

RIVERINE FLOOD INUNDATION MAPPING, HAZARD, AND VULNERABILITY ASSESSMENT,
IN THE LOWER OMO-GIBE RIVER SUB-BASIN, ETHIOPIA



TSEHAY FIKADU ONCHO

A THESIS SUBMITTED TO
THE DEPARTMENT OF WATER RESOURCES ENGINEERING
COLLEGE OF CIVIL ENGINEERING AND ARCHITECTURE

PRESENTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR
THE DEGREE OF MASTER'S IN WATER RESOURCES ENGINEERING
(SPECIALIZATION IN HYDRAULIC ENGINEERING)

SCHOOL OF POSTGRADUATE OFFICE
ADAMA SCIENCE AND TECHNOLOGY UNIVERSITY

JUNE, 2025
ADAMA, ETHIOPIA

Riverine Flood Inundation Mapping, Hazard, And Vulnerability Assessment, in the Lower Omo-Gibe
River Sub-Basin, Ethiopia

Tsehay Fikadu Oncho

Advisor: Mengistu Addis (Ph.D.)



A Thesis Submitted To
The Department of Water Resources Engineering
College Of Civil Engineering and Architecture

Presented In Partial Fulfillment of The Requirement for The Degree of Master's in
Water Resources Engineering (Specialization in Hydraulic Engineering)

School Of Postgraduate Office
Adama Science and Technology University

June, 2025
Adama, Ethiopia

DECLARATION

I hereby declare that this Master's Thesis entitled “Riverine Flood Inundation Mapping, Hazard, and Vulnerability Assessment, in the Lower Omo-Gibe River Sub-Basin, Ethiopia” is my original work. That is, it has not been submitted for the award of any academic degree, diploma or certificate in any other university. All sources of materials used for this thesis have been duly acknowledged through appropriate citations.

Name of student

Signature

Date

RECOMMENDATION

I, the advisor of this thesis, hereby certify that I have read and revised version of the thesis entitled “Riverine Flood Inundation Mapping, Hazard, and Vulnerability Assessment, in the Lower Omo-Gibe River Sub-Basin, Ethiopia” prepared under my guidance by Tsehay Fikadu Oncho submitted in partial fulfillment of the requirements for the degree of masters of science in Water Resources Engineering (Specialization in Hydraulic Engineering). Therefore, I recommend the submission of a revised version of the thesis to the department following the applicable procedures.

Mengistu Addis (PhD)

Major Advisor/Supervisor

Signature

Date

APPROVAL SHEET

I, the advisor of the thesis entitled “Riverine Flood Inundation Mapping, Hazard, and Vulnerability Assessment, in the Lower Omo-Gibe River Sub-Basin, Ethiopia” and developed by Tsehay Fikadu Oncho, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor

Signature

Date

We, the undersigned members of the Board of Examiners of the thesis by Tsehay Fikadu Oncho, have read and evaluated the thesis entitled “Riverine Flood Inundation Mapping, Hazard, and Vulnerability Assessment, in the Lower Omo-Gibe River Sub-Basin, Ethiopia” and examined the candidates during the open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Water Resources Engineering (Specialization in Hydraulic Engineering).

Chairperson

Signature

Date

Internal Examiner

Signature

Date

Eternal Examiner

Signature

Date

Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

Department Head

Signature

Date

School Dean

Signature

Date

Office of Postgraduate Studies

Signature

Date

ACKNOWLEDGEMENT

First and foremost, I would like to express my deepest gratitude to the Almighty God for His boundless grace, guidance, and strength throughout my academic journey. It is through His divine support that I have been able to successfully complete this MSc thesis.

I wish to extend my sincere appreciation to my advisor, **Dr. Mengistu Addis**, for his invaluable academic mentorship, insightful guidance, and unwavering support during the course of this research. His expertise and constructive feedback have played a crucial role in shaping the quality and direction of this work.

I am profoundly grateful to *Florensis Abyssinia PLC* for sponsoring my Master's studies. I would like to particularly acknowledge **Mr. Ronald Vigberberg**, Farm General Manager, for his trust and support, which provided me the opportunity to pursue advanced education. I also extend my sincere thanks to **Mr. Habtamu Worku**, Human Resources Manager, for his continued facilitation and encouragement throughout the duration of my studies.

Finally, I am deeply indebted to my father, **Mr. Fikadu Oncho**, whose unwavering support, sacrifices, and constant encouragement have been a source of strength and inspiration throughout my life and academic journey. His belief in my potential has been instrumental in the realization of this achievement.

Contents

DECLARATION	ii
RECOMMENDATION	iii
APPROVAL SHEET	iv
ACKNOWLEDGEMENT	vi
Contents	vii
LIST OF TABLES	x
LIST OF FIGURES	xi
LIST OF ACRONYMS	xiii
ABSTRACT.....	xiv
1. INTRODUCTION	1
1.1 Background	1
1.2 Statement of the Problem	3
1.3 Objectives:.....	5
1.3.1 General Objectives.....	5
1.3.2 Specific Objectives:	5
1.4 Research questions	6
1.5 Significance of the Study	6
1.6 Scope of the study	7
2. LITERATURE REVIEW	8
2.1 The concept of flood	8
2.2 Estimation of Flood Quantiles	8
2.3 Hydrodynamic models	10
2.3.1 Hydraulic Modeling (HEC-RAS)	12
2.3.2 HEC-RAS-One Dimensional (1D) Model	12
2.3.1 HEC-RAS Two-Dimensional Model (2D Model).....	13
2.4 Flood Inundation Mapping.....	14
2.5 Flood Hazard Assessment	17
2.6 Flood Vulnerability Assessment	18
2.7 Research Gaps	20

3.	MATERIALS AND METHODS.....	23
3.1	Study Area Description	23
3.1.1	Location	23
3.1.2	Climate.....	24
3.1.3	Soil	24
3.1.4	Land Use	25
3.2	Datasets	26
3.3	Hydrological Data Quality Assessment	28
3.3.1	Filling of Missed Hydrological Data	28
3.3.1	Data Homogeneity Analysis	29
3.3.2	Test for Outliers	30
3.4	Flood Quantile Estimation Methods	31
3.5	Computational Methodology.....	33
3.5.1	1D HEC-RAS Modeling.....	34
3.5.1	Flood Inundation Mapping	35
3.6	Model Calibration and Validation hydrodynamic model.....	36
3.6.1	Calibration.....	36
3.6.2	Validation.....	36
3.7	Flood Hazard Assessment	37
3.7.1	Flood Frequency Analysis Using HEC-SSP.....	37
3.7.2	Terrain and Spatial Data Processing	37
3.7.3	Hydraulic Modeling with HEC-RAS 1D.....	38
3.7.1	Flood Hazard Classification.....	38
3.8	Flood Vulnerability Assessment	38
4.	RESULTS AND DISCUSSIONS.....	41
4.1	Hydrological Data Analysis	41
4.1.1	Data Homogeneity Analysis	41
4.1.2	Outlier Detection and Treatment	41
4.2	Goodness of Fit Test and Quantile Analysis.....	41
4.2.1	Goodness of Fit Analysis	41
4.2.1	Flood Quantiles Estimation.....	44

4.3	HEC-RAS Model Simulation and Computation	44
4.3.1	Geometric data	44
4.3.2	Flow Data.....	46
4.4	Calibration and Validation of HEC-RAS Model	47
4.4.1	Calibration.....	47
4.4.2	Model Validation	51
4.5	Flood Hazard Assessment	55
4.5.1	Flood Inundation Extent Analysis Across Return Periods	56
4.5.2	Spatial Distribution of Flood Inundation by Woreda and Return Period	57
4.5.3	Flood Hazard Levels	61
4.5.4	Comparative Analysis of Hazard Area Change from Depth to Velocity Factor	64
4.6	Flood Vulnerability Assessment	65
4.7	Discussions.....	67
4.7.1	Flood Inundation Analysis by Return Periods	67
4.7.2	Flood hazard level analysis across different return periods.....	68
4.7.3	Discussion on Vulnerable Land Use and Land Cover to Flood Inundation	69
5.	CONCLUSION AND RECOMMENDATION.....	71
5.1	Conclusion.....	71
5.2	Recommendations	72
	REFERENCES	75
	APPENDICES	84

LIST OF TABLES

Table 2. 1 Summary of Key Hydrodynamic Models for Flood Inundation Mapping	15
Table 3. 1 Data needed and their sources	27
Table 3. 2 Lower Omo River Basin downstream of Koysha Dam Hydrological Stations from MOWE.....	27
Table 3. 3 Software Used during the Study	28
Table 3. 4 L-Moments of some common distributions (Hosking, 1990).....	32
Table 4. 1 Outlier detection and treatment.....	41
Table 4. 2 HEC-SSP statistical software generated output KS test	44
Table 4. 3 Flood quantiles for different return periods for the hydrological stations	44
Table 4. 4: Calibration result of Omorate River Water Surface Elevation (Water level).....	50
Table 4. 5: Performance criteria for model calibration and validation (Tamiru & Dinka, 2021). 50	
Table 4. 6: NDWI Analysis for Landsat image 9 (August 20, 2016).....	52
Table 4. 7: MNDWI Analysis for Landsat image 9 (August 20, 2016).....	53
Table 4. 8 Validation Results.....	55
Table 4. 9 Flood Hazard Classification.....	56
Table 4. 10 Flood Inundation Coverage In terms of Woredas.....	60

LIST OF FIGURES

Figure 3. 1 Location Map of the Study Area.	23
Figure 3. 2 Monthly average rainfall distribution of the station	24
Figure 3. 3 Soil Map of Lower Omo Sub-Basin.....	25
Figure 3. 4 LULC Map of Lower Omo Sub-Basin.....	26
Figure 3. 5 Data process algorithm and 1D model in HEC-RAS	40
Figure 4. 1 Cumulative Distribution Function (CDF) for Omorate Station	42
Figure 4. 2 Probability Density Function (PDF) for Omorate Station.....	43
Figure 4. 3 Quantile-Quantile (QQ) Plots for Omorate Station.....	43
Figure 4. 4 Geometric data for Lower Omo River generated from HEC-RAS	45
Figure 4. 5 Manning’s Roughness Coefficient Settings for the River.....	46
Figure 4. 6 Quantile flow profiles input for simulation purposes of the model.....	47
Figure 4. 7 Water Surface Profiles for All Return periods for Omorate station generated from model return periods of 2-20 years	48
Figure 4. 8 Water Surface Profiles for All Return periods for Omorate station generated from model return periods of 50-200 years	49
Figure 4. 9 Stage discharge (Rating) Curve for the Omorate station 123031.4.....	49
Figure 4. 10: Inundation boundary of the HEC-RAS for the year August 2016	52
Figure 4. 11 NDWI August 2016 Landsat 9 Water Body.....	53
Figure 4. 12: NDWI August 2016 Landsat 9 Water Body	54
Figure 4. 13 Flood Periods Vs Inundation Areas in Hectare	56
Figure 4. 14 Hazard Inundation at Hamer Area 2 Year Return Period.....	58
Figure 4. 15 Hazard Inundation at Kuraz Area 2 Year Return Period.....	58
Figure 4. 16 Inundation Map Around Hamer Woreda for 5 Year Return Period.....	59
Figure 4. 17 Inundation Map Around Kuraz Woreda for 5 Year Return Period.....	59
Figure 4. 18 Hazard Inundation at Hamer Area 200-Year Return Period	60
Figure 4. 19 Hazard Inundation at Kuraz Area 200-Year Return Period	61
Figure 4. 20 Flood Hazard Levels In terms of Inundation Depth as Factor from return periods of (2-20 Year).....	62
Figure 4. 21 Flood Hazard Levels In terms of Inundation Depth as Factor from return periods of (50-200 years)	62
Figure 4. 22 Flood Hazard Levels In terms of Inundation Velocity as Factor from return periods of (2-20 Year).	63
Figure 4. 23 Flood Hazard Levels In terms of Inundation Velocity as Factor from return periods of (50-200 years).....	63
Figure 4. 24 Percent of Hazard level Area change from depth to velocity for return periods (2-20 Years).....	64
Figure 4. 25 Percent of Hazard level Area change from depth to velocity for return periods (50- 200 Years).....	65

Figure 4. 26 Vulnerable LULC for different Woredas in different return periods from (2-20 Year)	66
Figure 4. 27 Vulnerable LULC for different Woredas in different return periods from (50 - 200 Year).	66

LIST OF ACRONYMS

GIS	Geographic Information System
RS	Remote Sensing
HEC-RAS	Hydrologic Engineering Center's River Analysis System
NDRMC	National Disaster Risk Management Commission
UNOCHA	United Nations Office for the Coordination of Humanitarian Affairs
2D	Two-Dimensional
1D	One-Dimensional
GPA	Generalized Pareto
EV1	Extreme Value Type I
LP3	Log Pearson Type III
BRT	Buishand Range Test
VNR	Von Neumann Ratio
AD	Anderson-Darling Test
KS	Kolmogorov-Smirnov Test
MoM	Method of Moments
ML	Maximum Likelihood
SNHT	Standard Normal Homogeneity Test
ARIMA	AutoRegressive Integrated Moving Average
RFFA	Regional Flood Frequency Analysis

ABSTRACT

Flooding is a significant natural hazard in Ethiopia, frequently resulting in property damage, loss of life, and disruption of livelihoods. With increasing frequency and severity, floods pose a serious threat to sustainable development and demand effective management strategies. This thesis focuses on the Lower Omo-Gibe River Basin, where flood inundation, hazard, and vulnerability were analyzed using the HEC-RAS hydrodynamic model integrated with geospatial tools. The main objectives were to simulate flood extents and water surface profiles, delineate flood hazard zones, evaluate the applicability of HEC-RAS for flood mapping, and assess the vulnerability of communities and assets in flood-prone areas. Regional flood frequency analysis was conducted using L-moment-based methods, with streamflow data from three gauging stations. Generalized Extreme Value and Gumbel distributions were selected as the best fits for estimating flood quantiles for return periods ranging from 2 to 200 years. These quantiles were input into the HEC-RAS model to determine flood depth, extent, and velocity. The model was calibrated at Omorate station and showed strong performance ($NSE = 0.87$, $PBIAS = -3.79$, $R^2 = 0.83$) with an adjusted Manning's n value of 0.03. Simulation results revealed an increasing trend in inundation extent with longer return periods, with the 200-year event causing the highest flood levels. Kuraz, Hamer Bena, and Dizi woredas were identified as the most vulnerable areas. Land use and land cover analysis indicated that croplands, rangelands, and built-up zones are highly susceptible to flooding. The study highlights the importance of integrating hydrodynamic modeling and geospatial analysis in flood hazard assessment. Recommendations include improving DEM accuracy, enhancing data accessibility, promoting ecosystem-based flood management, and using model outputs for planning, mitigation, and long-term disaster risk reduction.

Key Words: Hydrodynamic model, GIS, Vulnerability, Flood Inundation, Flood Hazard

1. INTRODUCTION

1.1 Background

Floods are considered the most damaging menace in the world. Floods have a negative impact on the socioeconomic development of many countries and claim more lives than any other hydrometeorological disaster (Shadmehri Toosi et al., 2020). Additionally, in many parts of the world, the frequency and intensity of these flood events are increasing, which poses major questions for the sustainable development of flood-prone countries (Dewan, 2015). Since the 1950s, human activity and increasing greenhouse gas emissions have caused temperature and precipitation increases, which are the main causes of these exceptional floods (Bhandari et al., 2017).

Recent years have seen the presentation and validation of flood risk and hazard mapping results, mostly due to the work of geographic information systems (GIS) and remote sensing (RS) (Sajjad et al., 2020). RS and GIS are considered to be helpful geospatial tools for mapping flood characteristics and their impacts on social, economic, and environmental aspects. These geospatial tools have been widely used to map the results of simulation models of past flood events, including flood levels and inundation extents. They have also been used to identify the critical infrastructure that is at risk (Dasallas & Lee, 2019; Santillan et al., 2016). In regions that are susceptible to floods, these technologies can aid in the creation of early warning systems. RS is an essential tool for obtaining the data required to develop and validate the flood model result, evaluate the danger of flooding, and identify the infrastructure that is vulnerable (e.g., urban and commercial districts, transportation infrastructure, health and education facilities, etc.). However, the development of automated flood models, flood risk assessments (which attribute different levels of flooding to urban areas, settlements, and agricultural lands), flood inundation maps, and other statistical analyses that may be useful in the formulation of flood disaster management plans at various flood event levels are all made possible by the use of GIS (Santillan et al., 2016).

Flooding is One of the major natural catastrophes in Ethiopia, it has severely destroyed livelihoods and lives in many parts of the country. Ethiopia's lowland plains and highland ranges, which have natural drainage systems produced by the main river basins, and excessive rainfall are the main causes of floods in the country. Long stretches of intense rainfall that overflow rivers and submerge

lowland plains areas adjacent to the rivers are the usual source of floods in the country. Parts of the Somali region along the Wabe Shebelle, Genale, and Dawa Rivers, Omo-Gibe rivers; low-lying Gambella districts along the Baro River; and parts of the Oromia and Afar regions along the upper, middle, and downstream plains of the Awash River are among the primary river flood-prone areas (NDRMC, 2018).

Without a doubt, the most common, pervasive, and destructive natural danger on Earth is flooding. They significantly impact the ecosystem and community in the floodplains they impact. According to (Getahun YS, 2015), floods occur when an area of land outside of water bodies is inundated with more water than can be carried by a river channel, lake, pond, reservoir, drainage system, dam, or other water-related structure. Due to the combined influence of hydrological and climatic factors, floods are one of the most destructive natural occurrences. This is a natural phenomenon in which water in a channel, whether man-made or natural, overflows and briefly floods the ground surface outside the body of water.

When a nation lacks structural affordability because of financial restraints, the severity of floods becomes evident (Chen et al., 2014). People who live adjacent to rivers worldwide are currently at great risk from river floods (Cirella & Iyalomhe, 2018). Ethiopia is not an exception to the rapidly rising number of households affected by this calamity and left without shelter throughout Africa (Desalegn & Mulu, 2021; Thiemig et al., 2011). The country's topography, heavy rainfall, unanticipated river bank damage, overflowing river banks, lack of adequate urban drainage systems, steep channel design slopes, and changes in land use and cover have all made it more vulnerable to flooding (Gashaw & Legesse, 2011).

The development of plans for risk mitigation, flood management, and other preventive measures, as well as the coordination of flood relief efforts, depend heavily on the early mapping, monitoring, and impact assessment of flood events. It is usually challenging to obtain this information using conventional techniques due to the time and spatial features of floods (Psomiadis et al., 2020). Assessing flood risk and management practices is essential for determining flood risks, flood-prone areas, and future mitigation strategies. Understanding the characteristics of floods is essential for creating flood control action plans and assessing the results of various management techniques. In situ observations of flood occurrences are the most straightforward way to interpret the risk of flooding. However, it is impossible to observe the floods firsthand in many developing

countries. Additionally, all flood analyses based on observations are limited to specific flood occurrences. Accordingly, one of the alternate approaches for conducting flood risk modeling studies is to use the RS data (Albu et al., 2020; Hagen & Lu, 2011; Psomiadis et al., 2020).

The outcomes of simulation models of historical flood events, such as flood levels and inundation extents, have been extensively mapped using these geospatial methods. Additionally, they have been employed to determine which vital infrastructure is at danger (Dasallas & Lee, 2019; Santillan et al., 2016). These technologies also make it easier to create flood forecasts and early warning systems in flood-prone areas, which lowers flood risks and helps people get ready for emergencies (Asare-Kyei et al., 2015; Baky et al., 2019). In order to create and validate the output of the flood model, estimate the probability of flooding, and identify the infrastructure that is at danger (such as commercial and urban areas, transportation infrastructure, health and education institutions, etc.), RS is a crucial tool. GIS enables the development of automated flood models, flood risk assessments that categorize urban areas, settlements, and agricultural lands based on different levels of flooding, flood inundation maps, and other statistical analyses that may be helpful in the development of flood disaster management plans at different flood event levels, claim, (Santillan et al., 2016).

The hydrodynamic and hydraulic models are the primary tools utilized in inundation mapping. Planning flood management, identifying geographically distributed variables of relevance, simulating flood events, and predicting vulnerable areas are their main uses. In general, they use mathematical formulas based on the concepts of mass and momentum conservation to explain the fluid motion and dynamics of the flood wave. The user can choose models with different dimensionalities (1D, 2D, etc.), mesh representations (structured, unstructured, etc.), numerical schemes (finite volume, finite difference, etc.), and equations (Kinematic Wave, Diffusion Wave, Muskingum, etc.) according to the project objectives and study area (Ongdas et al., 2020).

1.2 Statement of the Problem

Flooding is a common issue in Ethiopia. Both the frequency and magnitude have rapidly increased during the last few decades. The destruction of crops and the resulting malnourishment, damage to roads and the electrical system, and loss of life and property are the main consequences of floods. The United Nations reported on May 13, 2021, that over 70,000 people had been displaced due to flooding that began in late April and affected three districts in Ethiopia. According to a

UNOCHA assessment conducted between April 26 and May 10, 2021, the flooding has significantly impacted Ethiopia's Somali, Afar, and Southern Nations, Nationalities, and People (SNNP) regions. Strong winds and rain have caused flooding in the woredas of Gulina, Ewa, Beyalo, Dulecha, Harunka, and Mile, forcing some 27,400 people to evacuate their homes in the Afar Region (FloodList, 2021).

Over 500,000 people have been affected and nearly 300,000 have been uprooted by Ethiopia's catastrophic floods and heavy rains since July. Due to abnormally high rainfall during the June–September Kiremt season, flooding started throughout the nation in late July. By early August, 30,000 people had been displaced by the Awash River flood, according to a UN assessment. The Afar region was home to many of these individuals. Additionally, Gambella, Oromia, SNNP, and Amhara suffered significant harm. According to a September 6 report by the UN Office for the Coordination of Humanitarian Affairs (OCHA), "severe summer season (June-September) rains continue to create flooding in many parts of the country." Approximately 300,000 people have been relocated out of the 500,000 people affected thus far. On September 1, the Awash River overflowed once more, submerging portions of the Amibara and Awash Fentale woredas in the Afar area. According to local reports, at least five people had died when the government dispatched a military helicopter to evacuate flood victims. OCHA also pointed out that the releases from the Koka and Kesem dams put settlements downstream at greater danger of floods. The National Disaster Risk Management Commission (NDRMC), in collaboration with the Oromia and Afar regions, is trying to (FloodList, 2020).

The most recent flooding in the South Ethiopia Region occurred in Dasenech Woreda, South Omo Zone, on August 19. Five kebeles in Dasenech Woreda were flooded by the Omo River overflow due to heavy rains in the upstream highlands in the South and Southwest Ethiopia Regions, primarily in the Gamo, Goffa, Wolayita, Konso, Dawuro, and Keffa zones, as well as backflow of water from Lake Turkana. According to reports, 12,000 people have been relocated, and more flooding is anticipated in the coming days due to upstream woredas experiencing heavy rains. This puts numerous other communities at risk, including Omorate Town, the capital of Dasenech Woreda. Two partners are sponsoring dike works, while one partner is supplying food for 54,000 people in the woreda as part of the government's flood mitigation and response activities. The

South Omo Zone, which has a population of 79,000, has frequently experienced flooding as a result of the Omo River overflow and water released from the Gilgel Gibe 3 dam (OCHA, 2024).

