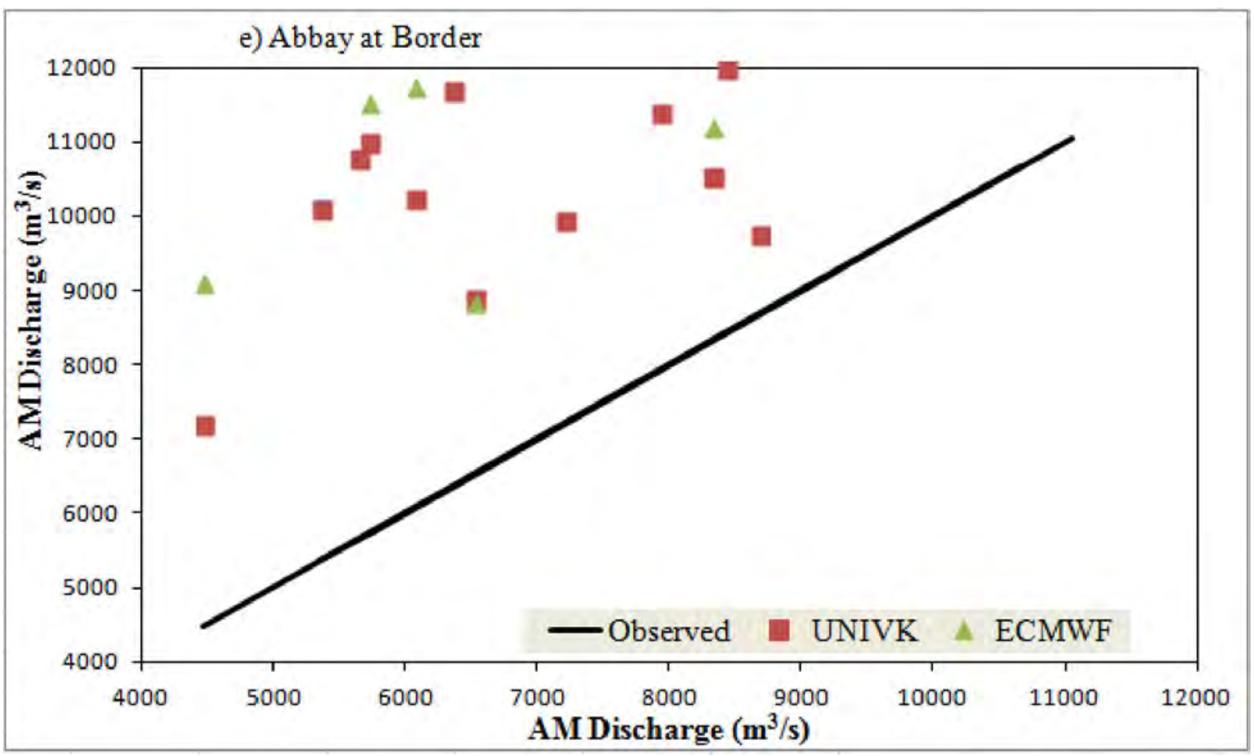


Figure 4.3: Scatter diagram for comparison of the two reanalysis and observed AM discharge (continued)

4.1.1 Evaluation of ECMWF reanalysis AM discharge

Comparsion of the performance of earth2observe ECMWF reanalysis as mentionend in Table 4.1, based on percentage of bias (PBIAS) criterion, which estimates bias percentage of reanlysis annual maximum (AM) discharge compared to observed AM discharge, small deviations are verified demonstrating that the AM discharge overestimation occurred in volume amount of -4.43% for Kessie and underestimation occured in volume amount of using ECMWF reanalysis AM discharge data. Also large deviation is verified demonstrating that the AM discharge overestimation occurred in volume amount of -22.30 and -131.41% for Gilgel Abbay and Border respectively and underestimation is occurred in volume amount of 30.08% and 39.9% for Main Beles and Bahirdar respectively in case of ECMWF reanalysis data. Values of PBIAS in volume amount of AM discharge for ECMWF reanalysis range from -4.43 to 39.9%.

Using guidelines given in Moriasi et al. (2007) for evaluating systematic quantification of watershed simulations at a monthly time step, the percentage error in volume amount of AM discharge performed well (±10% < PBIAS < ±15%) for Kessie (PBIAS = -4.43%), satisfactory (±15% ≤ PBIAS < ±25%) for Gilgel Abbay (PBIAS = -22.3%) and unsatisfactory (PBIAS ≥ ±25%) for Main Beles (PBIAS = 30.08%) and Border (PBIAS = -131.41%) stations in case of ECMWF reanalysis. The result of earth2observe ECMWF reanalysis AM discharge product at Kessie and Border have shown small and large discrepancy in PBIAS respectively as compared to the monthly discharge product from the finding of (Fitsume et al, 2015), the PBIAS of monthly discharge product was -7.889% for Kessie and 0.67% for Border and the monthly discharge was underestimated for Border. We can concluded that the ECMWF reanalysis annual maximum discharge data is bias for all five selected stations, which might be influenced by uncertainty in the observed data such as the inability to measure daily high flow, data quality of daily observed discharge (especially for Border), the insufficient representation of the catchment area and bias of satellite observations. Therefore, the ECMWF reanalysis AM discharge data need bias correction to be reliable for planning and design of water management problems at five observed stations.

The degree of agreement for peak amount of AM discharge of ECMWF reanalysis and observed is measured by Nash-Sutcliffe efficiency (NSE). As mentioned in Table 4.1, we can concluded that the peak amount of ECMWF reanalysis AM discharge not exactly much the peak amount of observed AM discharge which performed unsatisfactory (NSE $\leq$ 0.5) as guidelines given in Moriasi et al. (2007), for Gilgel Abbay (NSE = -3.55), for Kessie (NSE = 0.15), at Bahirdar (NSE = -0.65), for Main Beles (NSE = -0.98) and for Border (NSE = -50.1).

4.1.2 Evaluation of UNIVK reanalysis AM discharge

Comparsion of the annual maximum (AM) discharge performance of the earth2observe UNIVK reanalysis as mentioned in Table 4.1, based on percentage of bias (PBIAS) criterion, which estimates bias percentage of UNIVK reanalysis AM discharge compared to the observed ones, small deviations are verified demonstrating that the AM discharge overestimation occurred in volume amount of 10.65% for Bahirdar and underestimation occured in volume amount of 4.28% for Kessie using UNIVK reanalysis. Also large deviation is verified demonstrating that the AM discharge overestimation occurred in volume amount of -28.90% and -68.3% at Gilgel Abbay and Border respectively and underestimation occurred for in volume amount of 28.71% for Main Beles. The values of PBIAS in volume amount of AM discharge for UNIVK reanalysis range from -28.9 to 28.71%.

Using guidelines given in Moriasi et al. (2007), the percentage error in volume amount of AM discharge performed very good (PBIAS $\leq \pm$ 10%) for Kessie (PBIAS = 4.28%), good ($\pm$10% < PBIAS < $\pm$15%) for Bahirdar (PBIAS = -10.65%), satisfactory ($\pm$15% $\leq$ PBIAS < $\pm$25%) and unsatisfactory (PBIAS $\geq \pm$25%), for Main Beles (PBIAS = 28.71%), Gilgel Abbay (PBIAS = -28.90%) and Border (PBIAS = -68.3%) stations in case of UNIVK reanalysis. The earth2observe UNIVK reanalysis AM discharge at Kessie and Border have shown discrepancy in PBIAS as compared to the monthly discharge product from the finding of (Fitsume et al, 2015), the PBIAS of monthly discharge product was -18% for Kessie and 23% for Border and the monthly discharge was overestimated for Kessie an underestimated for Border.

In similar to ECMWF, we can concluded that UNIVK reanalysis AM discharge is biased for five observed stations, which is highly influenced by uncertainty in the observed data such as the inability to measure daily high flow, data quality of daily observed discharge (especially for Border), the insufficient representation of the catchment area, bias of satellite observation and remote sensing are the sources of error for overestimation and underestimation of reanalysis dataset. Similar to ECMWF, UNIVK reanalysis also need bias correction for five gauged stations.

The degree of agreement for peak amount of annual maximum (AM) discharge of UNIVK reanalysis and observed is measured by Nash-Sutcliffe efficiency (NSE). As mentioned in Table 4.1, we can concluded that the peak amount of AM discharge of UNIVK reanalysis not exactly much the peak amount of observed AM discharge which performed unsatisfactory for NSE ≤ 0.5 according to guidelines given in Moriasi et al. (2007), at Gilgel Abbay (NSE = -3.2), for Kessie (NSE = 0.06), for Bahirdar (NSE = -1.32), Main Beles (NSE = -0.26) and for Border (NSE = -12.3).

4.1.3 Reanalysis datasets mismatch with the in-situ data

The reanalysis dataset (water resources reanalysis which includes ECMWF and UNIVK) for all selected stations mismatch with the in-situ observed data is may be due to the inaccuracy use of many sources of earth observations (such as satellite and ground-based remote sensing, in situ measurements, vertical profiles, etc.). The error and uncertainties introduced by the model to simulate the reanalysis dataset, because the two earth2observe global reanalysis data represent the simulated output of the model. The Earth2Observe of first version of the water resource reanalysis (wrr1) is based on a set of different land surface and hydrological models simulations (more information at http:/www.earth2observe.eu). The bias of components of input data to simulate the ECMWF and UNIVK reanalysis dataset for extraction of the RivOut (river) discharge as the output are some of the explanation. The bias described in this section not tested in this study, but they are explained as a possible source of error for reanalysis datasets.

4.2 Extreme flow quantiles from observed AM discharge

4.2.1 Selected distributions for observed AM discharge

At-site flow analysis for each five observed station are carried out, and the goodness of-fit-test (Ang and Tang, 1975a), using Kolmogorov-Smirnov and Chi-square tests, to four most commonly applied distributions; LN3, GEV, EV1 and LP3, are investigated. Table 4.2, shows selected distributions for observed AM discharge of the stations by Kolmogorov-Smirnov (KS), Chi-square (χ^2) and Coefficient of determination (R^2) tests. See Appendix-D, for detail results of Kolmogorov-Smirnov and Chi-square tests.

The Probability-Probability (P-P) plot

The probability-probability (P-P) plot is a graph of the empirical CDF values plotted against the theoretical CDF values. It is used to determine how well a specific distribution fits to the observed data. See for the graphs with Coefficient of determination (R^2) results Appendix-H.

The Quantile-Quantile (Q-Q) plot

It is a graph of the input (observed) data values plotted against the theoretical (fitted) distribution quintiles (more information at http://www.mathwave.com). Both axes of this graph are in units of the input data set. The Q-Q plot for Border stations is shown as example in Figure 4.4. See for the graphs of all selected stations with Coefficient of determination (R^2) results in Appendix-G.

Table 4.2: Selected distributions for observed AM discharge by KS, χ2 and R2 tests

Name of stations	Kolmogorov-Smirnov (KS)	Chi-Square (χ^2)	Coefficient of determination (R^2)	Selected Distribution
Gilgel Abbay near Marawi	GEV	LP3	GEV	GEV
Abbay near Kessie	LN3	GEV	GEV	GEV
Abbay at Bahirdar	LP3	EV1	LP3	LP3
Main Beles at Bridge	EV1	LN3	EV1	EV1
Abbay at Border	GEV	GEV	GEV	GEV

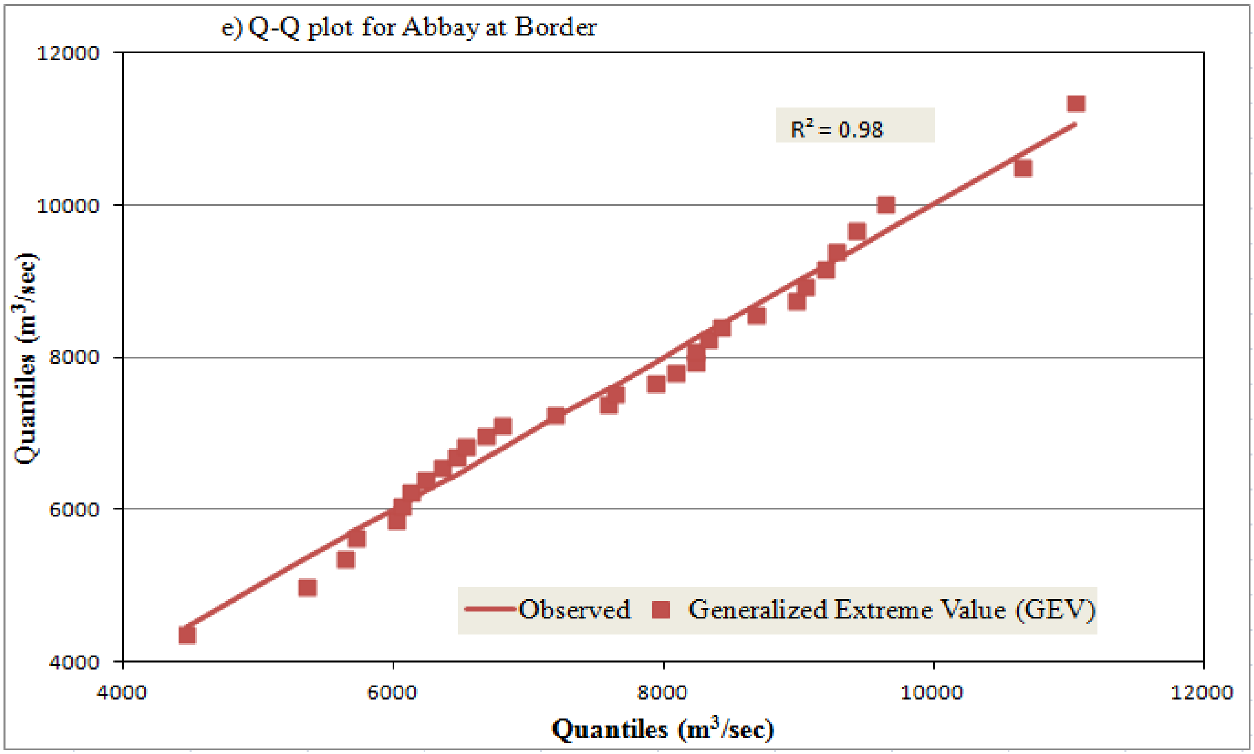


Figure 4.4: Q-Q plot (observed data plotted against the fitted distribution) for Border station

4.2.2 Parameters of selected distributions for observed discharge

At-site parameters estimation of selected distributions for observed annual maximum (AM) discharge of five stations were done by using easy-fit statistical computer software and the result are shown in Table 4.3 below.

Table 4.3: Estimated at-site parameters of selected distributions for observed AM discharge

Name of stations	Selected distributions	Parameters	Value
Gilgel Abbay near Marawi	GEV	k	0.13
		σ	59.64
		μ	318.28
Abbay near Kessie	GEV	k	0.10
		σ	2808
		μ	3953.7
Abbay at Bahirdar	LP3	α	9.12
		β	-0.16
		γ	7.32
Main Beles at Bridge	EV1	σ	233.99
		μ	552.34
Abbay at Border	GEV	k	-0.207
		σ	1580.2
		μ	6977

4.2.3 Extreme flow quantiles estimation from observed discharge

After selection of best-fit distributions for observed annual maximum discharge of the stations, the result quantile (X_T) which correspond to different return periods, T in year were computed from the statistics of the adopted distribution. The return period is related to the probability of non-exceedence (F) by the relation, F = 1-1/T where F = F(X_T) is the probability of having a flood of magnitude equal or less than $X_{T.}$ An annual maximum event has a return period (or recurrence interval) of T years if its magnitude is equaled or exceeded once, on the average, every T years. The reciprocal of T is the exceedance probability, 1- F, of the event, that is, the probability that the event is equaled or exceeded in any one year (Bedient, 2002).

The results of estimated extreme flow quantiles from observed AM discharge for five selected stations in the sub-basin are shown in Table 4.4 for recurrence intervals: 2, 10, 25, 50, 200, 500, 1000, 2000, 10000 years.

Table 4.4: Estimated extreme flow quantiles from at site observed AM discharge for 5 stations

T	F	Estimated extreme flow quantiles (m^3/s) from observed AM discharge				
		Gilgel Abbay	Kessie	Bahirdar	Main Beles	Border
		GEV	GEV	LP3	EV1	GEV
2	0.5	340.7	5001.9	355.8	638.1	7534.7
10	0.9	473.6	11040.2	607.8	1078.9	9818.4
25	0.96	553.5	14537.8	710.0	1300.8	10671.2
50	0.98	619.4	17355.4	776.7	1465.4	11203.9
200	0.995	768.5	23559.7	890.2	1791.5	12055.3
500	0.998	882.1	28143.5	953.7	2006.3	12495.5
1000	0.999	977.2	31897.8	996.8	2168.6	12776.8
2000	0.9995	1080.9	35920.4	1036.2	2330.8	13020.4
10000	0.9999	1360.2	46407.1	1115.5	2707.5	13467.4

4.3 Extreme flow quantiles from ECMWF reanalysis AM discharge

4.3.1 Selected distributions for ECMWF reanalysis AM discharge

At site quantiles estimation from ECMWF reanalysis discharge is carried out, and the goodness of-fit-tests (Ang and Tang, 1975a), using Kolmogorov-Smirnov and Chi-square tests, to four distributions; LN3, GEV, EV1 and LP3, are investigated. Table 4.5, shows selected distributions for ECMWF reanalysis AM discharge of the selected stations by Kolmogorov-Smirnov, Chi-square and Coefficient of determination tests. See Appendix-E, for detail results of Kolmogorov-Smirnov and Chi-square tests.

The Probability-Probability (P-P) plot

The probability-probability (P-P) plot is a graph of the empirical CDF values plotted against the theoretical CDF values (more information at http://www.mathwave.com). It is used to determine how well a specific distribution fits to the ECMWF reanalysis AM discharge. See for the graphs with Coefficient of determination (R^2) results Appendix-J.

The Quantile-Quantile (Q-Q) plot

It is a graph of the input (ECMWF reanalysis) data values plotted against the theoretical (fitted) distribution quantiles. Both axes of this graph are in units of the input data set. For example the Q-Q plot for Border stations is shown in Figure 4.5. See for the graphs all stations with Coefficient of determination (R^2) results in Appendix-I.

Table 4.5: Selected distributions for at site ECMWF reanalysis by KS, $\chi 2$ and R2 tests

Name of stations	Kolmogorov-Smirnov (KS)	Chi-Square (χ^2)	Coefficient of Determination (R^2)	Selected distribution
Gilgel Abbay near Marawi	LP3	LP3	LP3	LP3
Abbay near Kessie	LN3	LN3	LN3	LN3
Abbay at Bahirdar	LN3	GEV	LN3	LN3
Main Beles at Bridge	LP3	EV1	EV1	LP3
Abbay at Border	GEV	GEV	GEV	GEV

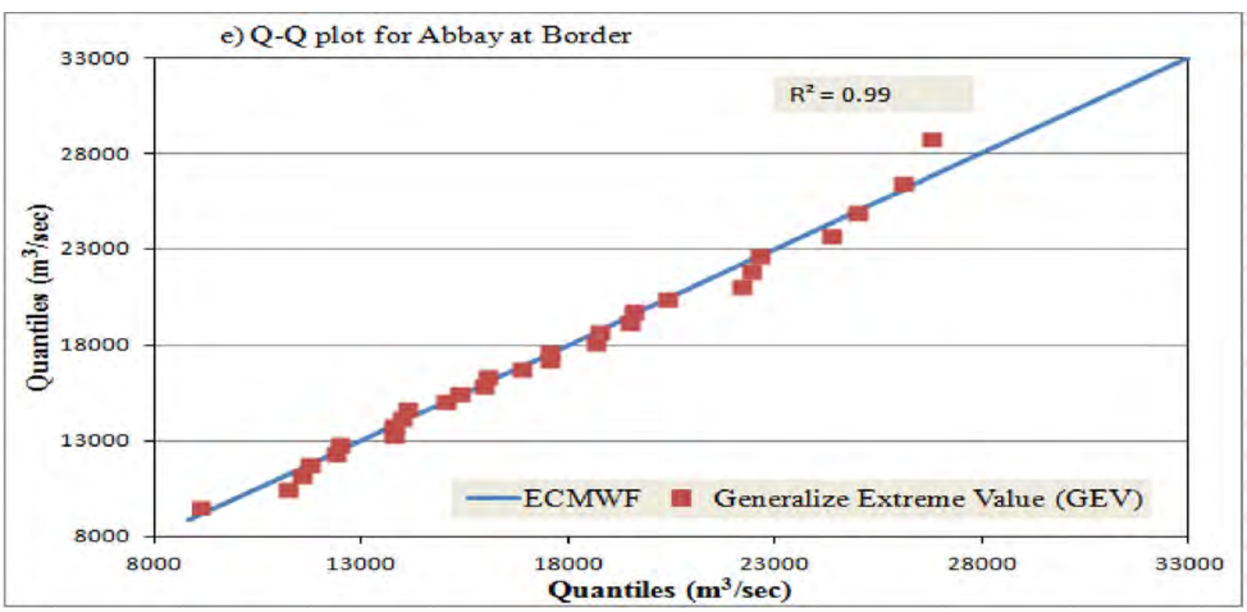


Figure 4.5: Q-Q plot (ECMWF reanalysis data plotted against the fitted distribution) for Border

4.3.2 Parameters of selected distributions for ECMWF reanalysis

At site parameters estimation of selected distributions for ECMWF reanalysis AM discharge of five stations were done by using easy-fit software (http://www.mathwave.com) and the result are shown in Table 4.6.

Table 4.6: Estimated at site parameters of selected distributions for ECMWF reanalysis

Name of stations	Selected distributions	Parameters	Value
Gilgel Abbay near Marawi	LP3	α	16.89
		β	0.09
		γ	4.52
Abbay near Kessie	LN3	σ	0.26
		μ	8.84
		γ	-775.65
Abbay at Bahirdar	LN3	σ	1.23
		μ	4.12
		γ	115.3
Main Beles at Bridge	LP3	α	3.23
		β	0.29
		γ	5.08
Abbay at Border	GEV	k	-0.04
		σ	4841.8
		μ	15006

4.3.3 Extreme flow quantiles estimation from ECMWF reanalysis

After selection of best-fit distributions for ECMWF reanalysis AM discharge of the stations, the desired quantiles estimates (X_T) which correspond to different return periods, T in year and non-exceedence probability (F) were computed from the statistics of the adopted distribution.

The results of estimated extreme flow quantiles from ECMWF reanalysis AM discharge for five selected stations in the sub-basin are shown in Table 4.7 for recurrence intervals: 2, 10, 25, 50, 200, 500, 1000, 2000, 10000 years.

Table 4.7: Estimated extreme flow quantiles at site for 5 stations from ECMWF reanalysis

T	F	Estimated extreme flow quantiles (m^3/s) from ECMWF annual peak discharge				
		Gilgel Abbay	Kessie	Bahirdar	Main Beles	Border
		LP3	LN3	LN3	LP3	GEV
2	0.5	400.8	6154.9	177.1	376.2	16768.3
10	0.9	669.9	8865.4	414.7	832.4	25448.0
25	0.96	829.7	10103.7	648.8	1216.8	29586.7
50	0.98	959.9	10986.9	890.1	1597.4	32561.8
200	0.995	1251.4	12680.0	1588.9	2685.9	38227.2
500	0.998	1471.4	13769.7	2253.6	3739.9	41796.6
1000	0.999	1654.6	14586.3	2891.7	4781.1	44412.8
2000	0.9995	1853.7	15399.6	3668.3	6091.4	46959.8
10000	0.9999	2385.9	17287.1	6137.4	10579	52619.5

4.4 Extreme flow quantiles from UNIVK reanalysis AM discharge

4.4.1 Selected distributions for UNIVK reanalysis AM discharge

At-site quantiles estimation for UNIVK reanalysis AM discharge is carried out, and the goodness-of-fit-test (Ang and Tang, 1975a), using Kolmogorov-Smirnov and Chi-square tests, to four candidate distributions are investigated. Table 4.8, shows selected distributions for UNIVK reanalysis of the stations by Kolmogorov-Smirnov, Chi-square and Coefficient of determination tests. See Appendix-F, for detail results of Kolmogorov-Smirnov and Chi-square tests.

