Civil and Environmental Research www.iiste.org
ISSN 2224-5790 (Paper) ISSN 2225-0514 (Online)
Vol.14, No.2, 2022

The Impact of Rainfall -Runoff on the Performance of Main Irrigation Canal and Cross Drainage of Omo-Kuraz I and II Sugar Project (The Case of Omo-Gibe Basin)

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Abstract
Flood is serious economic losses like damage main irrigation canal and installed infrastructure on sugar project. The objective of this research was to provide an estimation of rainfall-runoff effect on main canal irrigation scheme. The hydrograph characteristics of observed and simulated events are compared using various evaluation criteria consisting of Nash-Sutcliffe coefficient (NSE) is between 0.8 and 0.9, relative volume error (RVE) between -10 and 10%, and coefficient of determination (r2) is between 0.8 and 0.9 during calibration and validation period. Among the catchments of the basin that are used in the regional modeling work and nine Model Parameters are selected among those commonly used in regionalization studies. Four parameter regionalization methods (linear regression, spatial proximity, area ratio and sub-basin mean) were applied to transfer model parameter values from the gauged to the un-gauged catchments except area ratio method. In regional model, gauged catchments Model Parameters and Physical catchment characteristics of un-gauged catchments were used to develop the equations in order to predict discharge of un-gauged catchments. To have better understanding of model parameter performance, the sensitivity analysis of nine model parameters were performed manually by trial and error. The evaluation demonstrations that time of concentration (TC), storage coefficient(R), maximum storage (MS) and constant rate (CR) are more sensitive than others. Therefore, spatial proximity method is recommended in predicting discharge for un-gauged catchments for this research and obtained 85.1m3/s, 1.6m3/s, 9m3/s, 0.6m3/s,1.1m3/s, 14.3m3/s and 28.2m3/s peak flow for cross drainage three, culvert outlet four, culvert outlet three, culvert outlet two, culvert outlet one, cross drainage thirteen and cross drainage fourteen un-gauged sub catchments respectively. To determined predicted peak discharge using L-moment method in flood frequency analysis of selected gauged catchment. Finally, flood damage protection structures like dyke must be recommended for temporary, but redesign depend on peak discharge is necessary.
Keywords: HEC-HMS, Regionalization, Stream flow simulation, L-moment, un-gauged catchments, Omo-Gibe sub-basin
DOI: 10.7176/CER/14-2-02
Publication date: April 30th 2022

1. INTRODUCTION

Flooding is a natural or a manmade phenomenon that is caused due to an overflowing of water over a land surface or river banks, when the volume of water is more than the carrying capacity of the drainage system. Floods are further classified into two. Flash floods which occur suddenly or unexpectedly are generated from high precipitation that creates excess runoff. And river flood which occurs naturally when the volume of water in water bodies like rivers is increased due to heavy rainfall **[1].**

The global land area (excluding Antarctica) is 133.4067 million km^2, the average precipitation depth is 777.4 mm, the total precipitation volume is103, 709.8 km^3; the average runoff depth is 358.9 mm, the total runoff volume is 47,884.0 km^3, and the runoff coefficient is 0.4617. Africa's runoff depth is 229.9 mm, the lowest, which is only 64.1% of the world average **[2].**

Ethiopia has 12 river basins with an annual runoff volume of 122 billion m^3 of water and an estimated 2.6 - 6.5 billion m^3 of ground water potential, which makes an average of 1168.182 m^3 of physically available water per person per year in 2021, a relatively seen current volume 3**].**

Lower Omo has experienced a lot of flooding problems in recent years but it is anticipated that this will be regulated by of Gibe III hydropower dam with a capacity of 13.8 BM^3. The width of the river in the lower reach during flood time may vary from 800 m to 3 km. The river depth is around 4-30 m at these locations **[3].**

The impacts rainfall-runoff of high rate of growth Omo-Kuraz particularly in the study area reflected flooding and over topping as well as main canal, cross drainage structures, road culvert and road materials are washed way. It is obvious, hydrological alterations and channel disturbances along streams because of changes stream geomorphology and hydrologic processes happen. So, this leads to make assess the problem using HEC-HMS model.

Estimation of flow at un-gauged catchment is usually based on transferring or extrapolating information from gauged to un-gauged site, a process called "Regionalization". The area ratio, spatial proximity, sub-basin mean and regional model regionalization methods are used to predict stream flow at un-gauged catchments. The most common approaches that have been used for estimating flow at un-gauged catchment is the use of conceptual rainfall-runoff models whose parameters can be regionalized, as the catchments with similar characteristics show similar hydrological behavior **[4].**

In this study HEC-HMS model, Regionalization, L-moments method and GIS technique were applied to estimate stream flow in watershed. The hydrological modeling is accomplished by dividing the watershed in to different sub-catchments. To compute deficit and constant rate loss method and converting excess rainfall to runoff model in Clark unit hydrograph of HEC-HMS model.

To understand the required quantity of runoff prediction is important know about the flash flood through infrastructure of main canal, road and command area of irrigation scheme.

Concerned body and organizations working in the area of irrigation scheme, road and storm water drainage infrastructures can use it as a reference for proper design, implementation, maintenance of irrigation main canal, cross drainage and road surface drainage.

Omo-Kuraz sugar cane development project is one of the new developing sugar cane projects in Ethiopia. It expected to covers about 1750km2 areas. In Omo-kuraz left bank the total area designed was 193.48km2.Until 21/07/2013 covered by sugarcane has reached 164.10km2 (Large Scale irrigation project) and the land development is on-going.

The scope of study was located Omo-Kuraz Sugar Left Bank Main Canal area. The impact of storm runoff on the performance of main canal was from Omo-Kuraz 1 project and Omo-Kuraz 2 sugar factory. This study was not including all command area problem. The selected area depends on impact of storm runoff portion.

2. MATERIALS AND METHODS

2.1 Description of Study Area

2.1.1 Location of Study Area

The specific study area is delineated based on the outlet points of cross drainage structures and high way road culverts. The study area and Omo-kuraz left bank command area is shown in Figure 3.1.

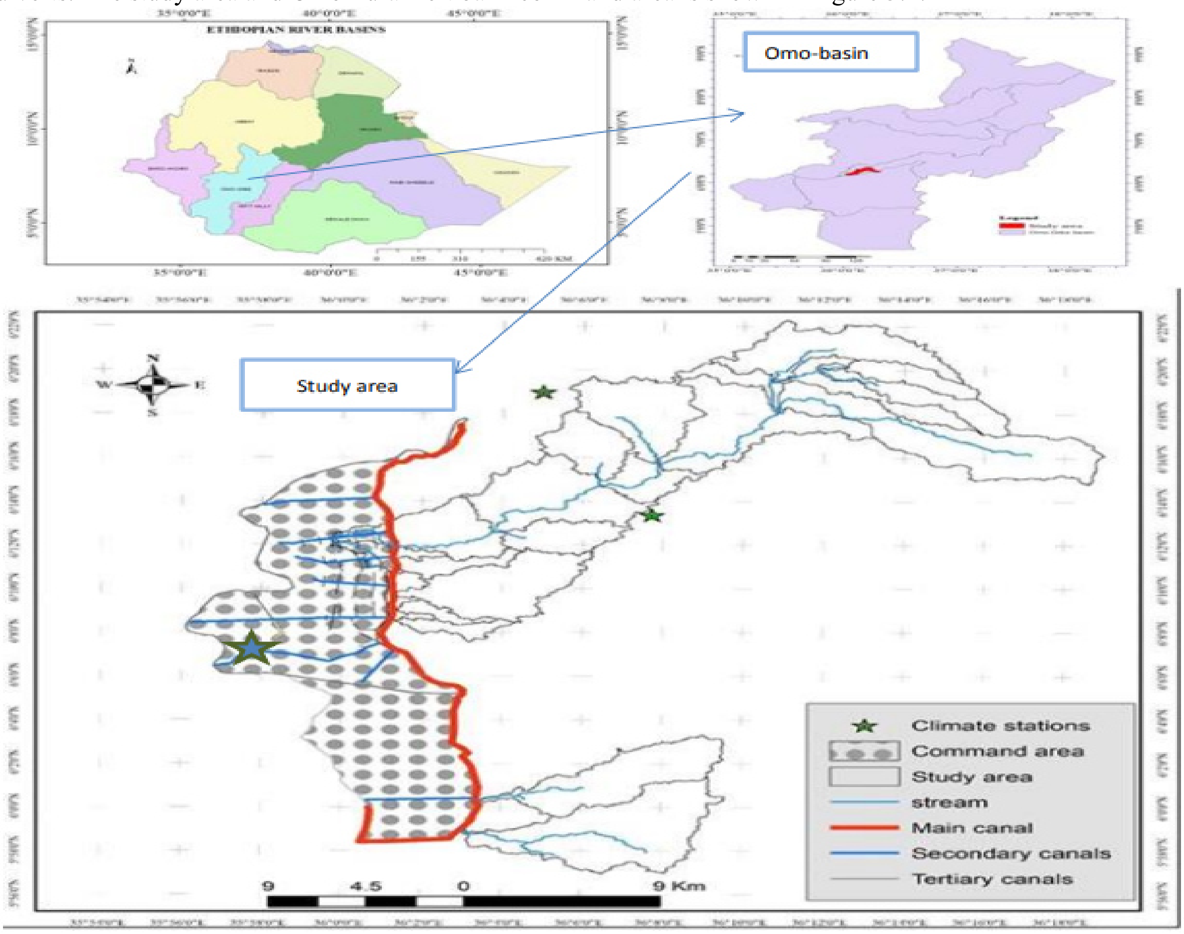

Figure 2. 1: Location of the study area:

Top left indicates the location of Omo basin within Ethiopia river basins, Top right indicates the location of our study area within Omo basin, and the lower map represents the salient features of the study area including affected command land and canal system.

The types of canal depending on alignment in Omo-Kuraz left bank project is contour canal. The main canal which is aligned approximately parallel to the contour lines and this canal can irrigate the areas on one side only. In Omo-kuraz left bank main canal diverted from Omo River. The total areas of the flash flood receiving command area is about 193.48km^2.

The design discharge from design document of Omo-kuraz left bank and design discharge from design document of Eny highway in Omo-Kuraz three up to Omo-Kuraz one project. See below table 2.1 and 2.2 respectively.

Table 2. 1: The design discharge from design document of Omo-Kuraz left bank

Name of structure	Design discharge,m^3/s	Location		Type of structure
		Easting	Northing	
CD3	17	170529	685906	box culvert
CD13	9.5896	174269	664456	Siphon(box culvert)
CD14	17.13	174055	661485	Siphon(box culvert)

Table2.2: The design discharge from design document of eny highway in Omo-Kuraz three up to Omo-Kuraz one project

The design discharge estimated using ERA 2002 design manual before Omo-Kuraz meteorological station was installed.

Name of structure	Design discharge,m3/s	Easting	Northing	Type of structure
CO1	12.27	170101	678872	pipe culvert
CO2	_	170549	681164	pipe culvert
CO3	29	170468	682302	slab/box culvert
CO4	10.35	170560	684189	pipe culvert

All the culverts with defined watershed except CO2 which is localized flow relief structure.

2.1.2 Climate

The altitude Omo-Kuraz area varies between 430 and 500 m a.s.l. Thus, the area experiences typically a "tropical semi-arid climate (Kolla agro-climate). The mean maximum and minimum monthly temperature of the command area are 34.52^{0}C to 20.12^{0}C.The maximum temperature ranges between 32.34^{0}C in July to 38.8^{0}C in February and the minimum temperature ranges between 17.94^{0}C in January to 21.6^{0}C in March, respectively. The monthly relative humidity varied between 49.68% in February and 75.60% in April with the annual average of 67.30%. Mean daily pan evaporation is 5.3mm/day. Mean daily Sunshine hours are 6.81. Mean Wind speed measured at 2m height is 1.34m/s.