Heavy rains caused the Omo River in southern Ethiopia to overflow across 34 districts, displacing about 79,000 people, according to local media on Tuesday. A local chief named Ato Tadele Hate told Sheger Radio that the federal government and humanitarian organizations need to act quickly to help after several days of rain devastated cattle and agricultural lands. Hate bemoaned, "This destruction is turning into a persistent problem." Similar issues were brought on by last year's torrential rains, and the present flooding has affected places where residents had previously been forced to migrate because of the floods. Additionally, he emphasized the urgency of taking quick action to redirect the Omo River and stop further overflows.

Hate voiced worries about Omorate, a city on the Omo River's bank that is in grave danger of being completely destroyed by the flood. "We fear that Omorate, which is home to thousands, would be completely wiped out by the floods unless prompt action is taken," he warned. During the rainy season, flooding and frequent, severe landslides are especially common in southern Ethiopia. Without prompt action, the situation is expected to worsen and the rains are expected to continue, according to Tilahun Bishaw, the local leader of the Ethiopian Red Cross Association (Anadolu Ajansı, 2024).

1.3 Objectives:

1.3.1 General Objectives

The general objective of the study was to comprehensively understand flood dynamics, associated hazards, and vulnerability in the Lower Omo-Gibe River Sub-basin using advanced HEC-RAS modeling and geospatial modeling techniques.

1.3.2 Specific Objectives:

- To simulate flood extents and water surface profiles in the Lower Omo-Gibe River Sub-basin using the HEC-RAS hydrodynamic model.
- To identify and map flood hazard zones based on HEC-RAS simulation outputs and geospatial analysis.

- To Evaluate the performance and accuracy of the HEC-RAS model for inundation mapping using available ground data.
- To evaluate spatial vulnerability of land use land cover.

1.4 Research questions

- How accurately can the HEC-RAS model simulate flood extents and water surface profiles in the Lower Omo-Gibe River Sub-basin?
- What are the spatial distributions and severity levels of flood hazard zones in the Lower Omo-Gibe River Sub-basin as derived from HEC-RAS simulations?
- How accurately does the HEC-RAS model simulate flood inundation extents compared to observed ground data in the study area?
- Which land use/land cover types in the study area are most vulnerable to flood inundation, and how does their spatial distribution affect overall flood risk?

1.5 Significance of the Study

For poor countries whose inhabitants primarily depend on agriculture, flood assessment is essential (Trambadia et al., 2023). By providing a thorough analysis of flood inundation patterns, the proposed study will advance our understanding of flood dynamics in the Lower Omo-Gibe River basin. Future efforts to evaluate and reduce flood risks and protect infrastructure, towns, and agricultural areas will require this knowledge. The study will use cutting-edge modeling approaches by using HEC-RAS model. Compared to conventional techniques, this novel approach will allow for more thorough and precise flood inundation evaluations, which will ultimately improve prediction accuracy and facilitate informed decision-making.

The study's findings will offer a solid foundation for the development of effective early warning systems. In order to limit potential mortality and property damage during flood events, it will be possible to distribute notifications to vulnerable locations in a timely manner by having a thorough understanding of the spatial and temporal patterns of flood inundation. Resource managers, legislators, and land use planners will greatly benefit from the findings. Determining high-risk locations, promoting sustainable development practices, and directing land-use planning decisions would all benefit from accurate mapping of flood inundation in the Lower Omo-Gibe River basin.

Given the potential effects of climate change on precipitation patterns and hydrological systems, this study will aid in efforts to adapt to the changing climate. Understanding how floods will evolve in the future will be essential for creating resilient infrastructure and adjusting land-use patterns in response to changing environmental conditions.

1.6 Scope of the study

The scope of the investigation is limited to particular thematic and geographic domains. Although seasonal flooding affects the upper, middle, and lower sub-basins of the Omo-Gibe River Sub-basin, the study's focus is limited to the Lower Omo-Gibe River basin due to time and resource restrictions. The assessment of flood risk and damage could not be completed due to the necessity for substantial data and funding for on-site data collecting.

2. LITERATURE REVIEW

2.1 The concept of flood

An extremely high level of a river, typically the point where the river overflows its banks and submerges the surrounding land, is called a flood. It is commonly known that floods have the potential to do serious damage to both people and property, as well as to cause financial losses by interfering with business operations. Predicting and controlling floods costs thousands of crores of rupees every year. For hydrologic design, the hydrograph of extreme floods and the phases associated with flood peaks offer important information. Furthermore, the flood peak is arguably the most significant and frequently utilized statistic among all the elements of the flood hydrograph (Subramanya, 2008).

Each year, a stream's flood peaks change in location, and the sum of their magnitudes forms a hydrologic series that allows a certain flood-peak value to be assigned a frequency. By using the hydrologic series created by the amplitude of the flood peaks at a specific site in a stream, which varies annually, one can attribute a frequency to a specific flood-peak value. In order to properly balance the structure to accommodate its influence, the peak flow that can be predicted at a specific frequency (let's say once per 100 years) is essential for designing almost all hydraulic systems. Numerous applications, such as the design of bridges, culvert waterways, dam spillways, and the evaluation of scour at a hydraulic structure, require the flood-peak values of a streaming site. A flood is defined by two characteristics: (i) the size of the peak, or the greatest rate of discharge; and (ii) the stage of the peak, or the elevation of the water surface at the peak flow. The design of (i) dam and barrage spillways and (ii) bridge and culvert waterway capacity are determined by the peak flow rate. This is a crucial scene (Subramanya, 2008).

2.2 Estimation of Flood Quantiles

Planning hydraulic structures and flood control systems necessitates predicting peak discharge at different frequencies since floods are frequent. Forecasting the peak flood for a longer return period is therefore difficult, and it gets considerably more difficult in an area that is not monitored. To estimate peak discharge at the location where discharge is measured, frequency distributions like Gumbel Extreme Value Type I (EV1) and Log Pearson Type III (LP3) were commonly used.

In addition to the two previously mentioned distributions, the RFFA scenario employed higher order distributions, including Generalized Extreme Value (GEV), Generalized Pareto (GPA), Generalized Logistic (GLO), Log Normal (LN3), and Pearson Type III (PE3) (Drissia et al., 2019).

Of the different methods for estimating the parameters of the distribution, the method of moments (MoM) and the maximum likelihood (ML) approach were widely used. In a study that used the machine learning method to estimate parameters in the Abiod watershed in Algeria, GPA was shown to be the most appropriate distribution (Benameur et al., 2017). Chi-square, the Anderson-Darling Test, the Kolmogorov-Smirnov goodness-of-fit tests, mean absolute relative deviation (ARD), and mean squared relative deviation (MSD) were used to determine which of the distributions was the best fit for each site (Heidarpour et al., 2017; Kamal et al., 2017).

Although MoM was widely used for parameter estimations in previous studies, the development of L moments by Hosking and Wallis (1993) was a landmark in flood frequency studies, especially RFFA. L moments, a robust method for RFFA, are a linear combination of probability-weighted moments. It is observed that L moments are simpler to interpret as distributional form metrics. The peak discharge for different frequencies at the site was estimated using this method, which was developed for RFFA (Drissia et al., 2019).

Goodness-of-fit (GOF) tests

The observed data are tested for distributional consistency using goodness-of-fit tests.

Chi-Square Test:

To determine if observed and anticipated frequencies in categorical data differ significantly from one another, a statistical method known as the chi-square test is employed. The chi-square test can be applied when fitting pdfs to temperature data by dividing the temperature range into bins and comparing the observed frequencies of temperature values in each bin with the expected frequencies based on the fitted pdf. The chi-square statistic is calculated and its significance is assessed using a chi-square distribution. Due to its poor fit between the observed and expected frequencies, a low p-value indicates that the chosen PDF may not be an accurate representation of the temperature data (Haddad, 2021).

Kolmogorov-Smirnov Test:

The Kolmogorov-Smirnov (KS) test is a non-parametric method for comparing the cumulative distribution function (or CDF) of a sample to a reference CDF. By comparing the CDF of the fitted pdf with the empirical CDF that was produced using the observed temperature data, the KS test is used to assess how well PDFs match temperature data. The KS statistic is calculated to represent the largest vertical distance between the two CDFs. The significance of the KS statistic is evaluated using the critical values of the Kolmogorov distribution. Since there is a significant discrepancy between the fitted pdf and the observed data, a lower p-value indicates a poor fit.

Anderson-Darling Test:

The Anderson-Darling (AD) test is another statistical metric used to assess how well a sample fits a particular distribution. It is similar to the KS test but gives more weight to the tails of the distribution. The AD test evaluates the discrepancy between the observed data and the fitted pdf by calculating the AD statistic. The AD statistic's significance is determined using critical values specific to the distribution being tested. If the p-value is below a preset threshold, it indicates a poor fit between the chosen PDF and the observed data (Haddad, 2021).

2.3 Hydrodynamic models

Flood inundation mapping plays a vital role in disaster preparedness, land-use planning, and water resources management. Hydrodynamic models are powerful tools used to simulate water flow and predict the extent of flood-prone areas under varying hydraulic and meteorological conditions. Several models have been developed, each varying in complexity, dimensionality, accuracy, and data requirements.

One of the most widely used models for flood inundation mapping is the **HEC-RAS (Hydrologic Engineering Center's River Analysis System)**, developed by the U.S. Army Corps of Engineers. HEC-RAS supports both 1D and 2D hydraulic modeling, making it versatile for simulating riverine flood events and mapping floodplains. The model can simulate steady and unsteady flow, perform sediment transport modeling, and provide flood extent and depth outputs. The release of HEC-RAS 5.0 and later versions enabled fully 2D unsteady flow simulations using high-resolution topography, improving its capability for inundation mapping in complex floodplains (Brunner,

2016). HEC-RAS is freely available, well-documented, and integrates easily with GIS through tools such as HEC-GeoRAS or RAS Mapper, which makes it a popular choice for academic and regulatory applications (Horritt & Bates, 2002).

Another well-established modeling system is **MIKE FLOOD**, developed by the Danish Hydraulic Institute (DHI), which allows fully coupled 1D–2D simulations by integrating MIKE 11 (1D river network) and MIKE 21 (2D overland flow) models. MIKE FLOOD is known for its high accuracy, flexibility, and ability to model complex hydraulic structures, urban drainage systems, and coastal interactions. It incorporates modules for rainfall-runoff processes, groundwater, sediment transport, and water quality (DHI, 2020). While it is powerful and highly customizable, it is commercial software and requires extensive data and expertise, which may limit its use in resource-constrained settings.

TUFLOW, developed by BMT, is another sophisticated hydrodynamic model capable of 1D/2D coupled simulations. It is widely used in urban and rural flood risk assessments. TUFLOW is known for its speed, accuracy, and GIS compatibility, making it suitable for detailed floodplain mapping and infrastructure planning. The model handles complex topography and land-use interactions effectively and supports real-time forecasting applications (Syme, 2008). However, similar to MIKE FLOOD, TUFLOW is commercial and requires advanced modeling skills.

Flood Modeller (formerly ISIS), developed by Jacobs, offers integrated 1D/2D flood modeling with robust tools for urban drainage, riverine flood, and coastal storm surge simulations. It is often used in regulatory flood risk studies in the UK and Europe. It includes rainfall-runoff modeling and supports real-time flood forecasting. Flood Modeller is user-friendly and well-supported but, like TUFLOW and MIKE FLOOD, it is a licensed product, which may restrict its accessibility in developing countries (Jacobs, 2020).

For large-scale flood modeling with limited computational resources, **LISFLOOD-FP** presents an efficient raster-based 2D hydrodynamic model developed by the University of Bristol. It is designed to simulate floodplain dynamics over large areas using simplified hydraulic equations (Bates & De Roo, 2000). LISFLOOD-FP is particularly suitable for regional or continental-scale flood hazard mapping where detailed input data is scarce. Although it is open-source and

computationally efficient, its simplified hydraulics may not capture fine-scale interactions in urban or channelized settings.

2.3.1 Hydraulic Modeling (HEC-RAS)

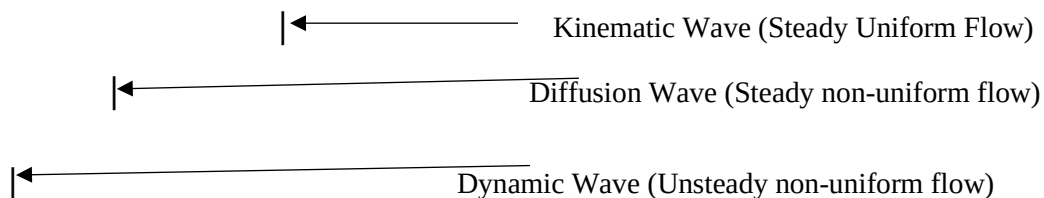
The HEC-RAS integrated software system is designed to be used interactively in a multitasking setting. Graphics, mapping, reporting tools, independent analysis components, data management and storage functions, and a graphical user interface are all part of the system. The river analysis components of the HEC-RAS system include one-dimensional and/or two-dimensional unsteady flow simulation, one-dimensional steady flow water surface profile calculations, quasi-unsteady or totally unsteady flow movable boundary sediment transport calculations (1D and 2D), and one-dimensional water quality analysis. One of the main characteristics of the four components is that they all use the same geometric data structure and hydraulic and geometric computing techniques. In addition to the four components for river analysis, the system features additional hydraulic design elements that can be used once the water surface profiles have been determined. HEC-RAS Mapper, a potent mapping and data integration tool, is an additional component of HEC-RAS. HEC-RAS can be used to do one- and two-dimensional hydraulic computations for a large network of natural and man-made streams, levee-protected areas, overbank/floodplain areas, etc. Here is a description of HEC-RAS's primary duties (Brunner, 2016a).

2.3.2 HEC-RAS-One Dimensional (1D) Model

HEC-RAS determines the flood plain and computes the water surface profile using both steady and unsteady flow analysis. The 1D Saint-Venant problem, which consists of the continuity equation (17) and momentum equation (18), is solved by unsteady flow routing (Ghimire et al., 2022). The following are these equations:

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = 0 \quad (1)$$

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x} \left(\frac{Q^2}{A} \right) + gA \frac{\partial H}{\partial x} + gA(S_0 - S_f) = 0 \quad (2)$$



where x is the measured distance in the channel's direction, g is the gravitational acceleration, t is time, Q is the water flow, and A is the cross-section area. H stands for the height of the water level above the datum. The energy slope is represented by S_f , whereas the river bed's slope is S_0 .

For slowly varying water profiles, 1D constant flow solves the energy equation to obtain the water surface elevation using an iterative standard step approach between the two succeeding cross-sections (Brunner, 2016a).

$$Z_1 + Y_1 + \frac{\alpha_1 V_1^2}{2g} = Z_2 + Y_2 + \frac{\alpha_2 V_2^2}{2g} + h_e \quad (3)$$

Section 1 and Section 2 elevations are indicated by Z_1 and Z_2 , respectively, whereas Section 1 and Section 2 water heights are shown by Y_1 and Y_2 , respectively. In Sections 1 and 2, the variables g and h_e stand for the gravitational acceleration and energy loss between the upstream and downstream cross-sections, respectively, while α_1 and α_2 represent the velocity weighting coefficients.

2.3.1 HEC-RAS Two-Dimensional Model (2D Model)

In the 2D model, either the diffusion wave equation or the full Saint-Venant equation is used. The 2D Saint-Venant equation needs more processing resources to tackle certain problems than the 2D diffusion-wave equation, which solves problems more quickly and steadily. The time step for carrying out the model is specified by Equation 5 for the diffusion-wave equation and Equation 4 (Courant condition) for the Saint-Venant equation (full momentum).

$$C = \frac{V \Delta T}{\Delta X} \leq 1 \text{ (with a max } C = 3) \quad (4)$$

$$C = \frac{V \Delta T}{\Delta X} \leq 2 \text{ (with a max } C = 5) \quad (5)$$

where ΔX is the average cell size, ΔT is the computing time step, V is the flood wave celerity, and C is the Courant Number. A finite volume approach is used to solve the 2D unsteady flow problem implicitly. This approach improves the stability and resilience of the model by allowing for larger time intervals than the explicit method as compared to traditional finite element technique (Brunner, 2016). The continuity and momentum equations in space and time are solved by the unsteady flow routing, as shown in the following equations.

$$\frac{\partial H}{\partial t} + \frac{\partial(hu)}{\partial x} + \frac{\partial(hv)}{\partial y} + q = 0 \quad (6)$$

$$\frac{\partial u}{\partial t} + \frac{u \partial u}{\partial x} + \frac{v \partial v}{\partial y} = -g \frac{\partial H}{\partial x} + vt \left(\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} \right) - cf \cdot u + fv \quad (7)$$

$$\frac{\partial v}{\partial t} + \frac{u \partial v}{\partial x} + \frac{v \partial v}{\partial y} = -g \frac{\partial H}{\partial y} + vt \left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right) - cf \cdot v + fu \quad (8)$$

Time (t), velocity components (u, v), gravitational acceleration (g), x- and y-direction (h(x,y,t)), total head (H), source (q) of the flux term (g), horizontal eddy velocity (vt), bottom friction coefficient (cf), hydraulic radius (R), and Coriolis coefficient (f) are the variables in this equation. While forces acting on the fluid from the inside or outside are indicated on the right side of the equations, acceleration is represented on the left. Additional details about the theoretical underpinnings of HEC-RAS can be found in the documentation manual (Brunner, 2016).

The 2D Saint-Venant equations control the surface flow. These equations are obtained from the continuity and momentum equations by applying a depth averaging technique. When developing 2D SV equations, the basic assumptions are the hydrostatic pressure distribution and small channel slope. The surface flow controlling equations are as follows (Kamboh et al., 2016).

2.4 Flood Inundation Mapping

Flood mitigation and adaptation begin with hazard mapping and inundation prediction. It is employed to identify regions that could flood in the event of heavy precipitation. After the design floods are determined, flood inundation maps are produced using a hydraulic model and all primary and secondary data that are accessible. When mapping flood inundation at the watershed level, hydrodynamic models such as FLUCOMP, ISIS, ONDA, MIKE11, SOBEK, Delft3D, and HEC-RAS are frequently used (Baky et al., 2019).

The whole Awash River basin was frequently flooded as a result of long-standing, ineffective land use management and excessive agricultural practices. For example, the sudden flood that flooded the town of Dire Dawa at midnight on August 6, 2006, was one of the worst flood events in the lower Awash River basin of Ethiopia (Namara et al., 2022a).

The study (Papaioannou et al., 2016) examined how sensitive flood inundation mapping was to the hydraulic modeling approach selected and the geographical resolution of riverine data. The

researchers employed a variety of hydraulic modeling techniques, including 1D models (HEC-RAS, MIKE 11), 2D models (MIKE 21, MIKE 21 FM), and coupled 1D/2D models (MIKE FLOOD), in addition to four types of riverine data: digital contours from 1:5000 scale maps, terrestrial laser scanner (TLS) data, and topographic land survey data. The lower Xerias River basin in Volos, Greece, which saw a significant flash flood in 2006, served as the study region. Using contingency tables, flood inundation maps were created for every data/model combination and compared to the actual flood extent in 2006. The findings demonstrated how sensitive flood mapping is to the choice of hydraulic modeling approach as well as DEM spatial resolution.

Flood events from 2010 and 2015 were used to calibrate and validate the HEC-RAS v5 model, respectively. The simulation procedure was used to optimize the values of the Manning's roughness coefficient (n). Water bodies were identified using a variety of water indices (NDWI, MNDWI1, MNDWI2) and satellite imagery from Landsat 5/8 and MODIS. The accuracy of the HEC-RAS simulations was evaluated using the flood extents determined by satellite. Good agreement between simulated and observed flood extents was demonstrated by the optimal n values for rivers and floodplains, which were 0.055 and 0.06 correspondingly. The middle region of the Indus River basin can benefit from early flood warnings using the combined HEC-RAS and satellite imagery technique. In conclusion, the work shows how hydrodynamic modeling and remote sensing data can be combined to enhance flood monitoring and early warning systems in areas with limited data, such as Pakistan's Indus River basin (Afzal et al., 2022).

Table 2. 1 Summary of Key Hydrodynamic Models for Flood Inundation Mapping

Model	Developer	Type	Advantages	Disadvantages	Best Use Case
HEC-RAS	US Army Corps of Engineers	1D / 2D	- Free and open-source - Good documentation - Strong GIS integration - Widely used and validated	- Limited representation of complex terrain in 1D mode - Accuracy depends on DEM resolution	Riverine flood mapping, dam breach analysis

MIKE FLOOD	DHI	1D / 2D	- Highly accurate and flexible - Advanced modules (rainfall-runoff, coastal, urban) - Professional support	- Expensive license - Steep learning curve - High data requirements	Urban flooding, coastal–river interaction modeling
TUFLOW	BMT Group	1D / 2D	- Fast and efficient - High-resolution mapping - Excellent GIS integration	- Commercial license - Requires technical expertise	Urban flood modeling, real-time forecasting
Flood Modeller	Jacobs Engineering	1D / 2D	- Integrated rainfall-runoff - Real-time forecasting - Regulatory compliance (e.g., UK EA)	- Paid software - Requires quality input data	Urban and riverine flood risk assessment, policy studies
LISFLOOD-FP	University of Bristol	2D (raster-based)	- Open-source - Ideal for large-scale analysis - Computationally efficient	- Simplified hydraulics - No user-friendly GUI - Less suitable for urban modeling	Regional or national flood hazard mapping

2.5 Flood Hazard Assessment

Elevation, land use, drainage density, average rainfall, slope, and soil type are the main factors that cause floods and are taken into account when evaluating flood hazards (Getahun YS, 2015). The Analytic Hierarchy Process (AHP), a multi-criteria decision-making method, was used to rank and assign weights to the sub-factors and map layer according to their level of effect on the result. A final map was produced after a weighted overlay analysis of these layers, and it was categorized based on how the flood hazard model showed the influence of each layer on flood danger (Farooq et al., 2019a).

Flood hazard = $\sum W_i X_i$ Where W_i = weight of factor i ; X_i = criterion score of factors i .

According to the predicted depth and extent of floods, flood dangers were divided into various zones in the study by (Farooq et al., 2019a). The central and lower parts of the river were identified as having high and extremely high flood threat zones. These regions are distinguished by low drainage density, low slopes, and flat terrain.

Using GIS, remote sensing, and hydraulic modeling, the study (Vojtek & Vojteková, 2016) provided a case study on evaluating flood risk and hazard at the local spatial scale. The researchers predicted maximum flood flows and used 1D hydraulic modeling to gather data on water depth and flow velocity in order to assess flood hazard. They used a thorough process to define flood risk, first estimating flood intensity based on water depth and velocity, then dividing flood hazard into low, medium, and high categories, defining vulnerability for various land use classes, and finally combining vulnerability and hazard to calculate overall flood risk. The authors point out that risk management and flood prevention are becoming more and more significant, even though traditional flood protection techniques are still crucial. The paper identifies a number of significant obstacles in this procedure, such as precisely calculating the maximum flood discharges, managing statistical approach uncertainties, and successfully combining hazard and vulnerability assessments.

The authors point out that risk management and flood prevention are becoming more and more significant, even though traditional flood protection techniques are still crucial. The paper identifies a number of significant obstacles in this procedure, such as precisely calculating the

maximum flood discharges, managing statistical approach uncertainties, and successfully combining hazard and vulnerability assessments.

A thorough flood hazard assessment and mapping research for a 60-kilometer section of the Swat River in northern Pakistan was reported by another study (Farooq et al., 2019a). To simulate the flood dynamics, the researchers used high-resolution 12 m WorldDEM data in conjunction with the HEC-RAS 2D hydrodynamic model. Manning's roughness, flood stage, and satellite-derived flood extent were among the inputs used to calibrate and validate the model using the historic 2010 flood event. The sensitivity analysis used to evaluate the study's findings was a crucial component.