The Probability-Probability (P-P) plot

The probability-probability (P-P) plot is a graph of the empirical CDF values plotted against the theoretical CDF values (more information at http://www.mathwave.com). It is used to determine how well a specific distribution fits to the UNIVK reanalysis AM discharge. See for the graphs with Coefficient of determination (R^2) results in Appendix-L.

The Quantile-Quantile (Q-Q) plot

It is a graph of the input (UNIVK) data values plotted against the theoretical (fitted) distribution quintiles. The Q-Q plot of Border station using fitted distribution and UNIVK reanalysis AM discharge is shown in Figure 4.6. Both axes of this graph are in units of the input data set. See for the graphs of all stations with Coefficient of determination (R^2) results in Appendix-K.

Table 4.8: Selected distributions for at site UNIVK reanalysis by KS, $\chi2$ and R2 tests

Name of stations	Kolmogorov-Smirnov (KS)	Chi-Square (χ^2)	Coefficient of determination (R^2)	Selected distribution
Gilgel Abbay near Marawi	GEV	EV1	GEV	GEV
Abbay near Kessie	EV1	LP3	LP3	LP3
Abbay at Bahirdar	GEV	LN3	GEV	GEV
Main Beles at Bridge	GEV	LP3	GEV	GEV
Abbay at Border	LN3	EV1	LN3	LN3

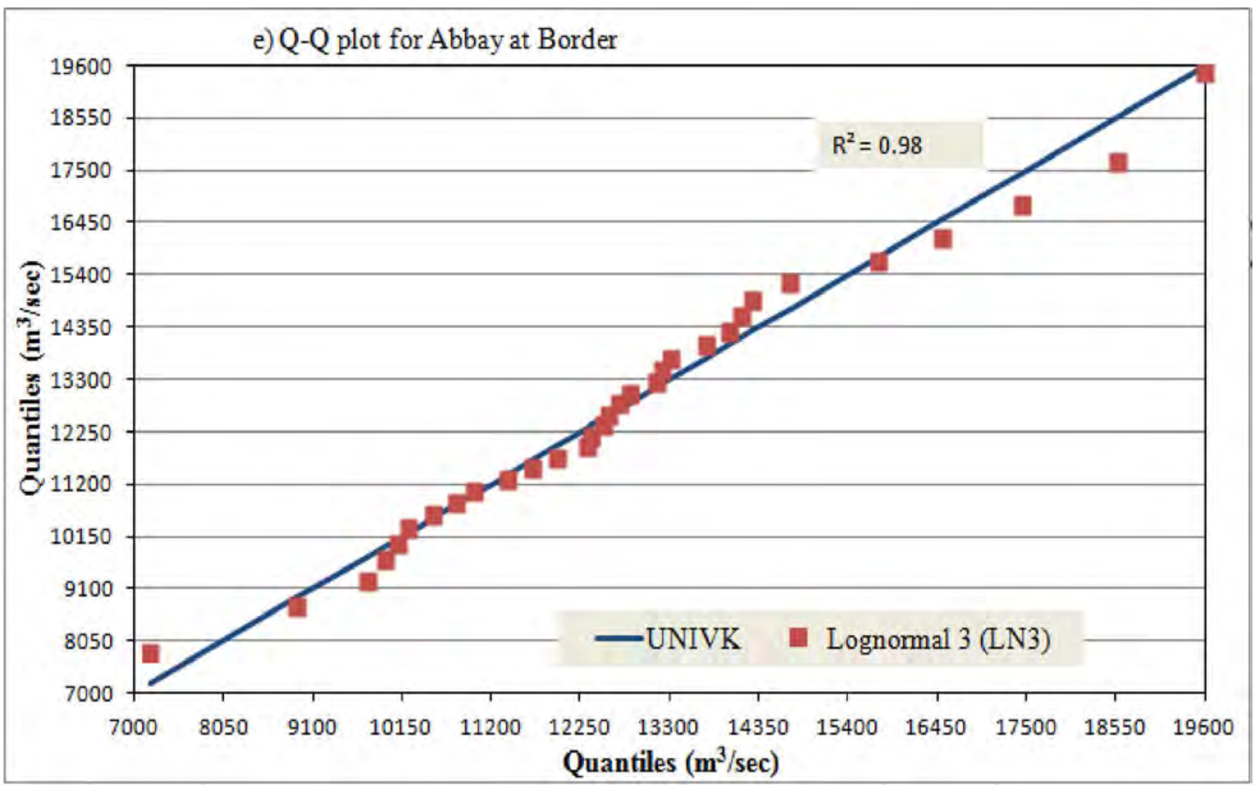


Figure 4.6: Q-Q plot (UNIVK reanalysis data values plotted against the fitted distribution quantiles) for Border station

4.4.2 Parameters of selected distributions for UNIVK reanalysis

Selected distributions for UNIVK reanalysis AM discharge of five stations were done by using easy-fit statistical computer software and the result are shown in Table 4.9.

Table 4.9: Estimated at-site parameters of selected distributions from UNIVK reanalysis

Name of stations	Selected distributions	Parameters	Value
Gilgel Abbay near Marawi	GEV	k	-0.19
		σ	129.38
		μ	411.23
Abbay near Kessie	LP3	α	295.64
		β	0.01339
		γ	4.6899
Abbay at Bahirdar	GEV	k	-0.03
		σ	250.88
		μ	276.16
Main Beles at Bridge	GEV	k	-0.24
		σ	138.58
		μ	437.67
Abbay at Border	LN3	σ	0.17
		μ	9.66
		γ	-3102.9

4.4.3 Extreme flow quantiles estimation from UNIVK reanalysis

After selection of best-fit distribution for UNIVK Reanalysis of the station, the desired quantiles estimates (X_T) which correspond to different return periods (T) in year and non-exceedence probability (F) are then computed from the selected distributions.

The results of estimated extreme flow quantiles from UNIVK reanalysis AM discharge for five selected stations in the sub-basin are shown in Table 4.10 for recurrence intervals : 2, 10, 25, 50, 200, 500, 1000, 2000, 10000 years.

Table 4.10: Estimated flow Quantiles at site for 5 stations from UNIVK Reanalysis

T	F	Estimated extreme flow quantiles (m^3/s) from UNIVK annual peak discharge				
		Gilgel Abbay	Kessie	Bahirdar	Main Beles	Border
		GEV	LP3	GEV	GEV	LN3
2	0.5	457.0	5676.3	367.7	486.3	12587.4
10	0.9	647.9	7679.4	825.1	677.4	16389.9
25	0.96	720.9	8609.7	1047.3	745.0	18001.6
50	0.98	767.1	9279.8	1208.8	785.9	19112.9
200	0.995	842.3	10579.5	1520.5	848.9	21166.3
500	0.998	881.9	11427.0	1719.9	880.1	22441.1
1000	0.999	907.5	12067.8	1867.5	899.4	23375.1
2000	0.9995	929.9	12710.9	2012.6	915.7	24288.5
10000	0.9999	971.9	14221.8	2339.8	944.3	26349.8

4.5 Reanalysis and observed extreme flow quantiles

In order to study the occurrence of floods for Gilgel Abbay, Kessie, Bahirdar, Main Beles and Border stations, Flood frequency analysis was undertaken on the annual maximum (AM) discharge of reanalysis (ECMWF and UNIVK) and observed daily discharge. Flood frequency analysis was undertaken on the annual maximum (AM) discharge according to (Cunnane, 1989). The reanalysis and observed annual maximum discharge of five stations were fitted to the most commonly applied skewed distribution, such as GEV, EV1, LP3 and LN3 (Pilon and Harvey, 1994). Table 4.11, shows the result of estimated extreme flow quantiles on the basis of the selected distributions for five stations at recurrence intervals: 2, 10, 25, 50, 200, 500, 1000, 2000, 10000 years from reanalysis (ECMWF and UNIVK) and observed AM discharge.

Table 4.11: Results of estimated extreme flow quantiles (m3/s) from reanalysis and observed AM discharge

T	Gilgel Abbay near Marawi			Abbay near Kessie		
	Observed using GEV	ECMWF using LP3	UNIVK using GEV	Observed using GEV	ECMWF using LN3	UNIVK using LP3
2	340.7	400.8	457.0	5001.9	6154.9	5676.3
10	473.6	669.9	647.9	11040.2	8865.4	7679.4
25	553.5	829.7	720.9	14537.8	10103.7	8609.7
50	619.4	959.9	767.1	17355.4	10986.9	9279.8
200	768.5	1251.4	842.3	23559.7	12680.0	10579.5
500	882.1	1471.4	881.9	28143.5	13769.7	11427.0
1000	977.2	1654.6	907.5	31897.9	14586.3	12067.8
2000	1080.9	1853.7	929.9	35920.4	15399.7	12710.9
10000	1360.2	2385.9	971.9	46407.1	17287.1	14221.8

T	Abbay at Bahirdar			Main Beles at Bridge		
	Observed using LP3	ECMWF using LN3	UNIVK using GEV	Observed using EV1	ECMWF using LP3	UNIVK using GEV
2	355.8	177.1	367.7	638.1	376.2	486.3
10	607.8	414.7	825.1	1078.9	832.4	677.4
25	710.0	648.8	1047.3	1300.8	1216.8	745.0
50	776.7	890.1	1208.8	1465.4	1597.4	785.9
200	890.2	1588.9	1520.5	1791.5	2685.9	848.9
500	953.7	2253.6	1719.9	2006.3	3739.9	880.1
1000	996.8	2891.7	1867.5	2168.6	4781.1	899.4
2000	1036.2	3668.3	2012.6	2330.8	6091.4	915.7
10000	1115.5	6137.4	2339.8	2707.5	10579	944.3

Table 4.11: Results of estimated extreme flow quantiles (m^3/s) from reanalysis and observed AM discharge (continued)

T	Abbay at Border		
	Observed-GEV	ECMWF-GEV	UNIVK-LN3
2	7534.7	16768.3	12587.4
10	9818.4	25448.0	16389.9
25	10671.2	29586.7	18001.6
50	11203.9	32561.8	19112.9
200	12055.3	38227.2	21166.3
500	12495.5	41796.6	22441.1
1000	12776.8	44412.8	23375.1
2000	13020.4	46959.8	24288.5
10000	13467.3	52619.5	26349.8

4.6 Comparison of reanalysis extreme flow quantiles with observed

The earth2observe global ECMWF, UNIVK reanalysis annual maximum discharge and in-situ observed annual maximum discharge data were used for the estimation of extreme flow quantiles for five selected stations. The extreme (high and low) flow quantiles estimated from reanalysis AM discharge data are evaluated with extreme flow quantiles estimated from observed AM discharge data for design and planning of water resources management problems. Figure 4.7 show comparison of estimated extreme flow quantiles from reanalysis (ECMWF and UNIVK) with the estimated extreme flow quantiles from observed AM discharge data.

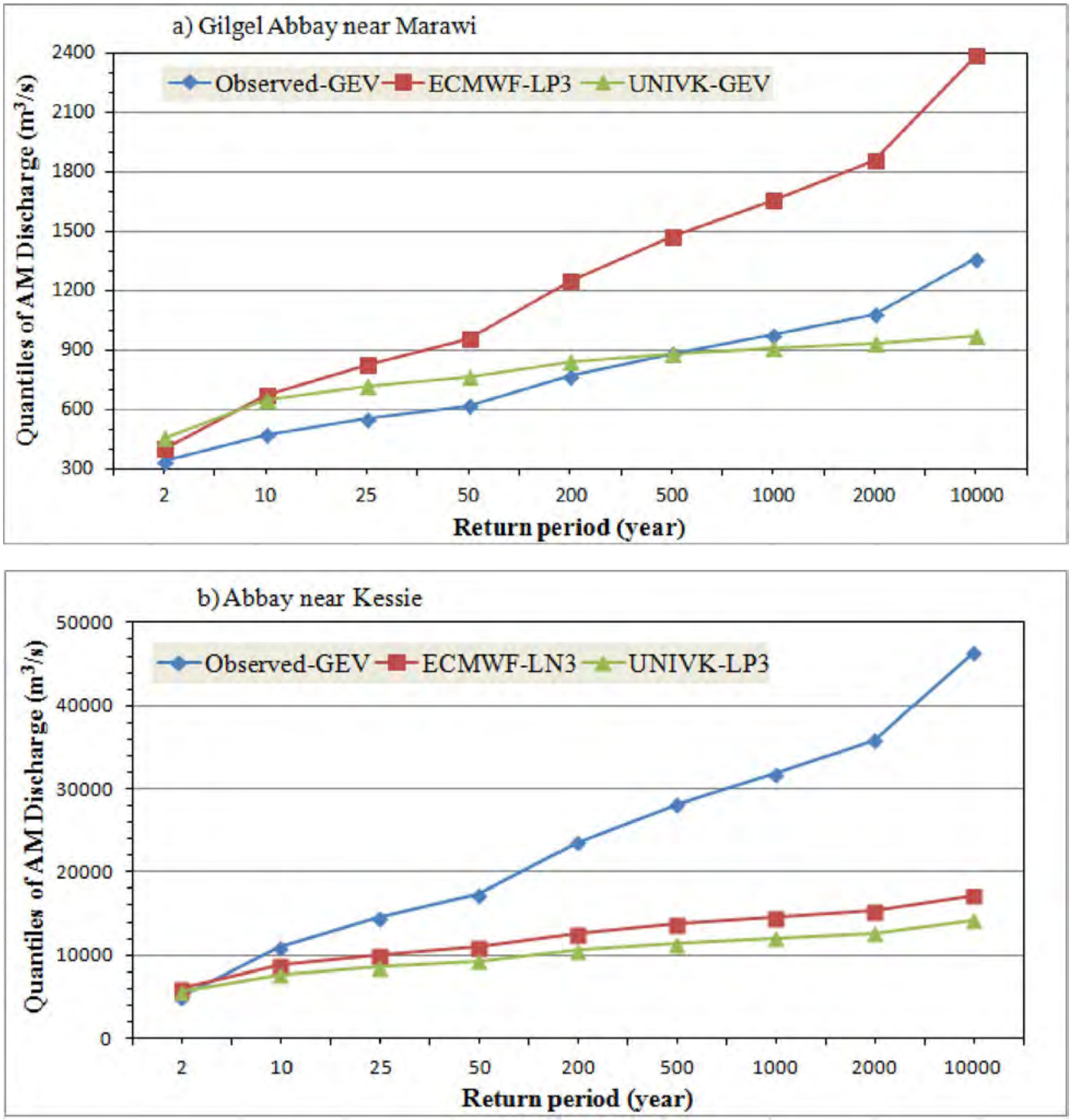
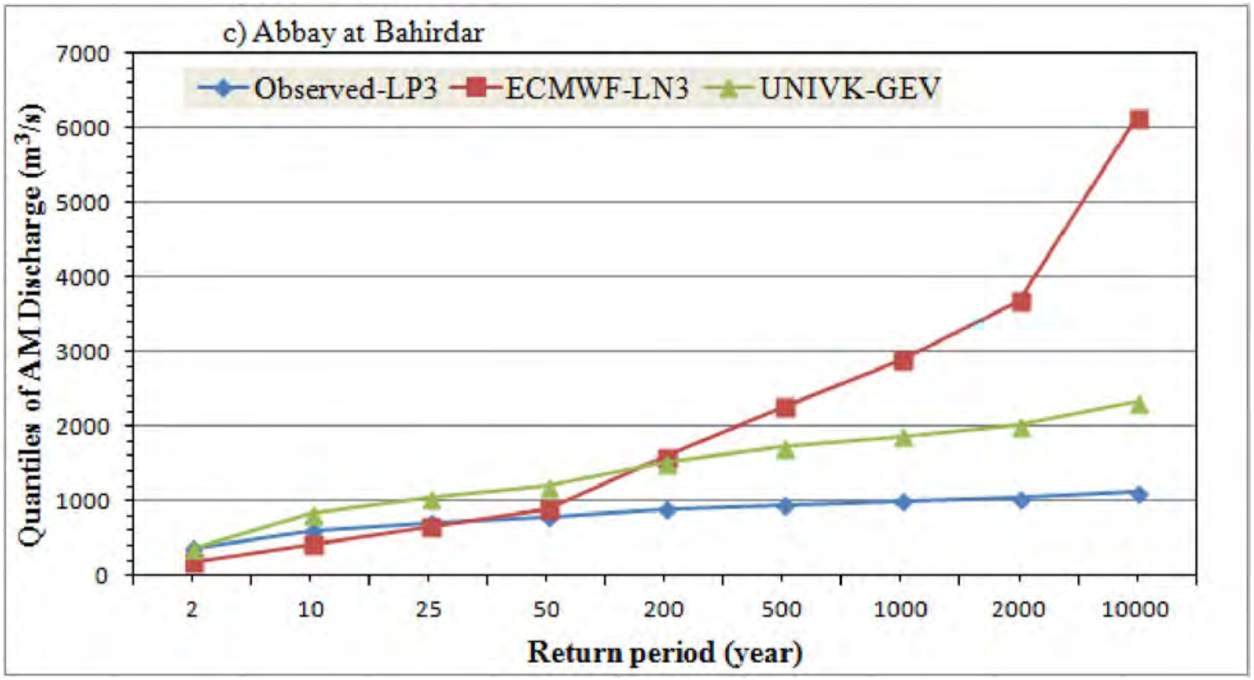


Figure 4.7: Comparison of estimated extreme flow Quantiles result from the reanalysis with the observed AM discharge



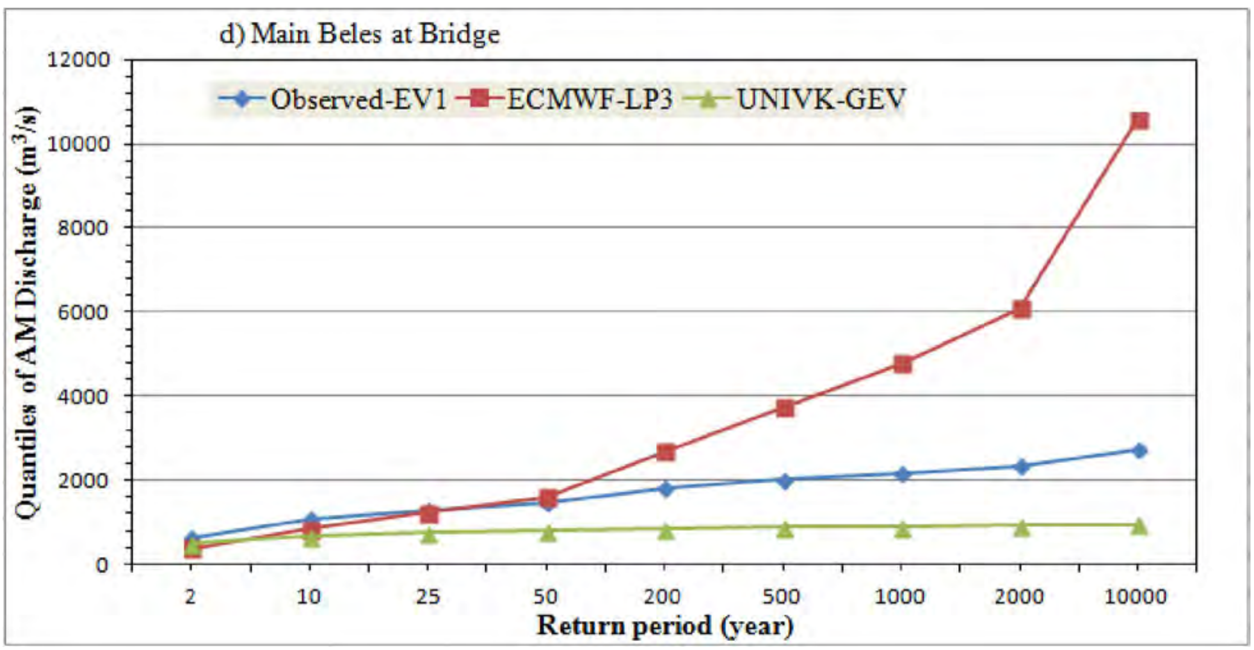


Figure 4.7: Comparison of estimated extreme flow Quantiles result from the reanalysis with the observed AM discharge (continued)

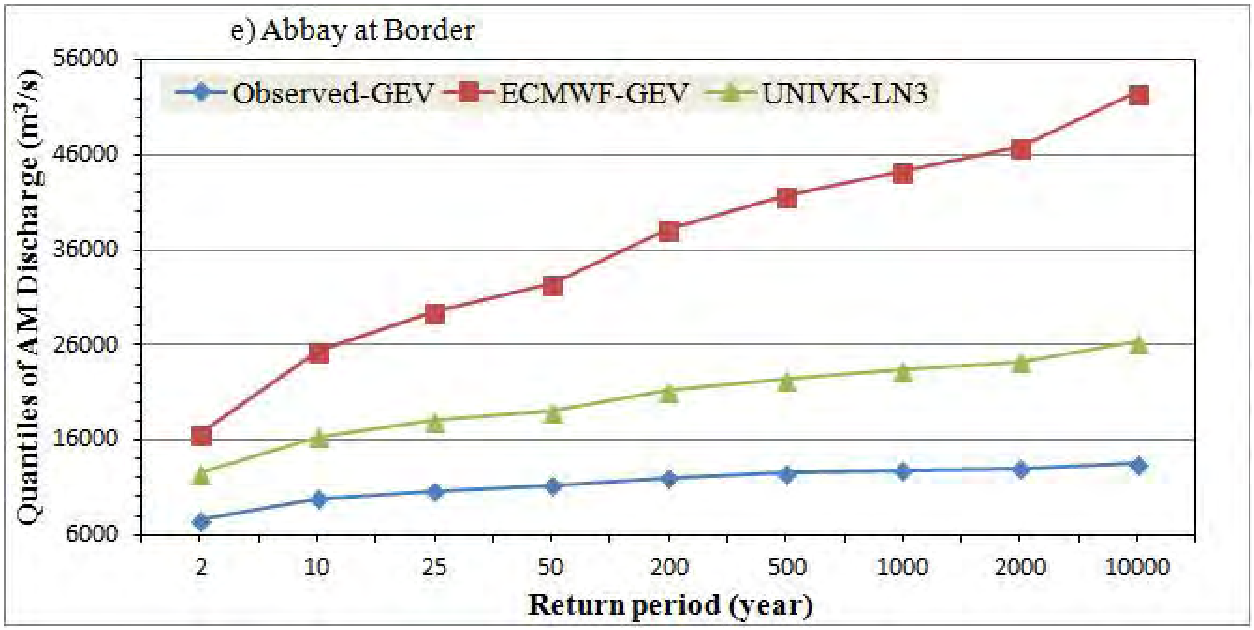


Figure 4.7: Comparison of estimated extreme flow Quantiles result from the reanalysis with the observed AM discharge (continued)

Table 4.12 shows percentage underestimate and overestimates values of extreme flow quantiles estimated from reanalysis (ECMWF and UNIVK) AM discharge data as compared to flow quintiles estimated from observed AM discharge at recurrence interval, T.