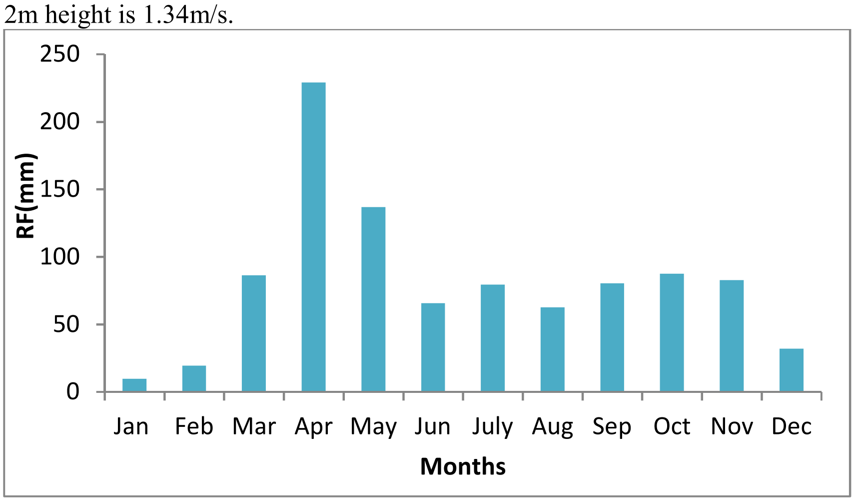

Figure 2. 2: In Omo-Kuraz meteorological station monthly average rainfall from June 2012-July 2019

2.1.3 Topography and slope

The mountainous areas are at altitudes of 2600-2800 m with some crests reaching 3500 m and the valley floors at 1000-1500 m. south to Jinka the relief flattens out to low hills developed on basalt and basement complex granites and gneisses at altitudes of 500-1400m with most slopes 10-15% but steeper in places, this continues to the Basin's southern boundary with the Rift Valley.

The lower Omo Basin lies at 400-600m and is composed of gently sloping alluvial-colluvial plains in the North and alluvial plains and fans of varying degrees of dissections in the south.

2.1.4 Land cover and land use

The land use catchment of study area has dominated by Shrub land, grassland and woodland. The good point here in a CD3 catchment is the uplands are better in controlling and absorbing floods since they are characterized by dense forests and woodlands.

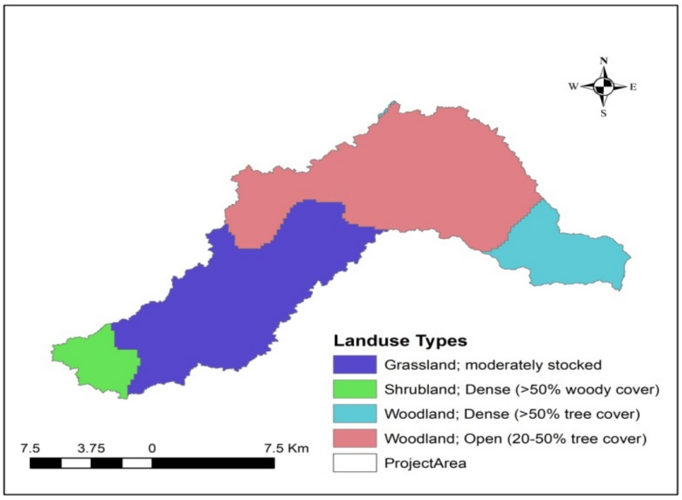

Figure 2. 3: Land use map of the study area on CD3 (2018 year)

The land use of CD 13 has woodland, shrub land and grassland its area coverage respectively 2.79Km2, 3.84Km2 and 23.93Km2. The land use of CD 14 has shrub land and grassland its area coverage respectively 3.51Km2 and 44.4Km2. The land use of CO1 has shrub land and grassland its area coverage respectively 0.3 Km2 and 4.5 Km2. The land use of CO2 has shrub land and grassland its area coverage respectively 0.73 Km2 and 2.73Km2. The land use of CO3 has shrub land and grassland its area coverage respectively 1.07 Km2 and 28.05Km2. The land use of CO4 has shrub land and grassland its area coverage respectively 2.52 Km2 and 3.73Km2.

2.1.5 Soil type

The CD3 catchment contains six type of soil classification according to FAO (Figure 2.3) which include all study area of soil type. About three quarter of the catchment is dominated by Eutric Fluvisols which sandy by nature (Table 2.3). The soil types near the outlet of the catchment have clayey type of textures with low infiltration capacity which results in lesser base flow. Loam soils are rare in the catchment and only exist in highest lands with coverage of less than 15 is10%.

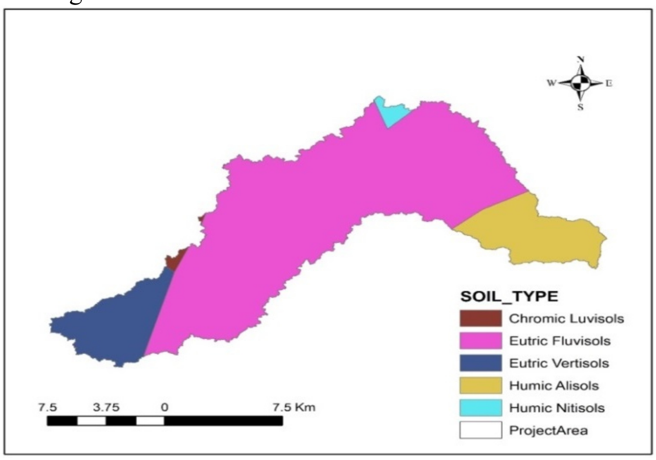

Figure2. 4: Soil map of the study area on CD3Such soil distribution gives us the information that floods near the culverts and cross drainage structures are high. This is also derived by the high base flow from the upper catchments.

Table 2.3: Hydrologic groups of soil types and their respective coverage

SOIL_TYPE	Hydrologic Group	Area (km^2)	Area (%)
Humic Nitisols	B	2.7	1.0
Chromic Luvisols	B	1.3	0.5
Humic Alisols	B	32.5	12.0
Eutric Vertisols	D	30.6	11.3
Eutric Fluvisols	A	202.9	75.1

The soil type of CD 13 has euvertisols and eufluvisols its area coverage respectively 3.41Km^2 and 27.04Km^2. The soil type of CD 14 has euvertisols and eufluvisols its area coverage respectively 4.73Km^2 and 42.72Km^2. The soil type of CO1 has euvertisols and eufluvisols its area coverage respectively 1.85 Km^2 and 2.89 Km^2. The soil type of CO2 has euvertisols and eufluvisols its area coverage respectively 2.27 Km^2 and 1.17Km^2. The soil type of CO3 has euvertisols and eufluvisols its area coverage respectively 4.27 Km^2 and 24.75Km^2. The soil type of CO4 has euvertisols and eufluvisols its area coverage respectively 4.07 Km^2 and 2.12Km^2

2.2 Data collection and processing

2.2.1 Data collection

Meteorological data

The Meteorological data from four meteorological stations were collected from National meteorological Organization in Omo-Gibe basin catchment that is used for this study.

Table 2.4: Summary of the rainfall stations

S.No	Station Name	Latitude (Degree)	Longitude (Degree)	Elevation (m)	Years of data used
1	Bonga	7.22	36.23	1650	1995-2018
2	Shebe	7.52	36.52	1635	1995-2018
3	Hana	6.22308	36.128889	586	1995- 2018
4	Bulki	6.316667	36.083333		1995-2018
5	Omo-Kuraz	6.18	36.03	483	2012-2018

Hydrological data

The flow is transferred using regionalization technique to my study area because catchment of study area is un-gauged. The regionalization technique that has been applied shall be discussed in the next sections. The daily flow data have been collected from three gauged stations from1995-2018.

Table 2.5: Summary of hydrological gauged stations

River	Station(site)	Reference	Sub-catchm.	Area(km^2)	X-Coordinate	Y-Coordinate
Woshi	Nr.Dimbra	91025	Sherma	281.25	170940.73	810215.04
Guma	Nr.Andra.	92004	Guma	477.23	196243.91	791238.74
Dincha	at bong	92005	Guma	219.98	199592.89	796752.48

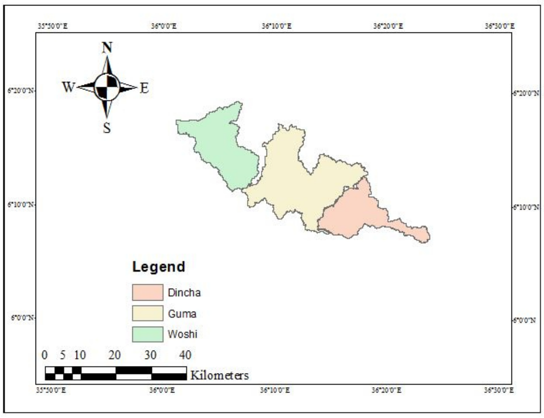

Figure 2. 5: Gauged catchments

2.3 HEC HMS modeling Result

In the Geospatial Hydrologic Modeling Extension (HEC-Geo HMS) version 10.3 with Arc Hydro extension in ArcGIS10.3, the study area was divided into two gauged and un-gauged. The seven un-gauged and three gauged based on available DEM data, and by HEC-HMS model.

In HEC-HMS 4.2.1 model the area after delineating, using HEC-GeoHMS.

2.3.1 HEC-HMS model inputs

Long-term average monthly potential evapotranspiration: Daily potential evapotranspiration was calculated based on four meteorological stations (Hana, Bulki, Bonga and Shebe) from 1995 to 2018 using Hargreaves equation located on Omo-Gibe sub-basin. The result of daily evapotranspiration is converted to long-term average monthly (see Figure 2.6). Figure 2.6 shown potential evapotranspiration increasing in dry season.

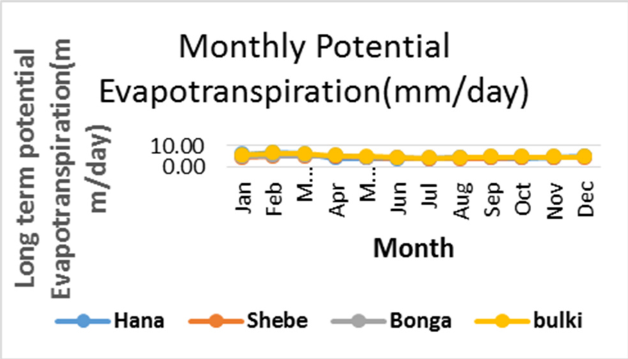

Figure 2.6: Average potential evapotranspiration (mm/day) (1995-2018)

2.3.1.1 Spatial data

This information includes soil types, land use/land cover and digital elevation model (DEM) that can be freely downloaded from online sources. The digital elevation model having a resolution of 30 m by 30m is downloaded from USGS website.

The spreadsheets are a powerful tool to calculate the statics of the arranged climate, flow and spatial data sets. Then, I prepared the input data for hydrological simulation on GIS interface using HEC Geo HMS extension. The input data are then imported into HEC -HMS graphical user interface. I have also collected ground truthing points using total station, GPS and Google earth maps.

2.3.2 Data processing

Rainfall data screening: Rough rainfall data screening of the four meteorological stations were first done by visual inspection of daily rainfall data. Because of long breaking in rainfall records of some station, absence of lengthy and overlapping period of record, data screening was done in the record of the hydrologic years of 1995 to 2018. As shown in the graph below from April to May there is high rainfall.