Effects on the simulated flood depths of employing various DEM datasets, such as 12 m WorldDEM, 30 m SRTM, 30 m ALOS, and 30 m ASTER. The researchers then utilized the 2D model to replicate the relevant flood extents and created synthetic flood hydrographs for return periods of 2, 5, 10, 25, 50, and 100 years. The study created thorough flood danger maps for the study area using the 12 m World DEM models. The exposure of various land cover classes, including orchards and farmland, to the simulated flood occurrences was also examined by the researchers.

2.6 Flood Vulnerability Assessment

When people or a region are exposed to flood hazards and are unable to deal with their effects, this is referred to as flood vulnerability. Understanding flood susceptibility is necessary because assessing and evaluating flood vulnerability can help manage floods more effectively and lessen their effects on different facets of society. The idea of vulnerability originated in the social sciences and is becoming more and more apparent in catastrophe study these days. Risk, exposure, and sensitivity are just a few of the components that make up the multifaceted concept of vulnerability. Scholars have been debating for decades whether it is possible to assess, assign, and statistically measure vulnerability among different populations. Within the context of hazard vulnerability, the study of vulnerability has expanded significantly over the past forty years to incorporate socioecological aspects (White and Haas 1975). The spatial, topographical, ecological, economic, and social aspects of vulnerability have all been effectively assessed using a variety of approaches (Sahana & Sajjad, 2019).

The study (Rehman et al., 2019), titled "A Systematic Review on Approaches and Methods Used for Flood Vulnerability Assessment: Framework for Future Research," offers a comprehensive examination of methodologies for assessing food vulnerability, particularly in the context of flooding. The authors emphasize the increasing significance of food vulnerability assessments due to climate change and urbanization, highlighting the multidimensional nature of food vulnerability that varies across different spatial and temporal contexts. The methodological framework presented categorizes existing approaches into several types, including hydrodynamic models, GIS, remote sensing, and machine learning techniques. The authors identify gaps in current methodologies, particularly the need for high-resolution data and integrated approaches that combine various techniques. The literature analysis includes a detailed review of articles from reputable journals, showcasing trends in keywords and citation patterns, which provides valuable insights for future scholars in the field.

Furthermore, the authors advocate for the use of artificial neural networks and advanced geospatial techniques to enhance the accuracy of food vulnerability assessments and suggest that future studies should focus on comprehensive evaluations that integrate social, economic, and environmental factors. The findings underscore the importance of understanding food vulnerability in developing effective policies for disaster risk reduction and enhancing community resilience, calling for a multidisciplinary approach to address the complexities involved. While the paper presents a thorough review of the literature and proposes a well-founded framework for future research, it could benefit from including more specific case studies that illustrate the application of these methods in real-world scenarios. Additionally, the strong emphasis on advanced technological solutions may overlook traditional methods that can still be effective, especially in resource-limited settings. Overall, this paper serves as a vital resource for researchers and practitioners in disaster management and food security, effectively outlining the challenges and opportunities in assessing food vulnerability and paving the way for future investigations that can inform policy decisions and community preparedness efforts (Rehman et al., 2019).

Flood vulnerability can be evaluated by classifying it into three categories: social, economic, and environmental vulnerability. These factors can be evaluated using a variety of indicators; for example, age, population density, impoverished communities, and difficulty obtaining essential services can all be used to gauge a population's susceptibility to flooding. Indicators such as land

degradation and damaged forests can be used to evaluate the environmental component. For social and economic components, poverty, the basis of land resources, and infrastructural accessibility can be taken into account. The flood hazard vulnerability model can also incorporate the gender, the cultural system, and the economy. But during the past 20 years, the concept of vulnerability has changed in relation to the flood vulnerability index (FVI). Accordingly, exposure, susceptibility, and resilience are all included in its revised definition (Rehman et al., 2019).

2.7 Research Gaps

The research gaps identified in the provided papers highlight several areas for further investigation. In the study (Woldegebrael et al., 2022), while a web-based tool for flood risk management is developed, it lacks extensive empirical validation in diverse geographical contexts. Future research should test this tool in various regions with differing hydrological characteristics to assess its adaptability and effectiveness. The paper (Woldegebrael et al., 2020), discusses the interrelationship between rainfall and flooding in the Awash and Omo-Gibe basins but does not fully explore how these relationships manifest in less studied or rural regions of Ethiopia. Additionally, there is a significant need for deeper analysis of long-term climate change impacts on rainfall patterns and flood occurrences, particularly given recent climate variability. The reliance on satellite data and weather stations presents another limitation; future studies should incorporate more localized data sources, including community-based monitoring systems. Furthermore, while the research suggests the necessity for effective flood mitigation strategies, it lacks detailed interventions or policies that could be implemented based on its findings.

Firstly, while the studies (Woldegebrael et al., 2020, 2022) provide insights into the relationship between rainfall and flooding, they may not sufficiently address the detailed mapping of flood inundation areas in varying topographies and land uses. A comprehensive assessment of flood inundation dynamics, particularly in less studied regions, is necessary to understand how different landscapes affect flood susceptibility.

Secondly, both papers emphasize rainfall as a primary trigger for flooding but do not fully integrate other critical factors such as soil saturation, land cover changes, and human activities (e.g., urbanization and agricultural practices) that contribute to flood hazards. Understanding these interactions is essential for more accurate hazard assessments.

Moreover, the vulnerability assessments presented in the studies could benefit from a more nuanced approach that considers socio-economic factors, population density, and infrastructure resilience. Identifying vulnerable communities and their specific needs can aid in developing targeted mitigation strategies and improving disaster preparedness. Lastly, there is a notable lack of temporal analysis in assessing how flood hazards and vulnerabilities evolve over time due to climate change and land-use changes. Long-term studies that track these trends are crucial for developing adaptive management strategies that can better withstand future flood events.

Identifying gaps in the thesis "Flood Modeling and Mapping of Lower Omo Gibe River Basin" by (Gurmu, 2018), Firstly, while the thesis addresses flood modeling, it may not provide a comprehensive inundation mapping that incorporates various scenarios, such as extreme weather events or changes in land use. Detailed inundation maps under different conditions could enhance understanding of flood risks in specific areas. Additionally, the assessment of flood hazards might lack a multi-dimensional approach that considers not just the physical extent of flooding but also factors like flood depth, velocity, and duration, which are crucial for determining the potential impact on communities and infrastructure.

Furthermore, the vulnerability assessment may not adequately address the socio-economic factors that contribute to community resilience or susceptibility to flooding. Factors such as population density, poverty levels, and access to resources should be integrated into the assessment to provide a clearer picture of how different communities are impacted by flooding. The thesis could also benefit from a more detailed analysis of the adaptive capacity of local populations and their ability to respond to flood risks, which is essential for effective risk management.

Lastly, the research might not sufficiently engage with local knowledge and perceptions regarding flood risks, which can provide valuable insights into community-specific vulnerabilities and inform more targeted mitigation strategies. By addressing these gaps, future studies could improve the understanding of flood inundation, hazards, and vulnerability, ultimately contributing to more effective flood management practices in the Lower Omo Gibe River Basin.

In the context of the Lower Omo-Gibe River Sub-Basin, there is a critical need for comprehensive riverine flood inundation mapping that accounts for diverse scenarios, including extreme weather events and changing land use patterns. Such mapping should not only delineate the physical extent

of flooding but also incorporate key factors like flood depth, velocity, and duration to assess the potential impacts on communities and infrastructure effectively.

Furthermore, an integrated flood hazard assessment is essential, moving beyond mere spatial analysis to include a multi-dimensional evaluation of flood characteristics. This approach would enhance the understanding of the risks associated with different flood events and inform decision-making for flood management strategies.

The vulnerability assessment must also consider socio-economic factors that contribute to community resilience or susceptibility. By integrating demographic data, economic conditions, and access to resources, a clearer picture of community vulnerabilities can be developed. Additionally, examining the adaptive capacity of local populations and their responses to flood risks will provide insights into effective risk management practices.

Finally, engaging with local knowledge and perceptions regarding flood risks is crucial. Understanding community-specific vulnerabilities will enable the development of targeted mitigation strategies that are culturally relevant and practically applicable. By addressing these gaps, this research aims to provide a holistic framework for flood management in the Lower Omo-Gibe River Sub-Basin, ultimately enhancing community resilience and safety against future flood events.

3. MATERIALS AND METHODS

3.1 Study Area Description

3.1.1 Location

One of the most significant river basins in the nation is the Omo-Gibe. Hydroelectric power plants and extensive irrigation projects are vital resources in the basin. It is located between 4°30' N and 9°30' N and between 35°E and 38°E in southwest Ethiopia. The Oromia and the Region of Nations, Nationalities, and Peoples of the South (SNNPR) share an equal portion of the basin, which is roughly 79,000 km² in size and into which the river empties into Lake Turkana. Each region receives between 25 and 75 percent of the basin. Two significant rivers drain it: the Gojeb River flows eastward and the Ghibe River flows south. The southern boundary of this confined river basin is Lake Turkana, Kenya, which is situated at 3°35'N 36°7'E. The Baro-Akobo Basin forms its western boundary, followed by the Blue-Nile Basin in the north and northwest, the Awash Basin in the northeast, and the Rift Valley Lakes Basin on the entire eastern side (Orkodjo et al., 2022).

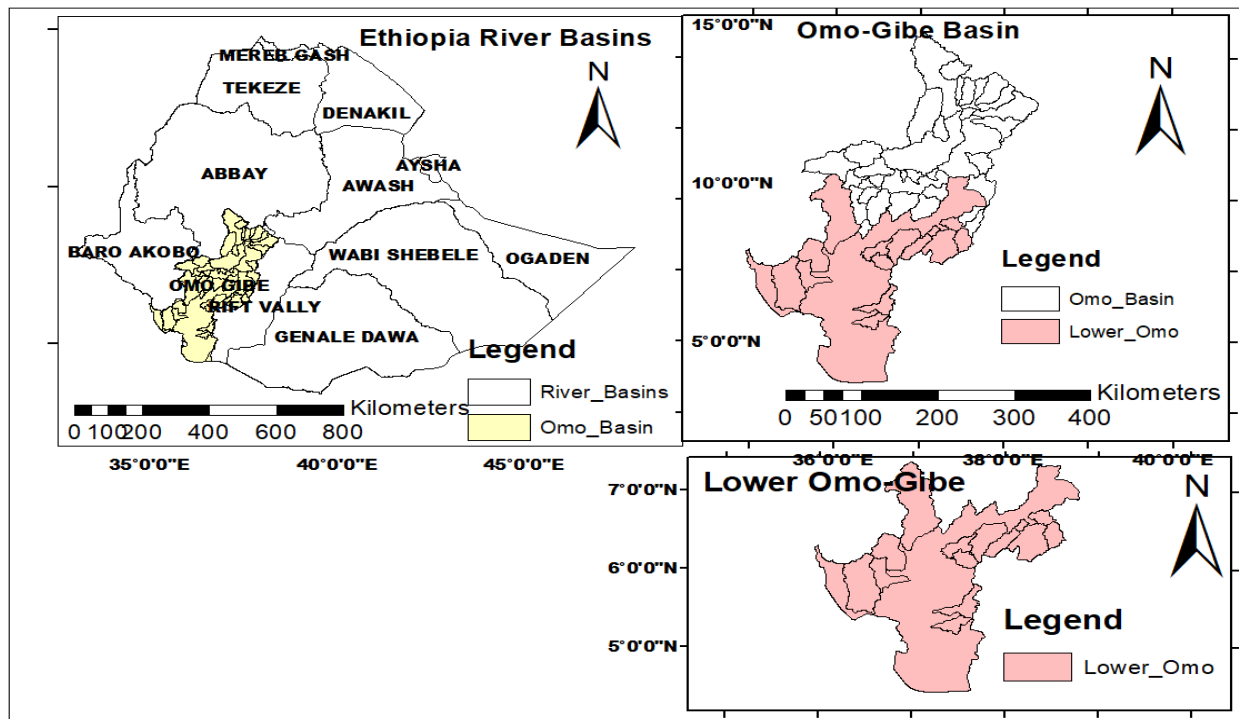


Figure 3. 1 Location Map of the Study Area.

3.1.2 Climate

The monthly average rainfall data for the Jinka and Omorate weather stations provides valuable insights into precipitation patterns from 1990 to 2022. In Jinka, the rainfall varies significantly throughout the year, with the highest average recorded in May at approximately 78.3 mm, while the lowest occurs in January with about 23.3 mm. Conversely, Omorate experiences lower overall rainfall, peaking in April with an average of around 45.3 mm and reaching its minimum in January with just 3.7 mm.

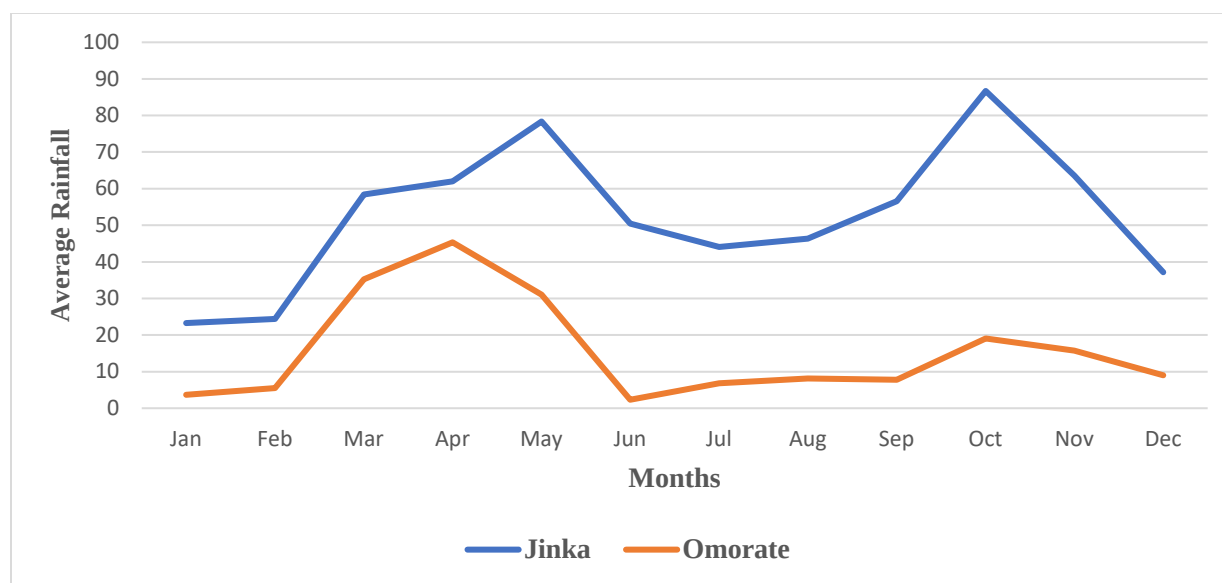


Figure 3. 2 Monthly average rainfall distribution of the station

3.1.3 Soil

The soil composition of the Lower Omo Sub-basin exhibits a diverse array of soil types, each varying in spatial extent and agricultural relevance. The most extensive soil type is **eutric fluvisols**, covering approximately **836,094 hectares**, indicating substantial fertility and high suitability for agriculture. **Chromic cambisols** follow, occupying around **514,841 hectares**, and are characterized by moderate development and favorable physical properties. **Dystic nitisols** and **chromic vertisols** also cover large portions of the sub-basin, with areas of about **531,472 hectares** and **447,604 hectares**, respectively—the latter being known for its high clay content and swelling behavior. **Orthic acrisols** account for approximately **275,782 hectares**, contributing to the basin's agricultural diversity despite their acidity and lower fertility. In contrast, **vertic luvisols** and **phaeozems** are among the least represented, covering only about **39 hectares** and **3,940 hectares**,

respectively. This wide variation in soil types underpins the Lower Omo Sub-basin's rich ecological diversity and agricultural potential.

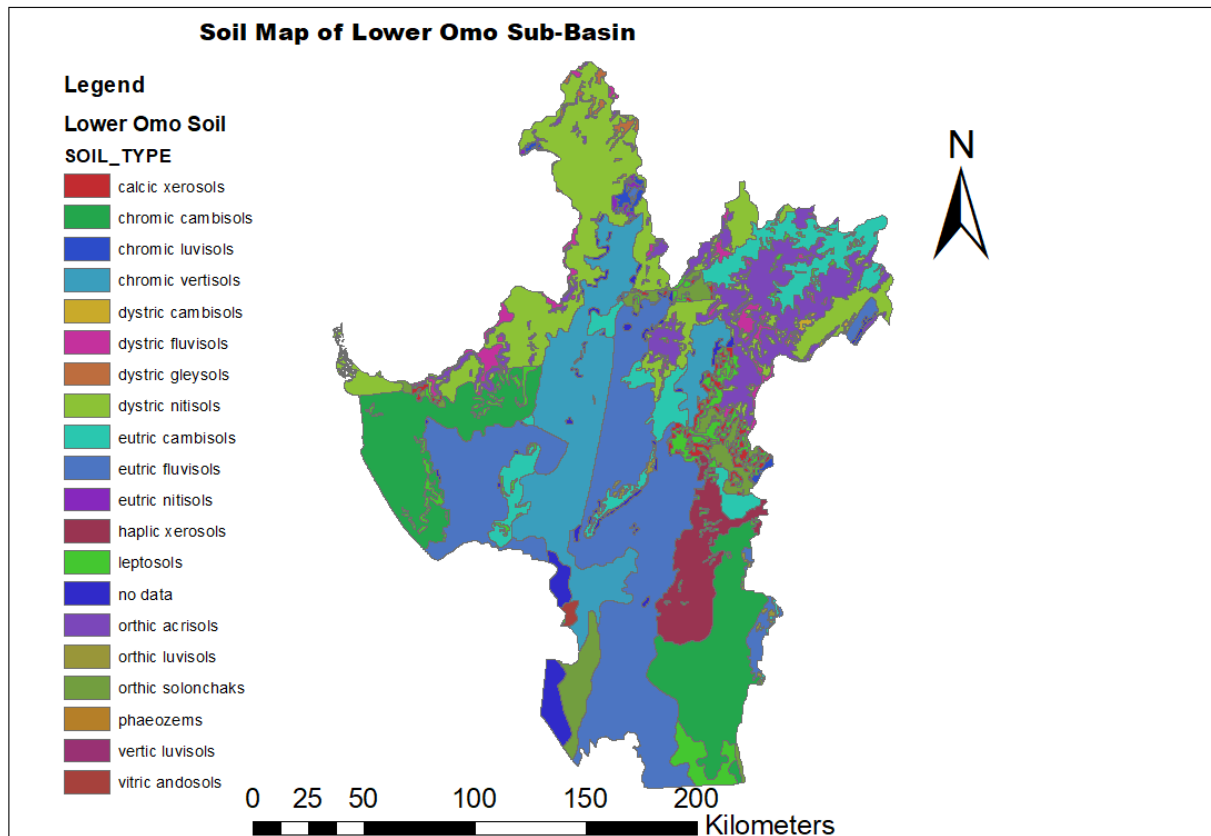


Figure 3. 3 Soil Map of Lower Omo Sub-Basin

3.1.4 Land Use

The Land Use Land Cover (LULC) data for the region reveals a diverse array of land types, each contributing uniquely to the landscape's ecological and economic functions. The most extensive land cover is **rangeland**, encompassing approximately **1,767,374 hectares**, which provides vital grazing areas for livestock and supports pastoral livelihoods. **Tree-covered areas** follow, covering around **1,321,875 hectares**, representing substantial forested zones that enhance biodiversity and deliver crucial ecosystem services. **Cropland** accounts for about **334,516 hectares**, indicating a significant footprint of agricultural activity across the region. **Water bodies** span roughly **67,898 hectares**, playing a key role in the hydrological cycle and supporting aquatic biodiversity. Additionally, **flooded vegetation** occupies around **19,704 hectares**, contributing to wetland

ecosystems and seasonal flood dynamics. **Built-up areas** and **bare ground** are less extensive, covering approximately **26,914 hectares** and **6,171 hectares**, respectively, reflecting limited urban development and sparsely vegetated or eroded landscapes. Altogether, this varied land cover pattern highlights the region’s ecological complexity and agricultural importance.

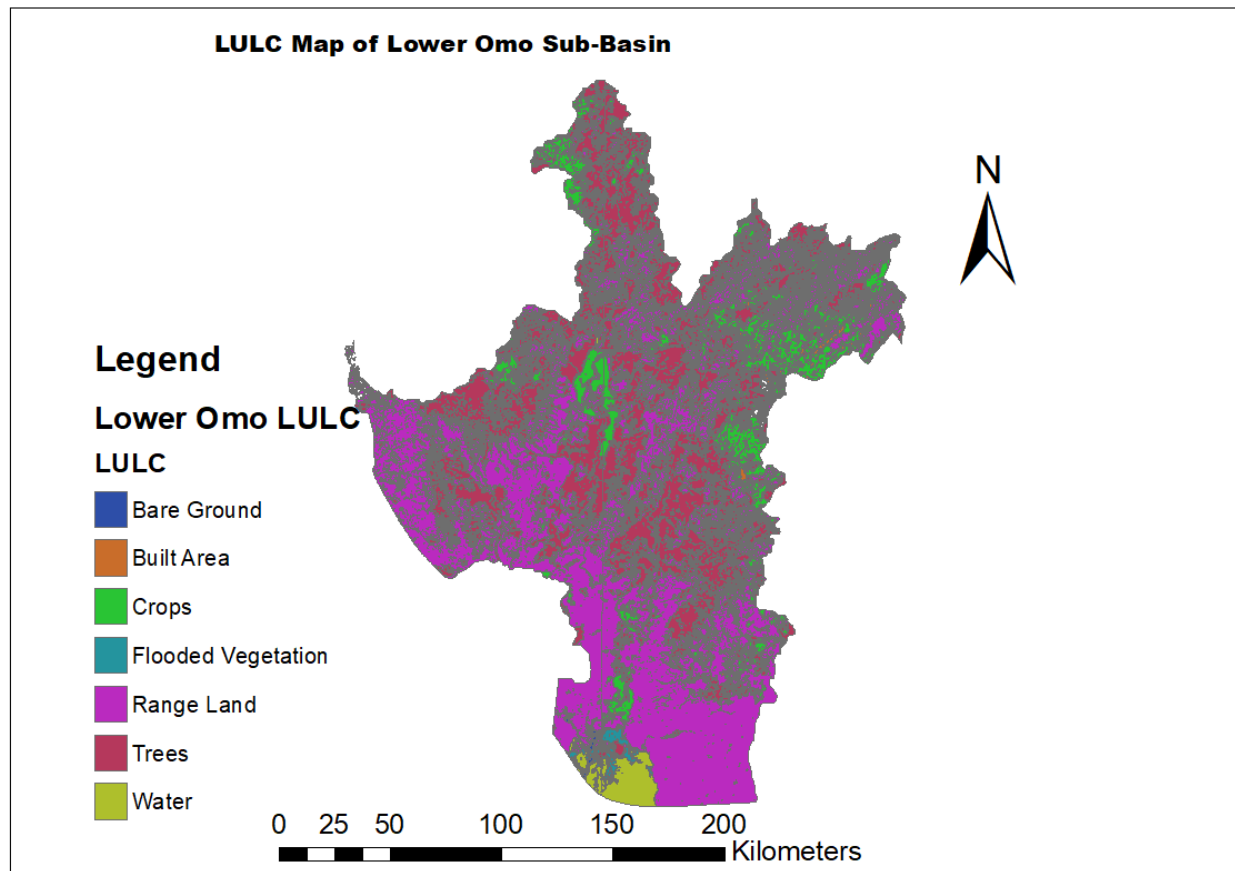


Figure 3. 4 LULC Map of Lower Omo Sub-Basin

3.2 Datasets

For the hydraulic modeling of HEC-RAS to configure the physical parameters of the flood plain into the model, a large amount of geometric and hydrologic data is required. Careful utilization of topological and geometric data is necessary to accurately transform the actual flood coverage area of the flood plain. Accurate mapping of flood inundation requires a high-resolution digital elevation model (DEM). A 12.5 m × 12.5 m high-resolution digital elevation model was acquired from the Alaska Satellite Facility (<https://vertex.dac.asf.alska.edu>) in order to achieve this objective. Arc GIS and its extension geospatial river analysis system, HEC-Geo RAS, were used

to extract river geometric cross-section features, such as the centerline, flow route lines, bank lines, XS cut lines, and Manning's roughness coefficient, from this high-resolution DEM (Namara et al., 2022; Tamiru & Dinka, 2021). One of the initial steps in flood hazard charting, flood risk assessment, and flood inundation mapping is the computation of the extreme flood value. Flood inundation mapping is a process-based work that tracks the pattern of findings from an analysis of the frequency of flooding within a certain watershed (flood plain), according to (Namara et al., 2022a). The River Analysis System (RAS) requires flow data (profile) to map the area of the floodplain that has been flooded. To do this, hydro-meteorological information was obtained from the Ethiopian Ministry of Water and Energy (MoWE) and the Ethiopian Meteorological Agency.