Table 4.12: Percentage underestimates and overestimates of extreme flow quantiles of reanalysis (ECMWF and UNIVK) at recurrence interval, T

T	Percentage underestimate and overestimate									
	Gilgel Abbay		Kessie		Bahirdar		Main Beles		Border	
	ECMWF	UNIVK	ECMWF	UNIVK	ECMWF	UNIVK	ECMWF	UNIVK	ECMWF	UNIVK
2	-18	-34	-23	-13	50	-3.3	41	24	-123	-67
10	-41	-37	19	30	32	-36	23	37	-159	-67
25	-49	-30	30	41	8.6	-47	6	43	-177	-68
50	-55	-24	36	46	-15	-56	-9	46	-191	-71
200	-63	-9	46	55	-78	-71	-50	53	-217	-75
500	-67	0.3	51	59	-136	-80	-86	56	-234	-79
1000	-69	7	54	62	-190	-87	-120	58	-247	-83
2000	-71	14	57	65	-254	-94	-161	61	-260	-86
10000	-75	28	62	69	-450	-109	-290	65	-291	-95

Note: Percentage underestimate/overestimate = $\pm \frac{x_o - x_e}{x_o} * 100\%$

Where x_e is the reanalysis extreme flow quantiles value, x_o is the observed extreme flow quantiles value and the plus (+) and minus (-) sign show underestimation and overestimation respectively.

4.6.1 Evaluation of extreme flow quantiles from ECMWF reanalysis

The extreme flow quantiles estimated from ECMWF reanalysis AM discharge data are compared to the quantiles estimated from observed AM discharge data. The ECMWF reanalysis data overestimate extreme flow quantiles and overestimation is getting larger when return period is getting larger for Gilgel Abbay and Border stations. The reanalysis underestimates when the return period is smaller than 50 year and overestimation is getting larger when return period is getting larger for Bahirdar and Main Beles stations. The ECMWF reanalysis AM discharge underestimate extreme flow quantiles when return period is greater than 2 year and larger return period is the larger underestimation for Kessie station.

At this stage of development, the ECMWF reanalysis product doesn't capture the peak discharges (Figure 4.3). As a result, the quantile flood estimates appear to be unreliable (Figure 4.7) for all the evaluated stations in the basin. For examples, for Gilgel Abbay and Border stations and for a design flood of low magnitude estimated from observed data, when high flood estimated from ECMWF reanalysis data are used for the design, this will result in conservative and unnecessary costly structure. For Kessie station after 2 year return period and for a design flood of high magnitude estimated from observed data, when low flood estimated from ECMWF reanalysis is used for the design, this will results in the loss of the structure itself causing thereby untold miserly to the people residing downstream, besides damaging valuable immovable properties.

The error for flow quantiles of ECMWF is due to the bias of reanalysis data, probability distribution and method of parameter estimation. But, bias of reanalysis AM discharge data is the critical issue for the error of estimated flow quantiles. For example the fitted probability distribution for the observed AM discharge of Main Beles station is Extreme Value type I (EV1) and the accuracy of fitting is not 100%, but relatively best as compared to other distribution used in this study, and for ECMWF reanalysis AM discharge, the fitted distribution is Log-pearson with three parameters (LP3) and the accuracy of fitting is also not 100%. Th inaccuracy of fitting is due to the quality of data, method of parameter estimation, and probability distribution. Therefore, because of the differences in parameter of distribution, fitted probability distribution and annual maximum (AM) discharge data of observed and ECMWF reanalysis, the extreme flow quantiles estimated by ECMWF reanalysis is biased (especially the reanalysis AM discharge has high significance on extreme flow quantiles to be biased) and similarly happen for other stations.

The reanalysis data is reliable for estimation flow quantiles, when all sources of error of flow quantiles are bias corrected. The Figure 4.8 below show the fitted distribution to the ECMWF reanalysis AM discharges for Main Beles station using Q-Q plot.

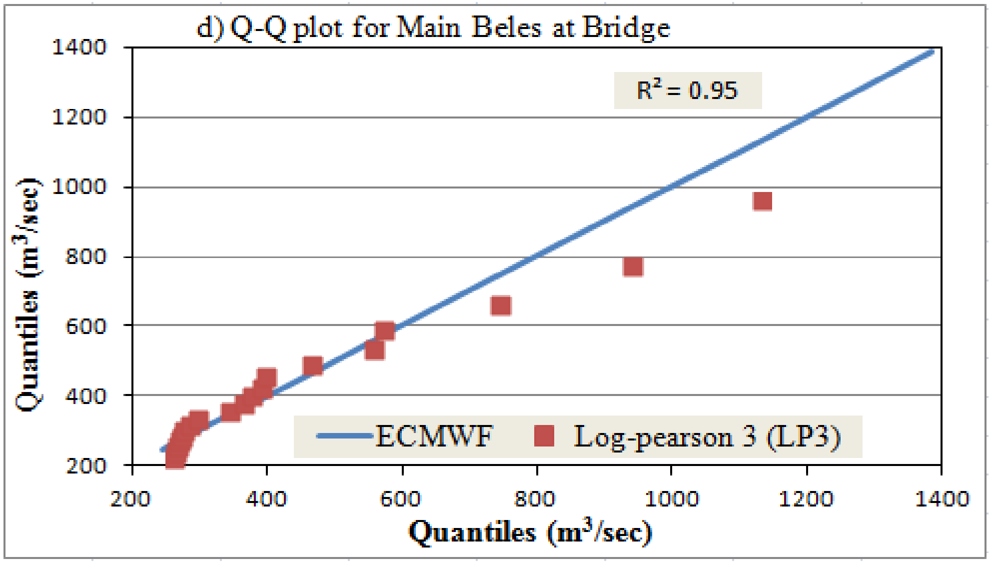


Figure 4.8: Q-Q plot of distribution and ECMWF reanalysis AM discharge for Main Beles

4.6.2 Evaluation of extreme flow quantiles from UNIVK reanalysis

The extreme flow quantiles estimated from UNIVK reanalysis AM discharge data are compared to the quantiles estimated from observed AM discharge. The UNIVK reanalysis AM discharge overestimate extreme flow quantiles for Bahirdar and Border stations and underestimate for Main Beles station and overestimation is getting larger when return period is getting larger for Bahirdar, Border and Main Beles stations. The UNIVK reanalysis overestimate the extreme flow quantiles when the return period is smaller than 500 year and the larger return period is the larger underestimation for Gilgel Abbay station. The UNIVK reanalysis underestimate the quantiles when return period is greater than 2 year and larger return period is the larger underestimation for Kessie station. The UNIVK reanalysis data works best at Bahirdar station when the return period is 2 year and at Gilgel Abbay station when return period is 200, 500 and 1000 years.

The UNIVK reanalysis AM discharge data is not reliable for design and planning of water resource project at each return period of T years specified in the study, because of its overestimation and underestimation of extreme flow quantiles. For examples, for Kessie station after 2 year return period and for a design flood of high magnitude estimated from observed data, when low flood estimated from UNIVK reanalysis AM discharge is used for the design, this will results in the loss of the structure itself causing thereby untold miserly to the people residing downstream, besides damaging valuable immovable properties. For Bahirdar and Border stations and for a design flood of low magnitude estimated from observed data, when high flood estimated from UNIVK reanalysis data are used for the design, this will result in conservative and unnecessary costly structure.

Similar to ECMWF, bias of UNIVK data, bias of probability distribution and method of parameter estimation are the cause of error for estimated extreme flow quantiles of reanalysis. For example the fitted probability distribution for the observed AM discharge of Main Beles station is (EV1) and the fitting has insignificant bias relatively to other distribution used in this study, and for UNIVK reanalysis AM discharge, the fitted distribution is Generalized extreme value (GEV) with insignificant bias relatively to other distribution.

Th inaccuracy of fitting distribution is as mentioned in section 4.6.2. Therefore, because of the differences of parameter of distribution, fitted probability distribution and annual maximum (AM) discharge data of observed and UNIVK reanalysis, the extreme flow quantiles estimated by UNIVK reanalysis is biased. Estimated extreme flow quantiles from the reanalysis data are reliable for design and planning of water resource project, when the sources of error for estimated flow quantiles are bias corrected. The Figure 4.9 below show the fitted distribution to the UNIVK reanalysis AM discharges for Main Beles station using Q-Q plot.

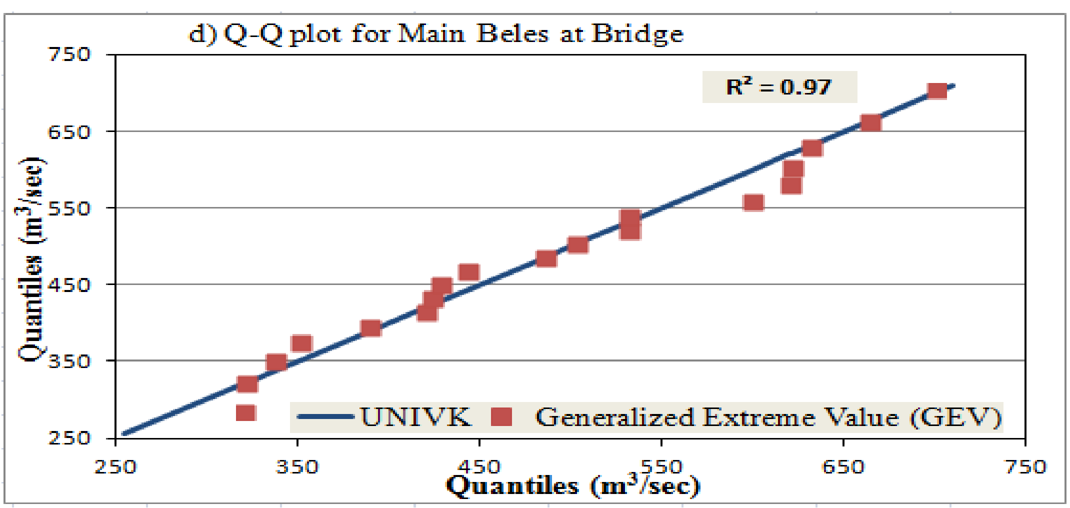


Figure 4.9: Q-Q plot of distribution and UNIVK reanalysis AM discharge for Main Beles

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The goal of this study was to evaluate extreme flow quantile estimated from the global reanalysis runoff data by reproducing annual maximum (AM) discharge data which are needed to estimate extreme flow quantiles in Blue Nile River Basin. For the study in the Blue Nile River basin five gauging stations (Kessie, Bahirdar, Border, Main Beles and Gilgel Abbay) were selected based on recorded length of data, independence and stationary, randomness and catchment area of the station. The stations were considered with a number of record years greater than or equal to 24 and neglected for a catchment area very less than grid pixel (2500km^2) of reanalysis in this study. The purposes of considering a number of record year greater than or equal to 24 was to match number of record year of the observed AM flow data with the reanalysis AM flow data and neglecting the stations with the catchment area very less than the area of grid pixel of reanalysis was to minimize the discrepancy between observed and reanalysis AM discharge data.

In this paper, two major reanalysis data, ECMWF and UNIVK reanalysis AM discharge data were compared with available in-situ observed AM discharge data for the Blue Nile basin for the period 1979-2002 at Kessie, Gilgel Abbay, Bahirdar, Main Beles and for a period of 1979-2009 at Border station and a year which has missing annual maximum discharge was removed for estimation of extreme flow quantiles and for comparison of reanalysis and observed AM discharge.

Annual maximum discharge (AM) data generation procedure for a Blue Nile Basin has been presented using a reanalysis (ECMWF and UNIVK) and extreme flow quantiles were estimated from the reanalysis and observed AM discharge at a return period of 2, 5, 10, 25, 50, 100, 200, 1000, 1000 years using flood frequency analysis.

Comparison of reanalysis (ECMWF and UNIVK) AM discharge with the observed AM discharge were done using percent bias (PBIAS) and Nash-Sutcliffe efficiency (NSE) and evaluation of extreme flow quantiles estimated from two reanalysis were done at each return period (T) specified in this study.

For selection of best fit distributions and methods of parameters estimation and also parameter estimation for at-site extreme flow quantile analysis easy-fit statistical computer software was employed at return period of T years from two reanalysis (ECMWF and UNIVK) and observed AM discharge.

The most commonly applied distributions such as: Generalized extreme value (GEV), Log-pearson with three parameters (LP3), Lognormal with three parameters (LN3) and Extreme value type I (EV1) were used to estimate extreme flow quantiles from ECMWF and UNIVK reanalysis and observed AM discharge data. Using the goodness-fit-test (Chi-square and Kolmogorov-smirnov) by easy-fit software and Coefficient of determination (R^2), the best fit distribution was selected from four most commonly used distributions to estimate extreme flow quantiles.

For observed AM discharge, the selected distributions were GEV for Gilgel Abbay, Kessie and Border, LP3 for Bahirdar and EV1 for Main Beles station. For ECMWF reanalysis, the selected distributions were LN3 for Kessie and Bahirdar, GEV for Border and LP3 for Main Beles and Gilgel Abbay stations. For UNIVK reanalysis, the selected distributions were GEV for Gilgel Abbay, Bahirdar and Main Beles, LP3 for Kessie and LN3 for Border station. Method of moment (MOM), maximum likelihood method (MLM) and L-Moment method were selected using easy-fit statistical computer software for parameter estimation of four most used distributions from observed and reanalysis (ECMWF and UNIVK) AM discharge data at five gauging stations. The MOM, MLM and L-Moment parameter estimation method were used for LP3 and EV1, LN3 and GEV distribution respectively.

On the basis of the research presented in this report, the following conclusions are offered.

- The ECMWF reanalysis annual maximum discharge overestimates by (PBIAS = -22.3%) for Gilgel Abbay, (PBIAS = -4.43%) for Kessie and (PBIAS = -131.41%) for Border stations and underestimate by (PBIAS = 39.9%) for Bahirdar and (PBIAS = 30.08%) for Main Beles stations. The UNIVK reanalysis annual maximum discharge overestimate by (PBIAS= -28.90%) for Gilgel Abbay, (PBIAS = 4.28%) for Kessie, (PBIAS = -10.65%) for Bahirdar and (PBIAS = -68.3%) for Border stations and underestimates by (PBIAS = 28.71%) for Main Beles station. The percentage bias of ECMWF reanalysis AM discharge data is good for Kessie, satisfactory for Gilgel Abbay and unsatisfactory for Main Beles and Border stations. The percentage bias of UNIVK reanalysis AM discharge data is very good for Kessie, good for Bahirdar and unsatisfactory for Main Beles, Gilgel Abbay and Border stations. The peak amount of AM discharge data from two reanalysis can not much the peak amount of observed AM discharge data which are unsatisfactory (NSE $\leq$ 0.5) for five gauging stations.

- For observed AM discharge, Generalized extreme value at Gilgel Abbay, Kessie and Border, Log-Pearson with three parameters at Bahirdar and Extreme value type I at Main Beles station are the most suitable distribution. For ECMWF reanalysis AM discharge, Lognormal with three parameters at Kessie and Bahirdar, Generalized extreme value at Border and Log-pearson with three parameters at Main Beles station can be considered as the most suitable distribution and for UNIVK reanalysis AM discharge, Generalized extreme value at Gilgel Abbay, Bahirdar and Main Beles, Log-pearson with three parameters at Kessie and Lognormal with three parameter at Border station are the most suitable distribution.

- The ECMWF reanalysis AM discharge overestimate extreme flow quantiles value for Gilgel Abbay and Border stations in contrast with the observed results. The overestimation is getting larger with the increase of the return period using ECMWF reanalysis for Gilgel Abbay and Border stations. The ECMWF reanalysis underestimate extreme flow quantiles, when the return period is smaller than 50 year for Bahirdar and Main Beles stations and underestimate, when return period is greater than 2 year for Kessie station. The UNIVK reanalysis AM discharge data overestimate extreme flow quantiles for Bahirdar and Border stations and underestimate for

Main Beles station in contrast to the observed estimates. The overestimation is increase with the increase of the return period using UNIVK reanalysis data for Bahirdar, Border and Main Beles stations. The UNIVK reanalysis data also overestimate extreme flow quantiles when the return period is smaller than 500 year for Gilgel Abbay station and underestimate, when return period is greater than 2 year for Kessie station.

- The estimated extreme flow quantiles at return period of 2, 5, 10, 25, 50, 100, 200, 1000, 1000 years, from the reanalysis (ECMWF and UNIVK) AM discharge data overestimate and underestimate the estimated extreme flow quantiles from observed AM discharge data, which are unreliable for design and planning of water resource project for five gauging stations. Especially for high flow quantiles from observed data (at Kessie and Border stations) the two reanalysis data are large in bias, which are not strictly work for design and planning of water resources project.

Therefore estimation of extreme flow quantiles from UNVIK and ECMWF reanalysis AM discharge data are not releable in design and planning of water resource project at five gauging stations in the Blue Nile basin. The sources of error for estimated extreme flow quantiles is due to the bias of reanalysis AM discharge data, probability distribution and method of parameter estimation.

5.2 Recommendations

The global reanalysis runoff data series is used as informative input to data developers /scientists and decision makers in the absence of sufficient discharge data. Critical examination of reanalysis annual maximum discharge data uncertainties may be important to take in to account when evaluating extreme flow quantiles estimation for flood management. Estimation of extreme flow quantiles from the reanalysis (ECMWF and UNIVK) AM discharge data are bias at a return period of 2, 5, 10, 25, 50, 100, 200, 1000, 10000 years for the design and planning of water resources project. So that it is advisable to extend this approach of reanalysis data for other parts of river basin to establish how the reanalysis data is reliable to estimate extreme flow quantiles, when the reanalysis AM flow data are reliable the problem related to the absence of observed sufficient discharge data for water resources project planning and design are reduced .

Moreover, further studies are required to improve the accuracy of extreme flow quantiles estimated from reanalysis AM flow data on the following points of this research:

- Correcting the bias of reanalysis annual maximum flow data
- Testing other probability distributions than used in this paper
- Testing other parameter estimation tool than used in this paper
- Testing the flow quantile estimation in other river basins
- Improving the representativeness of their data
- Testing the other components these datasets (for use)

6. REFERENCES

Abida, H. and Ellouze, M. (2008). Probability distribution of flood flows in Tunsia (Electronic version). Hydrology and Earth System Sciences, 12,703-714.

Admasu, G. (1989). Regional flood frequency Analysis. Technical Report. Royal Institute of Technology Stockholm, Sweden.

Ang. H-S. A. and Tang, H.W. (1975a). Probability Concepts in Engineering Planning and Design. Volume I- Basic Principles. John Wiley & Sons, Inc., New York.

BCEOM. (1999). Abbay River Basin Integrated Development Master Plan Project and Associates (ARBIDMPP). (1999). Abbay Basin Integrated Development Master Plan Project; Phase 2, Section II, Vol. III: Water Resources: Part 1 –Climatology and Part 2 - Hydrology.

Bedient, P.B., Huber, W.C. and Vieux, B.E. (2002). Hydrology and Floodplain Analysis (3rd ed.) Upper Saddle River, NJ: Prentice Hall.

Bobee, B., Cavadias, G., Ashkar, F., Bernier, J. and Rasmussen, P. (1993). Towards a systematic approach to comparing distributions used in flood frequency analysis. Journal of Hydrology 142, 121–36.

Box, G.P. and G.M. Jenkins. (1970). Time-Series Analysis, Forecasting and Conirol. Holden-Day, San Fran-cisco.

CDO: Climate Data Operators version 1.5.4 (http://code.zmaw.de/projects/cdo).

Chang, M. and R. Lee. (1974). Objective Double-Mass Analysis. In: Water Resources Research 10(6):1123-1126.

Chow, V. T., Maidment, D.R. and Mays, L. W. (1988). Applied Hydrology. McGRAW, Singapore.

Critchley, W. and Siegert, K. (1991). A manual for the design and construction of water harvesting schemes, Land and water division, FAO, Rome.

Cunnane, C. (1989). Statistical Distributions for Flood Frequency Analysis. World Meteorological Organization Operational Hydrology Report, No.33.

Dahmen, E.R., and Hall, M.J.(1990). Screening of Hydrological Data: Tests for Stationarity and Relative Consistency. Wageningen, The Netherlands. International Institute for Land Reclamation and Improvement/ILRI.

Dee, D. P., Uppala, S. M., Simmons, A. J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M. A., Balsamo, G., Bauer, P., Bechtold, P., Beljaars, A. C. M., van de Berg, L., Bidlot, J., Bormann, N., Delsol, C., Dragani, R., Fuentes, M., Geer, A. J., Haimberger, L., Healy, S. B., Hersbach, H., Hólm, E. V., Isaksen, L., Kållberg, P., Köhler, M., Matricardi, M., McNally, A. P., Monge-Sanz, B. M., Morcrette, J. J., Park, B. K., Peubey, C., de Rosnay, P., Tavolato, C., Thépaut, J. N., and Vitart, F. (2011). The ERA-Interim reanalysis: configuration and performance of the data assimilation system, Quart. J. Roy. Meteor. Soc., 137, 553-597, doi: 10.1002/qj.828.

Dutra, E., Balsamo, G., Viterbo, P., Miranda, P. M. A., Beljaars, A., Schar, C., and Elder, K. (2010). An Improved Snow Scheme for the ECMWF Land Surface Model: Description and Offline Validation, J. Hydrometeor., 11, 899 -916, doi: 10.1175/2010jhm1249.1.

Fisher, R. and Tippett, L. (1928). Limiting forms of the frequency distribution of the largest and smallest member of a sample. Proc. Cambridge Phil. Soc., 24:180–190.

Fitsume Teshome, Semu Moges, Dereje Hailu, Belete Berhanu. (2015). Evaluation of global reanalysis datasets for runoff estimation in the Blue Nile. Msc Thesis Paper, AAiT library.

Gebeyehu, A. (1989). Regional Flood Frequency Analysis, PHD thesis report.

Gunasekara, T. A. G. and Cunnane, C. (1992). Split sampling technique for selecting a flood frequency analysis procedure, J. Hydrol., 130,189–200.

Gupta, H., S. Sorooshian, and P. Yapo. (1999). Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration. Journal of Hydrologic Engineering 4:135-143.

Hamed, K. H., and Rao, A. R. (2000). Flood Frequency Analysis. CRC press LLC, Florida.

Harding, R., Best, M., Blyth, E., Hagemann, S., Kabat, P., Tallaksen, L. M., Warnaars, T., Wiberg, D., Weedon, G. P., Lanen, H. v., Ludwig, F., and Haddeland, I. (2011). WATCH: Current Knowledge of the Terrestrial Global Water Cycle, J. Hydrometeor., 12, 1149-1156, doi: 10.1175/jhm-d-11-024.1.

Hosking, J. R. M. and Wallis, J. R. (1986). Paleoflood Hydrology and Flood Frequency Analysis, Water Resources Research, 22:543-550.

Hosking, J. R. M., and Wallis, J. R. (1993). Some statistics useful in regional frequency analysis. Water Resources Research, 29(2), 271-281.

Hosking, J. R. M., Wallis, J. R. (1997). Regional Frequency Analysis. Cambridge University Press, Cambridge.

http://www.mathwave.com/easyfit-distribution-fitting.html.

http:/www.earth2observe.eu.

https://wci.earth2observe.eu/thredds/catalog.html.

https://wci.earth2observe.eu/thredds/catalog/ecmwf/wrr1/catalog.html.

https://wci.earth2observe.eu/thredds/catalog/univk/wrr1/catalog.html.

Jenkinson, A.F. (1955). The frequency distribution of the annual maximum (or minimum) of meteorological elements. Quarterly Journal of the Royal Meteorological Society 81, 158-171.

Loveland, T. R., Reed, B. C., Brown, J. F., Ohlen, D. O., Zhu, Z., Yang, L., and Merchant, J. W. (2000). Development of a global land covers characteristics database and IGBP DISCover from 1 km AVHRR data, Int. J. Remote Sens., 21, 1303-1330.

Moriasi, D.N., J.G. Arnold, M.W. van Liew, R.L. Bingner, R.D. Harmel, and T.L. Veith. (2007). Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. Transactions of the ASABE 50:885-900.