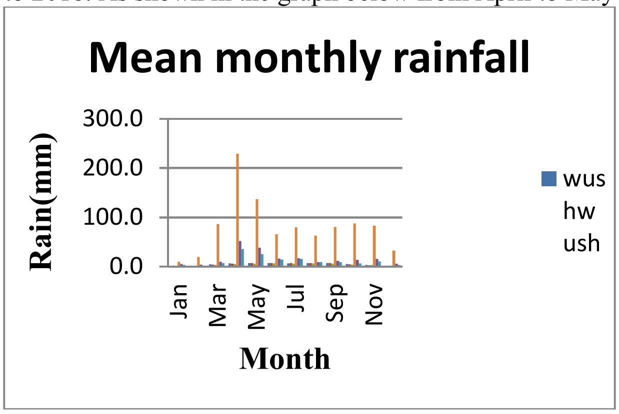

Figure 2.7: Mean monthly rainfall (mm) data series from 1995-2018

Rainfall data gap-filling: The missing data can be estimated by using the data of the neighboring stations **[5].**The methods are station average method, normal- ratio and quadrant methods. This method may not be accurate when the total annual rainfall at any of the x region gauges differs from annual rainfall at the point of interest by more than 10%.

Homogeneity of recording station: The homogeneity of the selected gauging stations monthly rainfall records have been carried out by non -dimensional zing using equation:

$$Pi = \frac{\overline{Pi}}{\overline{P}} * 100 \quad \text{---------------------------------}1$$

Where: - Pi=Non dimensional Value of P for the month i

$\overline{Pi}$ =Over years averaged monthly precipitation for the station i

$\overline{p}$ =the over years average yearly precipitation

Included in the computation of area rainfall all in the same figure and each other as shown in Figure 2.6.

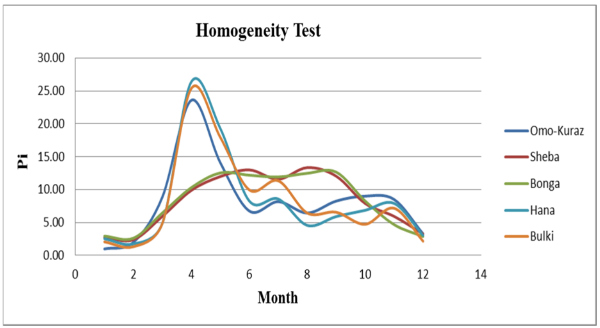

Figure 2.8: Homogeneity test for all RF stations

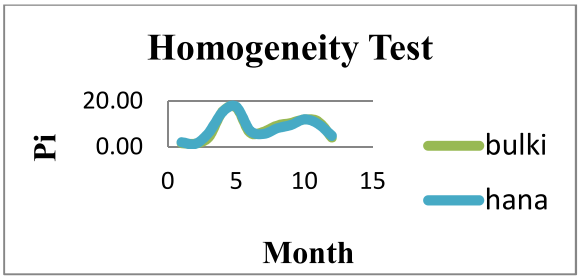

Figure 2.9: Homogeneity test for rainfall stations of Bulki and Hana

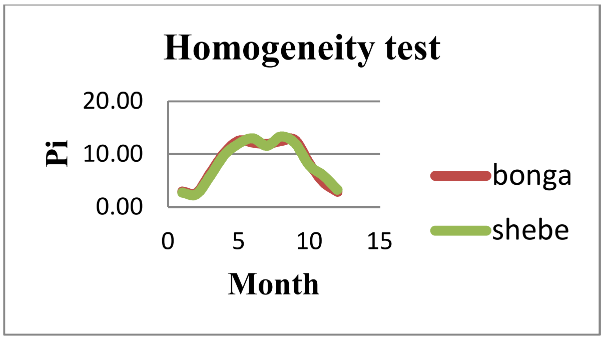

Figure 2.10: Homogeneity test for rainfall stations of Bonga and Shebe

2.3.2.1 Test for consistency of recording station

In order to check the consistency of two rainfall stations double mass curve was used. According to the double mass curves, all the stations were found to be consistent and no need of correction. **[6]** Figure 2.11 shows double mass curve graph analysis and the double mass curve for each rainfall stations below.

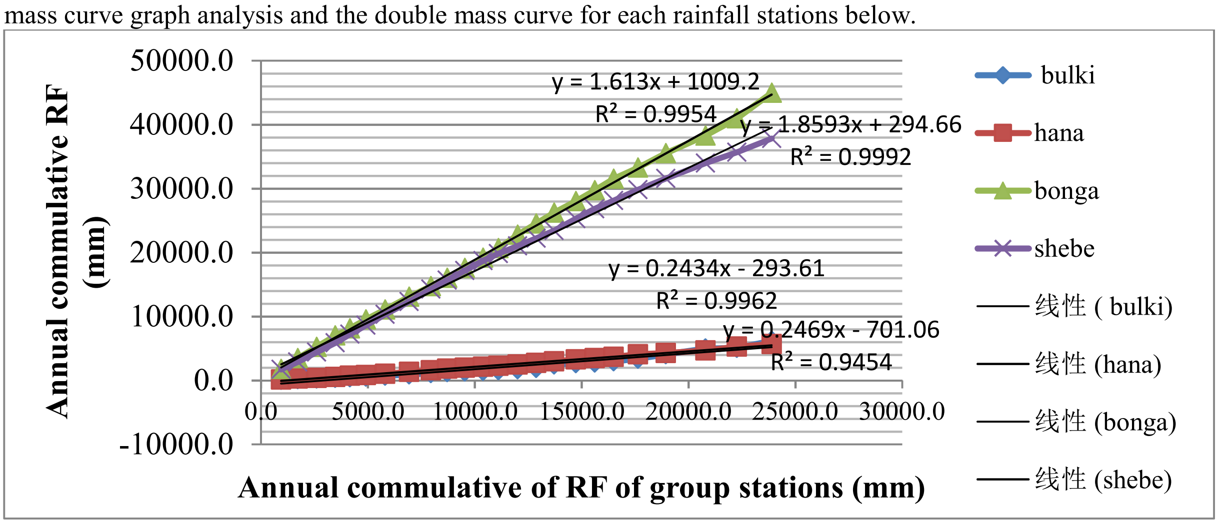

Figure 2.11: Double mass curve graph analysis for all statio

2.4 Catchment delineation and selection of representative catchments

There are gauged stations in the basin which was used to transfer seven un-gauged catchments were delineated for the availability of study.

Table 2.6:Sub-catchments of Omo-Gibe basin of un-gauged areas

Sub-catchments	Un-gauged location	Area(Km^2)
CD3	Un-gauged	248.8
CO4	Un-gauged	6.25
CO3	Un-gauged	29.11
CO2	Un-gauged	3.46
CO1	Un-gauged	4.8
CD13	Un-gauged	30.5
CD14	Un-gauged	47.5

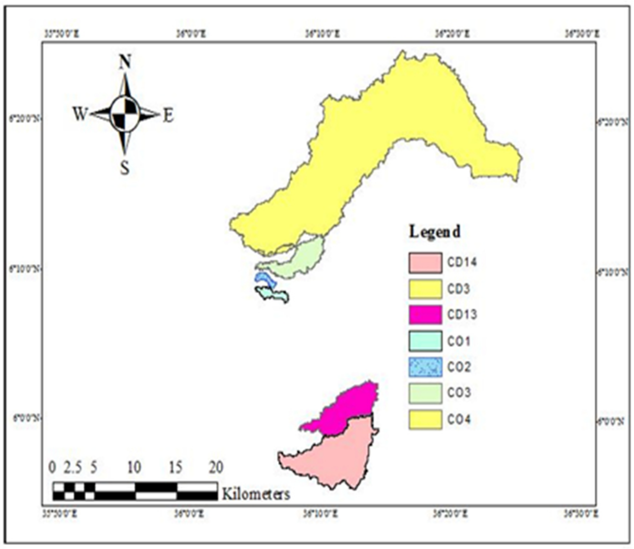

Figure 2.12: Sub-catchments of Omo-Gibe basin of un-gauged maP

Table 2.7:Sub-catchments of Omo-Gibe basin of gauged location

River	Station(site)	Reference	Sub-catchments gauged	Area(km^2)	X-Coordinate	Y-Coordinate
Woshi	Nr.Dimbra	91025	Sherma	281.25	170940.73	810215.04
Guma	Nr.Andra.	92004	Guma	477.23	196243.91	791238.74
Dincha	at bong	92005	Guma	230.1	199592.89	796752.48

From the above table for gauged catchments Sherma, Guma and Guma two sub catchments sub catchments covers large and small area respectively .for gauged catchments Guma two sub catchments covers large area whereas CO2 covers small area in un-gauged basin.

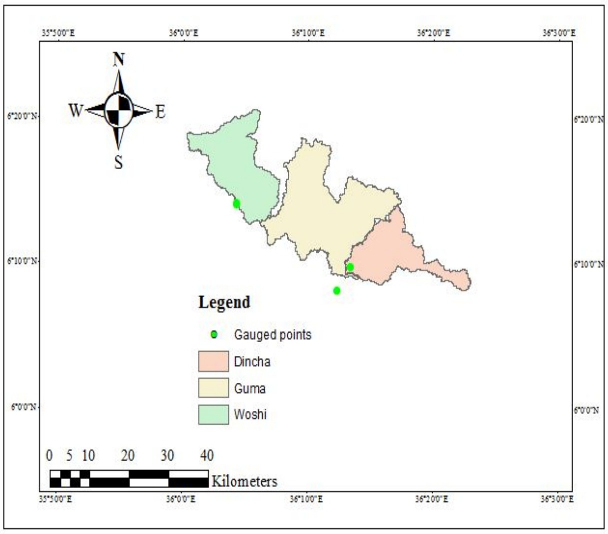

Figure 2.13: Sub-catchments of gauged location

2.5 Methods

2.5.1 Hydrological model development

2.5.2 Basin Model Development Using HEC-GeoHMS

One of the main input parameters for Geo-HMS processing is spatial hydrographic features. The Geo-HMS tool is designed to have the output files from the Arc-Hydro terrain preprocessing tools as inputs.

Geo-HMS Data Processing

In general, Geo-HMS uses spatial analyst tools to convert geographic information into parameters for each of the basins and flow lines. These parameters are used to create HEC-HMS Model that can be used within the HEC-HMS program.

2.5.3 HEC-HMS Modelling

Basin model:-The basin in model is the physical representation of watersheds (termed as "sub-basin" in HEC-HMS) and river systems into hydrological elements, each one configured with its proper method for the simulation of hydrologic processes.

Meteorological Model:-A meteorological model consists of the available Recorded time series rainfall data of each rainfall gauging stations that contribute to the catchment from the year 1995 to 2018.

Control Specifications:-The control specifications model determines the simulation time step and period or duration. In this study the starting date, 1-Jan-1995 and ending time00:00 and ending date and time, 31-Dec-2018, 00:00 with a time interval of 1day.

2.5.4 HEC HMS Model Parameterization

Infiltration loss model:-The loss models in HEC-HMS normally calculate the runoff volume by computing the volume of water that is intercepted infiltrated, stored, evaporated, or transpired and subtracting it from the precipitation **[7].**

The SCS-CN model assumes that the accumulated rainfall-excess depends upon the cumulative precipitation, soil type, land use and the previous moisture conditions as estimated in the following relationship:

$$P_e = \frac{(P-I_a)^2}{P-I_a+S} \text{------------------------------------}2$$

Where, P_e is the accumulated precipitation excess at time t (mm); P is the accumulated rainfall depth at time t (mm); I_a is the initial abstraction (initial loss) (mm) = 0.2 * S and S is the potential maximum retention (mm), a measure of the ability of a watershed to abstract and retain storm precipitation.