Table 3. 1 Data needed and their sources

Data needed	Purpose	Sources
Stream flow data	1D	Ministry of Water and Energy (MoWE)
Stream geometry	An input for HEC-RAS	Extracted from DEM
DEM 12.5m Resolution	Terrain file creation	Alaska Satellite Facility https://vertex.dac.asf.alska.edu
Water Level Data	Calibration	Ministry of Water and Energy (MoWE)
Sentinel 2 10m	Land use/Land cover classification	Sentinel 2 10m https://livingatlas.arcgis.com/landcoverexplorer/ .
Landsat-9 Image	Pre-flood images and during-flood images for validation	USGS Earth Explorer https://www.usgs.gov/programs/national-geospatial-program/national-map

Table 3. 2 Lower Omo River Basin downstream of Koysha Dam Hydrological Stations from MOWE.

SITE	Periods	Length of record	Catchment Area (km²)
Nr. JINKA	1982-2006	24	166
@Koysha Dam Site	1964-2014	50	
@ Omorate	2010-2020	10	266

Table 3. 3 Software Used during the Study

Name of Software	Purpose
HEC-RAS V 6	Flood inundation modeling and hazard Map Generation
ArcGIS 10.8	Hazard Map, Vulnerability Analysis, and HEC-RAS Result Visualization
HEC-SSP V 2.3	Statistical analyses of hydrologic data
Rainbow	Data homogeneity check

3.3 Hydrological Data Quality Assessment

3.3.1 Filling of Missed Hydrological Data

Like almost every other scientific field, hydrology has benefited immensely from the recent surge in available processing power and storage capacity as well as the impressive developments in scientific equipment built to collect large data sets. Many model applications and statistical studies, including extreme value analysis, are based on this time series. Therefore, these time series' precision and thoroughness are essential. As a result, filling in data gaps is crucial to preparing raw data collections. Missing data generally reduces the power and accuracy of statistical research methods (Gao et al., 2018).

Techniques For Handling Missed Data

Listwise and pairwise deletion

The technique of eliminating all observations for which one or more variables have missing data is known as listwise elimination. The primary benefit of listwise deletion is convenience. This approach has a number of issues because removing observations to address inadequate data will always lead to a lower sample size (Gao et al., 2018).

Single-imputation methods

Single-imputation procedures generate a single replacement for each missing value with a suitable value prior to data analysis.

Arithmetic mean and median imputation

Given how easily a complete dataset can be created, both methods are very practical. Arithmetic mean imputation fills in any missing values in the variable by taking the arithmetic mean of the observed values for the same variable, while median imputation fills in the missing values by using

the median of the observed values for the same variable. Median imputation is preferable when the underlying variable has a skewed distribution as opposed to a symmetric distribution. However, even when the strong MCAR assumption is true, these techniques distort the final parameter estimates. For instance, they lower the variance and standard deviation of estimates obtained from analyses of mean-imputed variables. The decrease in the standard deviation of estimates can be explained by the imputed values being the same and at the center of the estimations (Gao et al., 2018).

Multiple imputation

As previously mentioned, more sophisticated methods have been developed to mitigate the negative consequences of regression imputation. The basic concept is to replace each missing piece with two or more realistic values that represent a variety of options. For this reason, they are called multiple imputation approaches. As relevant techniques are widely incorporated into popular statistical software packages, recent advances in computational power have made multiple imputations viable. The main advantage of multiple imputation is that it prevents overstatement of conclusions regarding statistics like correlations and mistakes by accounting for the uncertainty associated with missing data. MI does, however, have some disadvantages. MI's main disadvantage is that it requires more processing effort due to the imputation and the consequences (Gao et al., 2018).

In contrast, multivariate imputation estimates missing values by taking into account the full set of accessible attributes. Modeling each feature with missing values as a function of other features leads to more intricate imputations. It is a useful technique for handling missing data in hydrological studies.

3.3.1 Data Homogeneity Analysis

For climatological research to accurately represent weather and climate changes, homogeneity testing is necessary. A number of factors, including human mistake, modifications to the instrument's environment, and technical flaws, can result in inhomogeneous climate data. The findings will show erroneous trends if the homogeneity is not examined before trend analysis. In this work, relative homogeneity tests were conducted by creating a reference series using the Anclim software application and computing the ratio of the observed series to the reference series. Individual station records were subjected to absolute homogeneity testing (Patakamuri et al.,

2020). Numerous methods, such as the Von Neumann ratio (VNR), Pettitt's test, the standard normal homogeneity test (SNHT), and the Buishand range test (BRT), can be used to perform homogeneity testing (Daba et al., 2020; Patakamuri et al., 2020).

Numerous methods, such as the Von Neumann ratio (VNR), Pettitt's test, the standard normal homogeneity test (SNHT), and the Buishand range test (BRT), can be used to perform homogeneity tests (Daba et al., 2020). The residual mass curve and homogeneity statistics for this study will be generated using a statistical software program called RAINBOW, which makes use of Buishand's homogeneity test. A homogeneity test based on cumulative deviations from the mean is offered by RAINBOW. The homogeneity of data in a time series can be assessed by computing the maximum (Q) and range (R) of the cumulative deviations from the mean. With 0.1, 0.05, and 0.01 degrees of freedom indicated by the 90%, 95%, and 99% confidence intervals, the null and alternative hypotheses were examined.

3.3.2 Test for Outliers

Outliers are data points that significantly depart from the general trend. Retaining or eliminating these outliers can have a significant impact on the size of statistical parameters derived from the data, especially for small samples. If the station skew is greater than +0.4, tests for high outliers are prioritized; if the station skew is less than -0.4, tests for low outliers are prioritized. When the station skew is between ± 0.4 , testing for both high and low outliers should be done before eliminating any outliers from the data set (Ven Chow et al., 1988).

The Grubbs and Beck (1972) test may be used to detect outliers.

$$XH = \exp(\bar{x} + KNs)$$

$$XL = \exp(\bar{x} - KNs)$$

Where, $\bar{x}$ and s are the mean and standard deviation of the natural logarithms of the sample, respectively

$$KN = -3.62201 + 6.28446N^{1/4} - 2.491436N^{1/2} + 0.491436N^{3/4} - 0.037911 * N$$

Where KN is the G-B statistic tabulated for various sample sizes and significance levels by Grubbs and Beck (1972) at 10% significant level.

3.4 Flood Quantile Estimation Methods

Flood inundation mapping is a process-based endeavor that tracks trends in the results of a selected catchment's flood frequency study (flood plain). The River Analysis System (RAS) requires a flow data profile to depict the floodplain region that has been inundated with water. Flood inundation mapping, flood risk estimation, and flood hazard display rely on the computation of extreme flood values (Namara et al., 2022a).

Choosing the right PDF for frequency analysis is an important step that can have a big impact on the estimated peak discharge values. The authors of the study (Baky et al., 2019) examined five PDFs: Gumbel, Pearson Type III (P3), Three-Parameter Log-Normal (LN3), Two-Parameter Log-Normal (LN2), and Log Pearson Type III (LP3) (EV1). and found that the best-fitting distribution varied per gauge station. This makes sense because the PDF selection can be influenced by the catchment's characteristics, the length of the currently available data record, and the anticipated return period. An analysis of flood frequency is necessary for managing and comprehending flood risk. It entails applying statistical methods to establish a connection between flood frequency and amplitude. To examine flood frequency, a variety of probability distribution models are available. The General Extreme Value distribution, the Log-Pearson Type III distribution, and the Gumbel distribution are some of the most widely used models. The particulars of the data and its intended use will determine the best model. The frequency of the anticipated maximum stream flow was examined using a Gumbel distribution in the study (Ukumo et al., 2022).

Theory of L-moments (LM)

An alternative to traditional moments are L-moments, which are obtained via linear combinations of order statistics. L-moments can be defined for any random variable Y that has a mean (Ul Hassan et al., 2019). The L-moment ratio diagrams' findings indicate that the normal and generalized extreme value (GEV) distributions typically offer the best fit to the temperature data. Other two- and three-parameter distributions, however, can also be good matches in some cases, according to the study. The results of alternative methods, such as GOF statistics, are in agreement with the conclusions drawn from the L-moment ratio diagrams (Haddad, 2021). The study highlights that comparing the fit of several pdfs across various stations may be done easily, effectively, and efficiently with the L-moment ratio diagram method. It offers important information on the temperature data set's higher-order moments, including shape, skewness, and

kurtosis. The L-moment ratio diagram, according to the author, can be applied in addition to conventional GOF criteria.

The first four L-moments in terms of the linear combination of PWM are defined as.

$$\lambda_1 = \beta_0 \quad (6)$$

$$\lambda_2 = 2\beta_1 - \beta_0 \quad (7)$$

$$\lambda_3 = 6\beta_2 - 6\beta_1 + \beta_0 \quad (8)$$

$$\lambda_4 = 20\beta_3 - 30\beta_2 + 12\beta_1 - \beta_0 \quad (9)$$

The location (mean) is represented by the first L-moment (λ_1), and the dispersion by the second L-moment. Below are the L-moment ratios as established by (Hosking, 1990).

$$\text{L-Coefficient of variation } (\tau_2) = \lambda_2/\lambda_1 \quad (10)$$

$$\text{L-Skewness } (\tau_3) = \lambda_3/\lambda_2 \quad (11)$$

$$\text{L-Kurtosis } (\tau_4) = \lambda_4/\lambda_2 \quad (12)$$

For any distribution, the unbiased sample estimators of β_i of the first four PWMs can be calculated in this way.

$$\beta_0 = (n - 1) / n \sum (y_j / n) \quad (13)$$

$$\beta_1 = (n - 1) / n \sum (j - 1) / (n - 1) y_j / n \quad (14)$$

$$\beta_2 = (n - 1) / n \sum (j - 1)(j - 2) / (n - 1)(n - 2) y_j / n \quad (15)$$

$$\beta_3 = (n - 1) / n \sum (j - 1)(j - 2)(j - 3) / (n - 1)(n - 2)(n - 3) y_j / n \quad (16)$$

Table 3. 4 L-Moments of some common distributions (*Hosking, 1990*)

Distribution	F(x) or x(F)	L-moments
Uniform	$x = \alpha + (\beta - \alpha)F$	$\lambda_1 = (1/2)(\alpha + \beta)$, $\lambda_2 = (1/6)(\beta - \alpha)$, $\tau_3 = 0$, $\tau_4 = 0$
Exponential	$x = \xi - \alpha \log(1 - F)$	$\lambda_1 = \xi + \alpha$, $\lambda_2 = (1/2)\alpha$, $\tau_3 = 1/2$, $\tau_4 = 1/6$

Gumbel	$x = \xi - \alpha \log(-\log F)$	$\lambda_1 = \xi + \gamma\alpha, \lambda_2 = \alpha \log 2, \tau_3 = 0, \tau_4 = 0.1504$
Logistic	$x = \xi + \alpha \log\{F / (1 - F)\}$	$\lambda_1 = \mu, \lambda_2 = \pi^{-1}\sigma, \tau_3 = 0, \tau_4 = 30\pi^{-1} \tan^{-1}\sqrt{2} - 9 = 0.1226$
Normal	$F = \Phi((x - \mu) / \sigma)$	$\lambda_1 = \mu, \lambda_2 = \pi^{-1}\sigma, \tau_3 = 0, \tau_4 = 30\pi^{-1} \tan^{-1}\sqrt{2} - 9 = 0.1226$
Generalized Pareto	$x = \xi + \alpha\{1 - (1 - F)^k\} / k$	$\lambda_1 = \xi + \alpha / (1 + k), \lambda_2 = \alpha / (1 + k)(2 + k), \tau_3 = (1 - k) / (3 + k), \tau_4 = (1 - k)(2 - k) / (3 + k)(4 + k)$
Generalized extreme value	$x = \xi + \alpha\{1 - (-\log F)^k\} / k$	$\lambda_1 = \xi + \alpha\{1 - \Gamma(1 + k)\Gamma(1 - k)\} / k, \lambda_2 = \alpha\Gamma(1 + k)\Gamma(1 - k), \tau_3 = -k, \tau_4 = (1 + 5k^2) / 6$
Log-normal	$F = \Phi((\log(x - \xi) - \mu) / \sigma)$	$\lambda_1 = \xi + \exp(\mu + \sigma^2 / 2), \lambda_2 = \exp(\mu + \sigma^2 / 2) \operatorname{erf}(\sigma / \sqrt{2}), \tau_3 = (6 - 1 / 256\pi^2) \operatorname{erf}(x / \sqrt{3})\exp(-x^2)dx / \operatorname{erf}(\sigma / \sqrt{2})$
Gamma	$F = \int_0^x t^{\alpha-1} \exp(-t / \beta) dt / \Gamma(\alpha)$	$\lambda_1 = \alpha\beta, \lambda_2 = \pi^{1/2}\beta \Gamma(\alpha + 1/2) / \Gamma(\alpha), \tau_3 = 6I_{-}(1/3)(\alpha, 2\alpha) - 3$

3.5 Computational Methodology

HEC-RAS is an integrated software system designed for interactive use in a multitasking environment. The components of the system include a graphical user interface (GUI), specific analysis components, data management and storage features, graphics, mapping, and reporting capabilities. The HEC-RAS system includes river analysis components for (1) one-dimensional steady flow water surface profile computations, (2) one-dimensional and/or two-dimensional unsteady flow simulation, (3) movable boundary sediment transport computations (1D and 2D) for quasi-unsteady or fully unsteady flow, and (4) one-dimensional water quality analysis.

The adoption of a single geometric data structure and shared geometric and hydraulic computing algorithms by all four components is a crucial component. In addition to its four core components for river analysis, the system includes various hydraulic design features that can be enabled once the water surface profiles are computed. Furthermore, HEC-RAS incorporates a robust mapping tool and geographic data integration system known as HEC-RAS Mapper. It is designed to perform

one- and two-dimensional hydraulic modeling for complete networks of both natural and engineered channels, including floodplains, overbank areas, and levee-protected regions (Brunner, 2016).

3.5.1 1D HEC-RAS Modeling

Geometric Data

For the hydraulic modeling of HEC-RAS to configure the physical characteristics of the flood plain into the model, a large amount of geometric data is required. It is strongly advised that suitable geometric and topographic data be used in order to accurately modify the actual coverage area of the flood plain (Namara et al., 2022a). A high-resolution digital elevation model (DEM) is necessary for accurate mapping of flood inundation. A 12.5 m × 12.5 m high-resolution digital elevation model will be obtained from the Alaska Satellite Facility.

(<https://vertex.dac.asf.alska.edu>) to accomplish this goal. Using highly accurate digital elevation modeling (DEM) is beneficial when creating accurate flooding maps. Therefore, the geometric features and cross-sections that will be fed into the 1D and 2D models utilizing the DEM dataset created using Ras mapper.

Flow and boundary conditions

The boundary condition flow data for both the 1D and 2D models will be provided by the Ethiopian Ministry of Water and Energy (MoWE). The 1D model utilizes estimated flood quantiles, while for both models, the downstream boundary condition is defined using the normal depth, calculated based on the average channel slope at the downstream location.

Running Steady flow

Once all geometric data have been entered, the required steady flow data are entered for the HEC-RAS simulation. A 1D steady state is selected for modeling based on the required model outputs, the level of detail, and the expected accuracy of the results. 1D steady flow models are the easiest to use and understand the results of. The flow regime to be selected, the number of profiles to be calculated, and the boundary conditions must be entered. The chosen flow regime is sub-critical, with slower velocity and relatively deep depths. Normal depth is chosen as the downstream boundary condition and QT is chosen as the upstream boundary condition out of the four boundary

conditions of the 1D steady-state flow. A normal depth boundary condition must be included in an energy slope. Based on that value, HEC-RAS will compute depth using Manning's equation.

3.5.1 Flood Inundation Mapping

Using a hydraulic model and all available primary and secondary data, flood inundation maps are then created following the determination of the design floods (Baky et al., 2019). This study employed a modeling software program called HEC-RAS 6.5 for inundation modeling.

The flood inundation mapping process using HEC-RAS involves several key stages. Initially, the **pre-processing** phase entails the preparation of essential input data, including high-resolution digital elevation models (DEMs), river geometry such as cross-sections and flow paths, hydraulic structures, and hydrological boundary conditions like flow hydrographs. This spatial and hydraulic data are often extracted and organized using GIS tools, such as HEC-GeoRAS, before being imported into HEC-RAS for modeling setup (Brunner, 2021). During the **processing** phase, HEC-RAS simulates hydraulic behavior by solving the Saint-Venant equations in either one-dimensional or two-dimensional frameworks, depending on the model complexity. Steady or unsteady flow simulations generate outputs including water surface elevations, flow depths, and velocities across the river channel and floodplain.

Following the simulation, the **post-processing** phase involves evaluating and validating these hydraulic outputs against observed data such as gauge records or satellite-derived flood extents to ensure model accuracy and reliability. Finally, the **RAS Mapper** tool within HEC-RAS is used to visualize and analyze the simulation results spatially. It converts hydraulic outputs into flood inundation maps, displaying flood extent, depth, and velocity over the study area, and facilitates the overlay of these results with land use and other geographic information for comprehensive flood risk assessment and management (Maidment, 2002; Brunner, 2021).

This section describes how to map flood inundation using a RAS mapper and HEC-RAS for the output of flood extent, depth, and velocity on the river channel and its floodplain with return times of 5, 10, 20, 50, 100, 200, and 500 years. The inundation mapping process consists of three steps: post-RAS processing, HEC-RAS processing, and RAS mapper processing.

3.6 Model Calibration and Validation hydrodynamic model

3.6.1 Calibration

Estimating channel roughness is crucial in the study of open-channel flow, particularly for hydraulic modeling. Various factors influence this parameter, including surface texture, vegetation, channel irregularities, and alignment. Channel roughness significantly impacts flood forecasting and inundation mapping, as it affects flow discharge, water level, and other hydraulic characteristics. Several studies (e.g., Farooq et al., 2019a; Namara et al., 2022a; Timbadiya et al., 2011; Trambadia et al., 2023) have focused on calibrating roughness values for different rivers to support hydraulic model development. In this study, the Manning's roughness coefficient for the river channel will be adjusted within the respective land cover grid to calibrate the HEC-RAS model.

3.6.2 Validation

Studies by Farooq et al. (2019a) and Tamiru & Dinka (2021) have validated the reliability of simulation results by comparing them with actual water bodies identified through satellite imagery using the Normalized Difference Water Index (NDWI). In this research, the NDWI-derived water extent will be compared to the flood inundation map generated by the HEC-RAS model. NDWI detects water bodies primarily using the green (Band 2) and near-infrared (Band 4) bands from remote sensing data, with short-wave infrared (SWI) and near-infrared (NIR) as key inputs. The comparison between the LANDSAT 8 satellite imagery, sourced from <https://earthexplorer.usgs.gov/>, and the HEC-RAS flood map will be based on the spatial overlap of the NDWI-identified water areas.

$$NDWI = \frac{NIR - SWI}{NIR + SWI}$$

The percentage of the overlapped region between the water body defined in the NDWI and HEC-RAS software was determined using the intersect tool in the Analysis toolbox of ArcGIS. After using a conversion tool to transform the raster formats of the two results (NDWI and HEC-RAS) into vectors (Polygons), the pertinent shape areas were found using ArcGIS's geometry computation techniques. The percentage of overlapped regions was calculated after both polygons were remapped to the same geographic coordinate system (Adindan UTM Zone 37 N) (Tamiru & Dinka, 2021).

Overlapping percentage (%) = $\frac{\text{Layer 1 (Km}^2\text{)}}{\text{Layer 2 (Km}^2\text{)}}$ Layer 1 is the area of the water body delineated in NDWI from flood events and Layer 2 is the area of the inundation map generated in HEC-RAS.

3.7 Flood Hazard Assessment

Flood hazard assessment was conducted to delineate and categorize areas along the Lower Awash River Basin based on their susceptibility to inundation, using outputs from a one-dimensional (1D) hydrodynamic model. The analysis relied on hydraulic parameters—specifically water depth and flow velocity—derived from HEC-RAS 1D simulations under varying flood frequency scenarios. The procedure involved flood frequency analysis using HEC-SSP, hydrodynamic modeling in HEC-RAS, and hazard classification in a GIS environment, integrating both physical parameters and spatial analysis techniques.

3.7.1 Flood Frequency Analysis Using HEC-SSP

Return periods were determined using statistical analysis of long-term annual peak discharge records from streamflow stations in the study area. The **HEC-Statistical Software Package (HEC-SSP)** was used to perform flood frequency analysis, where multiple distributions—such as Log-Pearson Type III, Gumbel, and Generalized Extreme Value (GEV)—were tested. The **best-fitting distribution** was selected based on statistical goodness-of-fit criteria, including the Kolmogorov-Smirnov and Anderson-Darling tests, as well as visual fit to observed data (USACE, 2019).

Design discharges corresponding to **return periods of 2, 10, 25, 50, 100, and 200 years** were extracted for use in HEC-RAS simulations. These intervals were chosen to represent a wide range of flood scenarios—from frequent, minor events to rare, extreme floods.

3.7.2 Terrain and Spatial Data Processing

Topographic input was provided by a **12.5-meter resolution Digital Elevation Model (DEM)** obtained from the **Alaska Satellite Facility (ASF)**. The DEM was preprocessed in ArcGIS to remove sinks and correct anomalies, ensuring hydrological consistency. This elevation data supported the creation of cross-sections and floodplain delineation in HEC-RAS.

3.7.3 Hydraulic Modeling with HEC-RAS 1D

The **HEC-RAS 1D** model was employed to simulate water surface profiles for each return period. River geometry, cross-sections, and Manning's roughness coefficients were defined based on survey data and land cover analysis. The model was calibrated using observed stage and discharge data, and validation was conducted using independent flood events where available. Simulations were run under steady flow conditions for each design discharge, and resulting water surface elevations were exported for post-processing. The **water depth raster** was generated by subtracting the ground elevation from the simulated water surface profile, while **flow velocity outputs** were extracted from the cross-section-based results within HEC-RAS.