Nash JE, Sutcliffe JV. (1970). River flow forecasting through conceptual models: Part I a discussion of principles. Journal of Hydrology 10:282– 290.

Pilon, P. J. and Harvey, K. D. (1994). Consolidated frequency analysis, Reference manual, Environment Canada, Ottawa, Canada.

Rao, A. R. and Hamed, K. H. (2000). Flood frequency analysis.CRC Press, New York, NY.

Solaiman, T.A. (2011). Uncertainty Estimation of Extreme Precipitations Under Climatic Change: A Non-Parametric Approach. PhD Thesis, Department of Civil and Environmental Engineering, The University of Western Ontario.

Stedinger, J. R., Griffis, V. W. (2007). Log Pearson Type 3 Distribution and Its Application in Flood Frequency Analysis. I: Distribution Characteristics. Journal of Hydrologic Engineering, ASCE.

Verzano, K., Bärlund, I., Flörke, M., Lehner, B., Kynast, E., and Alcamo, J. (2012). Modeling variable river flow velocity on continental scale: Current situation and climate change impacts in Europe, J Hydrol, 424–425, 238-251, doi: http://dx.doi.org/10.1016/j.jhydrol.2012.01.005.

Viterbo, P., Beljaars, A., Mahfouf, J. F., and Teixeira, J. (1999). The representation of soil moisture freezing and its impact on the stable boundary layer, Quart. J. Roy. Meteor. Soc., 125, 2401-2426, doi: 10.1002/qj.49712555904.

WAPCOS. (1990). Preliminary Water Resources Development Master Plan for Ethiopia. vol. VII, Annex J: Hydropower, Ethiopia Valleys Development studies Authority, Report, Addis Ababa, Ethiopia.

Weedon, G. P., Balsamo, G., Bellouin, N., Gomes, S., Best, M. J., and Viterbo, P. (2014). The WFDEI meteorological forcing data set: WATCH Forcing Data methodology applied to ERA-Interim reanalysis data, Water Resources Research, 50, 7505-7514, doi: 10.1002/2014wr015638.

7. APPENDIXES

Appendix-A: Detail results of Reanalysis (ECMWF and UNIVK) and observed Annual Maximum (AM) discharge (m^3/s)

year	Gilgel Abbay at Marawi			Abbay at Kessie			Abbay near Bahirdar		
	Observed	ECMWF	UNIVK	Observed	ECMWF	UNIVK	Observed	ECMWF	UNIVK
1979	280.194	408.945	640.068	3490.419	5878.81	7250.21	271.858	139.165	272.935
1980	412.617	628.423	600.491	4318.97	5695.21	4477.05	280.976	149.155	531.191
1981	513.21	638.184	588.754	4481.363	7151.54	6440.34	324.248	144.157	661.409
1982	321.92	259.964	359.447	2589.145	3682.05	4702.42	209.088	84.6139	796.024
1983	324.641	433.672	469.306	3138.904	5503.52	4972.01	201.452	436.109	131.998
1984	330.124	324.621	421.803	1416.55	3459.08	3511.52	86.968	136.932	31.0008
1985	655.373	444.732	518.511	6113.373	6610.47	7087.06	319.257	152.981	83.4445
1986	241.825	272.149	342.663	3707.559	5035.06	5480.48	382.227	158.676	301.976
1987	253.46	236.258	262.343	1809.73	3533.85	4138.26	209.088	84.025	84.8498
1988	277.699	426.692	563.19	9329.956	8780.37	9030.15	658.134	248.018	749.931
1989	438.188	476.912	480.526	3976.746	5643.3	4664.47	382.227	131.452	332.592
1990	387.944	394.132	447.012	3059.355	5982.63	6123.97	285.602	238.381	198.367
1991	352.596	433.472	359.715	–	6115	4953.02	605.911	265.5	368.792
1992	412.617	352.283	386.605	3760.502	5910.93	5090.03	344.675	159.176	908.902
1993	381.915	923.722	801.838	5816.284	11636.9	8488.04	542.51	256.355	673.679
1994	308.515	269.87	458.16	9886.52	6743.23	5754.22	542.51	159.136	227.339
1995	464.665	318.249	451.824	7510.437	6091.2	6097.23	193.984	271.444	393.587
1996	364.159	284.338	212.526	13694.22	6933.49	6212.93	577.217	131.751	776.421
1997	358.35	320.162	277.442	–	5059.26	5903.3	280.976	193.494	202.196
1998	298.031	734.185	649.581	4115.557	9699.56	7639.25	704.959	782.022	984.07
1999	298.031	583.498	584.141	9675.565	6937.53	5404.82	528.985	253.265	727.936
2000	381.915	691.54	437.832	13608.51	8234.93	5496.68	483.239	388.586	77.0333
2001	303.247	430.063	542.512	13551.55	5800.42	5612.15	365.85	239.383	294.578
2002	303.247	310.667	311.952	5527.938	5594.19	5150.71	216.894	203.521	147.356

Year	Abbay at Border			Main Beles at Bridge		
	Observed	ECMWF	UNIVK	Observed	ECMWF	UNIVK
1979	6017.8415	12333.6	12341.1	168.007	376.382	531.854
1980	7933.8302	15908.3	11401.6	–	687.582	522.823
1981	6798.6361	26070.6	13141.6	–	589.494	500.175
1982	5720.7103	11527.8	10998.6	–	371.477	256.954
1983	7197.6681	15346.8	9950.11	747.83	364.033	532.323
1984	4470.7195	9087.36	7188.24	182.027	267.764	321.977
1985	8979.7706	13748.7	12385.7	1549.223	270.813	620.125
1986	5351.2879	12428.6	10101.6	481.15	262.091	337.615
1987	5637.395	16850.7	10782.1	645.733	264.907	254.63
1988	9280.4639	17534.4	15757.2	1061.615	395.637	486.146
1989	7585.1794	22156.6	13304.3	769.211	572.15	663.355
1990	6126.0521	26755.2	17454.5	766.782	939.601	632.121
1991	7634.4378	16034.2	12837	637.429	465.585	700.131
1992	6683.7484	20336.9	14274.4	585.366	344.203	502.532
1993	8239.8357	19433.8	13732.8	806.604	1131.94	621.055
1994	10659.459	18731.4	12579.6	506.989	293.889	443.527
1995	6235.3684	17525.4	12526.1	790.047	261.227	388.869
1996	9643.1602	22575.9	14156.3	526.909	245.348	320.936
1997	6360.9716	13752.5	11686.8	713.9	391.359	420.871
1998	9045.109	19523	13998.9	769.897	744.386	424.232
1999	8329.1037	11185.1	10524.8	579.844	556.173	428.009
2000	9189.8148	33697.1	19599.1	1032.074	1385.61	599.564
2001	9423.8562	22400.3	14722.5	737.258	284.641	709.679
2002	6060.9932	11720.2	10230	377.546	275.964	351.178
2003	8680.5556	14069.3	9745.6			
2004	6525.2743	8825.33	8904.48			
2005	6457.8127	24933.8	16508			
2006	11051.853	15001.6	13211.5			
2007	8086.004	24295.6	18582.2			

2008	8421.4075	18622.1	11975			
2009	8239.8357	13945.2	12699.4			

Appendix-B: Detail description of candidate probability distribution (GEV, EV1, LN3, LP3)

I. The Generalized Extreme Value Distribution (GEV)

The Generalized Extreme Value (GEV) Distribution was introduced by Jenkinson (1955). It combines into a single form the three possible types of limiting distribution for extreme values, as derived by Fisher and Tippett (1928). The GEV is probably the most widely used distribution when measuring AM series of river flow.

The probability density function of the GEV distribution is given as:

$$f(x) = \frac{1}{\sigma} \exp\left[-\left(1 + k\left(x - \frac{\mu}{\sigma}\right)\right)^{-\frac{1}{k}}\right]\left[1 + k\left(x - \frac{\mu}{\sigma}\right)\right]^{-1-1/k} \text{.........................Eqn.B.1}$$

Where,

σ = Scale parameter

μ = Location parameter

k = Shape parameter

The cumulative distribution function of GEV distribution is of the form:

$$F(x) = \exp\left[-\left(1 + k\left(x - \frac{\mu}{\alpha}\right)\right)^{-\frac{1}{k}}\right] \text{..Eqn.B.2}$$

The inverse cumulative functions X, of this distribution is estimated as:

$$X = \mu + \frac{\sigma}{k}\left[1 - (-\ln F)^{k}\right] \text{..Eqn.B.3}$$

By inserting probability of non-exceedence, F = 1-1/T where T is the return period, the T-year flow quantile estimate is obtained as:

$$X_T = \mu + \frac{\sigma}{k}\left[1 - \left(-\ln\left(1 - \frac{1}{T}\right)\right)^{k}\right] \text{...Eqn.B.4}$$

II. Extreme Value type I (EV1)

The Extreme Value type 1 (EV1) distribution only uses two parameters, location (μ) and scale (σ). This is the current required method for all floods Frequency Analysis in Canada.

The probability density function of the EV1 distribution is defined as:

$$f(x) = \frac{1}{\sigma} \exp\left[-\left(\frac{x-\mu}{\sigma}\right) - \exp\left(-\left(\frac{x-\mu}{\sigma}\right)\right)\right] \text{..........Eqn.B.5}$$

The cumulative distribution function is given as:

$$F(x) = \exp\left[-\exp\left(-\left(\frac{x-\mu}{\sigma}\right)\right)\right] \text{..........Eqn.B.6}$$

Where,

σ = Scale parameter

μ = Location parameter

The inverse cumulative functions X, of this distribution is estimated as:

$$X(F) = \mu - \sigma \ln(-\ln F) \text{..........Eqn.B.7}$$

By inserting probability of non-exceedence, F = 1-1/T where T is the return period, the T-year flow quantile estimate is obtained as

$$X_T = \mu - \sigma \ln\left[-\ln\left(1 - \frac{1}{T}\right)\right] \text{..........Eqn.B.8}$$

III. Three-parameter Lognormal (LN3) distribution

Three-parameter lognormal distribution is similar to the two-parameter lognormal (LN2) distribution except that x is shifted by an amount (γ) which represents a lower bound. The normally distributed variable becomes ln(x-γ) with the probability density function given as:

$$f(x) = \frac{\exp\left[-\frac{1}{2}\left(\frac{\ln(x-\gamma)-\mu_y}{\sigma_y}\right)^2\right]}{(x-\gamma)\sigma_y\sqrt{2\pi}} \text{..........Eqn.B.9}$$

Cumulative distribution function is obtained in the form:

$$F(x) = \Phi\left(\frac{\ln(x-\gamma)-\mu_y}{\sigma_y}\right) \text{..........Eqn.B.10}$$

Where $\mu_y \sigma_y$ and γ are, respectively, scale, shape and location parameters for transformed variate ln(x- γ) and Φ = Standard normal distribution function for transformed variate ln(x- γ).

The LN3 inverse distribution function is:

$$X(F) = \gamma + \exp\left[\mu_y + \sigma_y \Phi^{-1}(F)\right] \text{..........} \text{Eqn.B.11}$$

By substituting probability of non-exceedence F = 1-1/T, where T is a return period, the T-year flow quantile is obtained as:

$X_T = \gamma + \exp\left[\mu_y + \sigma_y \Phi^{-1}(1 - 1/T)\right]$, Where Φ^{-1} is inverse normal distribution

IV. Log-Pearson III (LP3) Distribution

The LP3 distribution is a member of the family of Pearson Type 3 distributions, and is also referred to as the Gamma distribution. This is the current required method to be used for all floods Frequency Analysis in the United States. The LP3 distribution is complicated, as it has two interacting shape parameters (Stedinger, 2007). Similar to GEV it uses three parameters, shape (α), scale (β) and location (γ).

The probability density function of a LP3 distributed random variable is given by:

$$f(x) = \frac{1}{|\beta|\Gamma(\alpha)} \left(\frac{\ln(x) - \gamma}{\beta}\right)^{\alpha - 1} \exp\left(-\frac{\ln(x) - \gamma}{\beta}\right) \text{..........} \text{Eqn.B.12}$$

The cumulative distribution function is determined as:

$$F(x) = \frac{\Gamma(\ln(x) - \gamma)\ (\alpha)}{\beta\Gamma(\alpha)} \text{..........} \text{Eqn.B.13}$$

The LP3 inverse distribution function is:

$$\ln x_T = \gamma + \beta\left(\frac{\Phi^{-1}(F)}{3\alpha^{1/6}} - \frac{1}{9\alpha^{2/3}} + \alpha^{1/3}\right)^3 \text{..........} \text{Eqn.B.14}$$

By substituting probability of non-exceedence F = 1-1/T, where T is a return period, the T-year flow quantile is obtained as:

$\ln x_T = \gamma + \beta\left(\frac{\Phi^{-1}(1-1/T)}{3\alpha^{1/6}} - \frac{1}{9\alpha^{2/3}} + \alpha^{1/3}\right)^3$, Where Φ^{-1} represent inverse normal distribution.

For, $\beta = \frac{\sigma_y C_s}{2}$

$\alpha = \left(\frac{2}{C_s}\right)^2$

$\gamma = \mu_y - \frac{2 * \sigma_y}{C_s}$

Where μ_y, σ_y, Cs $_{and}$ represent mean, standard deviation and coefficient of skewness for a natural logarithm, y = lnx

Then the value of flow quantile at a return period T is given as follow:

$X_T = \exp(\ln x_T) = e^{\ln x_T}$...Eqn.B.15

Appendix-C: Methods of parameter estimation for candidate probability distributions

I. Method of moments (MOM)

The j-th sample moment of a random variable is defined as,

$E(x^j) = \frac{1}{n}\sum_{i=1}^{n} x_i^j \; E(x^j) \frac{1}{n}\sum_{i=1}^{n} x_i^j$...Eqn.C.1

Where x are the sample observation values, n is the sample size.

The j-th moment of a random variable of a distribution with probability distribution function (PDF) of f(x), is defined as,

$E(x^j) = \int_{-\infty}^{+\infty} x^j f(x)dx E(x^j) = \int_{-\infty}^{+\infty} x^j f(x)dx$..Eqn.C.2

If there are k parameters to be estimated for the distribution, the following system of equations can be obtained based the equation of j-th moment,

$E(x^j) = \int_{-\infty}^{+\infty} x^j f(x)dx = \frac{1}{n}\sum_{i=1}^{n} x_i^j \quad j = 1,2,\ldots,k$ Eqn.C.3

The k unknown parameters can be obtained by solving the above system of equations simultaneously.

II. Maximum likelihood method (MLM)

For a distribution with a PDF given by f(x) and parameters $\alpha_1, \alpha_2, \ldots, \alpha_k$, the likelihood function is defined as

$L(\alpha_1, \alpha_2, \ldots, \alpha_k) = \prod_{i=1}^{n} f(x_i\, \alpha_1 \alpha_2, \ldots \alpha_k)$..Eqn.C.4

The best value of a parameter should be the value that maximizes the likelihood L of occurrence of the observed sample; hence, the parameters $\alpha_1, \alpha_2, \ldots, \alpha_k$ be estimated by solving the following system of partial differentiation equations,

$\frac{dL(\alpha_1 \alpha_2, \ldots \alpha_k)}{d\alpha_j} = 0; j = 1,2,\ldots,k$ Eqn.C.5

In many cases, it is more convenient to work with the log-likelihood function

$$\frac{d(\ln L(\alpha_1 \alpha_2, .. \alpha_k))}{d\alpha_j} = 0; j = 1,2, .. k$$ Eqn.C.6

III. L-Moment Equations

The following L-Moments are defined in (Cunnane, 1989):

λ1= L1 =M100...Eqn.C.7

λ2= L2 =2M110 - M100...Eqn.C.8

λ3= L3 =6M120 - 6M110 + M100..Eqn.C.9

λ4= L4 =20M130 - 30M120 + 12M110 - M100...Eqn.C.10

The 4 L-Moments (λ1, λ2, λ3, λ4) are all derived using the 4 PWMs. Other useful ratios are L-CV (τ2), L-Skewness (τ3) and L-Kurtosis (τ4).

PWMs are needed for the calculation of L-Moments. The data first must be arranged in ascending order, and then apply the following equations.

M100= sample mean = $\frac{1}{N}\sum_{i=1}^{N} Q_i$..Eqn.C.11

M110 = $\frac{1}{N}\sum_{i=1}^{N} \frac{i-1}{N-1} Q_i$..Eqn.C.12

M120 = $\frac{1}{N}\sum_{i=1}^{N} \frac{(i-1)(i-2)}{(N-1)(N-2)} Q_i$...Eqn.C.13

M130 = $\frac{1}{N}\sum_{i=1}^{N} \frac{(i-1)(i-2)(i-3)}{(N-1)(N-2)(N-3)} Q_i$...Eqn.C.14

In which N is the sample size, Q is the data value, and i is the rank of the value in ascending order.

L-CV is similar to the normal coefficient of variation (CV). The standard equation for CV = standard deviation/mean, and shows how the data set varies. The larger the CV value, the larger the variation of the data set from the mean.

τ2 = L2/L1 (L-CV)...Eqn.C.15

L-Skewness is a measure of the lack of symmetry in a distribution. If the value is negative, the left tail is long compared with the right tail, and if the value is positive, the right tail is longer.

For GEV frequency analysis, a positive L-Skewness value is desired, as we are interested in the extreme events that occur in the right side tail of the distribution.

$\tau 3 = L3/L2$ (L-Skewness)...Eqn.C.16

I. Three-parameter lognormal (LN3) distribution parameter estimation

Table C-1 Equations for 3-parameter lognormal distribution parameter estimation using maximum likelihood method (MLM)

Parameters	MLM
μ	$\mu_y = \frac{1}{n}\sum_{i=1}^{n}\ln(x_i - \gamma)$
σ	$\sigma_y = \left(\frac{1}{n}\sum_{i=1}^{n}\left[\ln(x_i - \gamma) - \mu_\gamma\right]^2\right)^{05}$
γ	$\gamma = \sum_{i=1}^{n}(x_i - \gamma)^{-1}\left(\mu_y - \sigma_y^2\right) = \sum_{i=1}^{n}\frac{\ln(x_i-\gamma)}{(x_i-\gamma)}$

II. Log-Pearson III (LP3) distribution parameter estimation

One indirect method to estimate the parameters of the log-Pearson III distribution is to transfer the variable to y = lnx, and then estimate the parameters as for a Pearson III distribution.

Table C-2 Equations for LP3 distribution parameter estimation using method of moment (MOM)

Parameters	MOM
β	$\beta = \frac{\sigma_y C_s}{2}$
α	$\alpha = \left(\frac{2}{C_s}\right)^2$
γ	$\gamma = \mu_y - \frac{2*\sigma_y}{C_s}$

III. Extreme Value type 1 (EV1) distribution parameter estimation

Table C-3 Equations for EV1 distribution parameter estimation using method of moment (MOM)

Parameters	MOM
σ	$\sigma = \frac{\sqrt{6}}{\pi} m_2$
μ	$\mu = m_1' - 0577\ 2157\sigma$

Where $m_2 =$ standard deviation and $m_1' =$ mean of variable data

IV. Generalized Extreme Value (GEV) distribution parameter estimation

Table C-4 Equations for GEV distribution parameter estimation using L-moment method

Parameters	L-moment
k	$k = 7859\ 0c + 29554c$
σ	$\sigma = \frac{\lambda_2 * k}{(1-2^{-k})\Gamma(1+k)}$
μ	$\mu = \lambda_1 - \sigma\{1 - \Gamma(1+k)\}/k$

In which $c = \frac{2}{3+\tau 3} - \frac{\ln 2}{\ln 3}$ and Γ = the gamma function

Appendix-D: Detail results of Kolmogorov and Chi-square test for observed AM Discharge

Table-D1 Result of Kolmogorov-smirnov test for observed Annual Maximum (AM) Discharge

Name of stations	Distributions	Statistic	Critical at α=0.1	p-value	Remark	Selected Distribution
Gilgel Abbay at Marawi	LN3	0.079	0.242	0.995	Accepted	GEV
	LP3	0.088	0.242	0.984	Accepted	
	GEV	0.076	0.242	0.984	Accepted	
	EV1	0.092	0.242	0.976	Accepted	
Abbay near Kessie	LN3	0.102	0.247	0.952	Accepted	LN3
	LP3	0.124	0.247	0.276	Accepted	
	GEV	0.129	0.247	0.791	Accepted	
	EV1	0.148	0.247	0.639	Accepted	
Abbay at Bahirdar	LP3	0.109	0.242	0.905	Accepted	LP3
	GEV	0.128	0.242	0.777	Accepted	
	LN3	0.107	0.242	0.917	Accepted	
	EV1	0.133	0.242	0.738	Accepted	
Main Beles at Bridge	EV1	0.143	0.258	0.728	Accepted	EV1
	LN3	0.169	0.258	0.526	Accepted	
	GEV	0.174	0.258	0.494	Accepted	
	LP3	0.210	0.258	0.268	Accepted	
Abbay at Border	GEV	0.092	0.214	0.932	Accepted	GEV
	EV1	0.131	0.214	0.615	Accepted	
	LP3	0.094	0.214	0.923	Accepted	
	LN3	0.101	0.214	0.876	Accepted	

Table-D2 Result of Chi-square test for observed Annual Maximum (AM) Discharge

Name of stations	Distributions	Statistic	Critical at α=0.1	P-value	Remark	Selected
Gilgel Abbay at Marawi	GEV	0.014	2.705	0.906	Accepted	LP3
	LP3	0.012	2.705	0.599	Accepted	
	LN3	0.277	2.705	0.898	Accepted	
	EV1	0.519	2.705	0.471	Accepted	
Abbay near Kessie	GEV	0.495	4.605	0.781	Accepted	GEV
	EV1	3.055	4.605	0.217	Accepted	
Abbay at Bahirdar	EV1	0.496	4.605	0.780	Accepted	EV1
	GEV	0.781	4.605	0.677	Accepted	
	LN3	0.793	4.605	0.673	Accepted	
	LP3	0.819	4.605	0.664	Accepted	
Main Beles at Bridge	LN3	0.054	2.705	0.817	Accepted	LN3
	GEV	0.063	2.705	0.803	Accepted	
	EV1	1.102	2.705	0.294	Accepted	
Abbay at Border	GEV	1.022	6.251	0.796	Accepted	GEV
	EV1	2.060	6.251	0.560	Accepted	
	LP3	1.085	6.251	0.781	Accepted	
	LN3	1.121	6.251	0.772	Accepted	

Appendix-E: Detail results of Kolmogorov and Chi-square test for ECMWF reanalysis

Table-E1 Result of Kolmogorov-Smirnov test for ECMWF reanalysis AM discharge

Name of stations	Distributions	Statistic	Critical at α=0.1	p-value	Remark	Selected
Gilgel Abbay at Marawi	LN3	0.103	0.242	0.936	Accepted	GEV
	LP3	0.105	0.242	0.929	Accepted	
	GEV	0.097	0.242	0.962	Accepted	
	EV1	0.130	0.242	0.761	Accepted	
Abbay near Kessie	LN3	0.169	0.253	0.503	Accepted	LN3
	LP3	0.173	0.253	0.472	Accepted	
	GEV	0.183	0.253	0.401	Accepted	
	EV1	0.182	0.253	0.408	Accepted	
Abbay at Bahirdar	LP3	0.139	0.242	0.689	Accepted	LN3
	GEV	0.138	0.242	0.694	Accepted	
	LN3	0.128	0.242	0.774	Accepted	
	EV1	0.195	0.242	0.282	Accepted	
Main Beles at Bridge	EV1	0.232	0.258	0.176	Accepted	LP3
	LN3	0.092	0.258	0.987	Accepted	
	GEV	0.143	0.258	0.728	Accepted	
	LP3	0.142	0.258	0.737	Accepted	
Abbay at Border	GEV	0.061	0.214	0.999	Accepted	GEV
	LP3	0.064	0.214	0.998	Accepted	
	LN3	0.068	0.214	0.996	Accepted	
	EV1	0.073	0.214	0.991	Accepted	