The maximum retention, S, and watershed characteristics are related through an intermediate dimensionless parameter, the curve number (CN) as:

$$S = \frac{25400}{CN} - 254 \text{-------------------------------}3$$

Estimating CN:-CN of watershed can be estimated as a function of combined effects of the primary characteristics of the catchment area, including land use, soil type and antecedent watershed moisture using table published by SCS.

$$CN_{Composite} = \frac{\sum CN_i A_i}{\sum A_i} \text{---------------------------}4$$

CN $_{Composite}$ is the composite CN used for runoff computation; i is an index of watersheds subdivision of uniform

land use and soil types, CN_i is CN for the subdivision i and A_i is drainage area of the subdivision.
The Transform Model: A parametric model based on the average Unit Hydrograph (UH) derived from gauged rainfall and runoff data of a large number of small agricultural watersheds throughout the United States.
The peak discharge for the unit graph is computed as:

$$Q_P = \frac{CP_e A}{T_p} \text{-------------------------------}(5)$$

Where: Q_p = Peak outflow (cfs)
C= SCS Shape Factor (484 in foot pound system and 0.208 in metric)
A = Area (square miles)
P_e = Total excess precipitation, 1 inch (1 mm)
T_p = Time to peak (hrs.)
The shape factor is a user-definable variable. The default value is set to 484 and creates a unit hydrograph that has 3/8 of its area under its rising limb. This factor is higher in mountainous watersheds, for example, 600, while in flat, sandy areas will be lower, around 300. For this study, typical SCS peaking factor is used.
The Time to Peak, Tp, is computed as follows:

$$T_p = \frac{\Delta t}{2} + t_{lag} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

In which △t is excess precipitation duration in the computation?
The lag time (T_{lag}) is the time from the midpoint of excess rainfall duration △t to peak of a unit hydrograph in hour and calculated for each watershed based on the time of concentration Tc, as:

$$T_{lag} = 0.6 * T_c \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(7)$$

Where, T_{lag} and T_c are in minute.
The time of concentration can be estimated based on basin characteristics including topography and the length of the reach by Kirpich's formula.

$$T_c = 0.0078 * \frac{L^{0.77}}{S^{0.385}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

Where L is the reach length in feet, and S is the slope in (ft/ft).
The base length (T_b) of U.H in days was estimated as follows; Time base

$$T_b = 2.67 T_p \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

Modeling Base Flow
The base flow model based on the Exponential Recession method is used to explain the drainage from natural storage of the watershed. For the exponential recession model, the recession constant (*k*) and the base flow threshold (ratio-to-peak flow) were initially set for each watershed with values of 1 and 0.05.
Routing Model: The Muskingum method, which was developed by McCarthy, is a popular lumped flow routing technique, which was selected for this study **[8]**.
It is a straightforward hydrological flood routing technique used in natural channels, and it has been extensively applied in river engineering practice since its introduction in the 1930s.

$$S = K\left[XI + (1 - X)Q\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

In which the prism storage in the reach is KQ, where K is a proportionality coefficient, and the volume of the wedge storage is equal to KX (I - Q), where X is a weighting factor having a range of $0 \leq X \leq 0.5$.
HEC-HMS treats the different phases of rainfall-runoff processes with separate mathematical models **[9].**

2.5.5 Loss determination
The term loss refers to the amount of rainfall infiltrated into the soil. In this paper for Specified hyetograph method the deficit and constant rate loss method is chosen because it has been used for long term simulations and also it is "mature" model that has been used successfully in many studies throughout the US (USACE, 2002), easy to set up and use, and not too much demanding in terms of data where much is missing in the study area.

2.5.6 Selection of Representative Physical Catchment Characteristics
Runoff generation is governed by physical catchment characteristics. In Omo-Kuraz Omo-Gibe basin a SRTM DEM 30 × 30 m resolution were used. The GIS software and also Arc hydro and HEC-GeoHMS also used to extract some PCCs values with the help of GIS software. Selected catchment characteristics were used to develop methods to estimate stream flow characteristics for un-gauged catchments.

Hydrological Soil Groups
Soil properties influence the relationship between runoff and rainfall since soils have differing rates of infiltration. Permeability and infiltration are the principal data required to classify soils into Hydrologic Soils Groups

(HSG). (HEC 19 1984) Based on infiltration rates, the Soil Conservation Service (SCS) has divided soils into four hydrologic soil groups as (I)Group A:Sand, loamy sand or sandy loam, (II) Group B:Silt loam, or loam, (III)Group C :Sandy clay loam and (IV) Group D:Clay loam, silty clay loam, sandy clay, silty clay or clay **[10].**

2.5.7 Model calibration and validation

The available hydro-meteorological data in the year of record were split up in to two parts for model calibration and model validation. Using parameters adjusted in the calibration process, the model will be validated from the available data.

Performance evaluation of the model

Table 2.8: presents the indicators used in the current study. In the given relations, n stands for the total number of input samples, i represent the time series of the observed and simulated pairs, Q_i^s and Q_i^o stand for simulated and observed stream flow, and $Q_{avg.}$ is the observed average discharge in the stream.

Table 2.8: Criteria for evaluating the performance of the hydrological model and their corresponding classifications

Statistical indicators	Value	Classification of performance	Reference
The correlation between actual and predicted values (R^2)	0.85 to 1.00	Very good	
	0.70 to 0.85	Good	
	0.60 to 0.70	Satisfactory	
$R^2 = 1 - \frac{(Qi^o - Qi^s)}{(Qi^o - Qavg)}$	0.4 to 0.60	Acceptable	
	R2 ≤0.4	Unsatisfactory	**[11]**
Nash-Sutcliffe efficiency (NSE)	0.75 to 1.00	Very good	
	0.65 to 0.75	Good	
$NSE = 1 - \frac{\sum_{i=1}^{n}(Qi^o - Qi^s)^2}{\sum_{i=1}^{n}(Qi^o - Qavg)^2}$	0.50 to 0.65	Satisfactory	
	0.4 to 0.50	Acceptable	
	NSE≤ 0.4	Unsatisfactory	
Mean bias error (MBE)	MBE>0 (positive)	Overestimated predictions	
$MBE = \sum_{i=1}^{n} \frac{(Qi^s - Qi^o)}{n}$	MBE<0 (negative)	Underestimated	

2.5.8 Transformation of Stream flow Data from Gauged to Un-gauged Sites

Regionalization is the process of transferring information from comparable catchments to the catchment of interest **[12].**Stream flow simulation needs a model parameter optimization for gauged catchments by fitting observed and simulated stream flow **[13]**. There are four regionalization methods in order to predict stream flow for un-gauged catchments those are:

- ❖ **Regional model**: the methods of regionalization using similarity of catchment characteristics (regional model) were applied to estimate flow for un-gauged catchments [**14].**
- ❖ **Similarity of spatial proximity**: This method is based on the underlying principle that catchments that are close to each other will likely have a similar runoff regime since climate and catchment conditions will often only vary marginally in space **[15]**.Catchments are highly homogeneous with respect to topographic and climatic properties that means land cover, soil, geology and physiographic and climate physical catchment characteristics **[16]**.
- ❖ **Sub-basin mean method**: It represents the arithmetic mean **[17]** of calibrated model parameters of gauged catchments to simulate stream flow for un-gauged catchments.
- ❖ **Area ratio method**: If the area ratio between gauged and un-gauged catchments is greater than 50%, the model parameters of gauged catchments are not transferred to un-gauged catchments **[18].**

  Establishing the regional model

  After determining the model parameters through model calibration and selection of physical catchment characteristics, a method for establishing the relationship is applied [**19]**.With respect to regionalization two types of regression methods can be selected.

- ❖ **Simple regression method**

The relation between model parameters and PCCs will be based on a simple linear regression. The correlation coefficient of two variables is between -1 and 1. It is determined as follows.

$$t_{Cor} = |r| * \frac{\sqrt{n-2}}{\sqrt{1-r^2}}. \text{----------------------------}11$$

Where: tcor = t value of the correlation in T-distribution table, r = correlation coefficient and n is sample size.

Multiple Linear regression method: It is used to select independent variables (PCCs), which can efficiently determine the dependent variables (model parameters). Independent variables are whose value is to be determined while dependent variables are those having fixed value or already determined. The general regression equations described as follows,

$$\acute{Y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + --- + \beta_n X_n \text{-----------}12$$

Where: β1, β2, βn are regression coefficient, X_1, X_2, X_n, is independent variable (physical Catchment characteristics), Ỳ is dependent variable (model parameters) and βo is intercepting of regression line. **Forward selection:-**Starts with the predictor variable having the highest correlation with the criterion variable and continues adding variables so that the determination coefficient (R^2) is maximize at each step. A test of hypothesis is performed at each step and computation ends when all statistically significant predictor variables have been included **[6].**

2.5.9 Frequency analysis

Frequency analysis is method, which involves study and analysis of past records (historical data) of hydrologic events to predict the future probabilities (chances) of occurrence **[20]**. The Peaks-over-threshold sample is defined by all peak values that lie above a certain truncation level (usually called the threshold or base level) [**21]**. The Peaks-over-threshold model has more physical back-ground because it is compounded from the distribution of the annual number of exceedences above the threshold and their magnitudes [**22]**.

2.5.9.1 Evaluation of performance of fitted probability distributions

The selected probability distribution models in the observed peak discharge data adequacy were evaluated by goodness of criteria. The methods are Root Mean Square Error (RMSE), Relative Root Mean Square Error (RRMSE), Mean Absolute Deviation Index (MADI), Maximum Absolute Error (MAE) and Probability Plot Correlation Coefficient (PPCC)**[23].**

Root mean square error (RMSE)

The root mean square error of a distribution fitted to the observed discharge data at a site is the square root of the sum of the squares of the differences between the observed and predicted values. It is computed using the equation:

$$RMSE = \left(\frac{\sum (x_i - y_i)^2}{n - m} \right)^{1/2} \quad .... \; .... \; ...(13)$$

Where x_i, i=1,--,--, n are the observed values and y_i, i=1,--,--, n are the values computed from the assumed probability distributions, the number of parameters estimated for the distribution is denoted by m.

Relative root mean square error (RRMSE)

The relative root mean square error (RRMSE) provides a better picture of the overall fit of a distribution. It calculates each error in proportion to the size of observation thereby reducing the influence of outliers which are common features of hydrological data. It is defined as **[24].**

$$RRMSE = \left(\frac{\sum \left(\frac{x_i - y_i}{x_i} \right)^2}{n - m} \right)^{1/2} \quad .... \; ....(14)$$

Mean absolute deviation index (MADI)

The MADI is calculated by:

$$MADI = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{x_i - y_i}{x_i} \right| \quad .... \; ....(15)$$

Where x_i are the observed values, y_i the predicted values and N the number of data points. The smaller the value obtained for MADI is for a distribution, the more fitting it is for the actual data. Thus the distribution with smaller values of MADI indicates that it is more fitted to the observed data **[25].**

Maximum Absolute Error (MAE)

The MAE is calculated by:

$$MAE = \max(|x_i - y_i|) \quad .... \; ....(16)$$

Probability plot correlation coefficient (PPCC)

The probability plotting correlation coefficient (PPCC) gives the correlation between the ordered observations and corresponding fitted quantiles determined by a plotting position. It is defined as **[26]:**

$$PPCC = \frac{\sum [(x_i - \bar{x})(y_i - \bar{y})]}{\left[\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2 \right]^{1/2}} \quad ......(17)$$

Where $\bar{X}$ and $\bar{y}$ represent the mean values of the observed and predicted quantiles respectively. A value of

PPCC near 1 suggests that the observed data could have been drawn from the fitted distribution at a site **[27].**

2.6 Probability distribution models selected for study using L-moment
The observed flow data in HEC HMS model was used and determine predict peak discharge using L-moment method in flood frequency analysis of selected gauged catchment those are Dincha, Woshi, Guma. The probability distribution models selected by easyfit method for the study are the Generalized Extreme Value distribution (GEV) and done by Generalized Logistic distribution (GLO) and Generalized Pareto distribution (GPA).