3.7.1 Flood Hazard Classification

Flood hazard levels were classified using a combination of two hydrodynamic parameters—**water depth** and **flow velocity**—which directly influence the degree of risk to life, infrastructure, and the environment (Apel et al., 2009; Penning-Rowsell et al., 2005). This study applied a **threshold-based classification** system, assigning flood hazard into five levels: *Very Low*, *Low*, *Medium*, *High*, and *Extreme*. This method allows for detailed and nuanced mapping of hazard severity, aligned with approaches found in recent flood risk studies (Vojtek & Vojteková, 2016; Farooq et al., 2019). The study uses high-resolution DEM data and sophisticated modeling approaches to provide a thorough assessment of flood dangers in the River Swat. The results highlight the significance of non-structural flood mitigation strategies and offer insightful information for efficient flood hazard control in the research region. Assessing flood threats requires knowing the features of each flood and its probability of happening. Flood extent, depth, and flow velocity are the flood factors considered in the current study, which will employ flood frequency analysis to determine each flood's probability of occurring (Vojtek & Vojteková, 2016).

3.8 Flood Vulnerability Assessment

Flood vulnerability analysis in the journal article employs a structured approach using the Analytic Hierarchy Process (AHP) and Weighted Linear Combination (WLC) within a Geographic Information System (GIS) framework. AHP is utilized to prioritize various criteria affecting flood vulnerability, constructing a hierarchical model where the top level represents the overall goal of

flood risk assessment, followed by specific criteria and sub-criteria. Pairwise comparisons are made using a 9-point scale to determine the relative importance of each criterion, resulting in a comparison matrix that helps compute local priorities or weights for each criterion. Key factors for physical vulnerability include elevation, land use and land cover, distance to active channels, and geological characteristics, with significant weight assigned to lower elevations and cultivated land (Dandapat & Panda, 2017).

The analysis also incorporates social vulnerability by considering demographic factors such as population density, age distribution, gender, and socioeconomic status, establishing a hierarchy to weigh these factors based on their contribution to overall vulnerability. Additionally, coping capacity is assessed through indicators like literacy rates, availability of shelters and hospitals, and community flood awareness. The resulting Composite Vulnerability Index (CVI) is derived by combining the Physical Vulnerability Index, Social Vulnerability Index, and Coping Capacity Index using WLC. Data collection for this analysis comes from various datasets, including elevation maps, land use classifications, and population statistics. Overall, this robust methodology effectively integrates both physical and social factors, providing a comprehensive view of flood vulnerability in Paschim Medinipur district, while also enhancing spatial analysis capabilities through GIS (Dandapat & Panda, 2017).

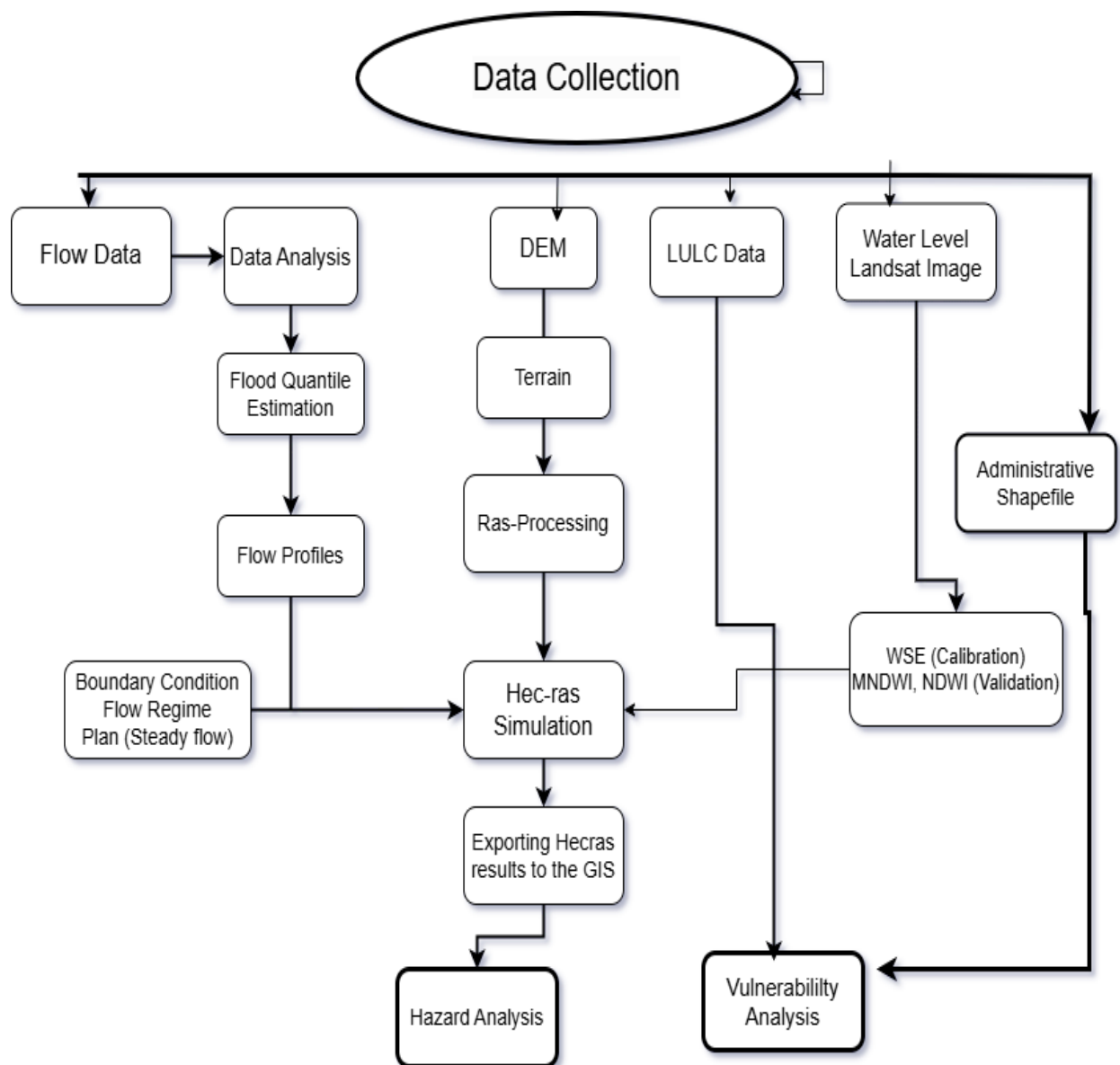


Figure 3. 5 Data process algorithm and 1D model in HEC-RAS

4. RESULTS AND DISCUSSIONS

4.1 Hydrological Data Analysis

4.1.1 Data Homogeneity Analysis

For this study, a statistical software package called RAINBOW was employed to generate the residual mass curve and compute the homogeneity statistics, which uses Buishand's homogeneity test. RAINBOW offers a homogeneity test based on the cumulative deviations from the mean. By evaluating the maximum (Q) and the range (R) of the cumulative deviations from the mean, the homogeneity of the data of a time series is tested.

4.1.2 Outlier Detection and Treatment

The Grubbs and Beck (1972) test was used to detect outliers. From [Table 4.1](#), listed stations, there are no outliers found. The data was automatically taken for the next analysis.

Table 4. 1 Outlier detection and treatment

Stations	Record year	KN	Higher Q	Lower Q	Outlier	Remark
@Koysha Dam Site	1964-2014	2.824197684	3525.218	34.243	-	Accepted
@OmoRate area	2010-2020	2.059154085	3228.259	8.348	-	Accepted
@Jinka	1982-2006	2.519466569	55.472	0.005	-	Accepted

4.2 Goodness of Fit Test and Quantile Analysis.

4.2.1 Goodness of Fit Analysis

The goodness of fit was assessed using the L-moment ratio diagram and the Kolmogorov-Smirnov (KS statistics test. The mathematical foundation of the L-moment ratio diagrams is explained below. Hosking (1990) first proposed the idea of L-moments, or linear combinations of probability-weighted moments (PWM). The best-fit PDF for the station's sample data was found using the nearest closed margin of the dispersion from the distributions (Haddad, 2021).

According to a study by (Drissia et al., 2019), LMRD offers a visual method for comparing different probability distributions and helps choose candidate distributions because it concentrates on higher-order moments like skewness and kurtosis. However, it needs a finite mean but not

higher moments, is less sensitive to changes in the data, and cannot be as responsive as other approaches.

The Kolmogorov-Smirnov (KS) test measures the greatest vertical distance between empirical and hypothesized CDFs and is a popular and reliable statistical technique for comparing actual data to theoretical distributions. For a thorough statistical evaluation, the fitted distribution for every stream flow station was fixed using the KS test for this study. The HEC-SSP software program for the L-moments (LM) distribution fitting approach was used to evaluate the KS statistics.

Out of all the distributions shown, the one with the lowest KS statistic indicates the best fit. For goodness of fit and quantile estimation, we used HEC-SSP statistical software. The following figures are Cumulative Distribution Function (CDF), Probability Density Function (PDF), and Quantile-Quantile (QQ) Plots, respectively, for OmoRate stations generated from HEC-SSP statistical software. The same procedure was used for the rest of the stations.

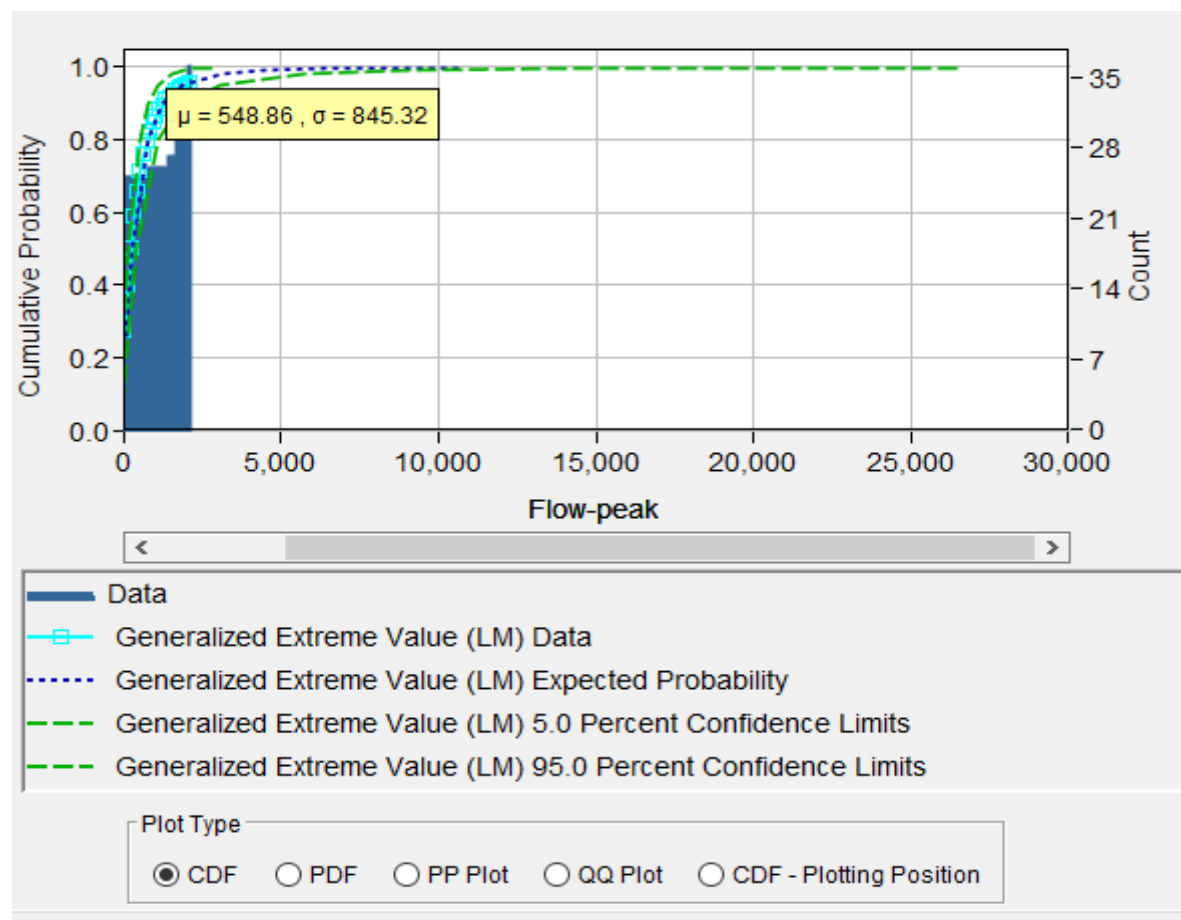


Figure 4. 1 Cumulative Distribution Function (CDF) for Omorate Station

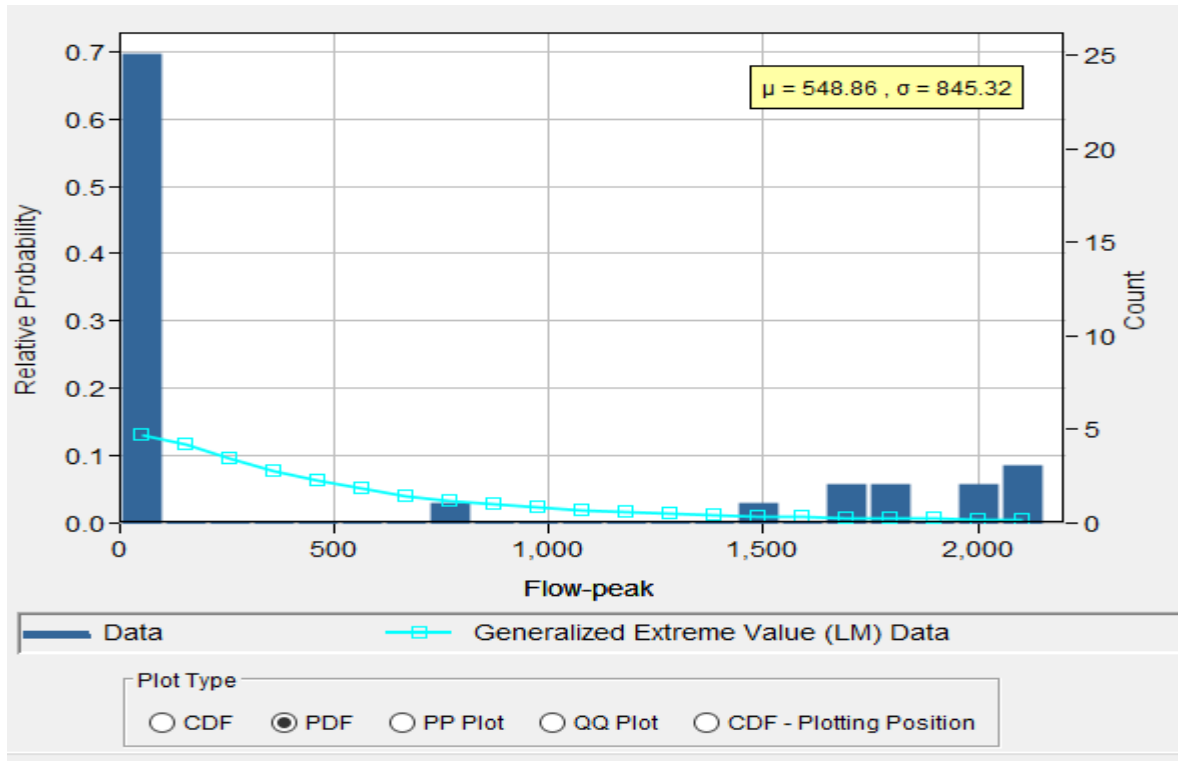


Figure 4. 2 Probability Density Function (PDF) for Omorate Station

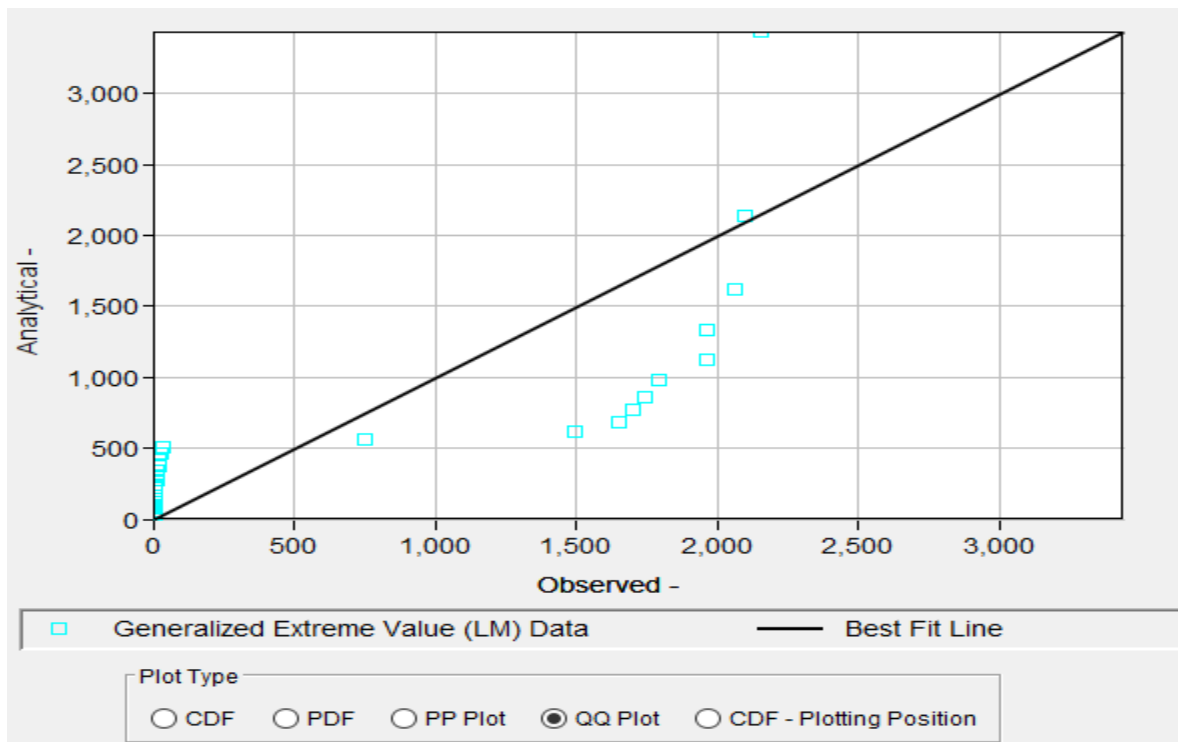


Figure 4. 3 Quantile-Quantile (QQ) Plots for Omorate Station

Table 4. 2 HEC-SSP statistical software generated output KS test

SITE	Kolmogorov-Smirnov (ks test)	Best fitted distribution
Koysha Dam site	0.148	Gumbel (LM)
OmoRate	0.442	Generalized Extreme Value (LM)
Jinka	0.131	Gumbel (LM)

4.2.1 Flood Quantiles Estimation

After analyzing the goodness of the fitted distribution, the flood quantiles were estimated as stated below in [Table 4.3](#).

Table 4. 3 Flood quantiles for different return periods for the hydrological stations

Koysha Dam site			OmoRate station			Jinka Station		
Return Period	% Exceedance	QT	Return Period	% Exceedance	QT	Return Period	% Exceedance	QT
2	50	2738	2	50	258.4	2	50	14.6
5	20	3903	5	20	776.6	5	20	23.1
10	10	4689	10	10	1263	10	10	29.1
20	5	5418	20	5	1896.9	20	5	34.8
50	2	6379	50	2	3106.5	50	2	42.3
100	1	7107	100	1	4472.4	100	1	48
200	0.5	7835	200	0.5	6458.7	200	0.5	53.6
500	0.2	8767	500	0.2	10636.1	500	0.2	61

4.3 HEC-RAS Model Simulation and Computation

4.3.1 Geometric data

Within the HEC-RAS model, river geometry parameters such as the stream centerline, bank lines, flow path lines, and cross-section (XS) cut lines were extracted from the TIN or topographic terrain model using the RAS Geometry menu in RAS Mapper. The river features were digitized following the flow direction from upstream to downstream along the centerline,

while the cross-section cut lines were drawn perpendicular to the centerline at selected intervals along the river. Accurately delineating these cross-sections within the model is a time-consuming and labor-intensive task requiring careful attention to detail.

It is strongly advised to consider the appropriate value of Manning's roughness coefficient n , since it plays a significant role in accurately measuring the water surface height. One of the best criteria for evaluating value is the description of the river channel. This includes natural channels, lined channels, and excavated channels (Namara et al., 2022b). As a result, Manning's roughness coefficient for the left channel, river bottom channel, and right channel was given 0.06, 0.03, and 0.04, respectively.