Table-E2 Result of Chi-square test for ECMWF reanalysis AM Discharge

Name of stations	Distributions	Statistic	Critical at α=0.1	P-value	Remark	Selected
Gilgel Abbay at Marawi	GEV	0.396	4.605	0.820	Accepted	LP3
	LP3	0.401	4.605	0.818	Accepted	
	LN3	0.251	6.251	0.969	Accepted	
	EV1	0.965	4.605	0.617	Accepted	
Abbay near Kessie	GEV	1.144	4.605	0.564	Accepted	LN3
	EV1	1.145	4.605	0.564	Accepted	
	LN3	0.928	4.605	0.628	Accepted	
	LP3	0.952	4.605	0.621	Accepted	
Abbay at Bahirdar	EV1	4.583	6.251	0.205	Accepted	GEV
	GEV	0.849	2.705	0.357	Accepted	
	LP3	0.919	2.705	0.337	Accepted	
Main Beles at Bridge	LN3	0.759	4.605	0.684	Accepted	EV1
	GEV	2.158	4.605	0.339	Accepted	
	EV1	0.768	2.705	0.380	Accepted	
	LP3	1.687	4.605	0.430	Accepted	
Abbay at Border	GEV	0.694	7.779	0.952	Accepted	GEV
	LP3	0.709	7.779	0.950	Accepted	
	LN3	0.717	7.779	0.949	Accepted	
	EV1	0.722	7.779	0.948	Accepted	

Appendix-F: Detail results of Kolmogorov and Chi-square test for UNIVK reanalysis AM discharge

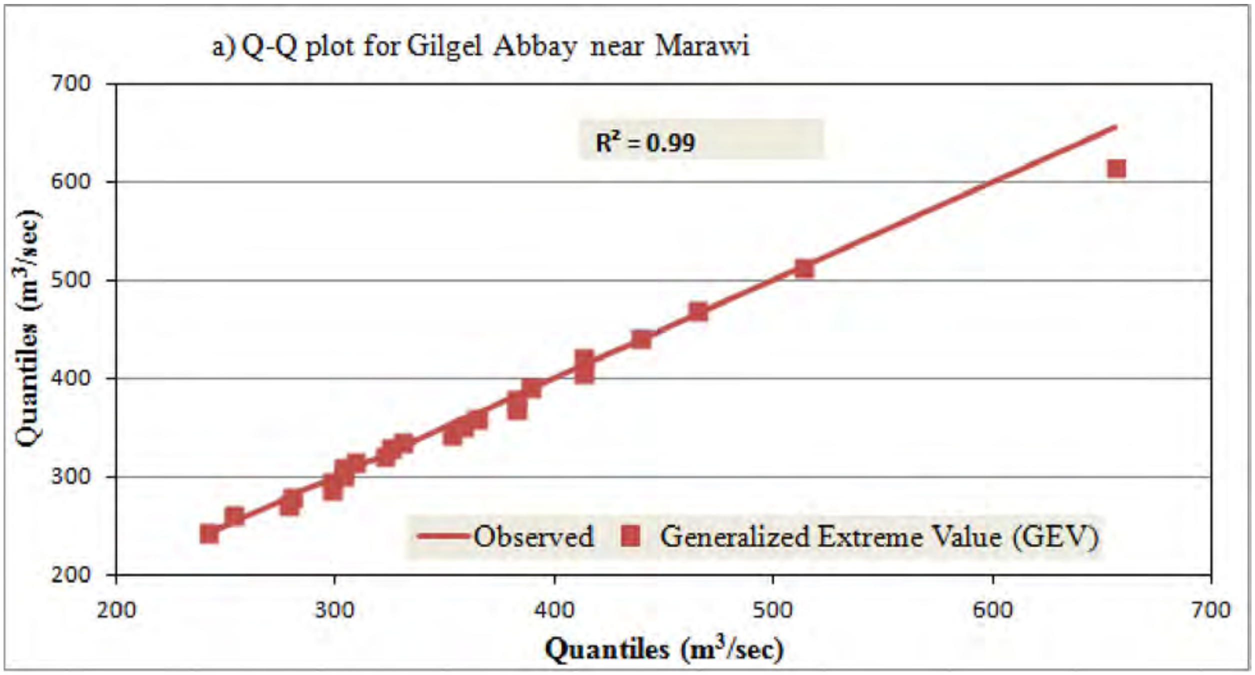
Table-F1 Result of Kolmogorov-Smirnov test for UNIVK reanalysis AM discharge

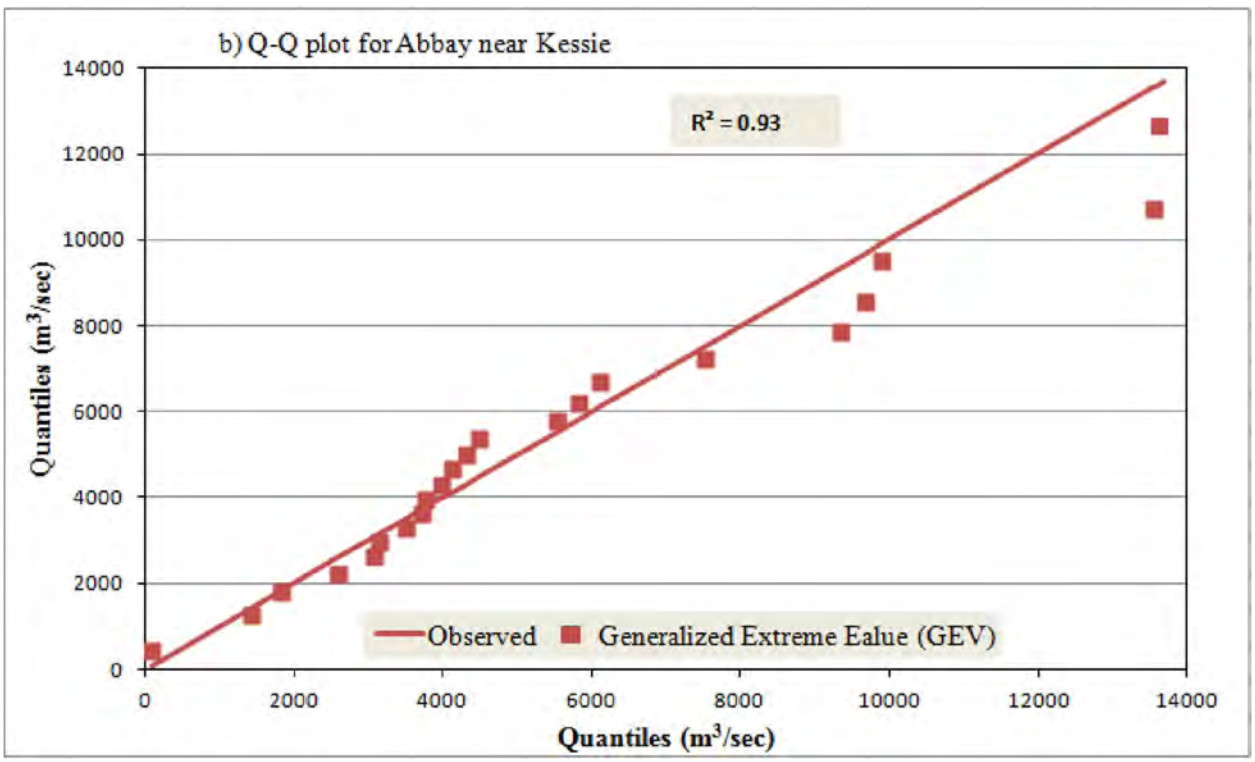
Name of stations	Distributions	Statistic	Critical at α=0.1	p-value	Remark	Selected
Gilgel Abbay at Marawi	LN3	0.082	0.242	0.992	Accepted	GEV
	LP3	0.075	0.242	0.997	Accepted	
	GEV	0.069	0.242	0.999	Accepted	
	EV1	0.111	0.242	0.897	Accepted	
Abbay near Kessie	LN3	0.074	0.253	0.999	Accepted	EV1
	LP3	0.077	0.253	0.997	Accepted	
	GEV	0.066	0.253	0.999	Accepted	
	EV1	0.064	0.253	0.999	Accepted	
Abbay at Bahirdar	LP3	0.134	0.242	0.729	Accepted	GEV
	GEV	0.145	0.242	0.643	Accepted	
	LN3	0.154	0.242	0.564	Accepted	
	EV1	0.158	0.242	0.535	Accepted	
Main Beles at Bridge	EV1	0.151	0.258	0.665	Accepted	GEV
	LN3	0.129	0.2528	0.826	Accepted	
	GEV	0.110	0.258	0.937	Accepted	
	LP3	0.123	0.258	0.867	Accepted	
Abbay at Border	LN3	0.079	0.214	0.980	Accepted	LN3
	LP3	0.085	0.214	0.965	Accepted	
	GEV	0.089	0.214	0.944	Accepted	
	EV1	0.109	0.214	0.812	Accepted	

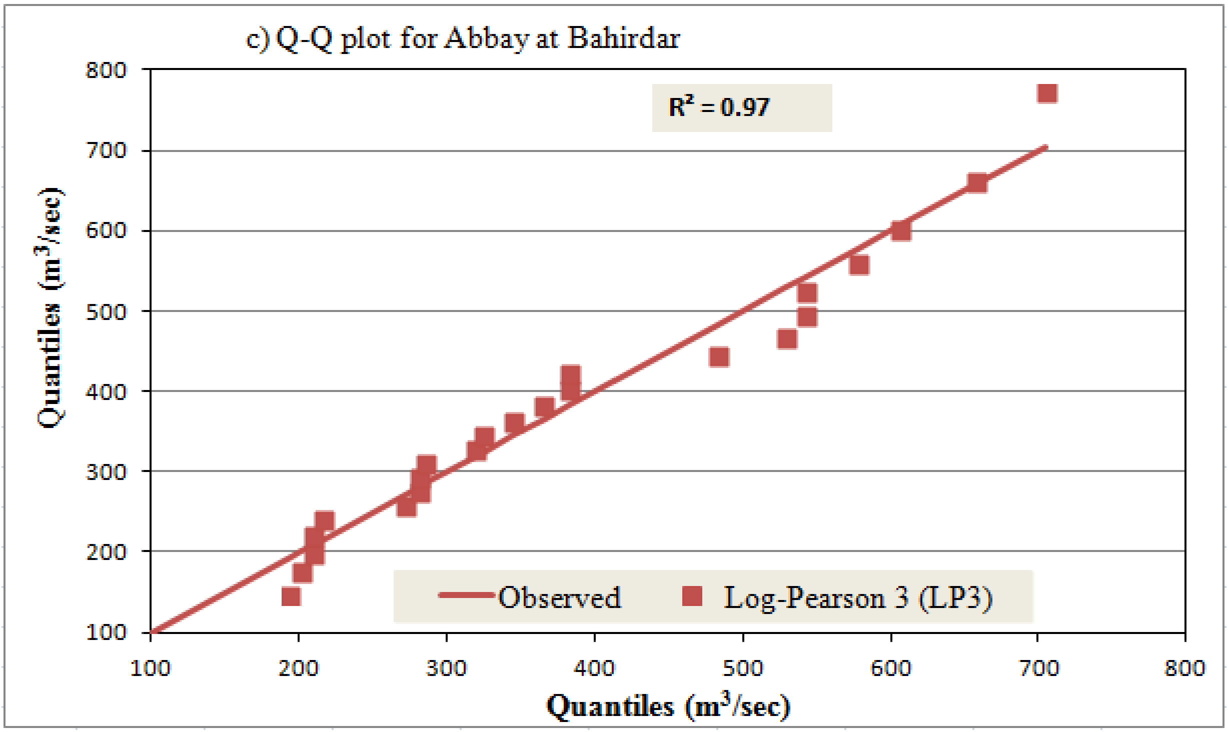
Table-F2 Result of Chi-square test for UNIVK reanalysis AM discharge

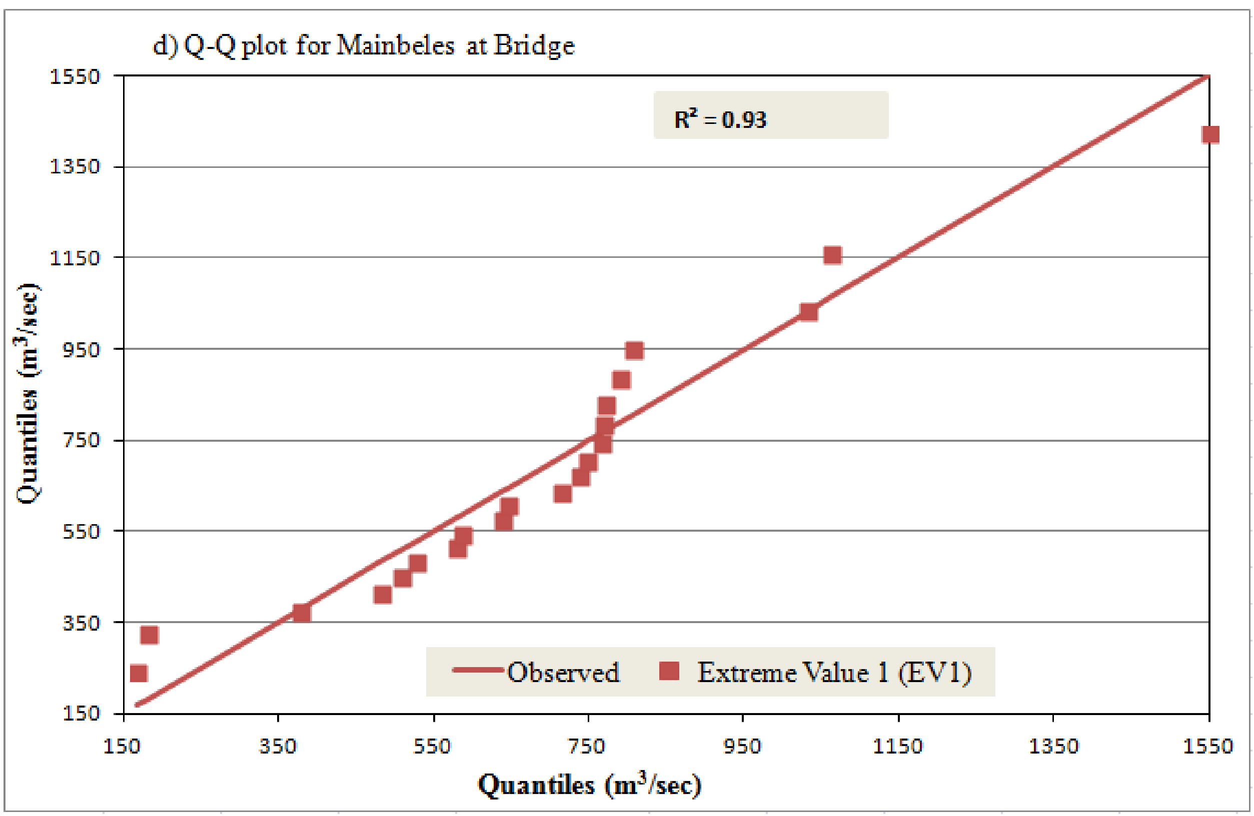
Name of stations	Distributions	Statistic	Critical at α=0.1	P-value	Remark	Selected
Gilgel Abbay at Marawi	GEV	0.091	4.605	0.955	Accepted	EV1
	LP3	0.105	4.605	0.948	Accepted	
	LN3	0.096	4.605	0.952	Accepted	
	EV1	0.025	4.605	0.987	Accepted	
Abbay near Kessie	GEV	0.205	4.605	0.903	Accepted	LP3
	EV1	0.113	4.605	0.945	Accepted	
	LN3	0.081	4.605	0.960	Accepted	
	LP3	0.069	4.605	0.965	Accepted	
Abbay at Bahirdar	EV1	0.992	4.605	0.608	Accepted	LN3
	GEV	1.019	4.605	0.600	Accepted	
	LP3	0.044	4.605	0.978	Accepted	
	LN3	0.328	4.605	0.848	Accepted	
Main Beles at Bridge	LN3	0.750	4.605	0.687	Accepted	LP3
	GEV	0.658	4.605	0.719	Accepted	
	EV1	0.715	4.605	0.699	Accepted	
	LP3	0.146	4.605	0.929	Accepted	
Abbay at Border	LN3	1.970	7.779	0.741	Accepted	EV1
	LP3	1.986	7.779	0.738	Accepted	
	GEV	1.373	7.779	0.848	Accepted	
	EV1	0.573	7.779	0.966	Accepted	

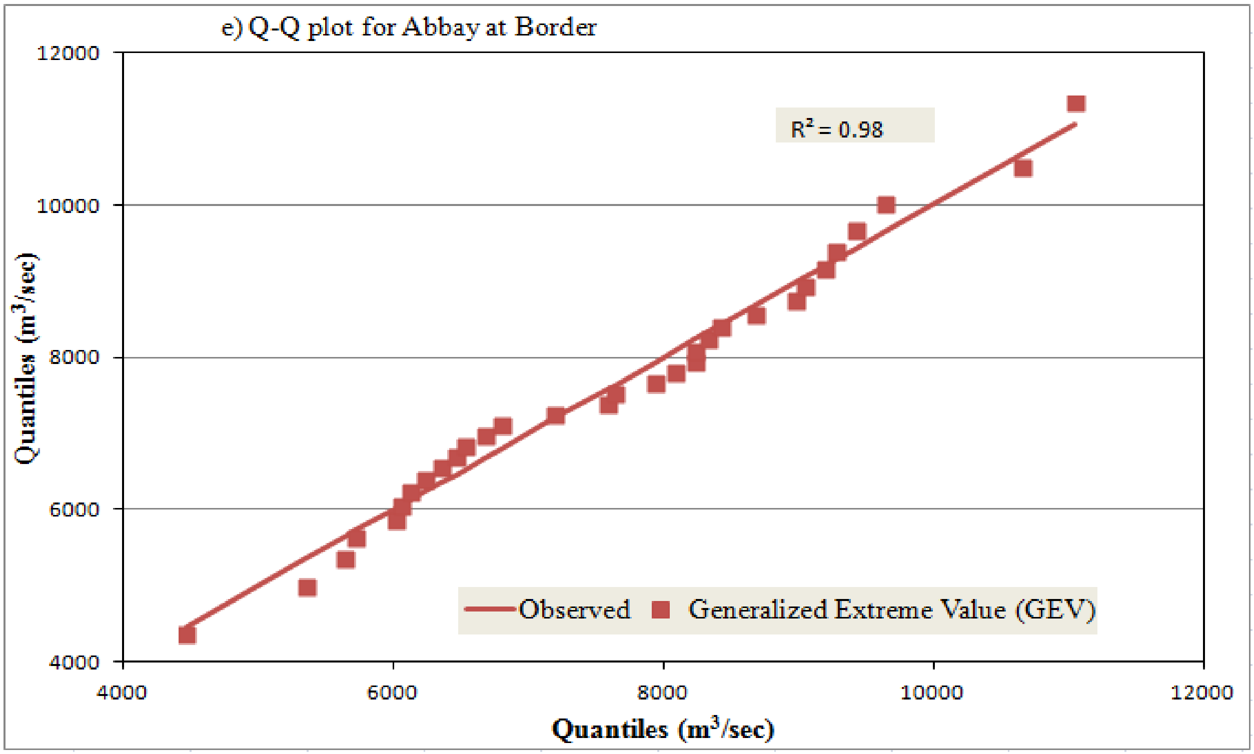
Appendix-G: Quantile-Quantile plot and R^2 results for observed AM Discharge



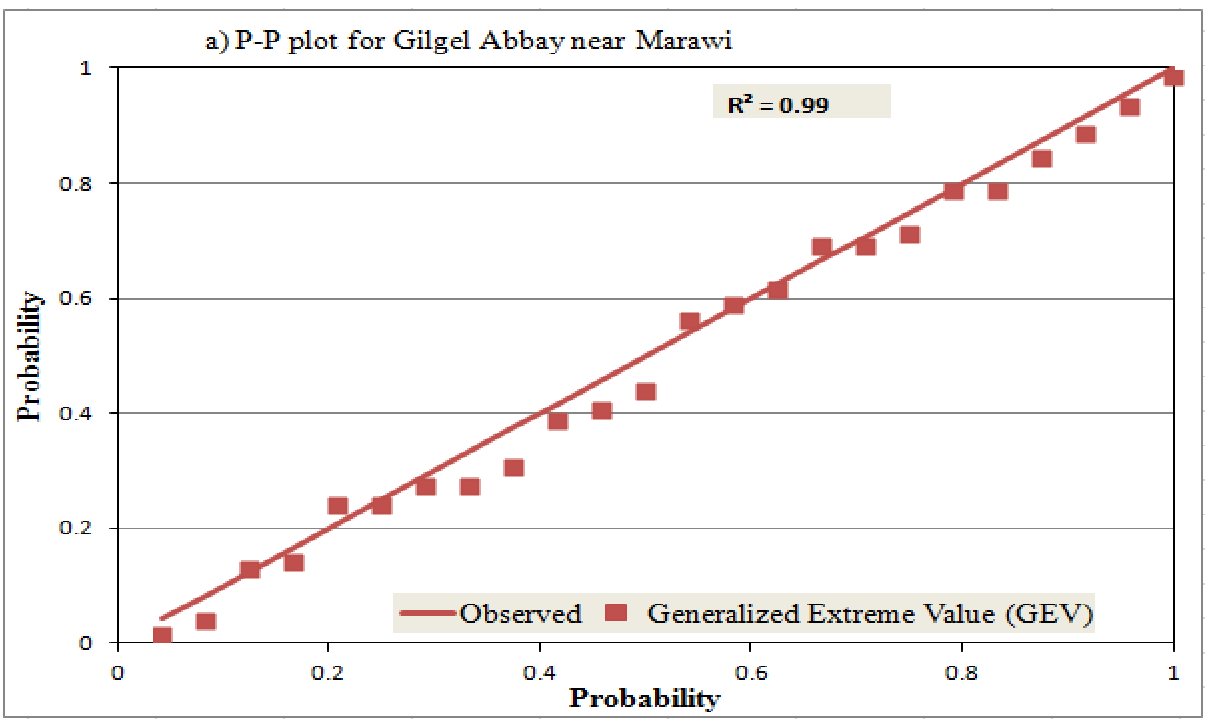


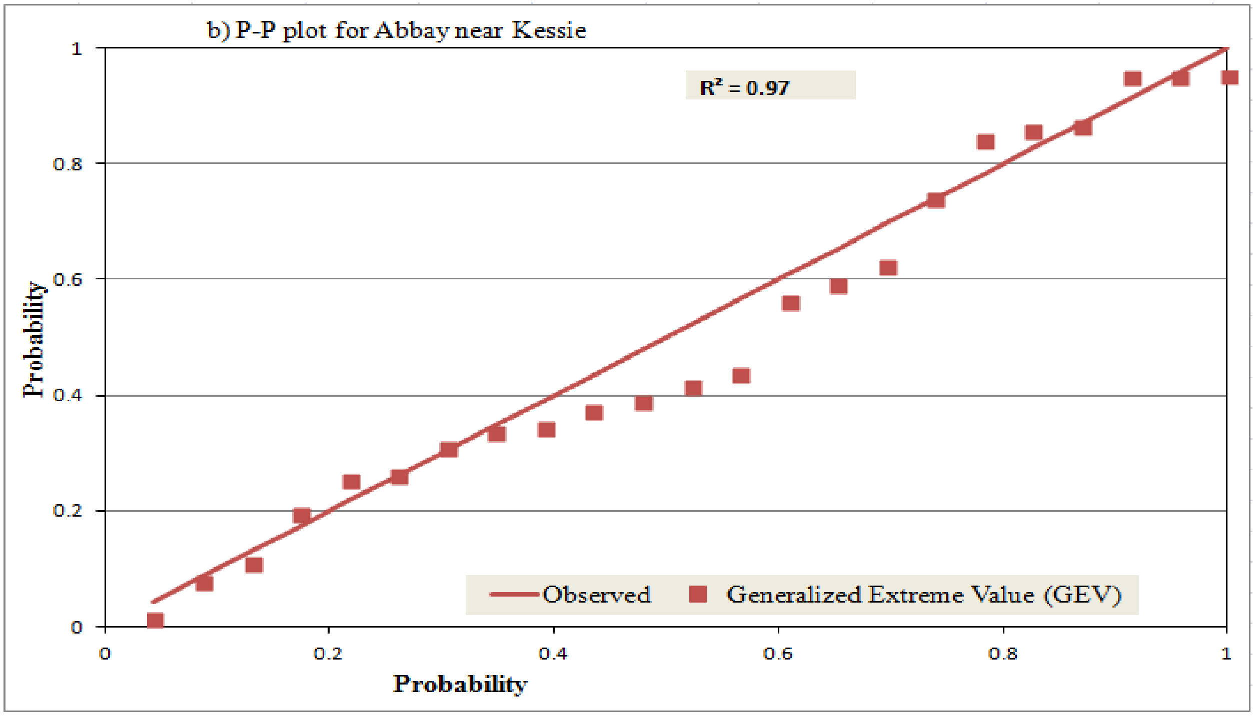

c) Q-Q plot for Abbay at Bahirdar
$R^2 = 0.97$
Observed
Log-Pearson 3 (LP3)
Quantiles (m^3/sec)
Quantiles (m^3/sec)
800
700
600
500
400
300
200
100
100
200
300
400
500
600
700
800