2.7 Parameter estimation using L-moments
Estimates of the parameters of the selected distributions were obtained following the L- moment procedures using the respective equations given in Table 3.9 ξ is the location parameter, α is the Scale parameter and k is the Shape parameter.

Table 2.9: L-Moment parameter estimates for selected probability distribution functions [28].

Distribution	Quantile Function	Parameter Estimates
Generalized Extreme Value (GEV)	$X(F)=\xi+\frac{\alpha}{k}(1-[-\ln(F)]^k)$	$\alpha=\frac{l_2 k}{\Gamma(1+k)\Gamma(1-2^{-k})}$ $\xi=l_1+\frac{\alpha(\Gamma(1+k)-1)}{k}$ $k=7.8590\ C+2.9554\ C^2$ $C=\frac{2}{3+\tau_3}-\frac{\ln 2}{\ln 3}$
Generalized Logistics (GLO)	$X(F)=\xi+\frac{\alpha}{k}\left[1-\left(\frac{1-F}{F}\right)^k\right]$	$\alpha=\frac{l_2}{\Gamma(1+k)\Gamma(1-k)}$ $\xi=l_1+\frac{(l_2-\alpha)}{k}$ $k=-\tau_3$
Generalized Pareto (GPA)	$X(F)=\xi+\frac{\alpha}{k}\left[1-(1-F)^k\right]$	$\alpha=l_2\left[(k+1)(k+2)\right]$ $\xi=l_1-l_2(k+2)$ $k=\frac{4}{\tau_3+1}-3$

3. RESULT AND DISCUSSION
3.1 Model Sensitivity Analysis, Calibration and Validation
3.1.1 Sensitivity analysis
The sensitivity analysis was applied by manually changing the value of one model parameter at a time and then estimating the values of selected objective functions: Nash and Sutcliffe efficiency (NSE), relative volume error (RVE), and coefficient of determination (R^2). For Guma catchment, the model response is most sensitive to time of concentration (TC) and storage coefficient(R). The remaining parameters are less sensitive crop coefficient (CC), initial deficit (ID), maximum deficit (MD), constant rate (CR), initial storage (IS), maximum storage (MS) and Impervious.

For Dincha catchment, the model response is most sensitive to maximum storage (MS) and constant rate (CR). The remaining parameters are less sensitive to crop coefficient (CC), storage coefficient(R), Initial deficit (ID), maximum deficit (MD), initial storage (IS), Time of concentration (TC) and Impervious.

For Woshi catchment the model response is most sensitive to Time of concentration (TC) and storage coefficient(R). The remaining other parameters are less sensitive to constant rate(CR), crop coefficient (CC), Initial deficit(ID),maximum deficit(MD), initial storage(IS) ,maximum storage(MS), and Impervious.

Table 3.1: The sensitive parameters of each catchment

Model parameter	**Dincha**	**Woshi**	**Guma**
TC (Hr)	-	81	45
R(Hr)	-	70	180
MS (mm)	9.9	-	-
CR (mm/Hr)	0.03	-	-

3.1.2 HEC-HMS model Calibration results
The HEC-HMS for the study area was calibrated manually using trial. The available observed data daily precipitation, potential evapotranspiration and stream flow were used. The HEC-HMS of the study area was calibrated for the second fourteen years (1998-2011) and then was further validated for the last seven years (2012-

2018). Three years warming period for the firstly (1995-1997).
Model calibration results shown in Table 3.2 the model performance (Dincha, Woshi, Guma) are satisfactory with objective functions below.

Table 3.2: Parameter range and initial model run results

Prior model parameters range		Optimized model parameters		
Model parameter	Interval	Dincha	Woshi	Guma
TC (Hr)	0.0167-1000	43	81	45
R(Hr)	0.01-1000	154	70	180
IS (%)	0.01-100	0.3	10	0.4
MS (mm)	0.001-1500	9.9	79	12
ID (mm)	0.001-1000	0.45	5	0.4
MD (mm)	0.001-1000	24.3	110	30
CR (mm/Hr)	0.001-300	0.03	0.64	0.001
Impervious (%)		2	11	8
CC ()	0.01-1.5	0.92	0.83	0.95
NSE		0.889	0.9	0.8
RVE (%)		5.1	4.3	-2.21

From HEC-HMS Model results there are three sub-catchments daily observed and simulated flow hydrographs and scatter plot of calibration 1998-2011 were done. A sub-catchment daily observed and simulated flow hydrographs and scatter plot of calibration 1998-2011 were presented in Figure 3.1 and Figure 3.2 respectively. The remaining part graphical and scatter plot of calibration results shown in below in Figure 3.3, Figure 3.4, Figure 3.5 and Figure 3.6.

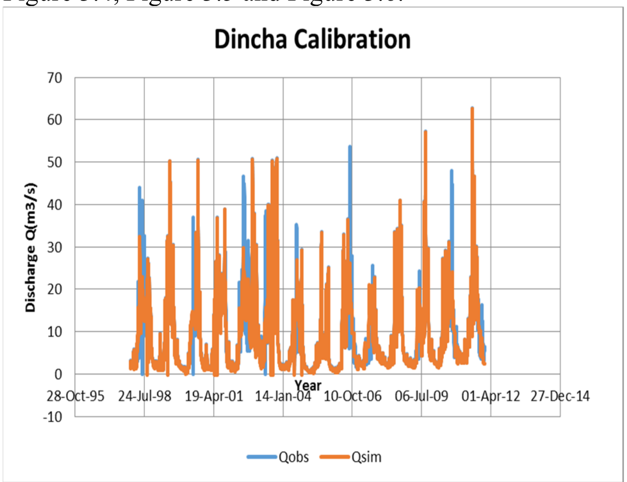

Figure 3. 1: Observed and simulated flow hydrographs Dinch catchment

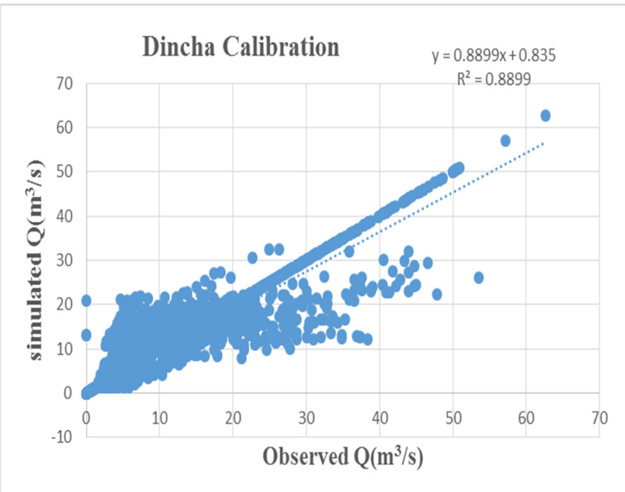

Figure 3. 2: Scatter plot comparison of observed and simulated flow for calibration period

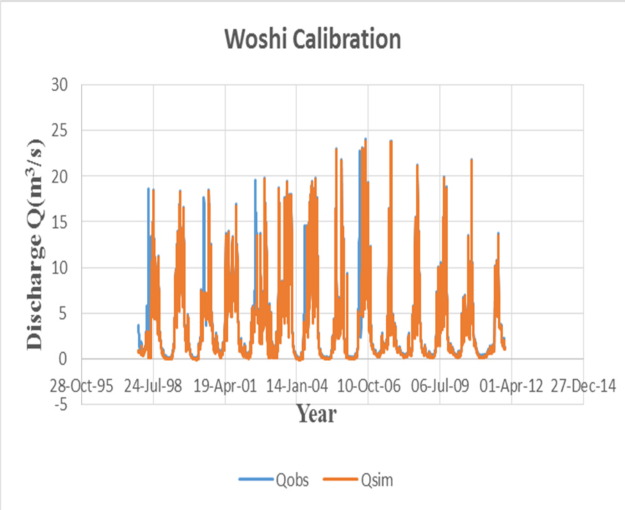

Figure 3.5: Observed and simulated flow hydrographs Woshi catchment

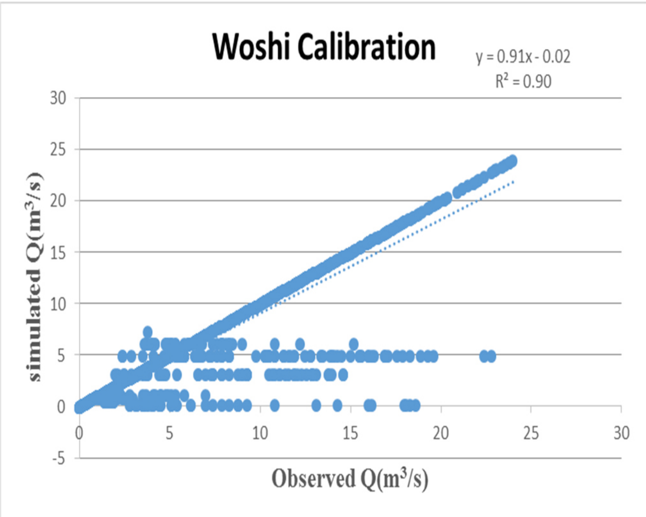

Figure 3.6: Scatter plot comparison of observed and simulated flow for calibration period

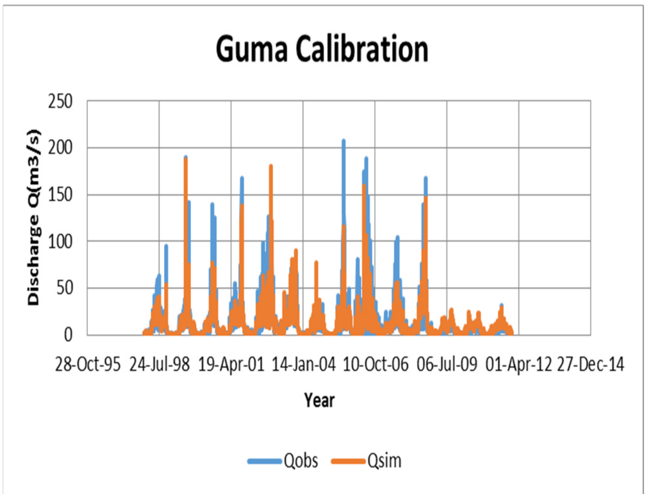

Figure 3.3: Observed and simulated flow hydrographs Guma catchment

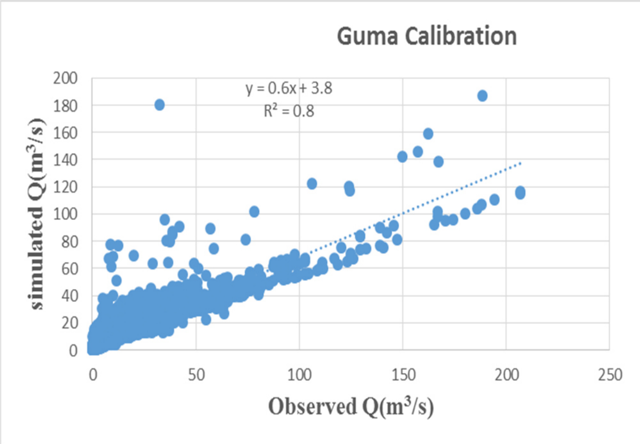

Figure 3.4: Scatter plot comparison of observed and simulated flow for calibration period

3.1.3 HEC-HMS model validation results

In this study, the results show that the model validation done catchment that satisfies the objective function Table 3.3.