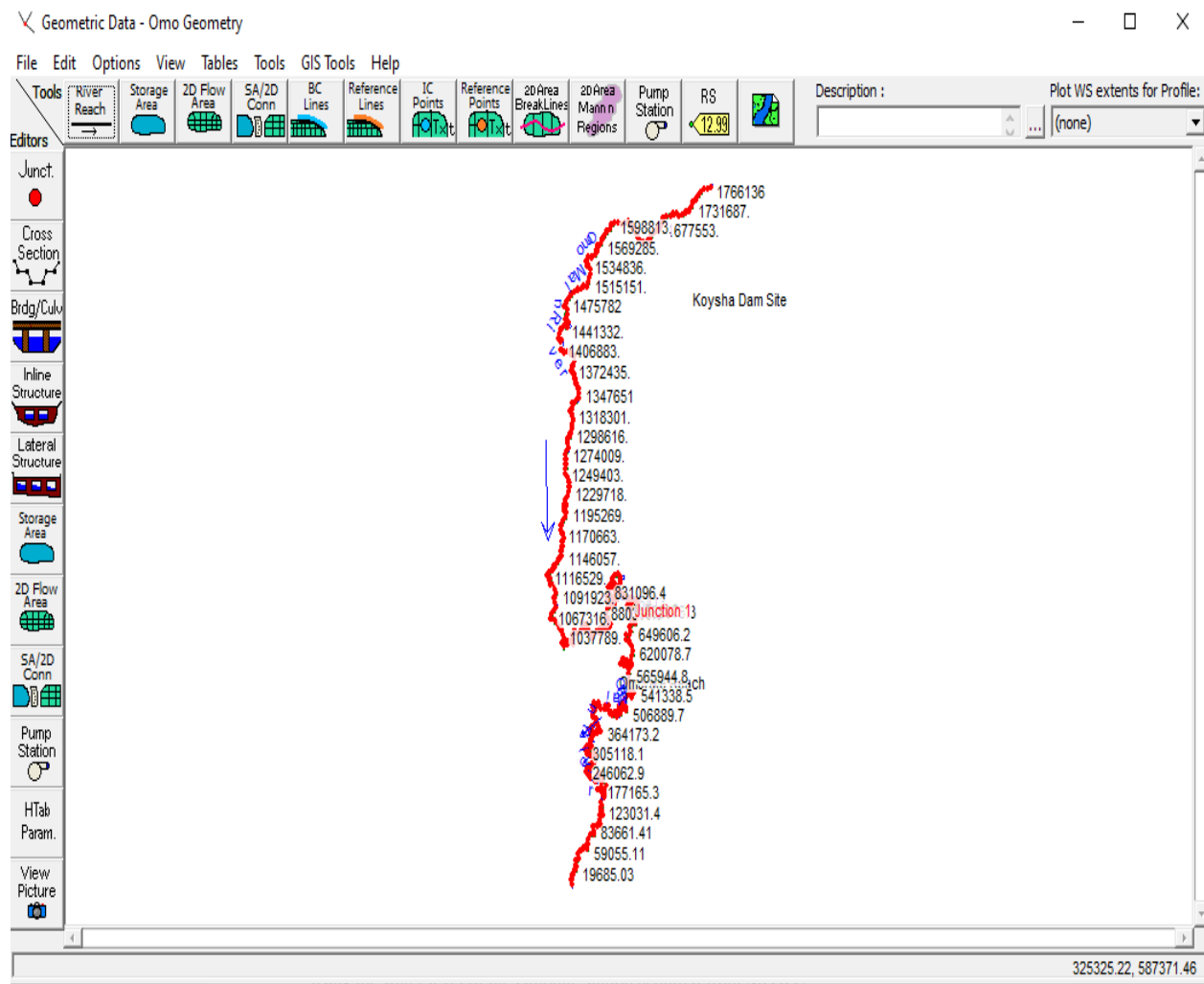


Figure 4. 4 Geometric data for Lower Omo River generated from HEC-RAS

Edit Manning's n or k Values

River: (All Rivers) ☐ Edit Interpolated XS's

Reach: All Regions

Channel n Values have a light green background

Selected Area Edit Options

	River	Reach	River Station	Frctn (n/K)	n #1	n #2	n #3
1	Nerie Nr Jinka	Reach 2	5413	n	0.06	0.03	0.04
2	Nerie Nr Jinka	Reach 2	4713	n	0.06	0.03	0.04
3	Nerie Nr Jinka	Reach 2	4429.133	n	0.06	0.03	0.04
4	Nerie Nr Jinka	Reach 2	3937.007	n	0.06	0.03	0.04
5	Nerie Nr Jinka	Reach 2	3444.881	n	0.06	0.03	0.04
6	Nerie Nr Jinka	Reach 2	2952.755	n	0.06	0.03	0.04
7	Nerie Nr Jinka	Reach 2	2460.629	n	0.06	0.03	0.04
8	Nerie Nr Jinka	Reach 2	2164	n	0.06	0.03	0.04
9	Nerie Nr Jinka	Reach 2	492.1259	n	0.06	0.03	0.04
10	Omo Main River	Koysha Dam Site	1766136	n	0.06	0.03	0.04
11	Omo Main River	Koysha Dam Site	1761214.	n	0.06	0.03	0.04
12	Omo Main River	Koysha Dam Site	1756293.	n	0.06	0.03	0.04
13	Omo Main River	Koysha Dam Site	1751372.	n	0.06	0.03	0.04
14	Omo Main River	Koysha Dam Site	1746450.	n	0.06	0.03	0.04
15	Omo Main River	Koysha Dam Site	1741529.	n	0.06	0.03	0.04
16	Omo Main River	Koysha Dam Site	1736608.	n	0.06	0.03	0.04
17	Omo Main River	Koysha Dam Site	1731687.	n	0.06	0.03	0.04
18	Omo Main River	Koysha Dam Site	1726765.	n	0.06	0.03	0.04
19	Omo Main River	Koysha Dam Site	1721844.	n	0.06	0.03	0.04
20	Omo Main River	Koysha Dam Site	1716923.	n	0.06	0.03	0.04
21	Omo Main River	Koysha Dam Site	1712002.	n	0.06	0.03	0.04
22	Omo Main River	Koysha Dam Site	1707080.	n	0.06	0.03	0.04
23	Omo Main River	Koysha Dam Site	1702159.	n	0.06	0.03	0.04
24	Omo Main River	Koysha Dam Site	1697238.	n	0.06	0.03	0.04

OK Cancel Help

Figure 4. 5 Manning's Roughness Coefficient Settings for the River

4.3.2 Flow Data

For this investigation, a 1-D steady-state flow condition was used. The maximum flood quantile for return periods 2, 5, 10, 20, 50, 100, and 200 had already been established. Following the successful simulation of the HEC-RAS 1D constant flow model, the model was calibrated using water level data from the Omorate station.

Steady Flow Data - Steady flow

File Options Help

Description :

Enter/Edit Number of Profiles (32000 max): Reach Boundary Conditions ...

Locations of Flow Data Changes

River: Add Multiple...

Reach: River Sta.: Add A Flow Change Location

Flow Change Location			Profile Names and Flow Rates							
	River	Reach	RS	2 Yr	5 Yr	10 Yr	20 Yr	50 Yr	100	200 Yr
1	Nerie Nr Jinka	Reach 2	5413	14.6	23.1	29.1	34.8	42.3	48	53.6
2	Omo Main River	Koysha Dam Site	1766136	2738	3903	4689	5418	6379	7107	7835
3	Omo Main River	Omorate Reach	693898	258.4	776.6	1263	1896.9	3106.5	4472.4	6458.7

Edit Steady flow data for the profiles (m3/s)

Figure 4. 6 Quantile flow profiles input for simulation purposes of the model

4.4 Calibration and Validation of HEC-RAS Model

After the successful simulation of the HEC-RAS 1D steady flow model, the model was calibrated using the water level of the Omorate station acquired from MOWE.

4.4.1 Calibration

Quantile Water Level for Omorate Station

Following Chow's (1959) recommendation, the water surface elevation at the Mille and Logia stations was calibrated by adjusting the river channel Manning's roughness coefficient (n) to vary between 0.03 and 0.043. R^2 , PBIAS, and NSE were utilized to assess the impact. The n values for Omorate Station varied as 0.03, 0.035, 0.040, and 0.043, as indicated in Appendices B, C1, and C2. Channel roughness is an important factor to take into account when developing a hydraulic model for mapping flood inundation and flood forecasting. The discharge, river stage, and other hydraulic characteristics are all impacted by the characteristics of the channel roughness, and these factors are interrelated. Estimating the channel roughness parameter is essential while researching open-channel flow, particularly in hydraulic modeling. Channel roughness is influenced by numerous factors, such as vegetation, surface roughness, anomalies in the channel, and channel alignment. Several studies have constructed the hydraulic model by varying the roughness of the channels in various rivers (Farooq et al., 2019; Namara et al., 2022; Tamiru & Dinka, 2021).

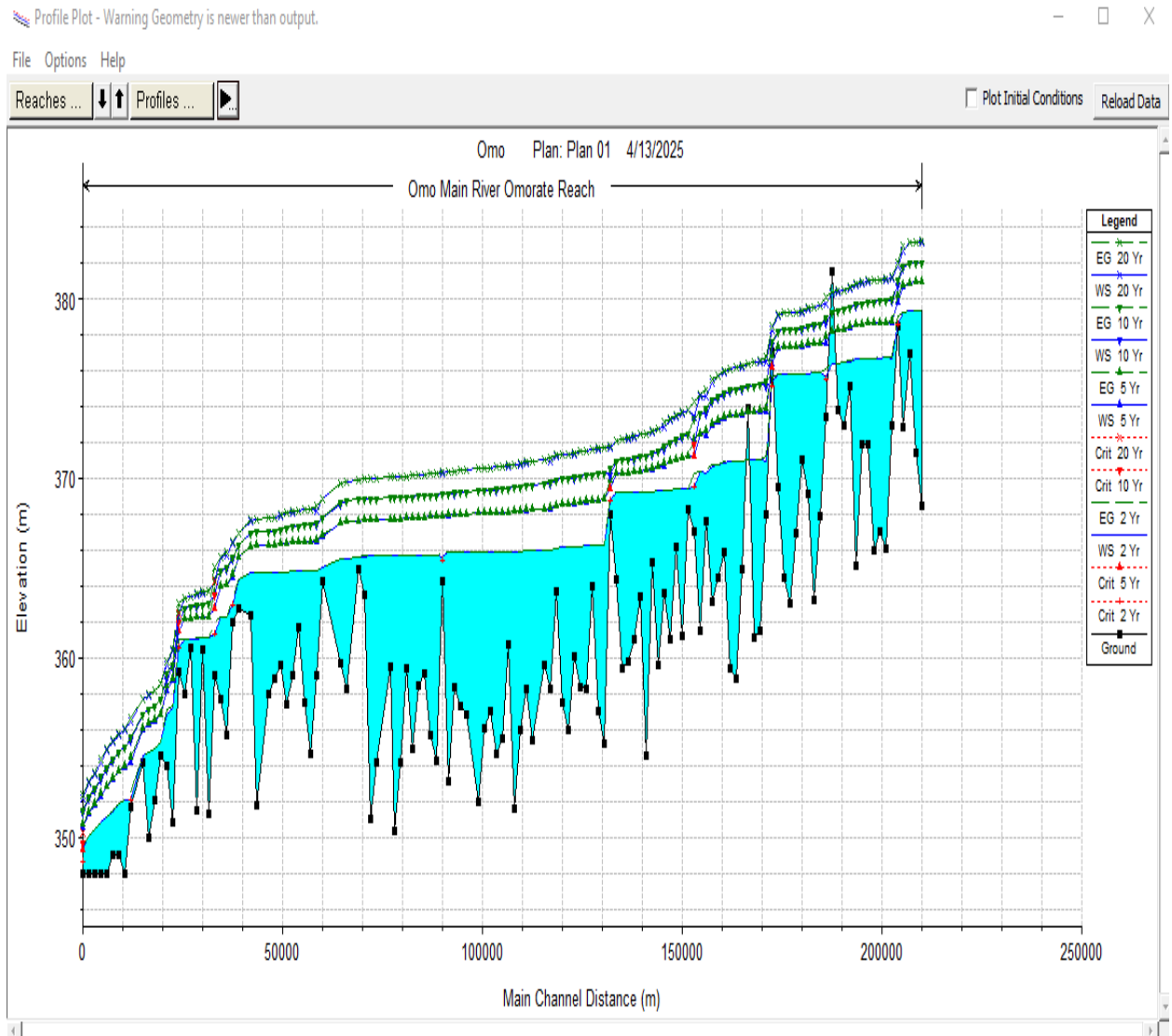


Figure 4. 7 Water Surface Profiles for All Return periods for Omorate station generated from model return periods of 2-20 years

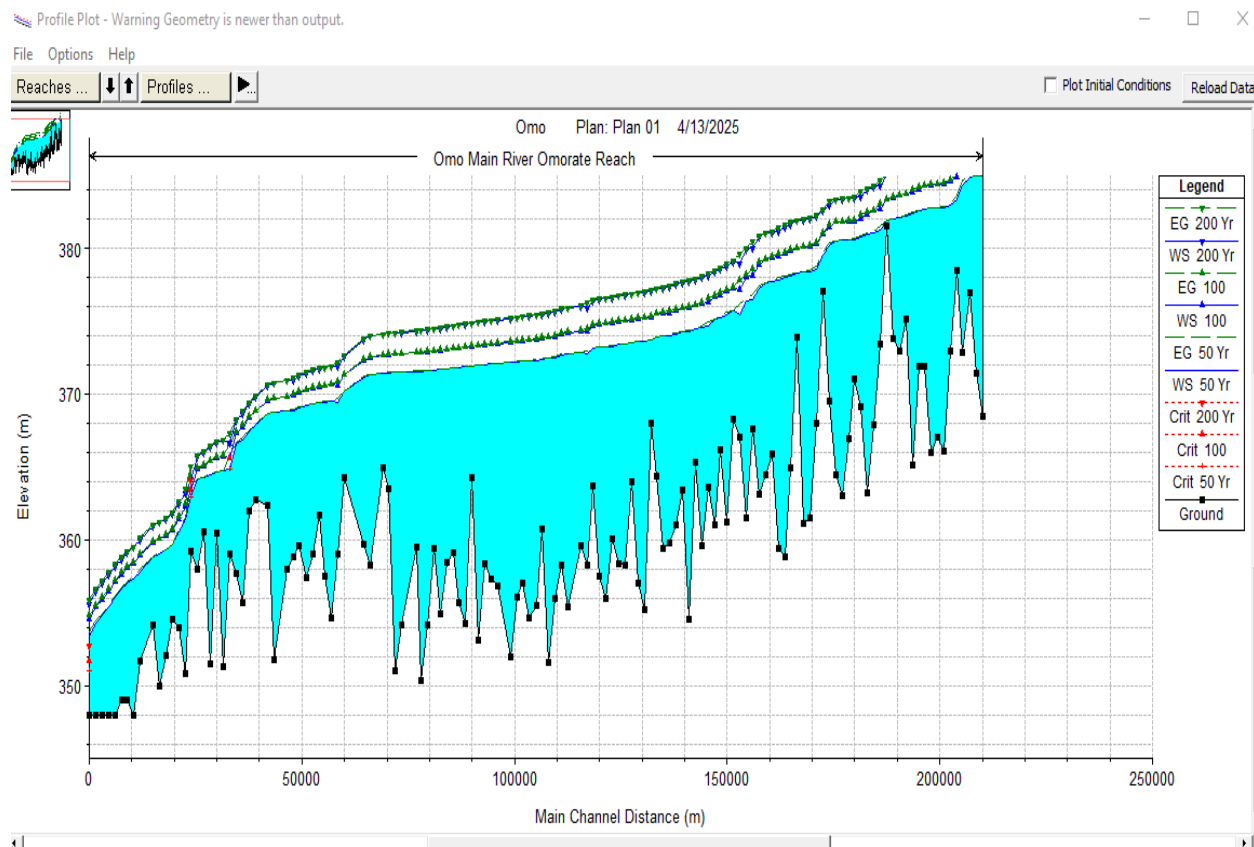


Figure 4. 8 Water Surface Profiles for All Return periods for Omorate station generated from model return periods of 50-200 years

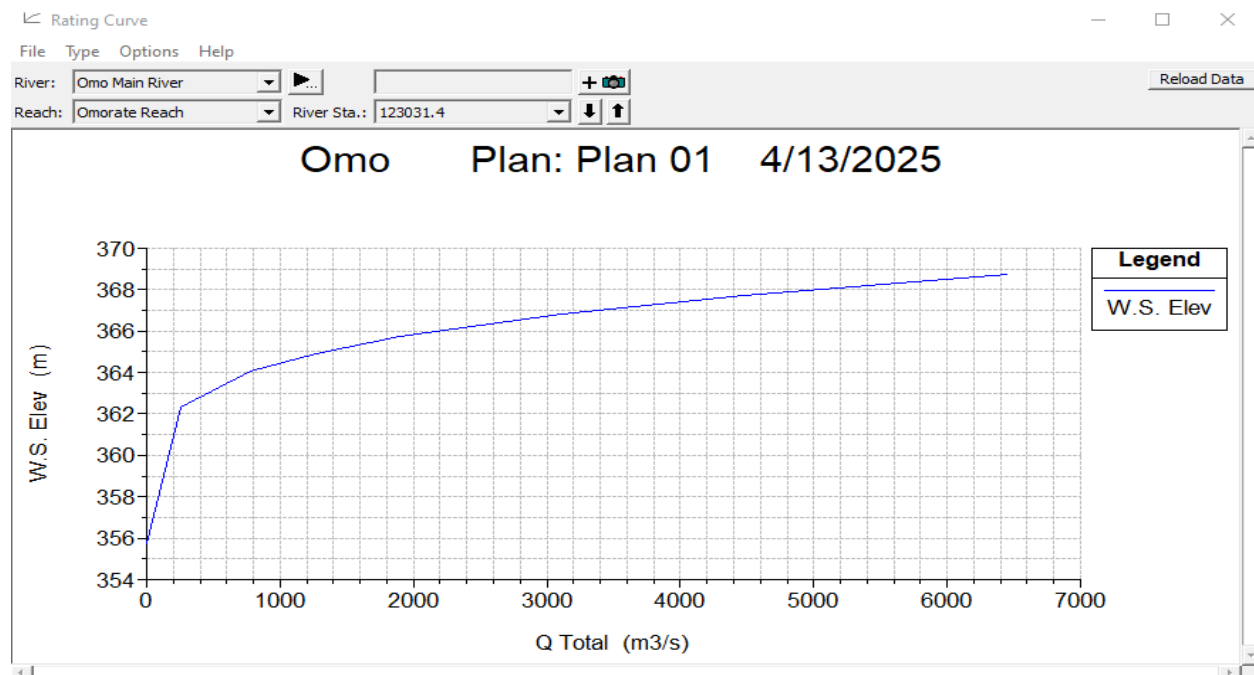


Figure 4. 9 Stage discharge (Rating) Curve for the Omorate station 123031.4

The water surface elevation generated from the HEC-RAS model was calibrated using observed water level data obtained from the Ethiopian Ministry of Water and Energy. To evaluate the model's performance, statistical indicators such as the Nash-Sutcliffe Efficiency (NSE), Percent Bias (PBIAS), and the Coefficient of Determination (R^2) were assessed. This was done by varying the bed channel Manning's roughness coefficient (n) with values of 0.030, 0.035, 0.040, and 0.043. Among these, the best performance was achieved with a roughness coefficient of $n = 0.030$, which yielded the highest agreement between simulated and observed water levels. Consequently, the final model simulation was conducted using the calibrated Manning's roughness coefficient of 0.030 for the bed channel as shown in [Tables 4.4, 4.5](#), and the [Appendices B, C, and D](#).

Table 4. 4: Calibration result of Omorate River Water Surface Elevation (Water level)

Calibrated Water level Results for Omorate River station 123031.4			
Manning's N	R^2	NSE	PBIAS (%)
0.03	0.8652	0.829427	-3.790560472
0.035	0.8642	0.815272	-4.424778761
0.04	0.8622	0.796942	-5.088495575
0.043	0.8621	0.787886	-5.442477876

Table 4. 5: Performance criteria for model calibration and validation (Tamiru & Dinka, 2021)

<u>Goodness of fit</u>	<u>NSE</u>	<u>PBIAS</u>	<u>R2</u>
Very good	$0.65 < NSE \leq 1.00$	$PBIAS < \pm 15$	$0.65 < R2 \leq 1.00$
Good	$0.55 < NSE \leq 0.65$	$\pm 15 \leq PBIAS < \pm 20$	$0.55 < R2 \leq 0.65$
Satisfactory	$0.40 < NSE \leq 0.55$	$\pm 20 \leq PBIAS < \pm 30$	$0.40 < R2 \leq 0.55$
Unsatisfactory	$NSE \leq 0.40$	$PBIAS \geq \pm 30$	$R2 \leq 0.40$

The ground-based observed data were used to calibrate the water level simulation in HEC-RAS for the flood quantiles at the Omorate station. The final NSE, PBIAS, and R^2 results for the model's performance were 0.829427 (Very Good), -3.790560472 (Very Good), and 0.8652 (Very Good) for the roughness coefficient of $N 0.03$ for the bed of the river canal.

4.4.2 Model Validation

The accuracy of these simulations has been validated in previous studies (Farooq et al., 2019b; Tamiru & Dinka, 2021) by comparing them with actual water bodies derived from satellite imagery using the Normalized Difference Water Index (NDWI). In this study, the flood inundation map generated by HEC-RAS will be evaluated against the water extent identified through NDWI. NDWI utilizes the green band (Band 2) and near-infrared band (Band 4) from remote sensing imagery to detect water bodies, with short-wave infrared (SWI) and near-infrared (NIR) serving as key inputs in the extraction process.

For the August 20, 2016, historical flood occurrence in Omorate River Station, the performance of the HEC-RAS inundation map and the LANDSAT image 9 remotely sensed imagery obtained from <https://earthexplorer.usgs.gov/> in NDWI and MNDWI was assessed based on overlapping areas.

$$\text{NDWI} = (\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$$

$$\text{MNDWI} = (\text{Green} - \text{SWIR}_1) / (\text{Green} + \text{SWIR}_1)$$

band 3(Green), band 5 (NIR), band 6 (SWIR).

The percentage of overlapped area between the water body defined in the NDWI, MNDWI, and HEC-RAS software was determined using the intersect tool in the Analysis toolbox of ArcGIS (version 10.8). After using a conversion tool to transform the raster formats of the two results (NDWI, MNDWI, and HEC-RAS) into vectors (Polygons), the pertinent shape areas were found using ArcGIS's geometry computation techniques. The percentage of overlapped regions was calculated after both polygons were remapped to the same geographic coordinate system (Adindan UTM Zone 37 N).

Overlapping percentage (%) = $\frac{\text{Layer 1 (Km}^2\text{)}}{\text{Layer 2 (Km}^2\text{)}}$ Layer 1 is the area of the water body delineated in NDWI, MNDWI from flood events, and Layer 2 is the area of the inundation map generated in HEC-RAS.