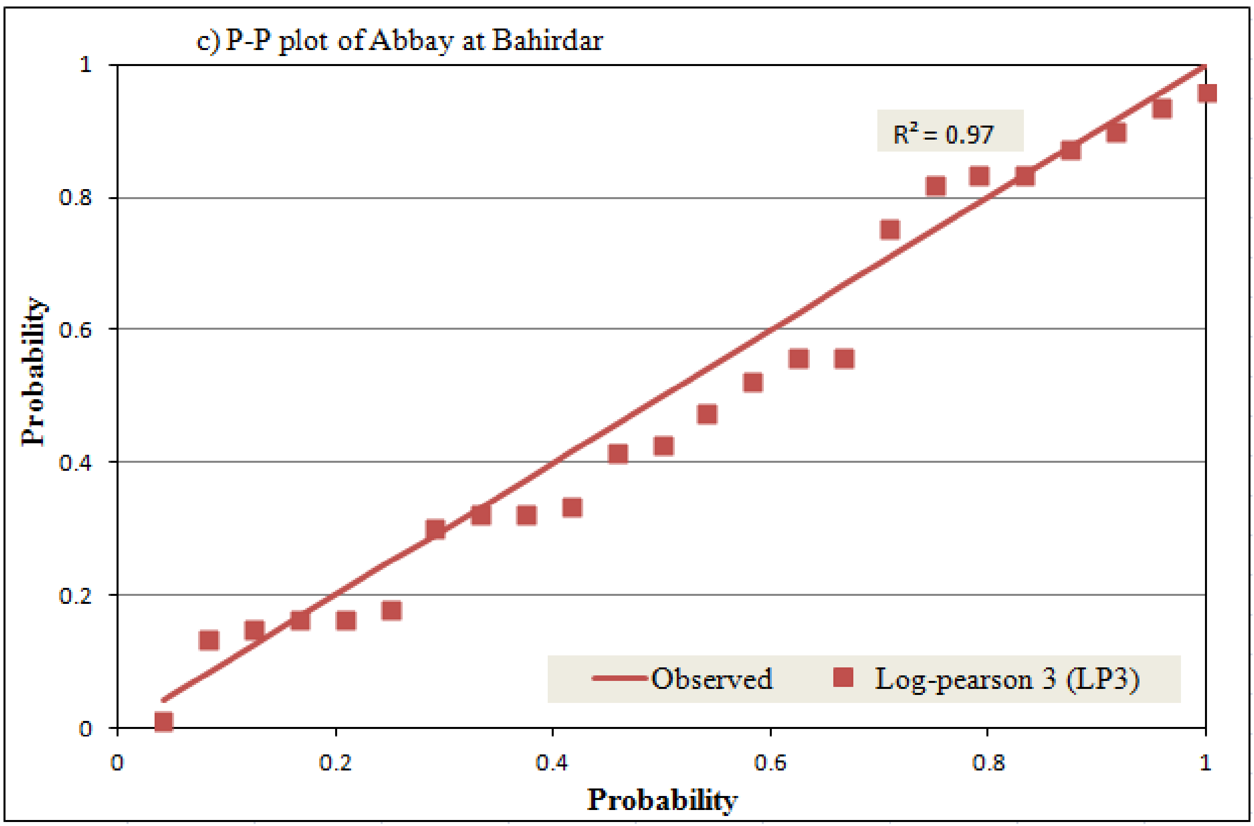

d) Q-Q plot for Mainbeles at Bridge
$R^2 = 0.93$
Observed
Extreme Value 1 (EV1)
Quantiles (m^3/sec)
Quantiles (m^3/sec)
1550
1350
1150
950
750
550
350
150
150
350
550
750
950
1150
1350
1550

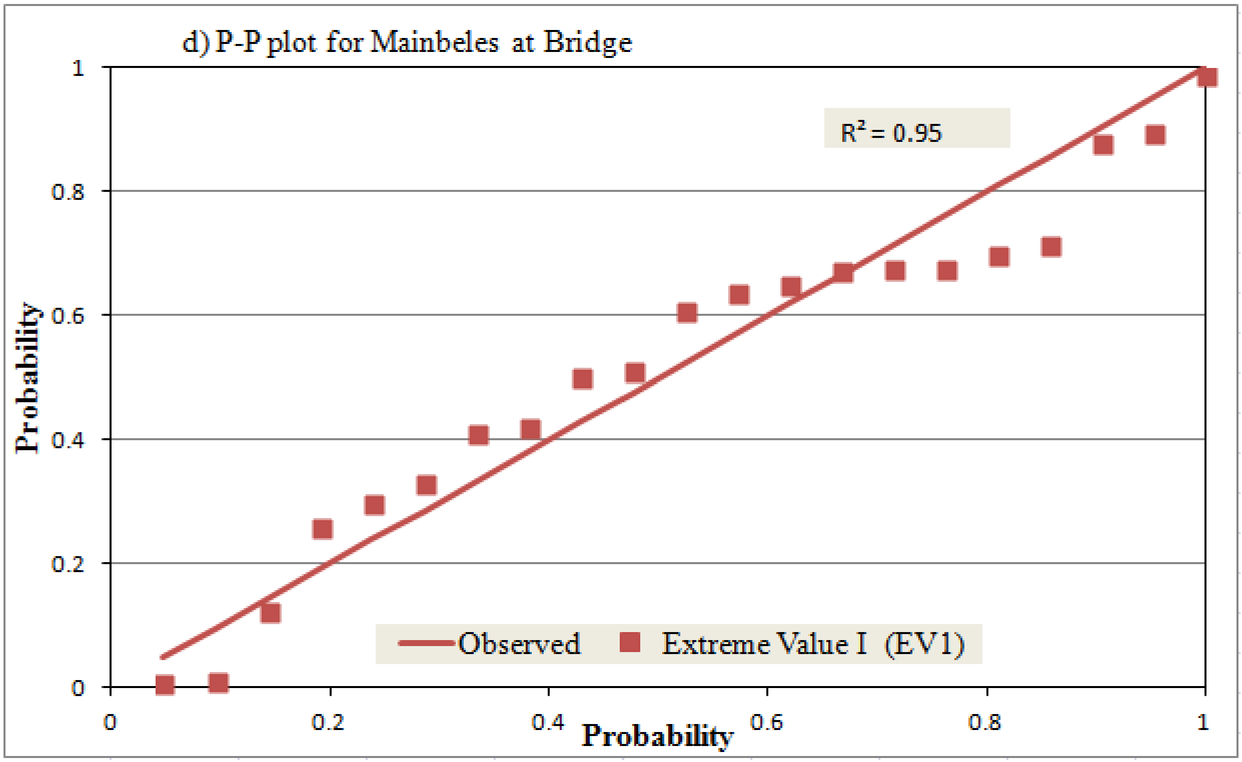


Appendix-H: Probability-Probability plot and R^2 results for Observed AM discharge

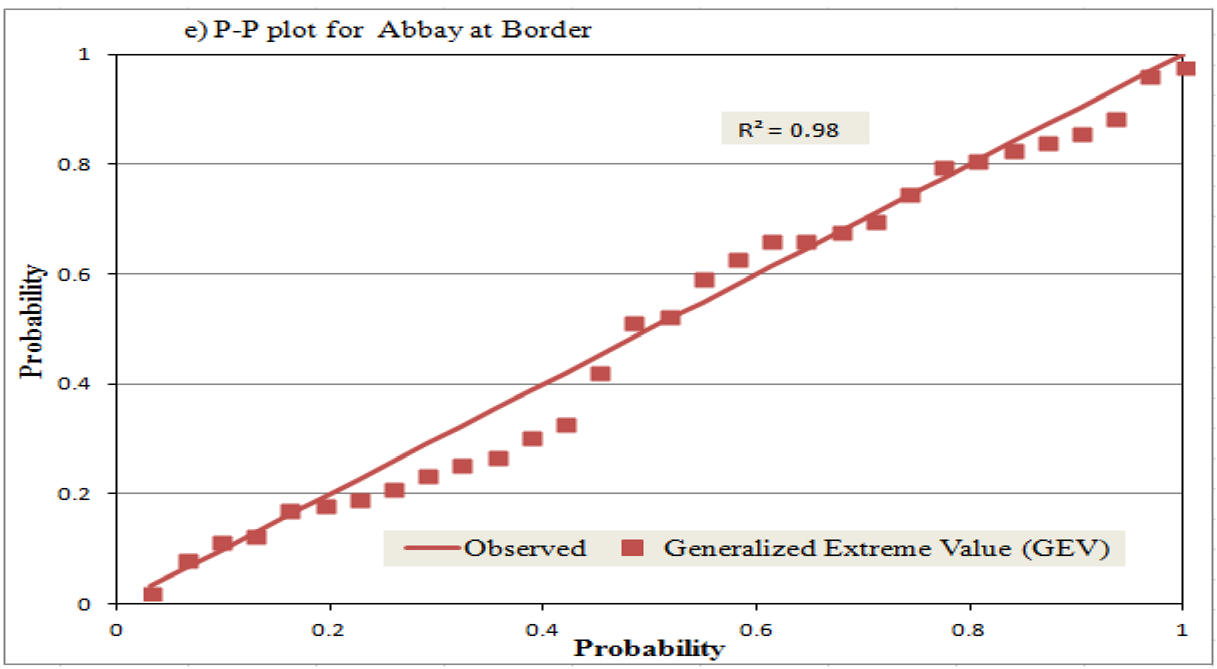



b) P-P plot for Abbay near Kessie
R² = 0.97
Observed
Generalized Extreme Value (GEV)
Probability
Probability
0
0.2
0.4
0.6
0.8
1


c) P-P plot of Abbay at Bahirdar
R² = 0.97
Observed
Log-pearson 3 (LP3)
Probability
Probability
0
0.2
0.4
0.6
0.8
1

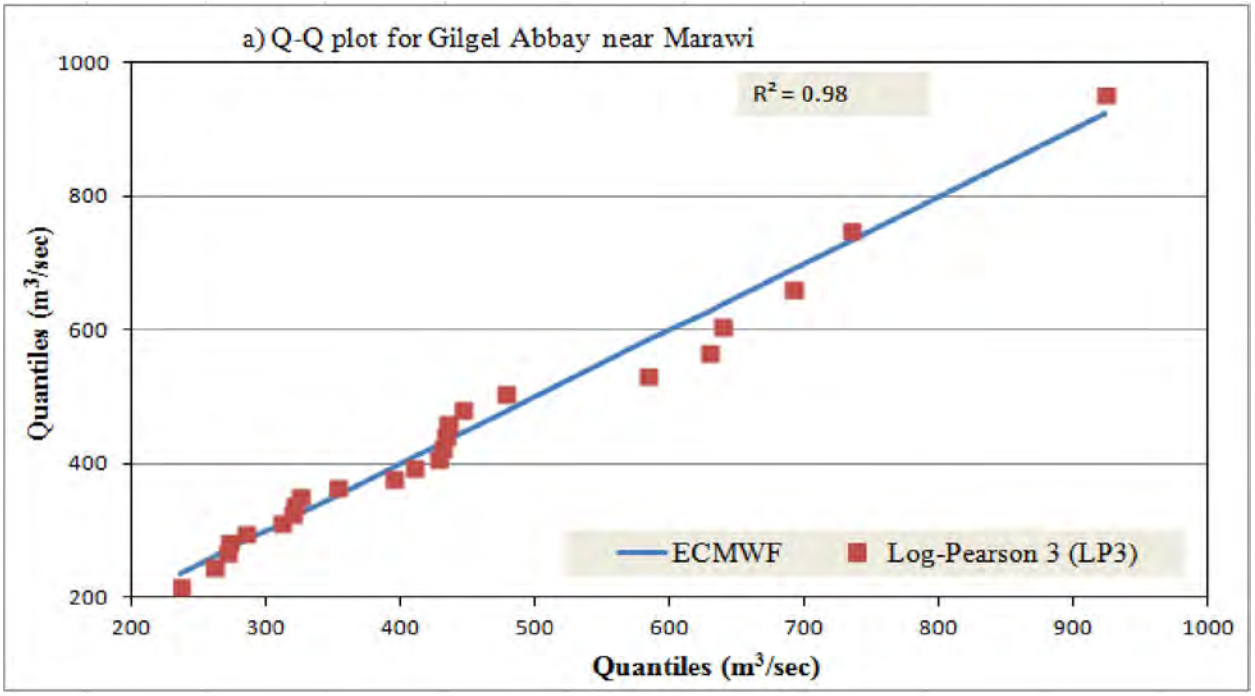


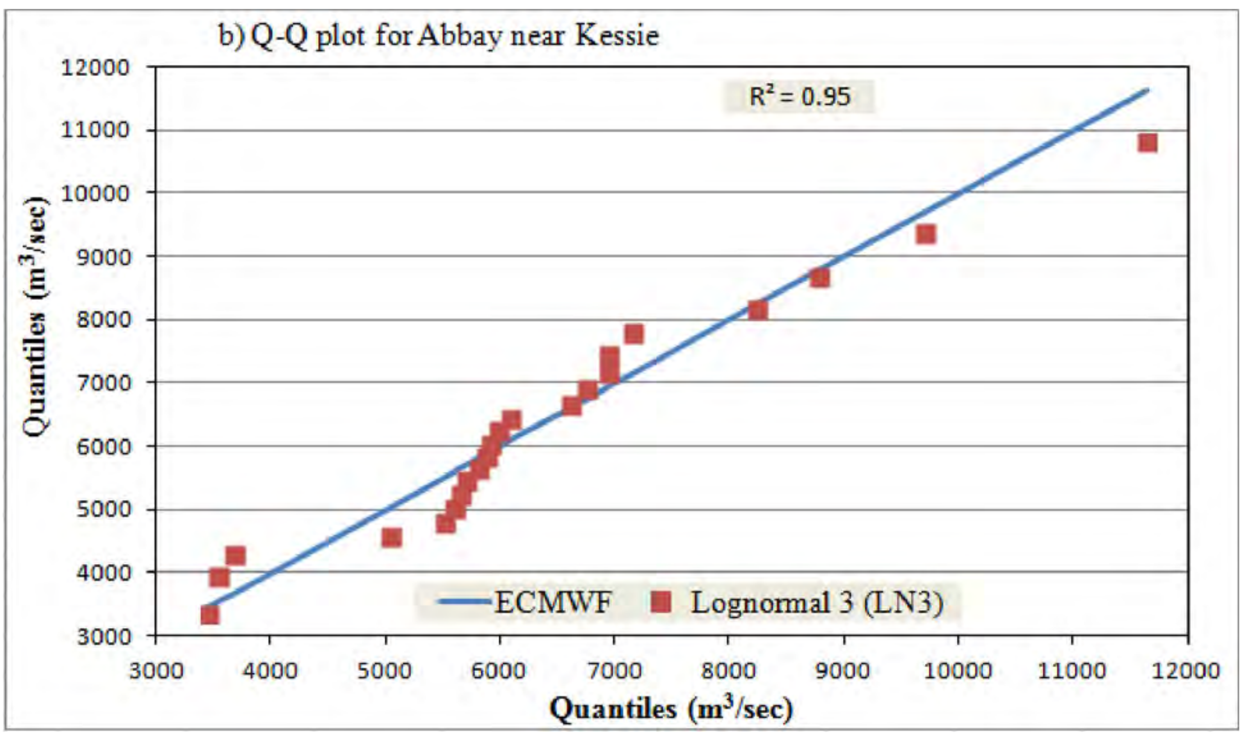
d) P-P plot for Mainbeles at Bridge
R² = 0.95
Observed
Extreme Value I (EV1)
Probability
Probability
0
0.2
0.4
0.6
0.8
1

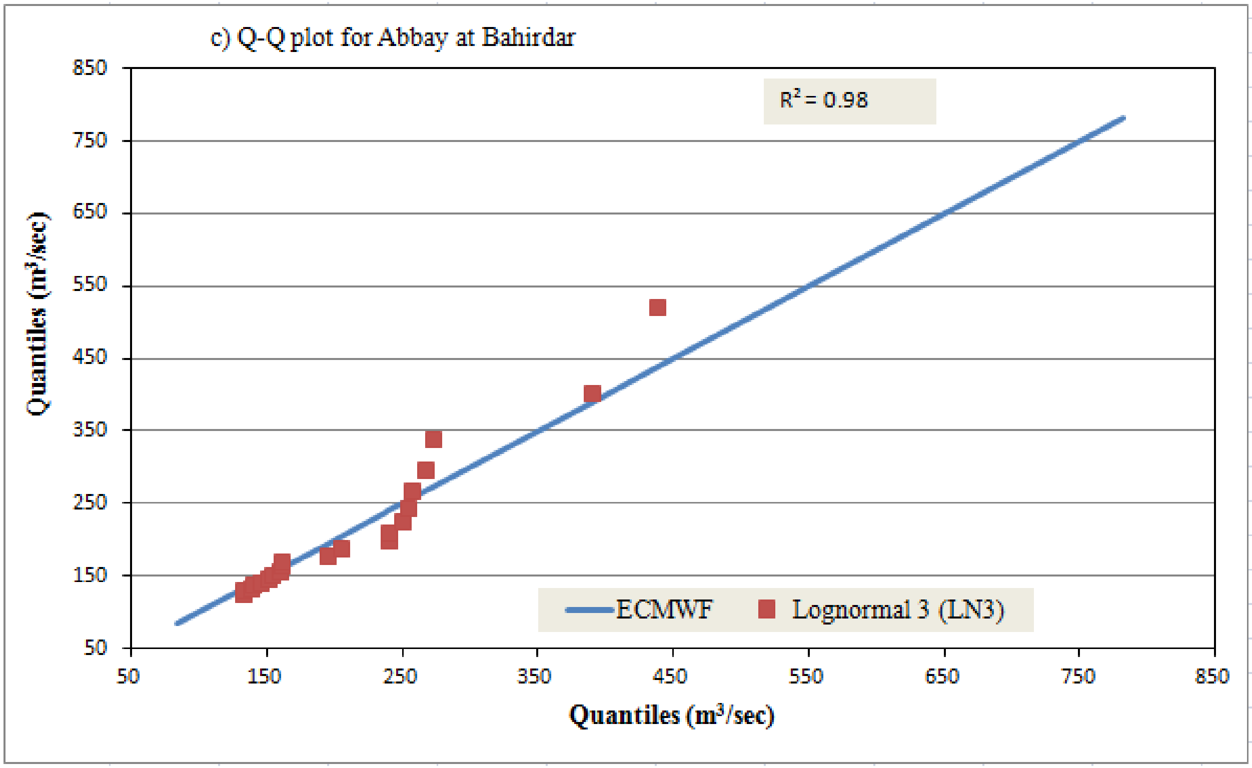


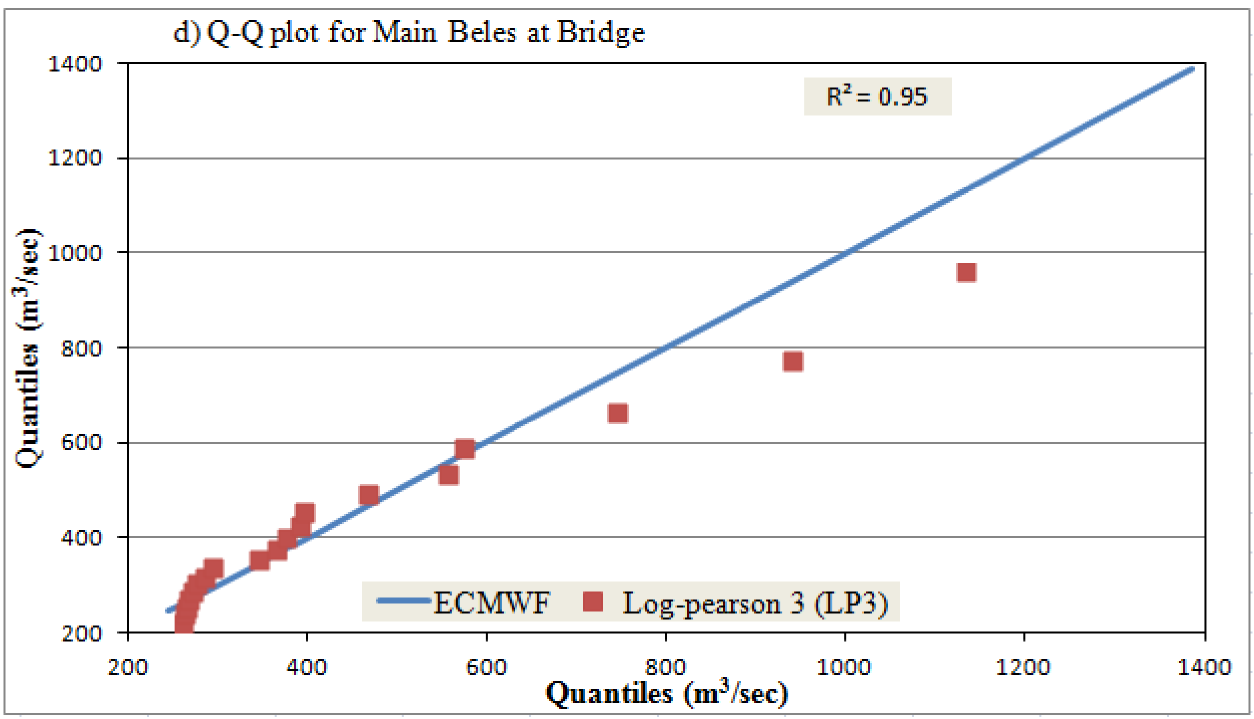
e) P-P plot for Abbay at Border
R² = 0.98
Observed
Generalized Extreme Value (GEV)
Probability
Probability
0
0.2
0.4
0.6
0.8
1