Table 3.3: Validation model parameter result of gauged catchments

Model Parameters	Gauged Catchments		
	Dincha	Woshi	Guma
TC (Hr)	43	48	18
R (Hr)	167	105	33
IS (%)	0.1	9	14
MS (mm)	9.7	320	10
ID (mm)	0.43	9	0.42
MD(mm)	23	149	2.3
CR (mm/Hr)	0.14	0.20	0.016
Impervious (%)	2	13	4
CC ()	0.91	0.95	0.84
NSE	0.81	0.72	0.92
RVE (%)	5.4	2	-2.3

Therefore, these results of estimated stream flows indicate that HEC-HMS model is good predictor of stream flow in Omo-Gibe basin. The validation model parameter results of gauged catchments that satisfy the objective functions for calibration also have good performance for validation.

3.2 Result of Regionalization

3.2.1 Catchment selection criteria for regionalization

The gauged catchment based on the results of calibration of river (Woshi, Guma,and Dincha) catchments were selected for regionalization because objective functions NSE value between 0.8 and 0.9, RVE between +10% or -10%. Therefore, these catchments model parameters were used for regionalization.

3.2.2 Multiple Linear regressions results

The multiple regressions was applied to establish regional model using optimized model parameters and PCCs of gauged catchments in Microsoft Excel, data analysis in stepwise multiple regression method. Depending on the R^2 ($\geq$0.85) and significance or p-value ($\leq$ 0.10 for 95% confidence interval) PCCs were selected to establish regression equations. Each model parameters in relation with regression analysis is shown (Table 3.4).

Time of concentration (TC): In this study TC has significant high co-linearity with maximum elevation and sum of stream length with R^2 is 1 and p-value is 0.01 and the result shown in (Table 3.4).

Storage coefficient(R): The linear regression equation showed that R has high co-linearity with catchment area and perimeter with R^2 of 1 and p-value is 0.02and the result shown in (Table 3.4).

Initial canopy storage (%): In this study IS has significant simple positive correlation with maximum elevation, sum of stream length, area and perimeter with R^2 is 1 and p-value is 0.001and the result shown in (Table 3.4).

Max canopy storage (mm): The parameter representing the supreme depth of water that can be intercepted by vegetation. The regression equation showed that MS has high co-linearity with humic nitisols, humic alisols, cultivation and natural forest with R^2 of 1 and p-value is 0.01 and the result shown in (Table 3.4).

Initial deficit (ID) it indicates initial condition that the amount of water that is required to saturate the soil layer to the maximum storage. The linear regression equation showed that ID has high co-linearity with maximum elevation, sum of stream length, area and perimeter with R^2 of 1 and p-value is 0.02 and the result shown in (Table

3.4).

Maximum deficit (MD): The maximum deficit agrees the amount of water the soil layer can grasp, specified as a depth. In this study MD has important simple positive correlation with cultivation, natural forest, shrubland and grassland with R^2 is 1and p-value is 0.039 and the result shown in (Table 3.4).

Constant rate loss (CR): The constant rate loss defines the percolation rate when the soil layer is saturated. The regression equation showed that CR has high co-linearity with maximum elevation, sum of stream length, area, and perimeter with R^2 of 1 and a p-value lie is 0.1 and the result shown in (Table 3.4).

Crop Coefficient- is used in the canopy component to adjust the soil water use of a specific plant relative to the reference. The regression equation showed that CC has high co-linearity with shrubland, grassland, woodland and SAAR with R^2 of 0.942 and a p-value lie is 0.094 and the result shown in (Table 3.4).

Impervious (%): The soil layer with a percolation rate slower than 60 minutes per inch any layer of material in the soil profile which has a percolation rate slow than 120 minutes per inch. The regression equation showed that impervious has high co-linearity with average slope, longest flow path, mean elevation, minimum elevation and maximum elevation with R^2 of 0.999 and a p-value lie is 0.026 and the result shown in (Table 3.4).

Table 3.4: The regional model for model parameters and PCCs links

	Coefficients		95% confidence interval				co-linearity
	B	Standard Error	t Stat	P-value	Lower bound	Upper bound	
Tc=Bo+B1*max elev+B2*sum strm len							
Bo	183.51	0.0	65535	0.01	183.51	183.51	
B1	-0.04	0.0	65535		-0.04	-0.04	1.00
B2	0.02	0.0	65535		0.02	0.02	
R=Bo+B1*Catchment area+B2*perimeter							
Bo	231.60	0.00	65535.00	0.02	231.60	231.60	
B1	-1.22	0.00	65535.00		-1.22	-1.22	1.00
B2	1.44	0.00	65535.00		1.44	1.44	
IS=Bo+B1*max elev+B2*sum strm len+B3*area+B4*perimeter							
Bo	36.26	0.00	65535.00	0.001	36.26	36.26	
B1	-0.01	0.00	65535.00		-0.01	-0.01	
B2	0.00	0.00	65535.00		0.00	0.00	1.00
B3	0.00	0.00	65535.00		0.00	0.00	
B4	0.00	0.00	65535.00		0.00	0.00	
MS=Bo+B1* Humic Nitisols+B2*Humic Alisols+B3*Cultivation+B4*Natural forest							
Bo	224.77	0.00	65535.00	0.01	224.77	224.77	
B1	-0.47	0.00	65535.00		-0.47	-0.47	
B2	0.00	0.00	65535.00		0.00	0.00	1.000
B3	-2.42	0.00	65535.00		-2.42	-2.42	
B4	0.00	0.00	65535.00		0.00	0.00	
ID=Bo+B1*max elev+B2*sum strm len+B3*area+B4*perimeter							
Bo	17.48561268	0	65535	0.02	17.48561268	17.48561268	
B1	-0.005080077	0	65535		-0.005080077	-0.005080077	
B2	0	0	65535		0	0	1.000000
B3	-0.000194363	0	65535		-0.000194363	-0.000194363	
B4	0	0	65535		0	0	
MD=Bo+B1*Cultivation+B2*Natural forest+B3*Shrubland+B4*Grassland							
Bo	427.45	0.00	65535.00	0.039953502	427.4523969	427.4523969	
B1	-4.15	0.00	65535.00		-4.146627743	-4.146627743	
B2	-3.44	0.00	65535.00		-3.443443043	-3.443443043	1.000
B3	0.00	0.00	65535.00		0	0	
B4	0.00	0.00	65535.00		0	0	
Imprevous=Bo+B1*Average slope+B2*Longest flw+B3*mean elev+B4*min elev+B5*max elev							
Bo	45.296	0.000	65535.000	0.026	45.296	45.296	
B1	0.000	0.000	65535.000		0.000	0.000	
B2	0.000	0.000	65535.000		0.000	0.000	0.9999990
B3	-0.018	0.000	65535.000		-0.018	-0.018	
B4	0.000	0.000	65535.000		0.000	0.000	
B5	0.000	0.000	65535.000		0.000	0.000	
CR=Bo+B1*max elev+B2*sum strm len+B3*area+B4*perimeter							
Bo	2.35274	0.00000	65535.00000	0.1	2.35274	2.35274	
B1	-0.00069	0.00000	65535.00000		-0.00069	-0.00069	
B2	0.00000	0.00000	65535.00000		0.00000	0.00000	1.0000
B3	-0.00011	0.00000	65535.00000		-0.00011	-0.00011	
B4	0.00000	0.00000	65535.00000		0.00000	0.00000	
CC=Bo+B1*Shrubland+B2*Grassland+B3*Woodland+B4*SAAR							
Bo	2.2546	0.335407627	6.7221	0.094016566	-2.0071	6.5164	
B1	0	0.0000	65535.0000		0.0000	0.0000	
B2	0	0.0000	65535.0000		0.0000	0.0000	0.942
B3	0	0.0000	65535.0000		0.0000	0.0000	
B4	-0.000832978	0.0000	-4.0415		-0.0035	0.0018	

3.2.3 Determining Model Parameters and Evaluating Stream Flow at Un-gauged Catchments

3.2.4 Determination of Model Parameters for un-gauged catchment

To determine model parameters for seven un-gauged catchments were selected in Omo-Kuraz (CD3, CO4, CO3, CO2, CO1, CD13 and CD14) in Omo-Gibe basin by three flow gauged catchments which are Sherma, Woshi, and Guma. To determine model parameters of those un-gauged catchments the following four methods were used:

Regional model method: Each model parameters estimated by regional model was derived using equation (Table 3.4) above.

Table 3. 1: Model parameters estimated for un-gauged catchments using regional model

Un-gauged catchments	TC	R	IS	MS	ID	MD	CR	Impervious.	CC
CD3	80	162	9	224	4.91	427.5	0.63	32.1	1.5
CO4	161	260	30	225	14.72	427.5	1.98	36.4	1.46
CO3	160	262	30	225	14.57	427.5	1.96	36.0	1.46
CO2	161	255	30	225	14.77	427.5	1.99	36.4	1.46
CO1	161	258	30	225	14.72	427.5	1.98	36.2	1.46
CD13	156	264	29	225	14.07	427.5	1.89	35.0	1.46
CD14	156	256	29	225	14.08	427.5	1.89	35.1	1.46

Area ratio method: Parameter set of gauged catchments are transferred to un-gauged catchments of comparable area based on the assumption on catchment area.

Table 3. 2: Area between gauged and un-gauged catchments (%)

Gauged catchment	Un-gauged catchment						
	CD3	CO4	CO3	CO2	CO1	CD13	CD14
Woshi	104.17	4500.02	966.17	8128.65	5859.40	922.14	592.11
Guma	287.28	12410.49	2664.57	22417.80	16159.50	2543.13	1632.96
Dincha	85.22	3681.62	790.46	6650.33	4793.78	754.43	484.42

In case of area ratio method gauged Woshi, Guma and Dincha catchments model parameters cannot transfer any un-gauged catchments because the area ratio between gauged and un-gauged catchments is greater than 50%.

Spatial proximity method: The transfer of catchment information will be based on physiographic, soil, land use land cover and climate that site of interest by computing the correlation of each catchment. The similarity of catchment characteristics between gauged and un-gauged catchments in Omo-Gibe sub-basin (specific place in Omo-Kuraz) are discussed below.

Physiography of catchment characteristics correlation (R^2)

Table3.3: Similarity of catchment characteristics between gauged and un-gauged on physiography

The catchment of CO4, CO3, CO2, CO1, CD3, CD13, CD14 have Average slope, longest flow path, mean elevation, minimum elevation, sum of stream length, area, perimeter, maximum elevation, hypsometric integral, circularity index, elongation ratio, drainage density and basin shape are correlated with gauged catchment of the same parameters.

Un-gauged Catchments	Gauged catchments		
	Guma	Woshi	Dincha
CO4	0.88	0.97	0.91
CO3	0.90	0.98	0.93
CO2	0.87	0.96	0.91
CO1	0.87	0.97	0.91
CD3	0.89	0.73	0.84
CD13	0.94	0.99	0.97
CD14	0.94	0.99	0.97

The correlations of un-gauged CD14 and CD13 have 0.94, 0.99, and 0.97 with gauged catchments of Guma, Woshi, and Dincha respectively. As the correlation result shows un-gauged CD14 catchment obtained model parameters from Woshi gauged catchment. Similarly, the correlations of other catchments were shown in the above table.

Land Cover catchment characteristics correlation

Table3.4: Similarity of catchment characteristics between gauged and un-gauged catchments on land use and land cover

The catchment of CO4, CO3, CO2, CO1, CD3, CD13, CD14 have Cultivation, Natural forest, Shrubland, Grassland and Woodland are correlated with gauged catchment of the same parameters.