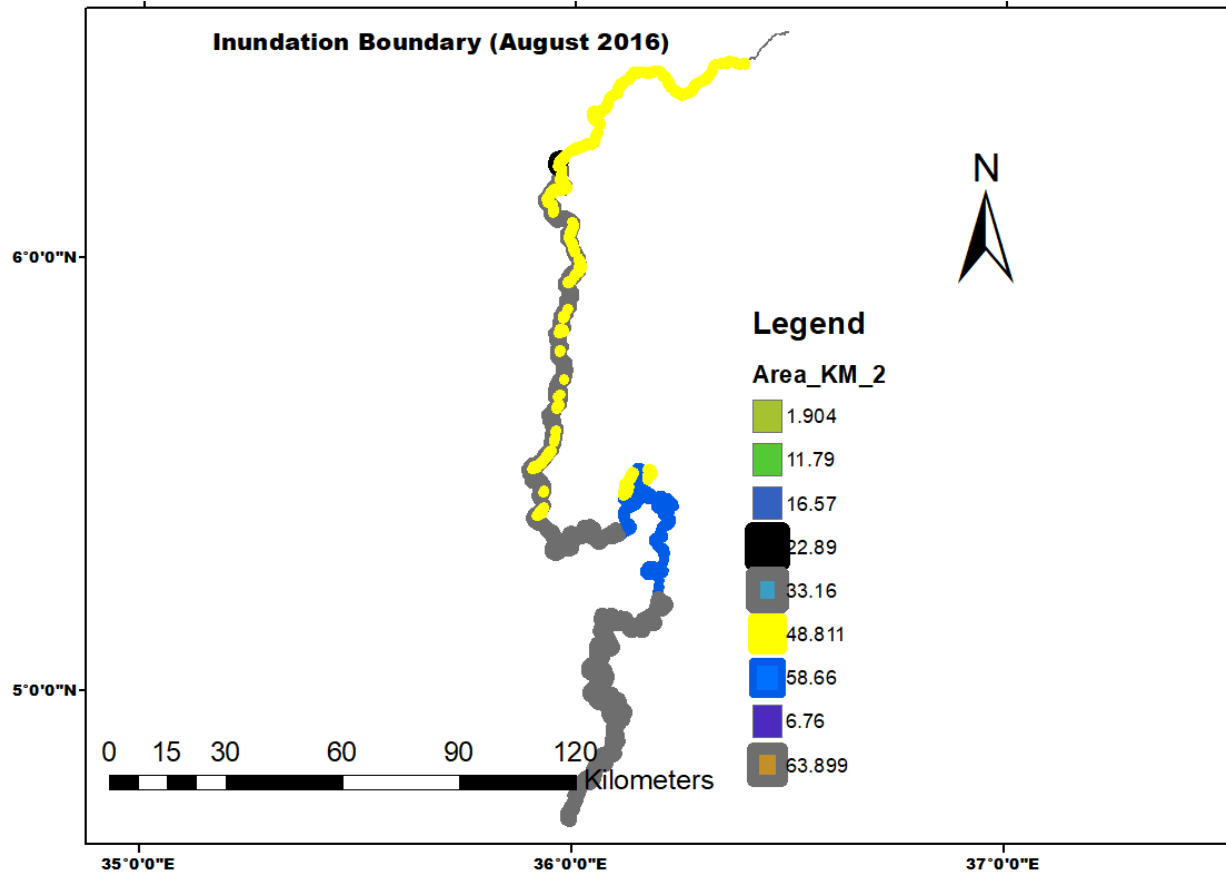


Figure 4. 10: Inundation boundary of the HEC-RAS for the year August 2016

Table 4. 6: NDWI Analysis for Landsat image 9 (August 20, 2016)

NDWI Analysis for Landsat image 9 (August 20, 2016)				
gridcode	Shape_Length	Shape_Area	Area (KM^2)	Band Value
1	371700	6322500	6.3225	-0.678895 - -0.35979
2	873960	14139900	14.1399	-0.35979 - -0.310918
3	1131900	17190000	17.19	-0.310918 - -0.262046
4	1358280	19012500	19.0125	-0.262046 - -0.216049
5	1728540	30828600	30.8286	0.03206 - 0.05706
6	1883700	32647500	32.6475	0.03206 - 0.080932
7	1674600	33414300	33.4143	0.080932 - 0.129804
8	1225440	33669000	33.669	0.129804 - 0.172926
9	1221540	72414000	72.414	0.172926 - 0.216049

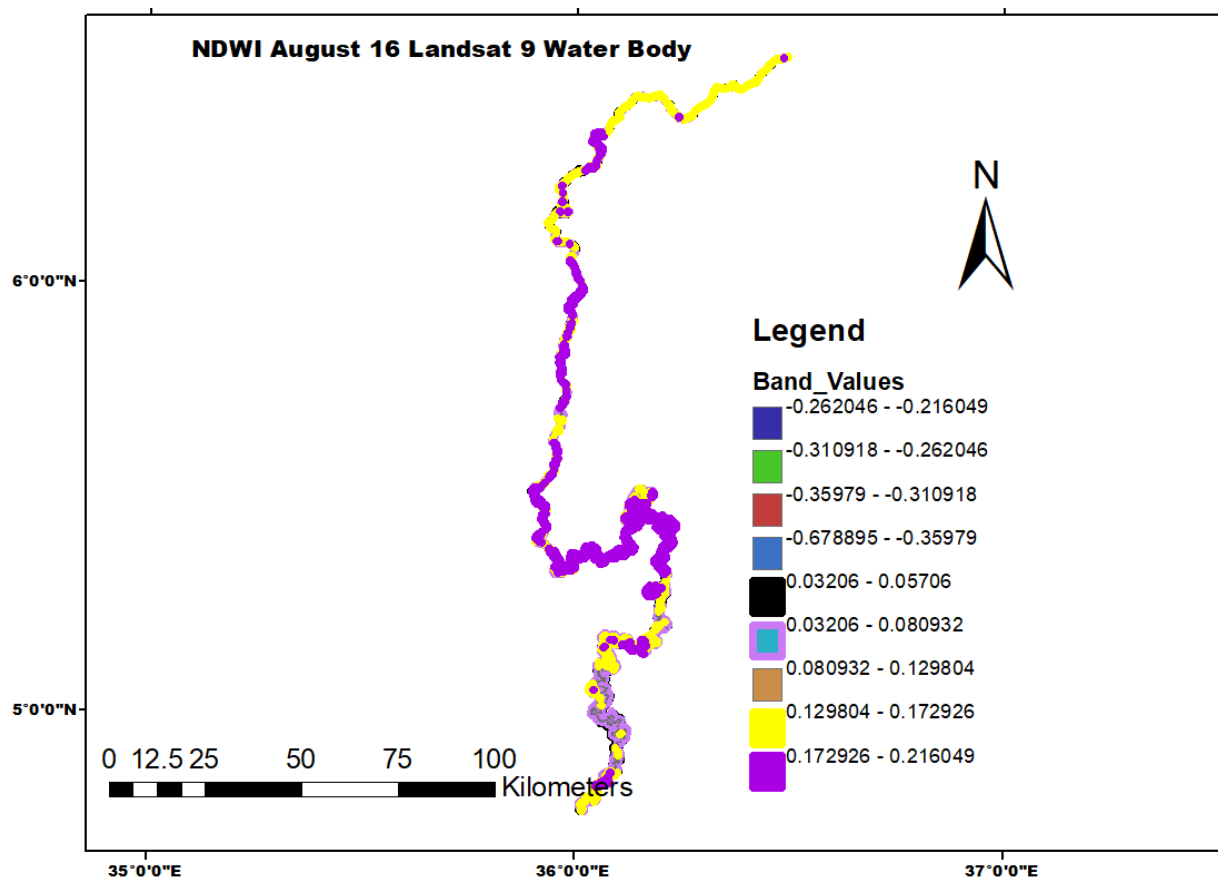


Figure 4. 11 NDWI August 2016 Landsat 9 Water Body

Table 4. 7: MNDWI Analysis for Landsat image 9 (August 20, 2016)

MNDWI Analysis for Landsat image 9 (August 20, 2016)				
gridcode	Shape_Length	Shape_Area	Area (KM^2)	Band Value
1	516180	13084200	13.0842	-0.701546 - -0.207345
2	1641600	35836200	35.8362	-0.207345 - -0.163994
3	2183580	44980200	44.9802	0.005074 - 0.064287
4	1823700	37530900	37.5309	0.064287 - 0.074436
5	1299000	23922900	23.9229	0.074436 - 0.120643
6	1147920	26638200	26.6382	0.120643 - 0.139462
7	1071060	30652200	30.6522	0.139462 - 0.163994
8	693240	23468400	23.4684	0.163994 - 0.200154
9	421200	23525100	23.5251	0.200154 - 0.408238

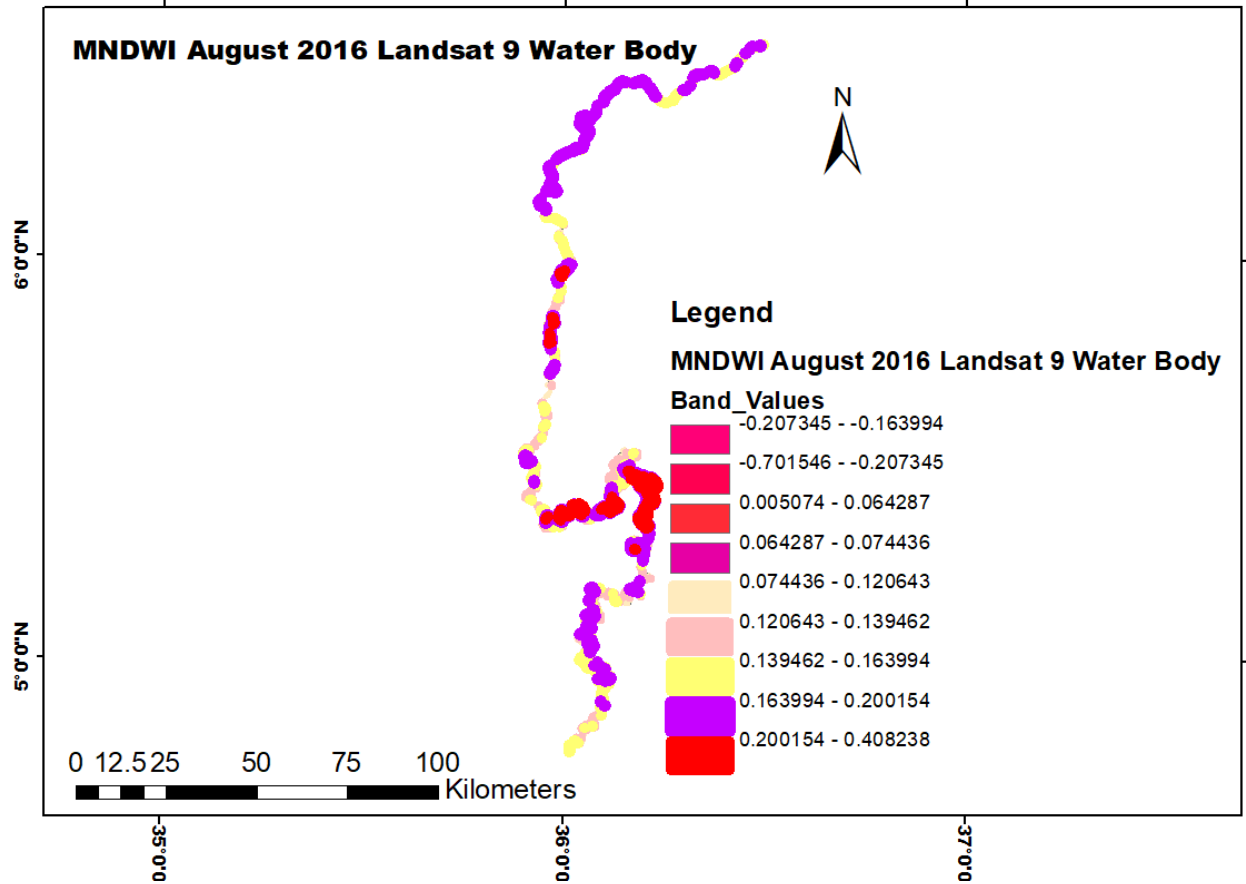


Figure 4. 12: NDWI August 2016 Landsat 9 Water Body

We validated the HEC-RAS model results by comparing the simulated flood extents with water bodies extracted from Landsat 9 satellite imagery using the Normalized Difference Water Index (NDWI) and the Modified Normalized Difference Water Index (MNDWI) for August 2016. These indices are effective in detecting surface water by analyzing the spectral reflectance of specific bands—green and near-infrared (NIR) for NDWI, and green and shortwave infrared (SWIR) for MNDWI. In this validation process, positive index values from both NDWI and MNDWI were classified as water bodies, enabling accurate delineation of inundated areas. Figure 4.4 illustrates the inundated area simulated by the HEC-RAS model, while Figures 4.5 and 4.6 show the spatial distribution of water bodies derived from NDWI and MNDWI, respectively. Furthermore, Tables 4.6 and 4.7 present the analyzed band values along with their respective water body areas, providing quantitative support for the comparison and enhancing the assessment of the model's accuracy.

Table 4. 8 Validation Results

	Layers	Areas (KM^2)	Overlapping Percentage (%)	Goodness of fit
1	Inundation Boundary	264.494196		
2	NDWI	202.9734	76.74021	Not good
3	MDWI	246.5541	93.22	Good Agreement

The study by Tamiru and Dinka (2021) assessed the inundation map based on overlapping areas, determining that an overlap exceeding 85% signifies strong agreement. Consequently, the validation result of the MNDWI aligns with the model results, exhibiting an overlapping percentage of 93.22%, as illustrated in [Table 4.8](#).

4.5 Flood Hazard Assessment

When determining the flood hazard in the model area, the flood intensity for each flood scenario was taken into account. We reasoned that a higher flood intensity in the inundated would result in a higher flood threat. Flood hazard mapping is the process of identifying areas that are likely to flood within a given return time. The degree of flood hazard is influenced by two hydrological parameters: flood velocity and inundation depths. The degree of flood hazard was separated into hazard groups according to inundation depth classes that corresponded to flooded depths (Ongdas et al., 2020; Vojtek & Vojteková, 2016).

Two processes—HEC-RAS and post-RAS processing—were employed to produce flood hazard maps. To ascertain and investigate the extent, depth, and velocity of the inundation during a flow with return periods of 2, 5, 10, 20, 50, 100, and 200 years, a simulation was conducted using the calibrated and validated model. The findings of inundation depth and flow velocity are used to calculate hazard levels in the 1D HEC-RAS model for flood inundation and hazard assessment.

Table 4. 9 Flood Hazard Classification

Hazard Level	Water Depth (m)	Flow Velocity (m/s)	Interpretation
Very Low	< 0.3	< 0.5	Shallow and slow flow; minimal or no damage expected
Low	0.3 – 0.6	0.5 – 1.0	Slightly elevated risk; minor disruption to people and property
Medium	0.6 – 1.0	1.0 – 1.5	Moderate hazard; potential to affect mobility and cause structural damage
High	1.0 – 2.0	1.5 – 2.0	High hazard; dangerous for people, vehicles, and weak structures
Extreme	> 2.0	> 2.0	Very high hazard; life-threatening, major structural damage likely

4.5.1 Flood Inundation Extent Analysis Across Return Periods

The spatial extent of flood inundation was analyzed for seven different flood return periods (2-, 5-, 10-, 20-, 50-, 100-, and 200-year events). The corresponding inundation areas were extracted and are presented in Figure 4.9. The results exhibit a progressive increase in inundation extent with increasing return periods.

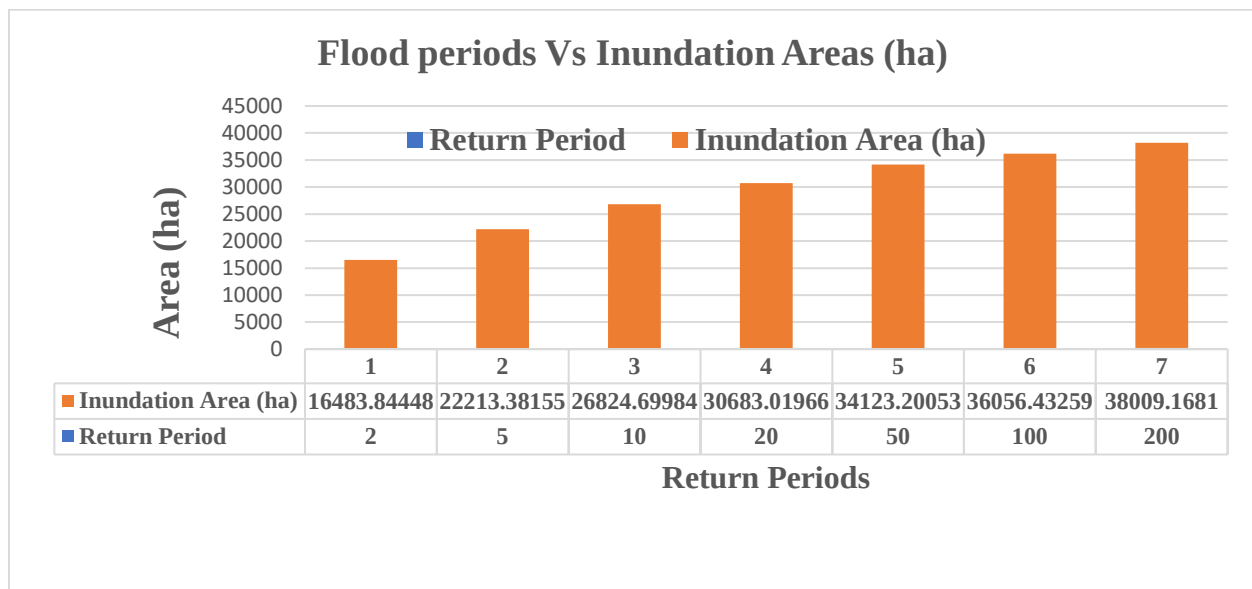


Figure 4. 13 Flood Periods Vs Inundation Areas in Hectare

As illustrated in Figure 4.12, the inundation area increased from approximately **16,483.85 hectares** for the 2-year return period to **38,009.1681 hectares** for the 200-year return period. This consistent upward trend indicates a positive correlation between the magnitude of flood events and the spatial extent of inundation.

The findings reveal that more extreme and less frequent flood events (e.g., 100- and 200-year return periods) inundate significantly larger areas. The rate of increase in inundation area becomes more gradual at higher return periods, suggesting the influence of topographic constraints on flood spread. For instance, the increase in inundated area between the 100- and 200-year events is only around 2,066 ha compared to 7,752 ha between the 2- and 5-year events.

This trend underscores the need for comprehensive flood risk management, particularly in floodplain areas vulnerable to rare but severe flood events. The results also highlight the importance of incorporating long-return-period scenarios into land-use planning and infrastructure development to enhance resilience against extreme hydrological events.

4.5.2 Spatial Distribution of Flood Inundation by Woreda and Return Period

The analysis of flood inundation extent across different return periods reveals a clear spatial and temporal pattern of increasing flood risk within the study area. The inundation area progressively increases with longer return periods, demonstrating the intensified impact of extreme hydrological events on the low-lying regions of the Omo River Basin. The simulated flood extents for return periods of 2, 5, 10, 20, 50, 100, and 200 years were calculated for each woreda, showing varying degrees of vulnerability, as shown in [Table 4.9](#).