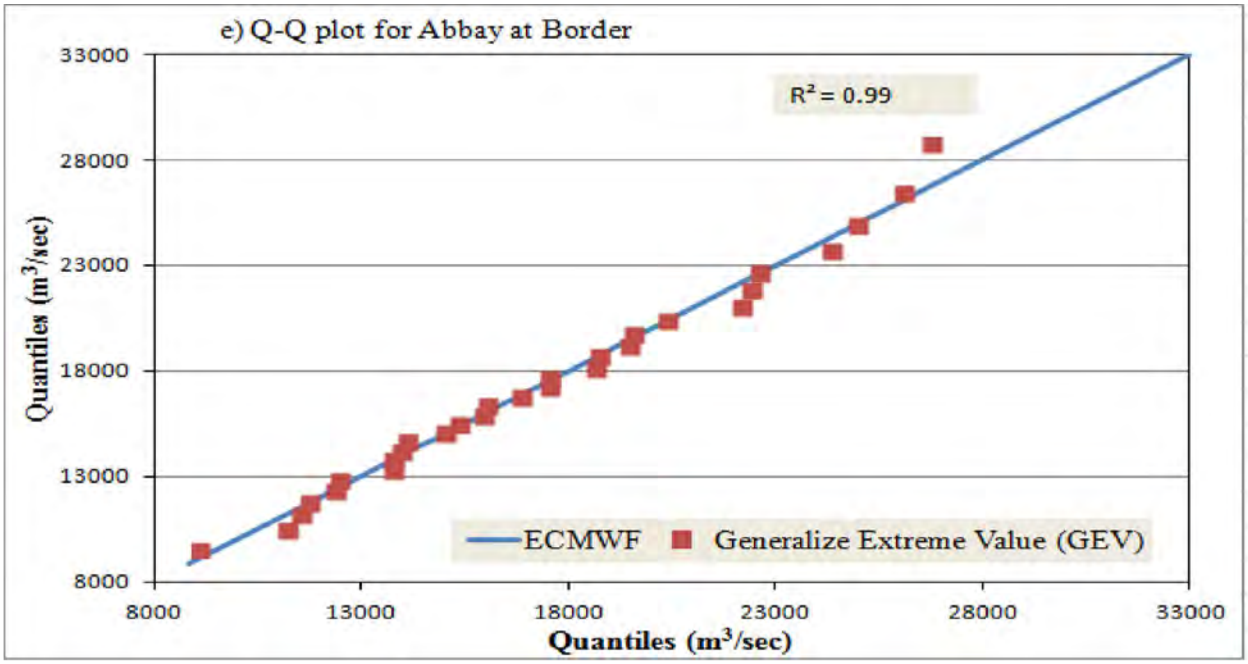
Appendix-I: Quantile-Quantile plot and R^2 results for ECMWF reanalysis AM discharge



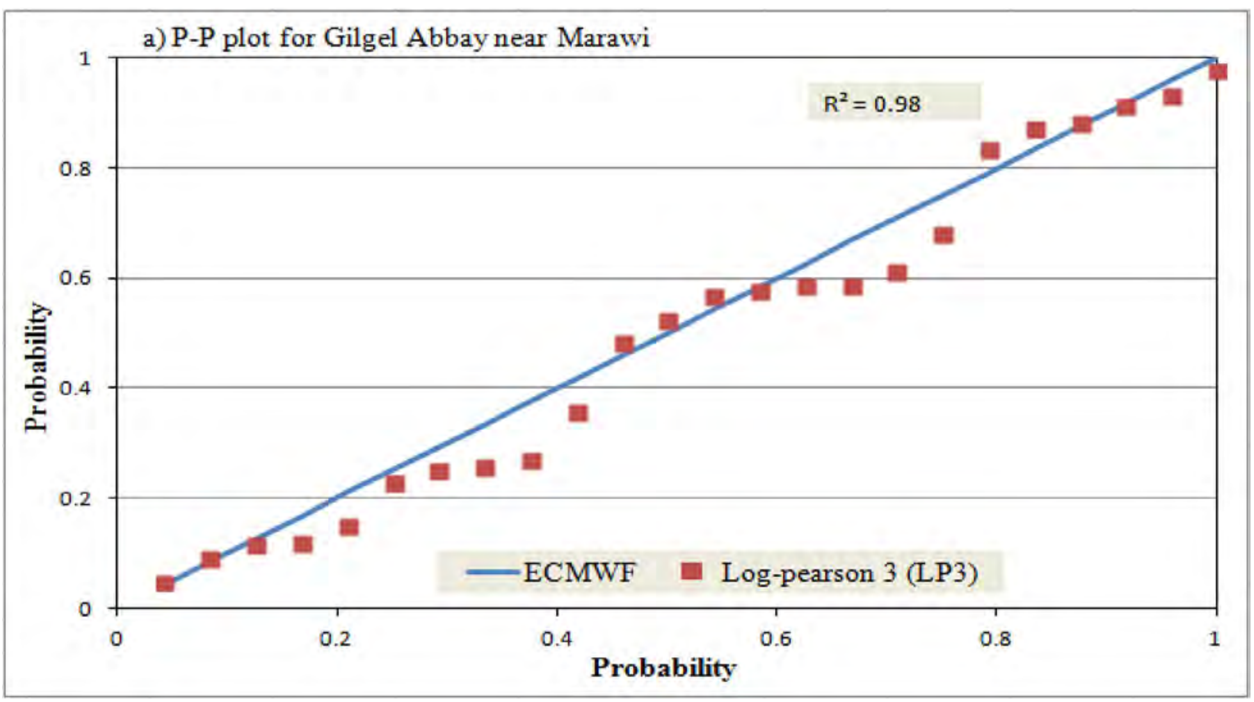


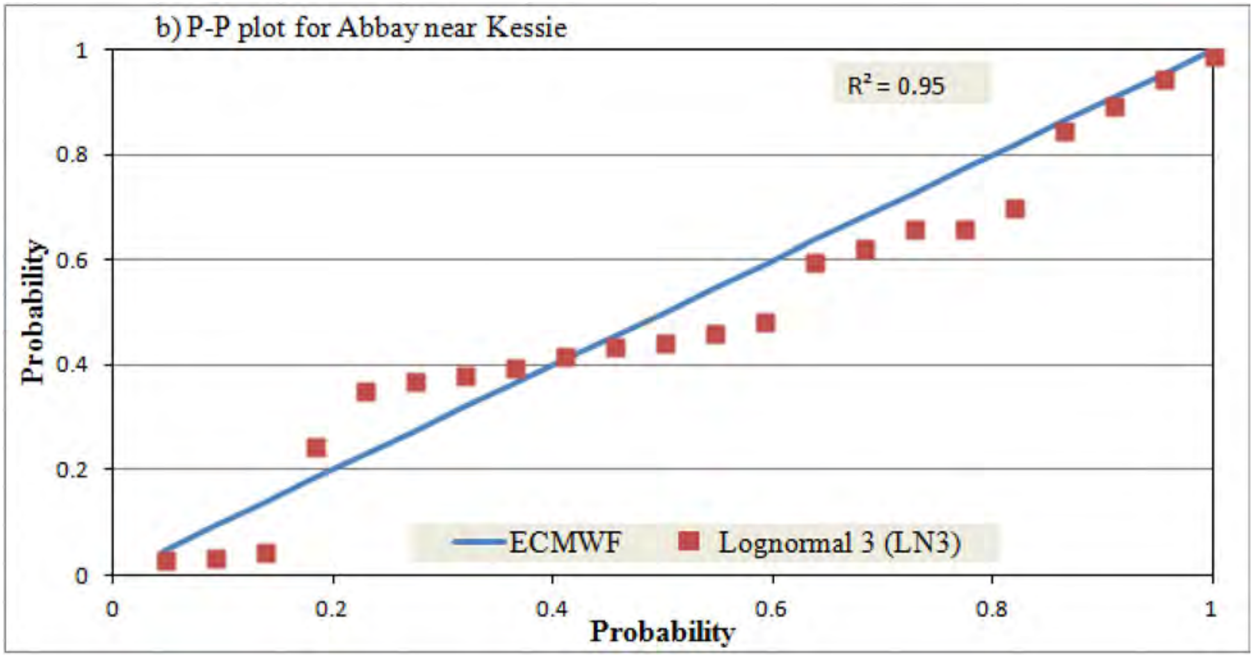

c) Q-Q plot for Abbay at Bahirdar
R² = 0.98
ECMWF
Lognormal 3 (LN3)
Quantiles (m³/sec)
Quantiles (m³/sec)
850
750
650
550
450
350
250
150
50
50
150
250
350
450
550
650
750
850

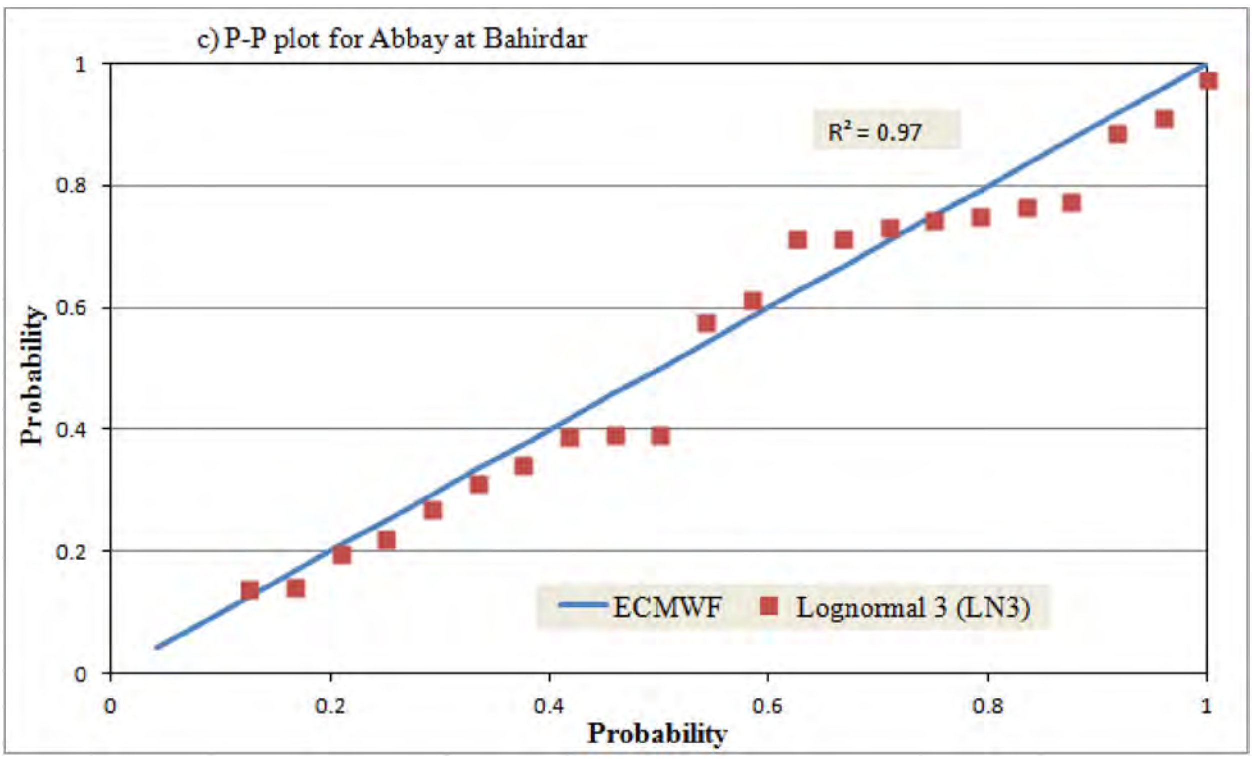

d) Q-Q plot for Main Beles at Bridge
R² = 0.95
ECMWF
Log-pearson 3 (LP3)
Quantiles (m³/sec)
Quantiles (m³/sec)
1400
1200
1000
800
600
400
200
200
400
600
800
1000
1200
1400

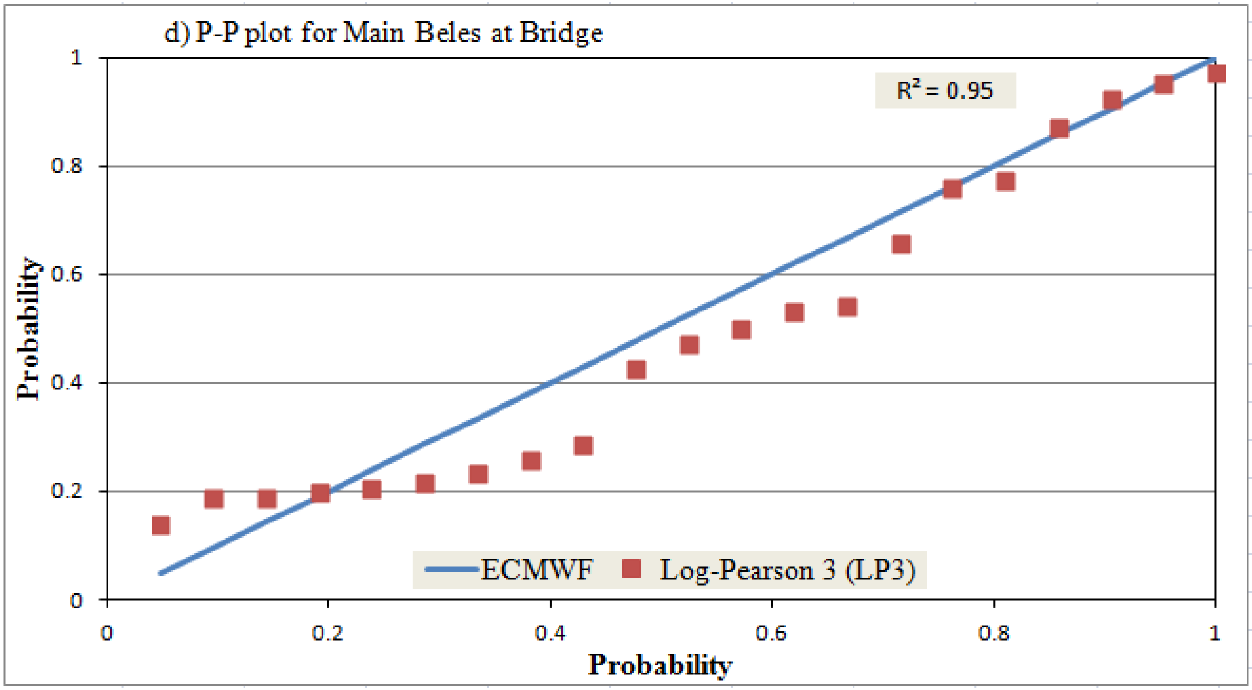


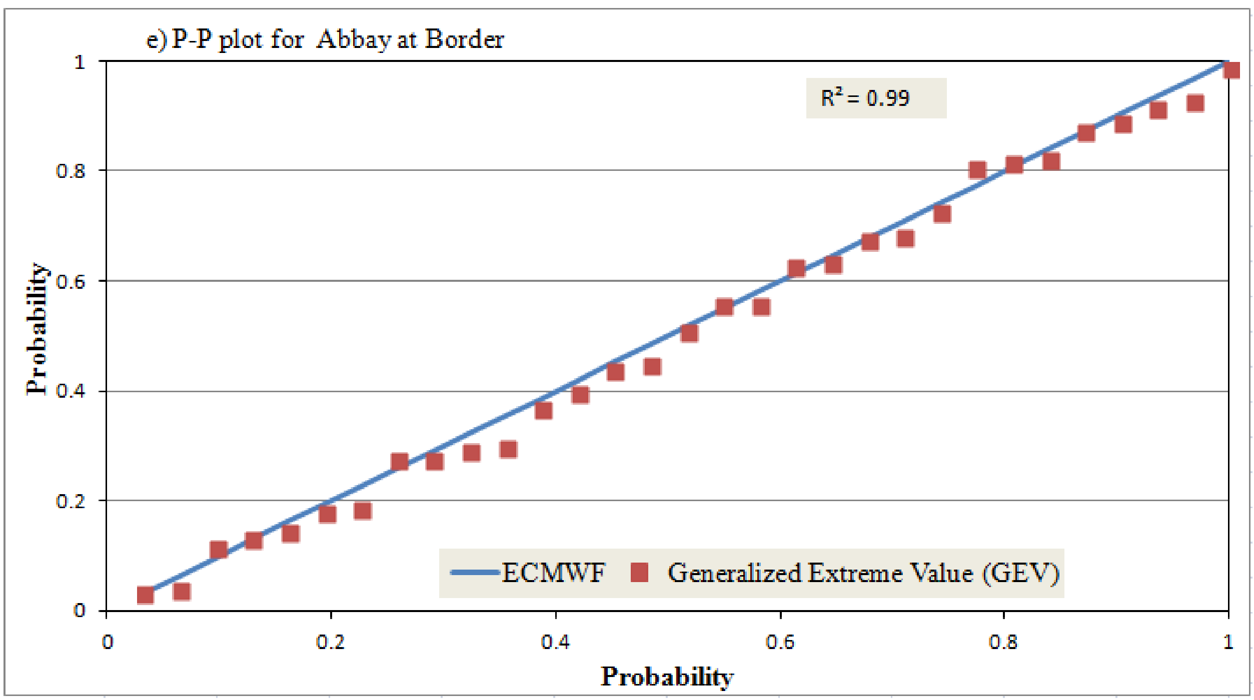
Appendix-J: Probability-Probability plot and R^2 results for ECMWF reanalysis AM discharge



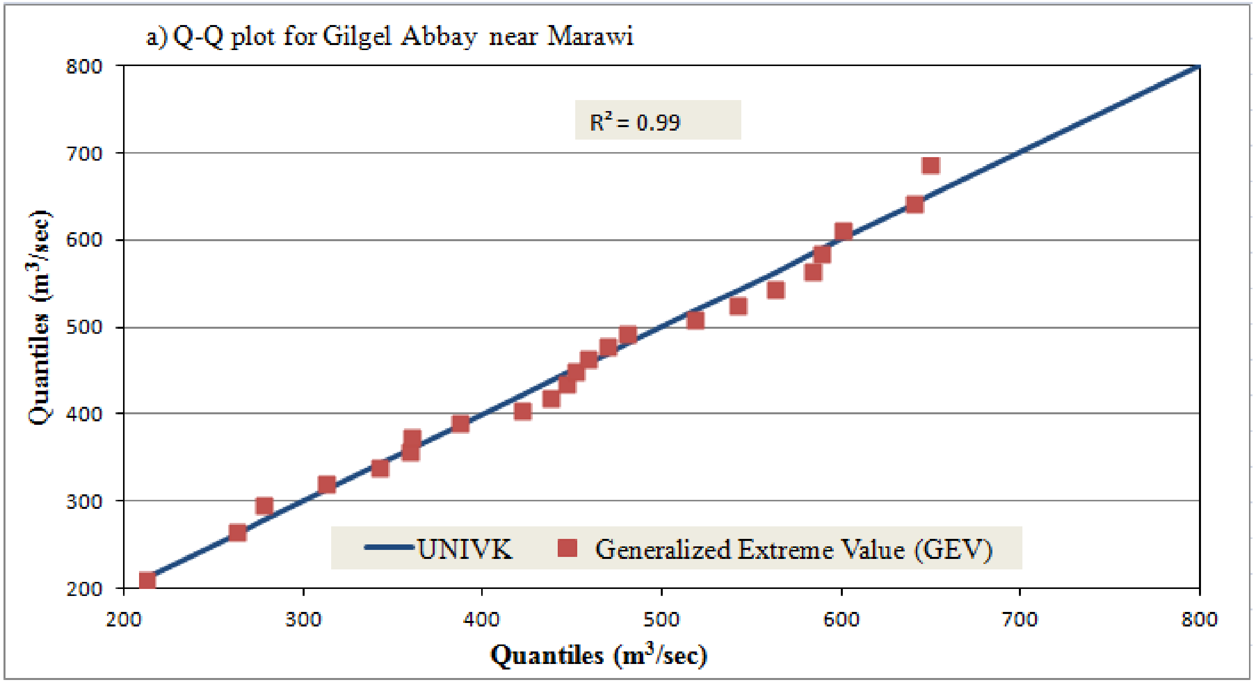

b) P-P plot for Abbay near Kessie
R^2 = 0.95
Probability
Probability
ECMWF
Lognormal 3 (LN3)
0
0.2
0.4
0.6
0.8
1

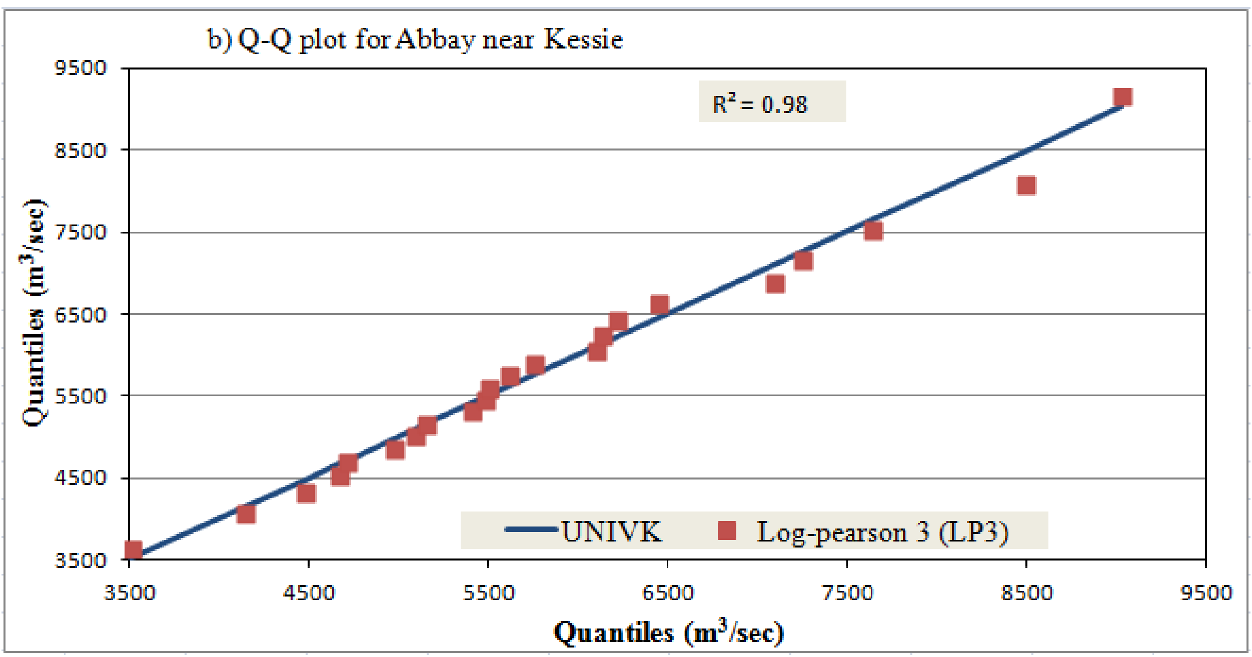

c) P-P plot for Abbay at Bahirdar
R^2 = 0.97
Probability
Probability
ECMWF
Lognormal 3 (LN3)
0
0.2
0.4
0.6
0.8
1