Un-gauged Catchments	Gauged catchments		
	Guma	Woshi	Dincha
CO4	0.29	0.19	0.24
CO3	0.13	0.01	0.10
CO2	0.2	0.06	0.16
CO1	0.14	0.02	0.11
CD3	0.36	0.41	0.29
CD13	0.21	0.07	0.17
CD14	0.14	0.02	0.11

The Land use land cover show that correlation outcome of un-gauged CD3 has 0.36, 0.41, and 0.29 with gauged catchments of Guma, Woshi and Dincha respectively. Show detail above in table.

Climate catchment characteristic correlation (R^2)

Table3.5:Similarity of climate catchment characteristics between gauged and un-gauged catchment.

Un-gauged Catchments	Gauged catchments		
	Guma	Woshi	Dincha
CO4	1	1	1
CO3	1	1	1
CO2	1	1	1
CO1	1	1	1
CD3	1	1	1
CD13	1	1	1
CD14	1	1	1

The Climate catchment characteristic show high that correlation outcome of un-gauged CO4 up to CD3 has 1, 1, and 1 with gauged catchments of Guma, Woshi and Dincha respectively.

Soil catchment characteristics correlation (R^2)

Table 3. 6: Similarity of catchment characteristics between gauged and un-gauged on soil

The catchment of CO4, CO3, CO2, CO1, CD3, CD13, CD14 have chromic luvisols, eutric vertisols, eutric fluvisols, humic nitisols and humic alisols are correlated with gauged catchment of the same parameters.

Un-gauged Catchments	Gauged catchments		
	Guma	Woshi	Dincha
CO4	0.34	0.15	0.28
CO3	0.22	0.09	0.18
CO2	0.34	0.15	0.27
CO1	0.37	0.16	0.3
CD3	0.17	0.12	0.07
CD13	0.2	0.09	0.16
CD14	0.19	0.08	0.15

3.2.5 In flood frequency analysis L-moment method of critical theory

The unbiased sample computed of the first four Probability Weighted Moments. The first four L-moment values expressed in period of PWMs. The value of λ_1 is a measure of central tendency; λ_2 is a measure of dispersion and L-CV is the coefficient of L-variation, L-skewness measures whether the distribution is symmetric with respect to the dispersion from the mean and L-kurtosis refers to the weight of the tail of a distribution.

Table 3. 11: The L-moment statistics for catchment Dincha obtained

Probability Weighted Moment Values		L- Moment Values		L- Moment Ratios		Basic Statistics	
bo	45.87142857	λ_1	45.87142857	L-CV	0.1274944	N	14
b1	25.85989011	λ_2	5.848351648	L-Skewness	-0.1191281	Mean	45.87142857
b2	18.0985348	λ_3	-0.696703297	L-Kurtosis	0.1507806	Variance	101.739120
b3	13.96953047	λ_4	0.881818182			Standard Dev.	10.901305
						C.V	0.229985

The calculated L-skewness value 0.119128147 lies in the range 0.050</L-skewness/≤0.150 suggested that the observed is moderate skewness. Also L-C_V value 0.12749443 indicates that the observed data is moderate variability.

The parameters of location (ξ), scale (α) and shape (k) of the selected distributions computed using the relevant equations calculated using important equation given in table 2.9 are as obtainable in table below.

Table 3. 12:Probability parameter estimate based on L-moment for catchment Dincha

Probability Distribution Model	Shape Parameter(k)	Scale Parameter(α)	Location Parameter(ξ)	Error
GPA	1.540955631	52.62002434	25.16267487	0.1
GLO	0.119128147	5.801637675	46.2635607	0.09
GEV	0.50935394	6.488416792	52.57554975	0.4

The estimated parameter values distributions given in Table 3.12 were applied to their respective quantile functions defined in formula Table 2.9 and the corresponding predicted discharge results are presented in Table 3.13. The predicted discharge values by the distributions were subjected to five statistical goodness-of- fit tests as described in table 3.13 in order to select the best among the candidate distributions that adequately fits the observed data at the station. The summary of the results of the goodness of fit tests are presented in Table 3.14 and it shows that the minimum value of RMSE, RRMSE, MADI, MAE and the value of PPCC closest 1 is obtained by applying GPA distribution to the observed data at the station.

Table 3. 1**3**: Observed and annual maximum discharge based on GPA, GLO and GEV using L-moment obtained catchment Dincha from algorithm two

Rank	Observed annual max discharge on hec-hms model (xi) (m^3/s)	Predicted annual max discharge(Yi) on GPA (m^3/s)	Predicted annual max discharge(Yi) on GLO (m^3/s)	Predicted annual max discharge(Yi) on GEV (m^3/s)
1	25.5	28.60675922	28.27259172	44.15510514
2	33.5	31.92022394	34.09804961	47.11320379
3	35.3	35.09854288	37.51854442	49.08142343
4	38.9	38.13664995	40.02634124	50.63062861
5	41	41.02882065	42.07147636	51.95047612
6	44	43.76851345	43.85346093	53.13033382
7	47.9	46.34815142	45.48266542	54.221481
8	50.3	48.7588114	47.03213228	55.2581178
9	50.6	50.98976312	48.56001388	56.26661393
10	50.7	53.02774899	50.12339682	57.27087691
11	51	54.85577819	51.79265675	58.29705328
12	53.6	56.45090399	53.67731742	59.38047707
13	57.2	57.77949	55.99751934	60.58210136
14	62.7	58.7842462	59.40123362	62.05075437

Table 3. 14 :Goodness of fit statistics based on L-moment for catchment Dincha obtained

GoF Statistics	RMSE	RRMSE	MADI	MAE	PPCC
GPA	2.3710909	0.055772752	0.007988275	3.915753796	0.976686234
GLO	2.118825361	0.051873095	0.001243958	3.298766385	0.990288811
GEV	10.8815753	0.323371107	0.219737753	18.65510514	0.988148527

The overall goodness of fit of each distribution was judged using a ranking scheme by comparing the five categories of test criteria based on the relative magnitude of the statistical test results. The distribution with the lowest RMSE, lowest RRMSE, lowest MADI, lowest MAE and highest PPCC at a station was considered the best fitting distribution or was assigned a score of 3, the next best was given the score 2, while the worst was given the score 1. The overall score of each distribution was obtained by summing the individual point scores for the station on catchment Dincha and the distribution with the highest total point score was selected as the best fit distribution model for the station on catchment Dincha. On the basis of the above analysis, GLO with the highest total score of 15 is selected as the best distribution for the station followed by GPA and then GEV. The best fit distribution model and the other two distribution were used to obtain estimates of quantile (Q_T) for a range of return periods (2years, 5years, 10years, 25 years, 50 years, 100 years) of hydraulic and hydrologic significance which results are presented table 3.14.

Table 3. 15: Scoring and ranking scheme for selected probability distribution models for river on catchment Dincha

Test Criteria	Distribution scoring		
	GPA	GLO	GEV
RMSE	2	3	1
RRMSE	2	3	1
MADI	2	3	1
MAE	2	3	1
PPCC	1	3	2
Total Score	9	15	6
Rank	2st	1rd	3rd

The results presented in Table 3.15 and show that though GLO is the best fit probability distribution model in comparison with GPA and GLO models.

Table 3. 16: Computed quintiles estimates based on selected return periods on catchment Dincha for GLO using algorithm two

Return periods(T)	(T-1)	[(T-1)^-k]	R=[1-(T-1)^-k]	Z=[(α/k)*(R)]	QT=(ξ+Z)	Exceedance probability E=(1/T)
2	1	1	0	0	46.2635607	0.5
5	4	0.847769	0.15223065	7.41375671	53.6773174	0.2
10	9	0.769702	0.23029757	11.2156789	57.4792396	0.1
25	24	0.684822	0.31517754	15.3494028	61.6129635	0.04
50	49	0.628999	0.37100083	18.0680422	64.3316028	0.02
100	99	0.578447	0.42155286	20.5299672	66.7935279	0.01

Table 3. 17 : The L-moment statistics for catchment Woshi obtained

Probability Weighted Moment Values		L- Moment Values		L- Moment Ratios		Basic Statistics	
bo	19.91428571	ʎ1	19.91428571	L-CV	0.0796821	N	14
b1	10.75054945	ʎ2	1.586813187	L-Skewness	-0.0474376	Mean	19.91428571
b2	7.418956044	ʎ3	-0.075274725	L-Kurtosis	0.2018698	Variance	7.733626374
b3	5.689835165	ʎ4	0.32032967			Standard Dev.	2.78678198
						C.V	0.13964547

The calculated L-skewness 0.0474376 value lies in the range 0.000</L-skewness/≤0.050 suggested that the observed is minor skewness. Also L-C_V value 0.0796821indicates that the observed data is moderate variability. The parameters of location (ξ), scale (α) and shape (k) of the selected distributions computed using the relevant equations calculated using important equation given in table 2.9 are as obtainable in table below.

Table 3. 18: Probability parameter estimate based on L-moment for catchment Woshi

Probability Distribution Model	Shape Parameter(k)	Scale Parameter(α)	Location Parameter(ξ)	Error
GPA	1.199200291	11.16431331	14.83775251	0.12
GLO	0.047437673	1.555298975	20.5786145	0.14
GEV	0.371410761	1.85159799	21.84258604	0.1

The estimated parameter values distributions given in Table 3.18 were applied to their respective quantile functions defined in formula Table 2.9 and the corresponding predicted discharge results are presented in Table 3.19. The predicted discharge values by the distributions were subjected to five statistical goodness-of- fit tests as described in table 3.20 in order to select the best among the candidate distributions that adequately fits the observed data at the station. The summary of the results of the goodness of fit tests are presented in Table 3.21 and it shows that the minimum value of RMSE, RRMSE, MADI, MAE and the value of PPCC closest 1 is obtained by applying GPA distribution to the observed data at the station.

Table 3. 19: Observed and annual maximum discharge based on GPA, GLO and GEV using L-moment obtained catchment Woshi

Rank	Observed annual maximum discharge on hec-hms model (xi) (m3/s)	Predicted annual maximum discharge(Yi) on GPA (m3/s)	Predicted annual maximum discharge(Yi) on GLO (m3/s)	Predicted annual maximum discharge(Yi) on GEV (m3/s)
1	13.7	15.57700729	16.20610155	19.61041681
2	16.9	16.30581005	17.53424154	20.36100647
3	18.4	17.02352063	18.35003691	20.87876946
4	18.5	17.72940329	18.96691071	21.29835549
5	18.6	18.42260248	19.48264368	21.66537018
6	19.4	19.10210935	19.9418912	22.00185596
7	19.8	19.76671429	20.3702741	22.32098886
8	19.8	20.41493682	20.78563936	22.63215712
9	19.9	21.04491743	21.2032079	22.94333914
10	21.2	21.65424084	21.63913442	23.2627128
11	21.8	22.23962388	22.11480229	23.60044996
12	23	22.7963026	22.66535015	23.97195428
13	23.8	23.31661713	23.36431959	24.40637335
14	24	23.7856656	24.4366077	24.98113171

Table 3. 20 :Goodness of fit statistics based on L-moment for catchment Woshi obtained

GoF Statistics	RMSE	RRMSE	MADI	MAE	PPCC
GPA	0.899278875	0.055086216	0.003635626	1.877007293	0.954803318
GLO	1.033767921	0.065822619	0.034494679	2.506101554	0.977068825
GEV	3.16892084	0.189422745	0.138064777	5.910416812	0.972793668

The overall goodness of fit of each distribution was judged using a ranking scheme by comparing the five categories of test criteria based on the relative magnitude of the statistical test results. The distribution with the lowest RMSE, lowest RRMSE, lowest MADI, lowest MAE and highest PPCC at a station was considered the best fitting distribution or was assigned a score of 3, the next best was given the score 2, while the worst was given the score 1. The overall score of each distribution was obtained by summing the individual point scores for the station on catchment Woshi and the distribution with the highest total point score was selected as the best fit distribution model for the station on catchment Woshi. On the basis of the above analysis, GPA with the highest total score of 13 is selected as the best distribution for the station as GEV and then GLO. The best fit distribution model of GPA distribution were used to obtain estimates of quantile (Q_T) for a range of return periods (2years, 5years, 10years, 25 years, 50 years, 100 years) of hydraulic and hydrologic significance which results are presented table 3.21.

Table 3. **21** :Scoring and ranking scheme for selected probability distribution models for river on catchment Woshi

Test Criteria	Distribution scoring		
	GPA	GLO	GEV
RMSE	3	2	1
RRMSE	3	2	1
MADI	3	2	1
MAE	3	2	1
PPCC	1	3	2
Total Score	13	11	6
Rank	1st	2rd	3rd

The results presented in Table 3.21 and show that though GPA and GLO is the best fit probability distribution model in comparison with GEV models.

Table 3.72: Computed quintiles estimates based on selected return periods on catchment Woshi for GPA using algorithm two

Return periods(T)	(T-1)	[(T-1)^-k]	R=[1-(T-1)^-k]	Z=[(α/k)*(R)]	QT=(ξ+Z)	Exceedence probability E=(1/T)
2	1	1	0	0	14.83775251	0.5
5	4	0.189674734	0.810325266	7.54396511	22.38171762	0.2
10	9	0.071725256	0.928274744	8.642051008	23.47980351	0.1
25	24	0.022123319	0.977876681	9.103835056	23.94158756	0.04
50	49	0.009399751	0.990600249	9.222288907	24.06004141	0.02
100	99	0.00404421	0.99595579	9.27214792	24.10990043	0.01

Table 3. 23: The L-moment statistics for catchment Guma obtained

Probability Weighted Moment Values		L- Moment Values		L- Moment Ratios		Basic Statistics	
bo	111.3785714	⅄1	111.3785714	L-CV	0.3594758	N	14
b1	75.70824176	⅄2	40.03791209	L-Skewness	-0.0371076	Mean	111.3785714
b2	56.89752747	⅄3	-1.485714286	L-Kurtosis	-0.0831704	4576.2279	4576.227967
b3	45.32377622	⅄4	-3.32997003			Standard Dev.	67.64782308
						C.V	0.607368385

The calculated L-skewness value 0.0371076 lies in the range 0.000</L-skewness/≤0.050 suggested that the observed is very minor skewness. Also L-C_V value 0.3594758 indicates that the observed data is large variability. The parameters of location (ξ), scale (α) and shape (k) of the selected distributions computed using the relevant equations calculated using important equation given in table 2.9 are as obtainable in table below.

Table 3. 24: Probability parameter estimate based on L-moment for catchment Guma

Probability Distribution Model	Shape Parameter(k)	Scale Parameter(α)	Location Parameter(ξ)	Error
GPA	1.15415093	272.0382807	-14.90704622	1
GLO	0.037107686	39.20843656	133.7317711	0.6
GEV	0.352218691	47.08091147	160.4872973	0.8

The estimated parameter values distributions given in Table 3.24 were applied to their respective quantile functions defined in formula Table 2.9 and the corresponding predicted discharge results are presented in Table 3.25. The predicted discharge values by the distributions were subjected to five statistical goodness-of- fit tests as described in table 3.26 in order to select the best among the candidate distributions that adequately fits the observed data at the station. The summary of the results of the goodness of fit tests are presented in Table 3.27 and it shows that the minimum value of RMSE, RRMSE, MADI, MAE and the value of PPCC closest 1 is obtained by applying GPA distribution to the observed data at the station.

Table 3. 8**5**: Observed and annual maximum discharge based on GPA, GLO and GEV using L-moment obtained catchment Guma from algorithm two

Rank	Observed annual maximum discharge on hec-hms model (xi) (m^3/s)	Predicted annual maximum discharge(Yi) on GPA (m^3/s)	Predicted annual maximum discharge(Yi) on GLO (m^3/s)	Predicted annual maximum discharge(Yi) on GEV (m^3/s)
1	17	3.133842715	25.02240702	104.3017509
2	19.8	20.9770225	57.73249814	123.0779357
3	31.5	38.60968085	77.95499691	136.0950164
4	35.3	56.01704078	93.31463422	146.686666
5	74.3	73.18185341	106.2020241	155.9852861
6	94.1	90.08369553	117.7139191	164.5404628
7	103.2	106.6979671	128.4832214	172.6829586
8	126.4	122.994406	138.9543785	180.6509872
9	139.1	138.9347839	149.5104246	188.6499929
10	167.1	154.4691174	160.5624521	196.8941331
11	167.4	169.5289313	172.6598459	205.6540479
12	188.3	184.013918	186.7118183	215.3449594
13	188.9	197.7608032	204.6314232	226.7608806
14	206.9	210.4462458	232.2999643	242.032856

Table 3. 96: Goodness of fit statistics based on L-moment for catchment Guma obtained

GoF Statistics	RMSE	RRMSE	MADI	MAE	PPCC
GPA	9.478074556	0.312906801	-0.001226674	20.71704078	0.991699094
GLO	30.85618931	0.910357648	0.485378604	58.01463422	0.969501624
GEV	79.34154502	2.650368016	1.50390816	111.386666	0.97838888

The overall goodness of fit of each distribution was judged using a ranking scheme by comparing the five categories of test criteria based on the relative magnitude of the statistical test results. The distribution with the lowest RMSE, lowest RRMSE, lowest MADI, lowest MAE and highest PPCC at a station was considered the best fitting distribution or was assigned a score of 3, the next best was given the score 2, while the worst was given the score 1. The overall score of each distribution was obtained by summing the individual point scores for the station on catchment Guma and the distribution with the highest total point score was selected as the best fit distribution model for the station on catchment Guma. On the basis of the above analysis, GPA with the highest total score of 15 is selected as the best distribution for the station as GLO and then GEV. The best fit distribution model of GPA distribution were used to obtain estimates of quantile (Q_T) for a range of return periods (2years, 5years, 10years, 25 years, 50 years, 100 years) of hydraulic and hydrologic significance which results are presented table 3.29.

Table 3. 27: Scoring and ranking scheme for selected probability distribution models for river on catchment Guma

Test Criteria	Distribution scoring		
	GPA	GLO	GEV
RMSE	3	2	1
RRMSE	3	2	1
MADI	3	2	1
MAE	3	2	1
PPCC	3	1	2
Total Score	15	9	6
Rank	1st	2rd	3rd

The results presented in Table 3.27 and show that though GPA is the best fit probability distribution model in comparison with GLO and GEV models.

Table 3. 28: Computed quintiles estimates based on selected return periods on catchment Guma for GPA using algorithm two

Return periods(T)	(T-1)	[(T-1)^-k]	R=[1-(T-1)^-k]	Z=[(α/k)*(R)]	QT=(ξ+Z)	Exceedence probability E=(1/T)
2	1	1	0	0	14.9070462	0.5
5	4	0.201897946	0.798102054	188.116047	173.2090007	0.2
10	9	0.079188136	0.920811864	217.0392709	202.1322247	0.1
25	24	0.025528654	0.974471346	229.687039	214.7799928	0.04
50	49	0.011201047	0.988798953	233.0641168	218.1570705	0.02
100	99	0.004974344	0.995025656	234.5317772	219.624731	0.01

3.3 Peak discharge result

Regionalization result of un-gauged peak runoff of each catchment from HEC-HMS model result below:-

Regional model: The methods of regionalization using similarity of catchment characteristics were applied to estimate flow for un-gauged catchments using simple regression method. This significant relationship established between PCCs and calibrated model parameters by using excel in data analysis.

Table 3. 29: The design discharge compare with predict on regional model method

Name of structure	Design discharge,m^3/s	Predict peak discharge,100 year in m^3/s
CD3	17	22.2
CD13	9.5896	5
CD14	17.13	15
CO1	12.27	0.2
CO2	_	1.1
CO3	29	4.2
CO4	10.35	3.1

Except CD3and CO2 all design discharge above the predict discharge on regional model method.

In this regional model method time of concentration, storage coefficient and maximum deficit has large variation in each catchment so, this make variation of flood.

Sub-basin mean method: The arithmetic mean of calibrated model parameters of gauged catchments to simulate stream flow for un-gauged catchments.

Table 3. 30: The design discharge compare with predict on sub-basin mean method

Name of structure	Design discharge, m^3/s	Predict peak discharge, 100 year in m^3/s
CD3	17	85.1
CD13	9.5896	8.9
CD14	17.13	15.1
CO1	12.27	1.7
CO2	_	0.8
CO3	29	7.5
CO4	10.35	3.9

Except CD3 and CO2 all design discharge above the predict discharge on sub-basin mean method

In this method the same model parameter but different Predict peak discharge. This show the same model parameter make in a separate catchment make variable flow. It may be depend on area.

3.3.1 Similarity of spatial proximity

Table 3. 31: The design discharge compare with predict on similarity of spatial proximity method

Name of structure	Design discharge, m^3/s	Predict peak discharge, 100 year in m^3/s
CD3	17	85.1
CD13	9.5896	14.3
CD14	17.13	28.2
CO1	12.27	1.1
CO2	_	0.6
CO3	29	9
CO4	10.35	1.6

The CD3, CD13, CD14 and CO2 are above design discharge done predict discharge on similarity of spatial proximity method.

In Omo-Kuraz over flood occurring structures are CD3, CD13, and CD14 also show in spatial proximity method. The other structures are over design. It has small runoff catchment generate low flood.

The input rainfall data of un-gauged catchment of CD3 has used Omo Kuraz, Hana and Bulki station of meteorology data. In addition CO1, CO2, CO3, CO4, CD13 and CD14 the input rainfall data of un-gauged catchment of station Hana meteorology data.

CD3 catchment's runoff was simulated by similarity of spatial proximity contributes the highest runoff volume compare to the other methods. **[29]** performed regionalization in Lake Tana basin to get optimized model parameters for gauged catchments and used regional model method, spatial proximity, area ratio and default parameter sets method to transfer the optimized model parameters to un-gauged catchments and he found that default parameter set and regional model is contributed the highest and lowest volume respectively.

4. CONCLUSION AND RECOMMENDATIONS

Conclusion

Arising from the results of this study, the following conclusion is made:-

In this study, the flood problems over Omo-Kuraz project site was re-investigated based on catchment characteristics of seven outlets that passes the flood under the main canal. Conventional hydrological modeling approach, HEC-HMS, has been conducted using catchment characteristics secondary and primary data sets, climate of the area, hydrology of the area, previous study on the site and the following conclusions has been made.

The calibration and validation results indicate a good agreement between the observed and simulated flow at gauged catchment of Woshi, Guma, and Dincha River. The parameter transfer techniques combined regional model method, Sub-basin mean method and similarity spatial proximity, which generate the flow for the study un-gauged outlets except area ratio method. The capacity of road culverts of the structures is sufficient to pass the coming peak flood, but CD13,CD14 and CD3 are under estimated and also the sediment deposit has dramatically decreased the efficiency of the structures, hence flooding has been happening.

The selected probability distribution models(GLO, GEV and GPA) can be utilized to predict the flood quintiles magnitudes (QT) at the station for return periods of interest in hydraulic and design. The best fit probability distribution model for analysing the annual maximum flood series in the Omo-Kuraz is Generalized Pareto distribution (GPA).

4.1 Recommendations

Upstream sediment problems erosion and deposition on the water passage shall be investigated in future research outputs, and I recommend upstream catchment treatment and removal of the sediment deposits before every rainy season. The long term plan must be done as per predicted peak discharge do the structure properly also Ethiopia road authority also monitors properly at the period of design.

It is additional recommended that the density of stream gauging networks in the areas should be construct in un-gauged area of study sub basin of Omo-Gibe basin.

5 REFERENCES

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