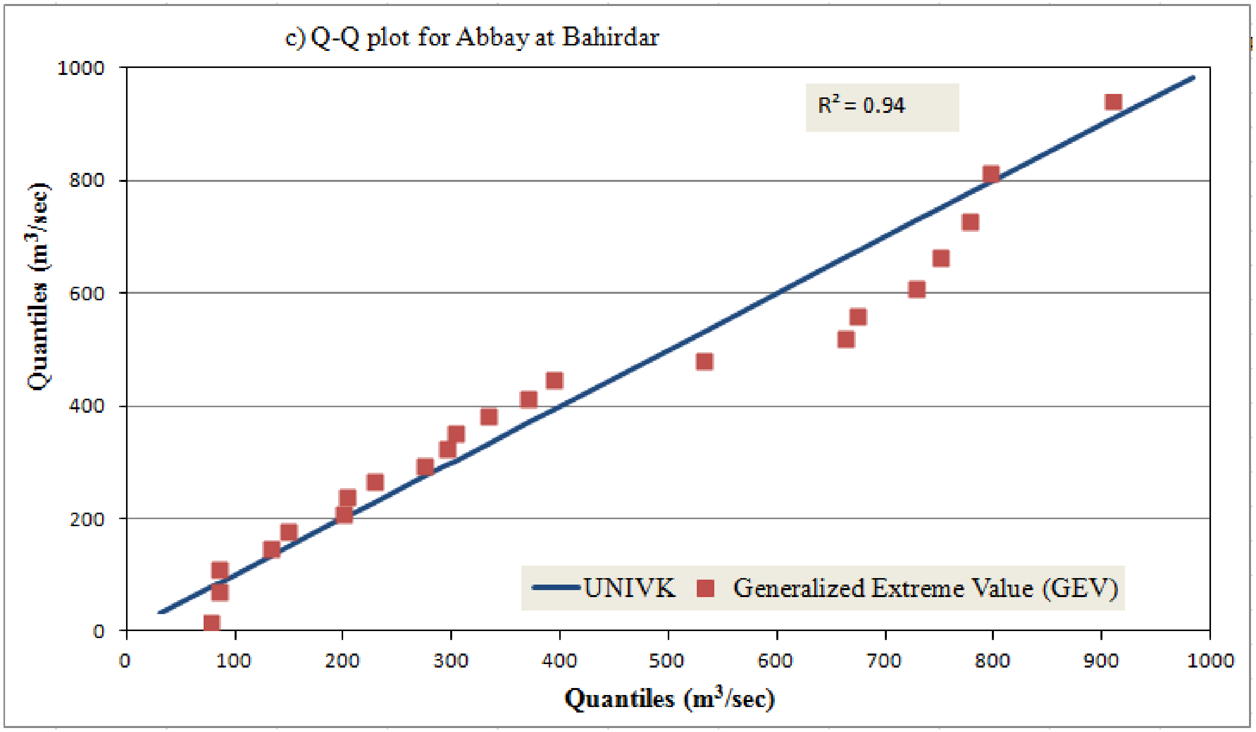

d) P-P plot for Main Beles at Bridge
R² = 0.95
ECMWF
Log-Pearson 3 (LP3)
Probability
Probability
0
0.2
0.4
0.6
0.8
1

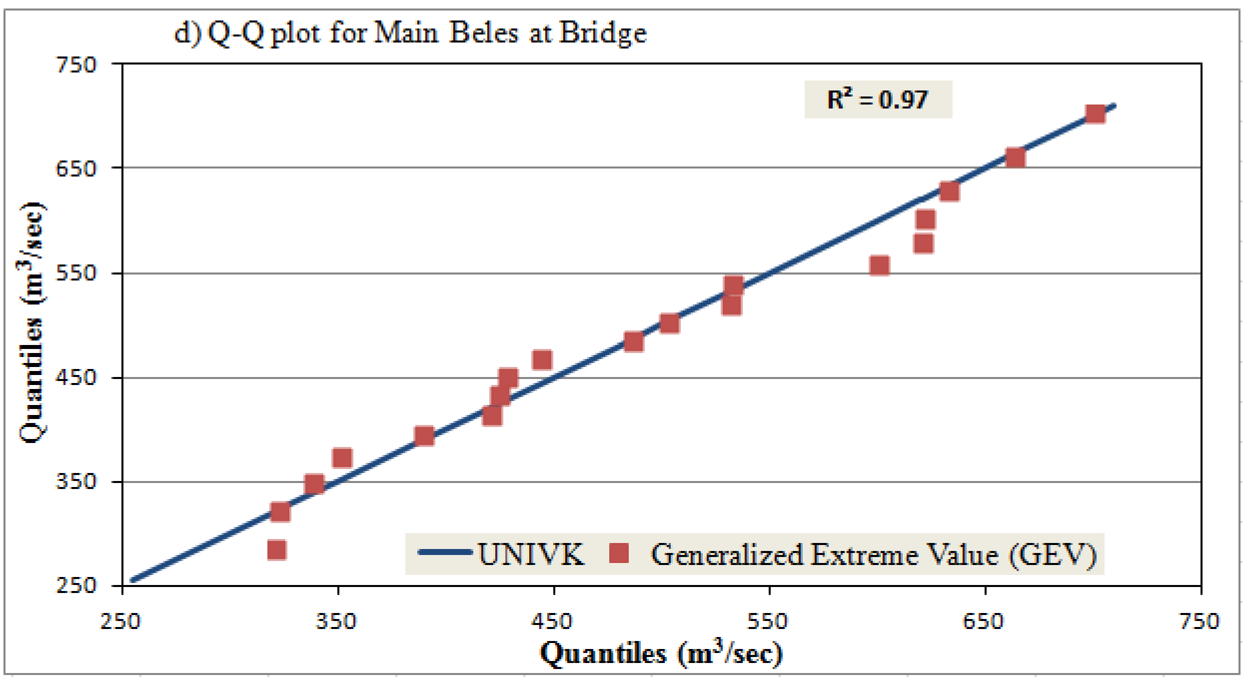

e) P-P plot for Abbay at Border
R² = 0.99
ECMWF
Generalized Extreme Value (GEV)
Probability
Probability
0
0.2
0.4
0.6
0.8
1

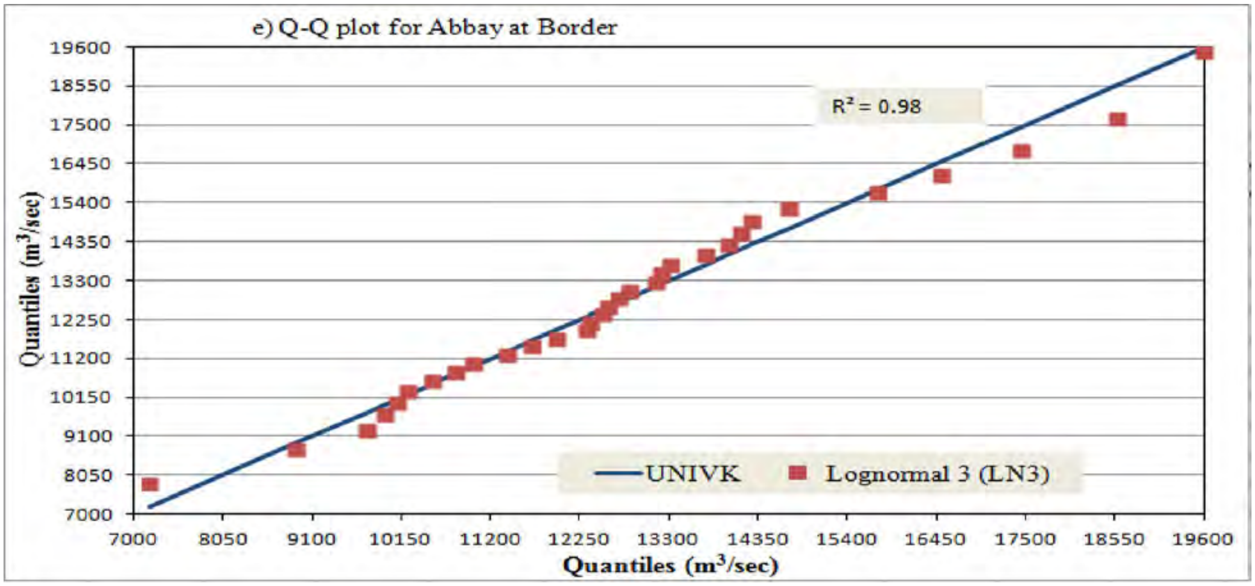
Appendix-K: Quantile-Quantile plot and R^2 results for UNIVK reanalysis AM discharge



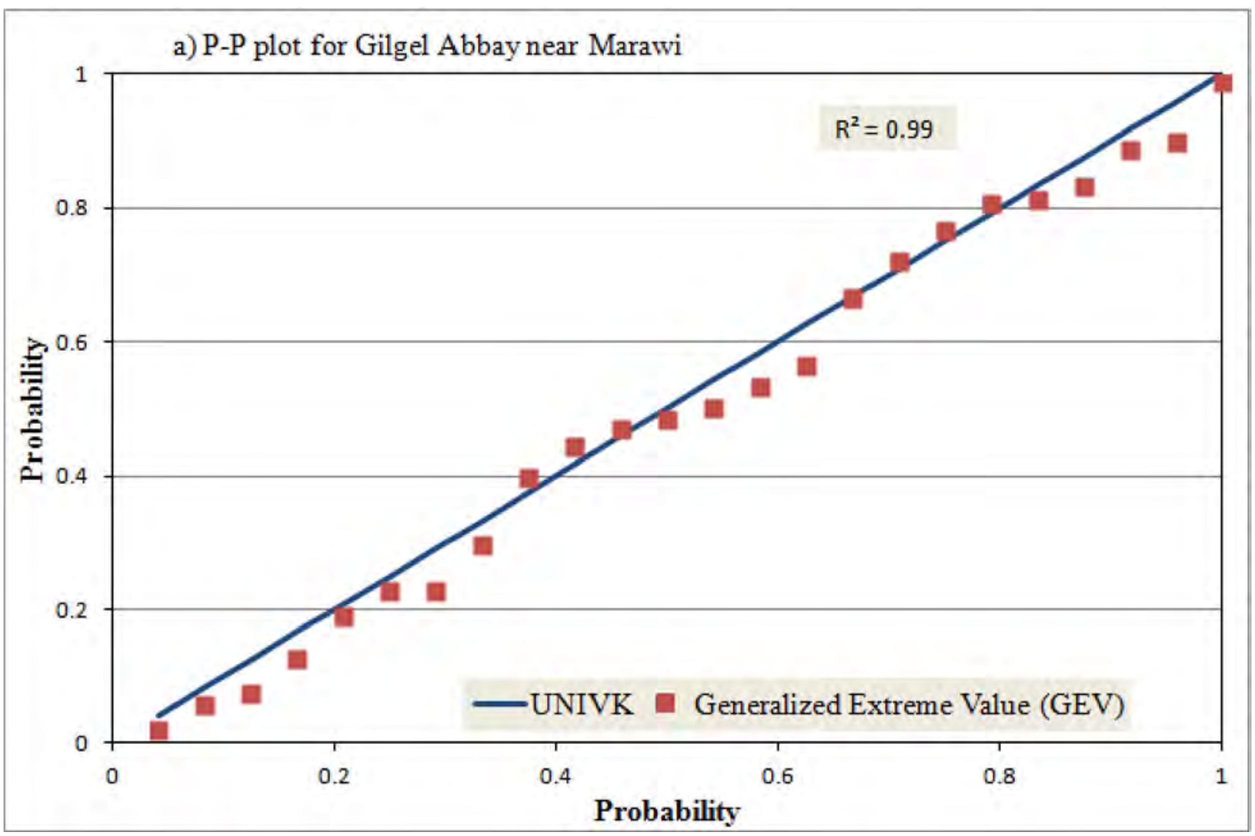


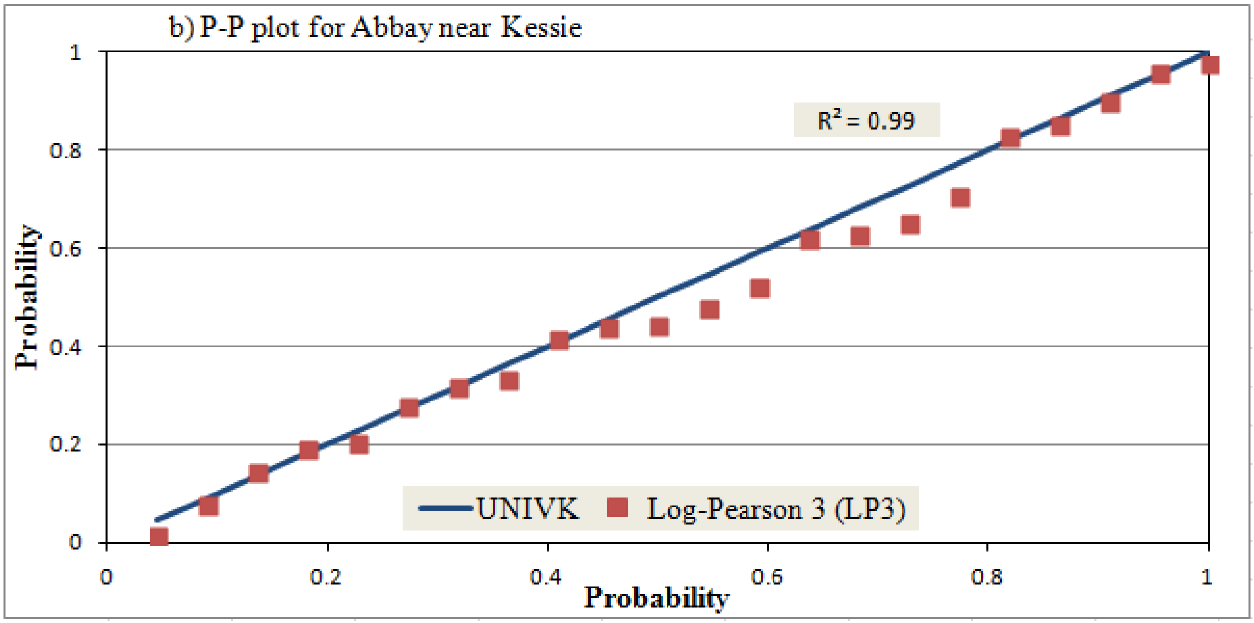

c) Q-Q plot for Abbay at Bahirdar
R² = 0.94
Quantiles (m³/sec)
UNIVK
Generalized Extreme Value (GEV)
Quantiles (m³/sec)
0
100
200
300
400
500
600
700
800
900
1000

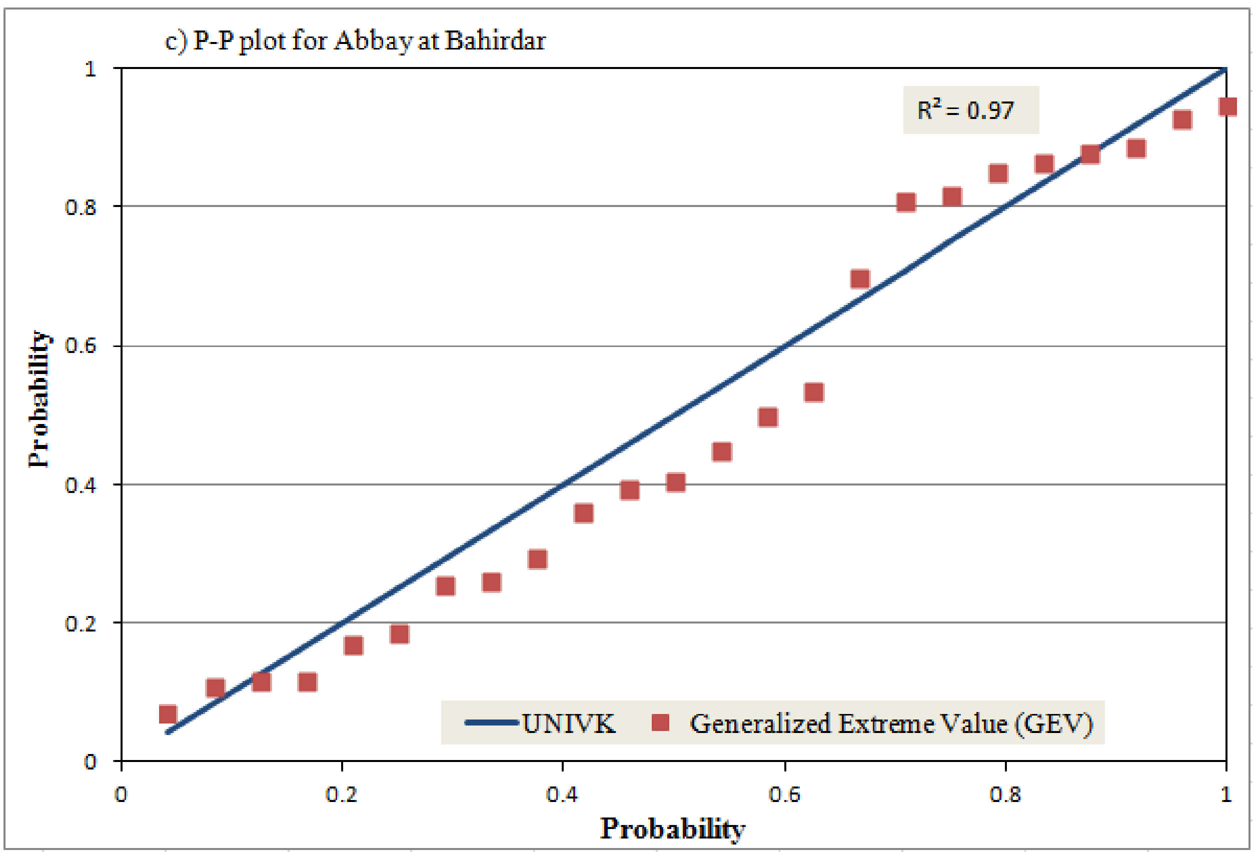

d) Q-Q plot for Main Beles at Bridge
R² = 0.97
Quantiles (m³/sec)
UNIVK
Generalized Extreme Value (GEV)
Quantiles (m³/sec)
250
350
450
550
650
750

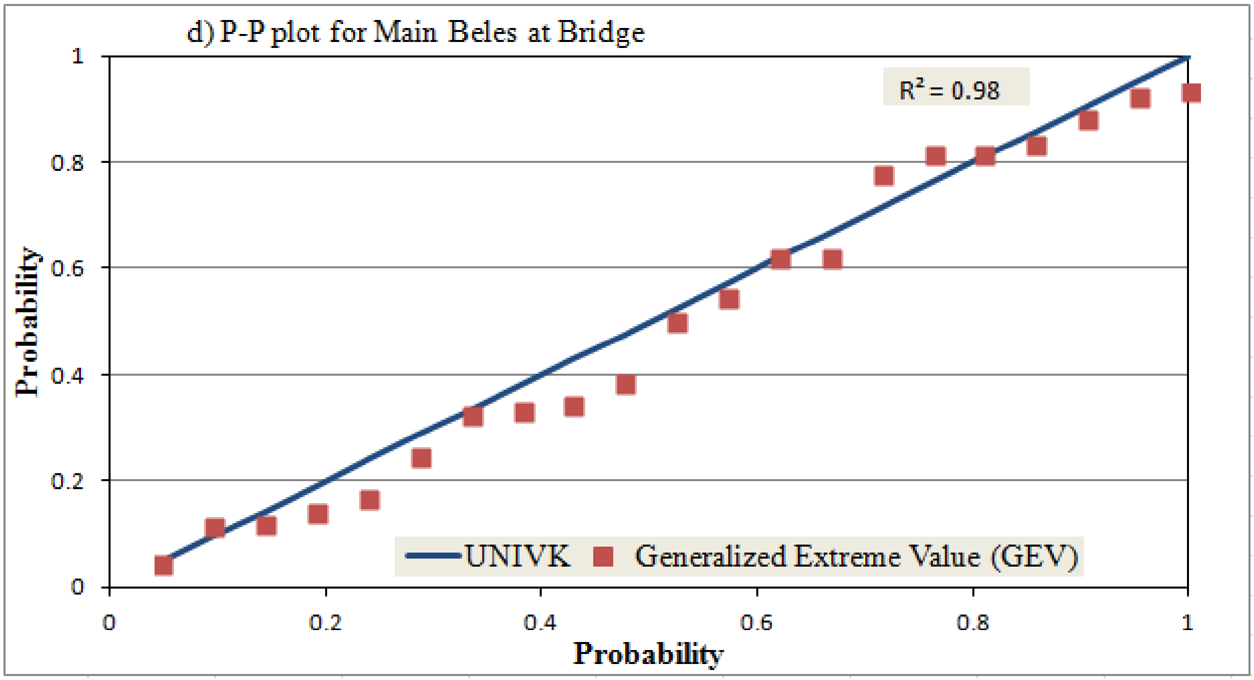


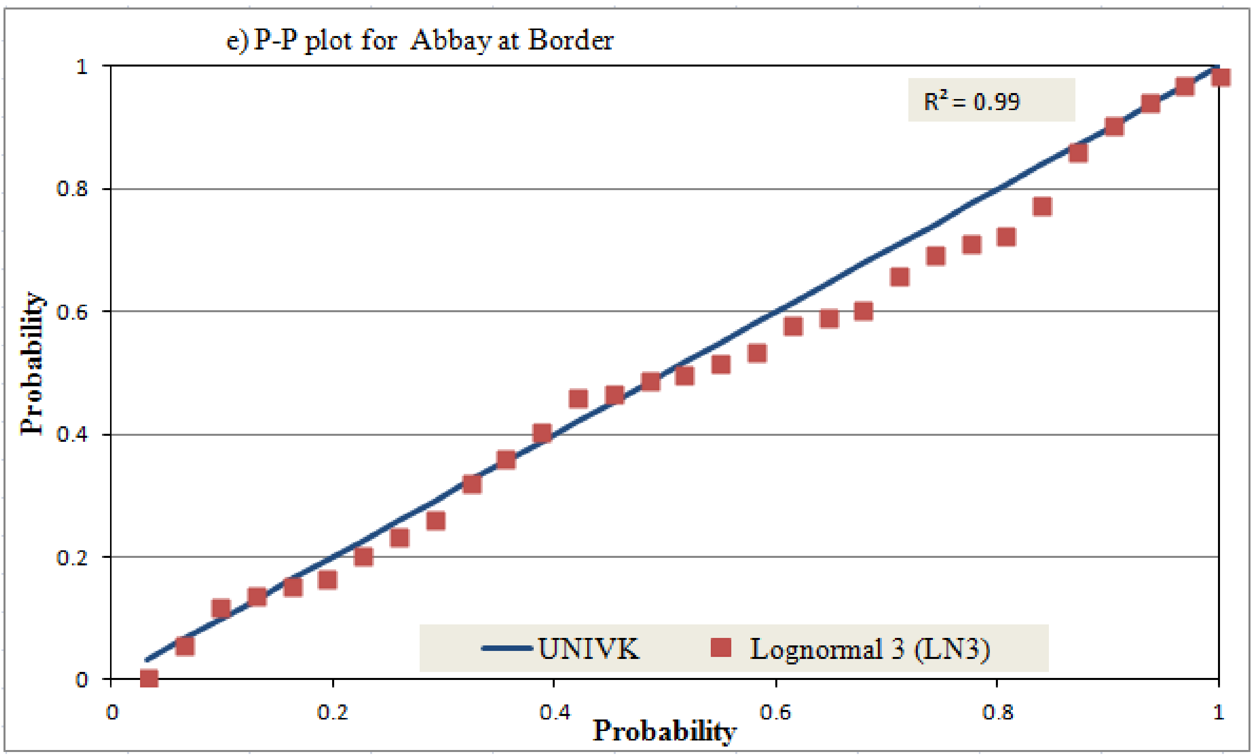
Appendix-L: Probability-Probability plot and R^2 results for UNIVK reanalysis AM discharge




b) P-P plot for Abbay near Kessie
R² = 0.99
UNIVK
Log-Pearson 3 (LP3)
Probability
Probability
0
0.2
0.4
0.6
0.8
1


c) P-P plot for Abbay at Bahirdar
R² = 0.97
UNIVK
Generalized Extreme Value (GEV)
Probability
Probability
0
0.2
0.4
0.6
0.8
1


d) P-P plot for Main Beles at Bridge
R^2 = 0.98
UNIVK
Generalized Extreme Value (GEV)
Probability
Probability
0
0.2
0.4
0.6
0.8
1


e) P-P plot for Abbay at Border
R^2 = 0.99
UNIVK
Lognormal 3 (LN3)
Probability
Probability
0
0.2
0.4
0.6
0.8
1