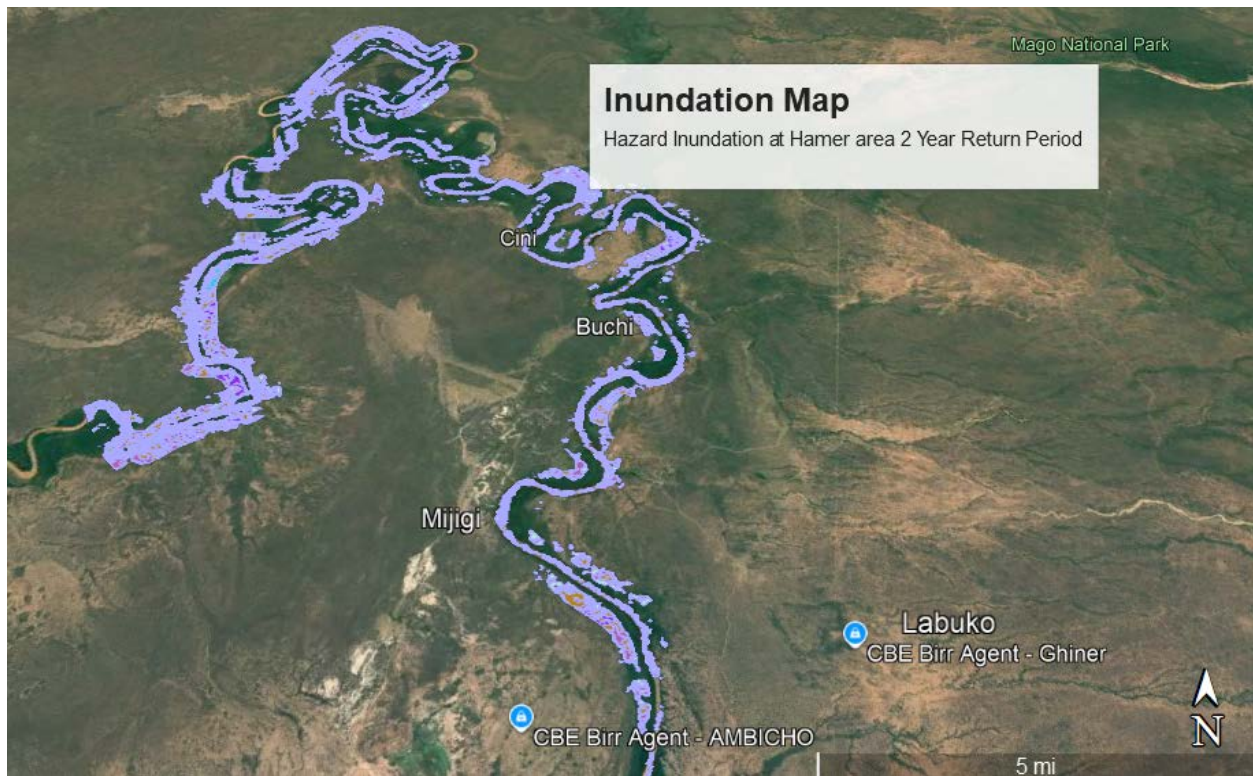


Figure 4. 14 Hazard Inundation at Hamer Area 2 Year Return Period

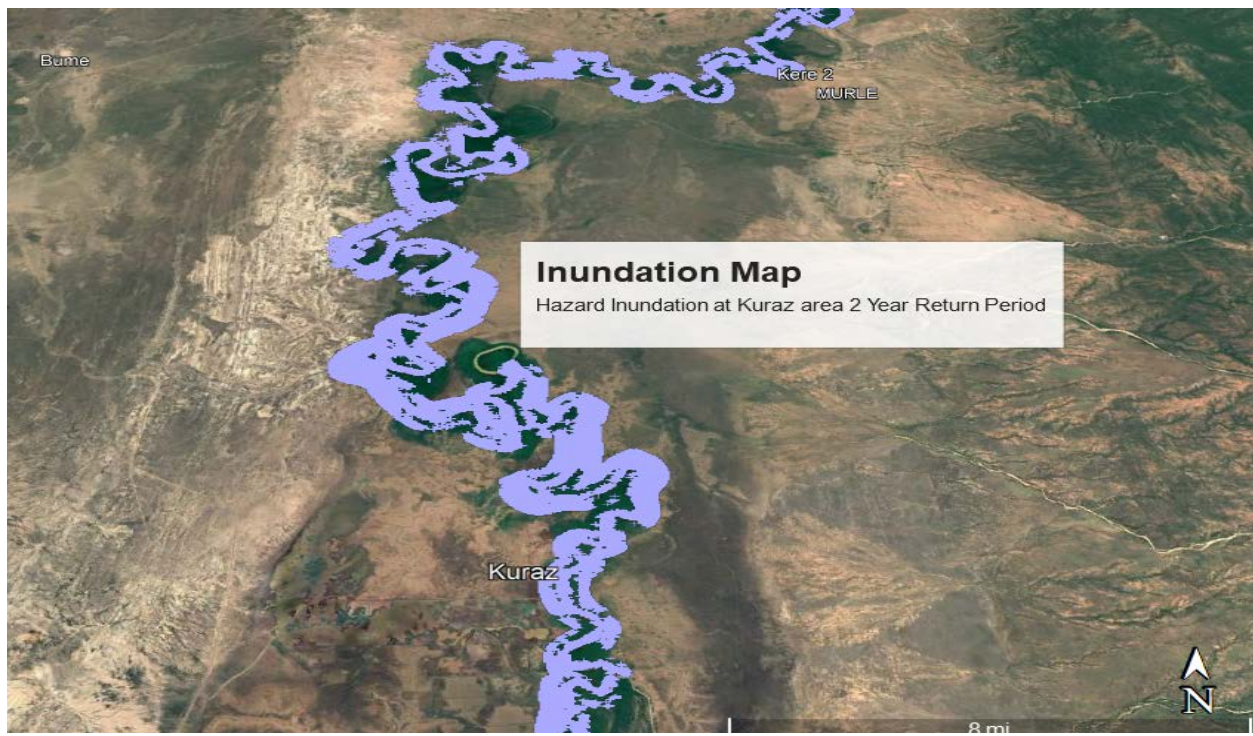


Figure 4. 15 Hazard Inundation at Kuraz Area 2 Year Return Period



Figure 4. 16 Inundation Map Around Hamer Woreda for 5 Year Return Period

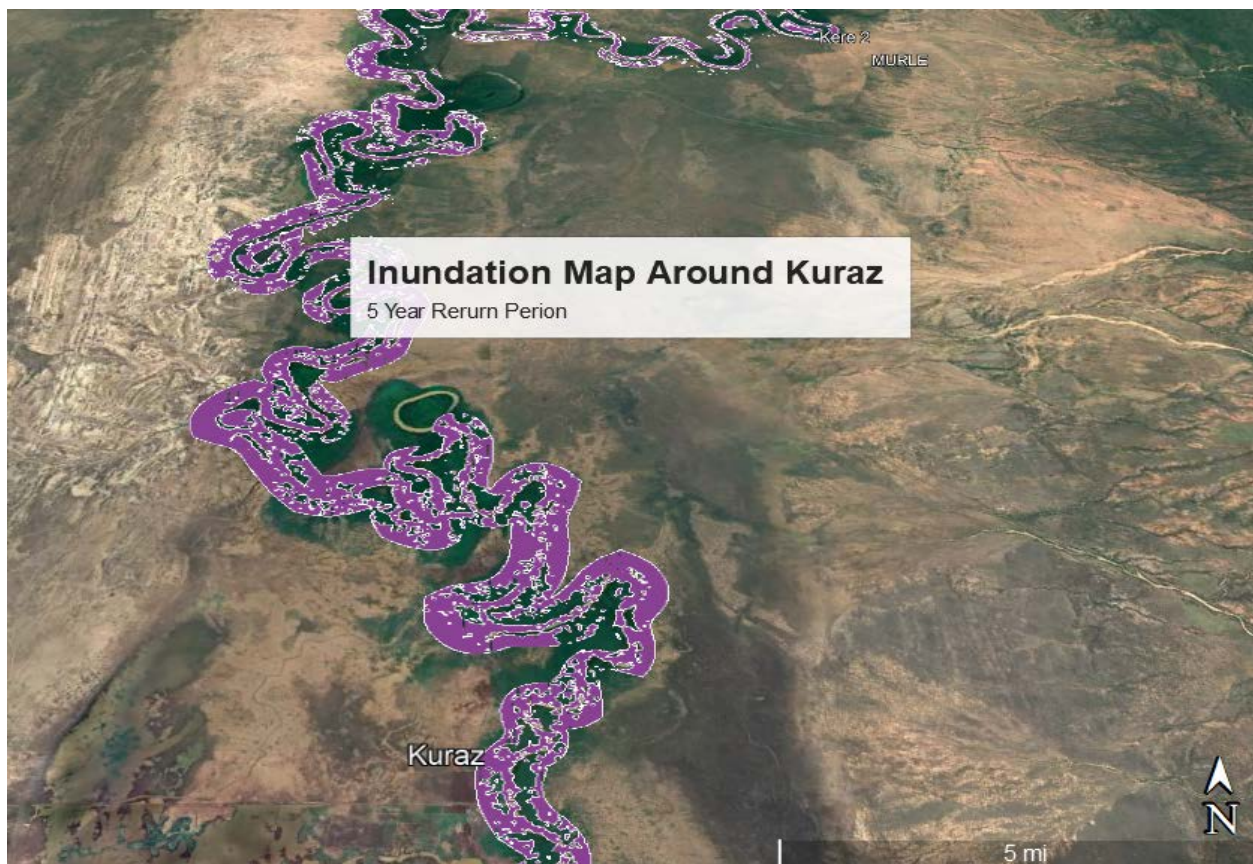


Figure 4. 17 Inundation Map Around Kuraz Woreda for 5 Year Return Period

Table 4. 10 Flood Inundation Coverage In terms of Woredas

Affected woredas	Return periods and Areas in Hectare						
	2 Year	5 Year	10 Year	20 Year	50 Year	100 Year	200 Year
Decha	788.9807	995.90	1016.57	1128.343	1141.311	1196.283	1251.25
Dizi	2415.09	2953.33	3210.952	4154.228	4085.298	4302.503	4485.44
Ela	74.92	91.77	97.38142	101.1478	108.7385	114.2697	118.34
Hamer Bena	3490.89	4474.09	5904.242	6469.717	7600.16	7852.28	8324.24
Kuraz	6910.42	10474.63	13133.06	14889.15	16946.68	18173.28	17243.29
Meinit	58.71	84.99	97.48565	104.0361	120.049	132.0118	143.43
Melekozza	185.55	196.26	210.035	215.4701	230.9418	239.3929	247.61
Silamago	2559.30	2942.41	3154.979	3620.931	3890.027	4046.411	4195.57

The total inundated area for the entire study region showed a strong increasing trend with return period up to the 100-year event. The cumulative inundated area rose from 16,483.86 ha under the 2-year return period to a peak of 36,056.42 ha for the 100-year return period. However, a slight reduction to 36,009.17 ha was observed under the 200-year scenario, primarily due to the noted decrease in flood extent within Kuraz. This pattern suggests a saturation threshold in flood spread for certain regions, beyond which additional discharge may not necessarily increase the floodplain coverage due to terrain constraints.

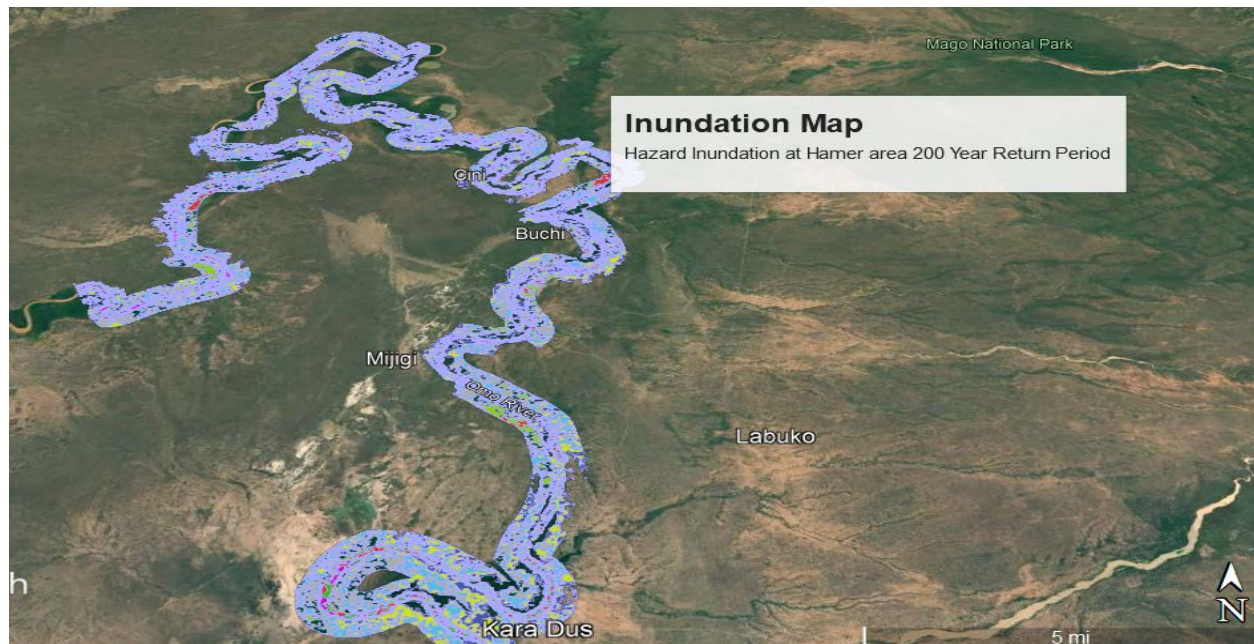


Figure 4. 18 Hazard Inundation at Hamer Area 200-Year Return Period

Overall, the results emphasize in [Appendix G](#), the heightened flood risk posed to certain woredas—particularly Kuraz, Hamer Bena, and Dizi—under extreme hydrological scenarios. These findings underscore the need for localized flood hazard planning, including early warning systems and structural or non-structural mitigation strategies, particularly for communities situated within the high-risk zones of these woredas.

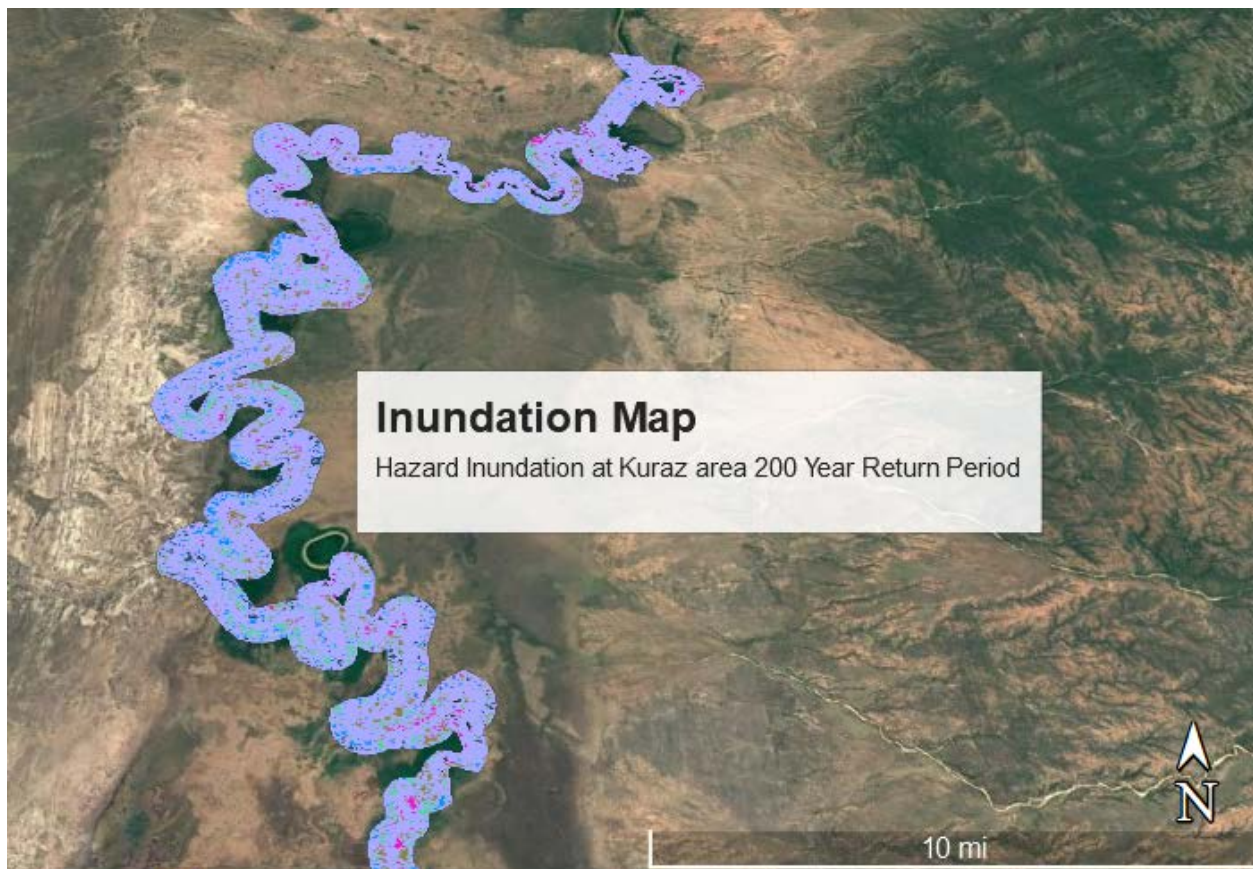


Figure 4. 19 Hazard Inundation at Kuraz Area 200-Year Return Period

4.5.3 Flood Hazard Levels

The flood hazard assessment across various return periods (2, 5, 10, 20, 50, 100, and 200 years) for the woredas of Decha, Dizi, Ela, Hamer Bena, Kuraz, Meinit, Melekozza, and Silamago reveals significant spatial and temporal differences in flood exposure severity. The results show that most woredas experience increasing flood hazard severity and spatial extent over time. Kuraz, Dizi, Hamer Bena, and Silamago face the highest risks, necessitating urgent mitigation and adaptation

strategies. In contrast, Ela and Meinit, while less affected, should also prepare for gradually escalating flood threats. The [Figures chart 4.14, 4.15, 4.16, 4.17, and Appendix E](#) are shown.

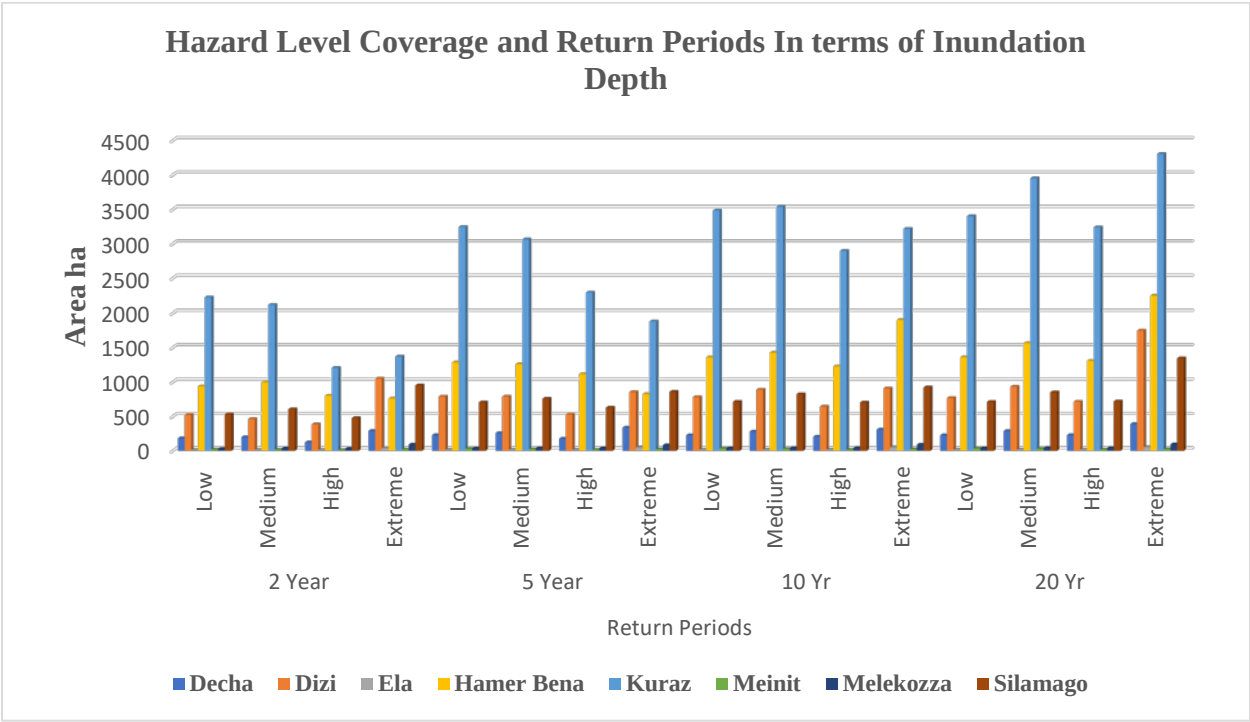


Figure 4. 20 Flood Hazard Levels In terms of Inundation Depth as Factor from return periods of (2-20 Year)

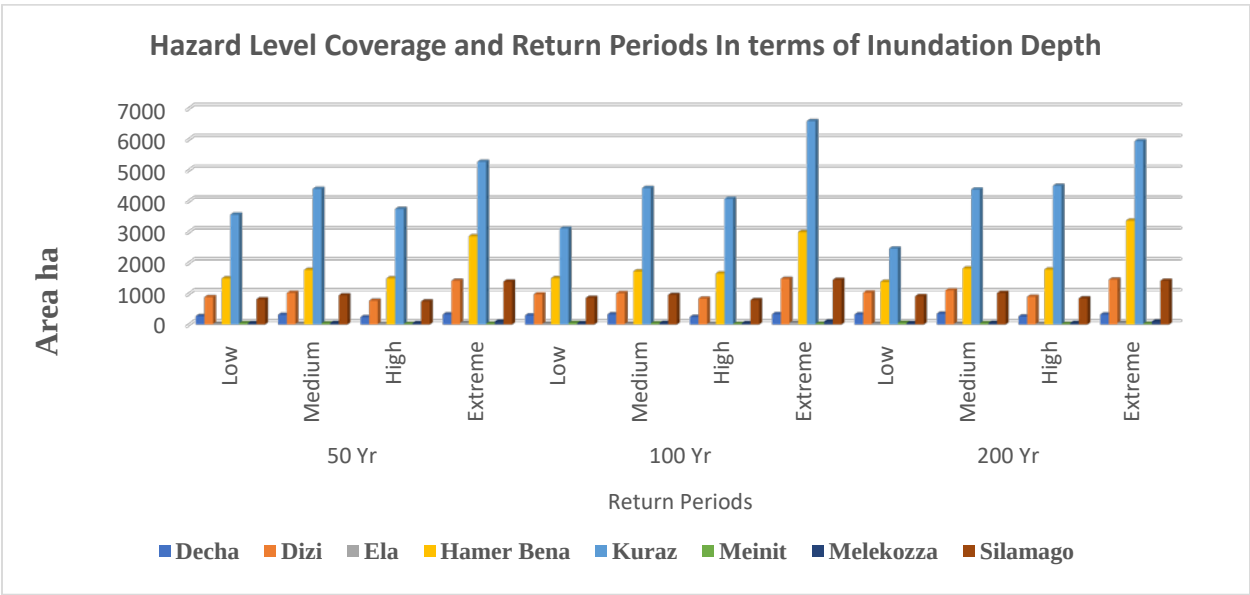


Figure 4. 21 Flood Hazard Levels In terms of Inundation Depth as Factor from return periods of (50-200 years)

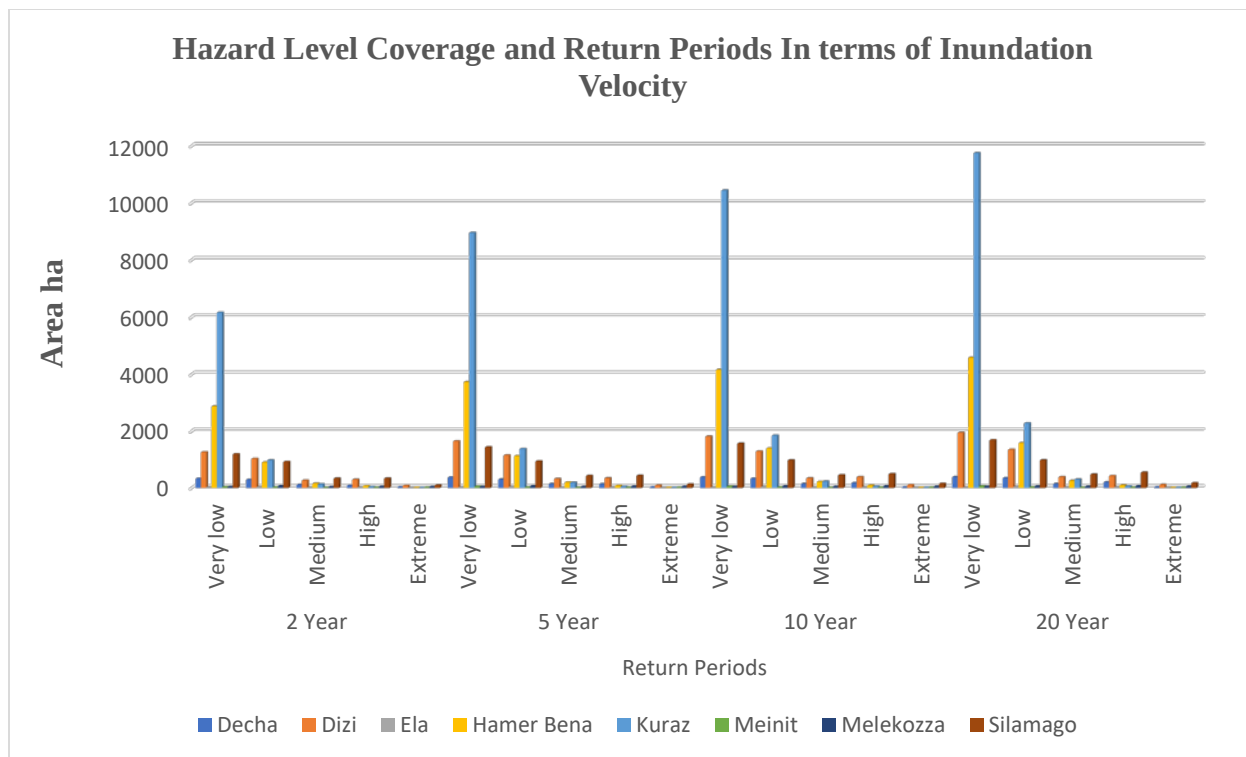


Figure 4. 22 Flood Hazard Levels In terms of Inundation Velocity as Factor from return periods of (2-20 Year).

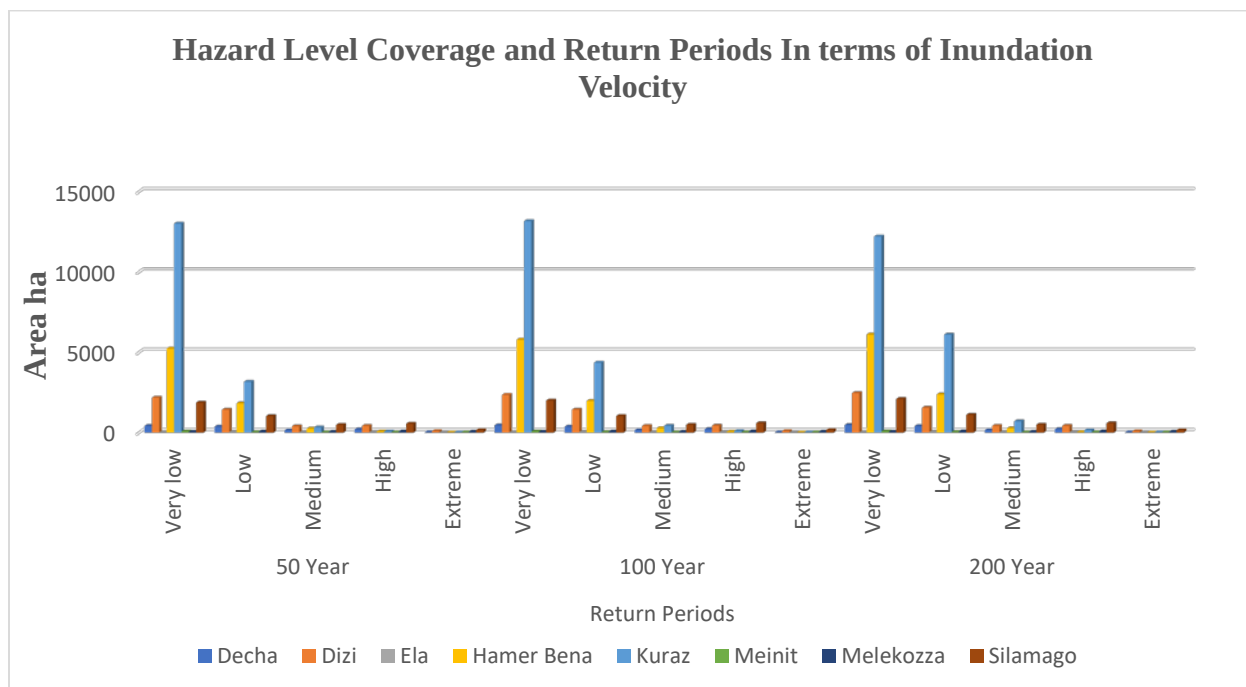


Figure 4. 23 Flood Hazard Levels In terms of Inundation Velocity as Factor from return periods of (50-200 years)

4.5.4 Comparative Analysis of Hazard Area Change from Depth to Velocity Factor

After analyzing the hazard levels using both depth and velocity factors, the percentage change was evaluated by shifting from depth-based to velocity-based assessment. The results indicate that **depth is more hazardous than velocity**, particularly when considering the medium, high, and extreme hazard levels across all affected woredas. This highlights the importance of prioritizing depth as a dominant factor in flood hazard assessments, as it consistently contributes to a higher spatial extent of severe risk zones compared to velocity, as Figures 4.18 and 4.19 show below.

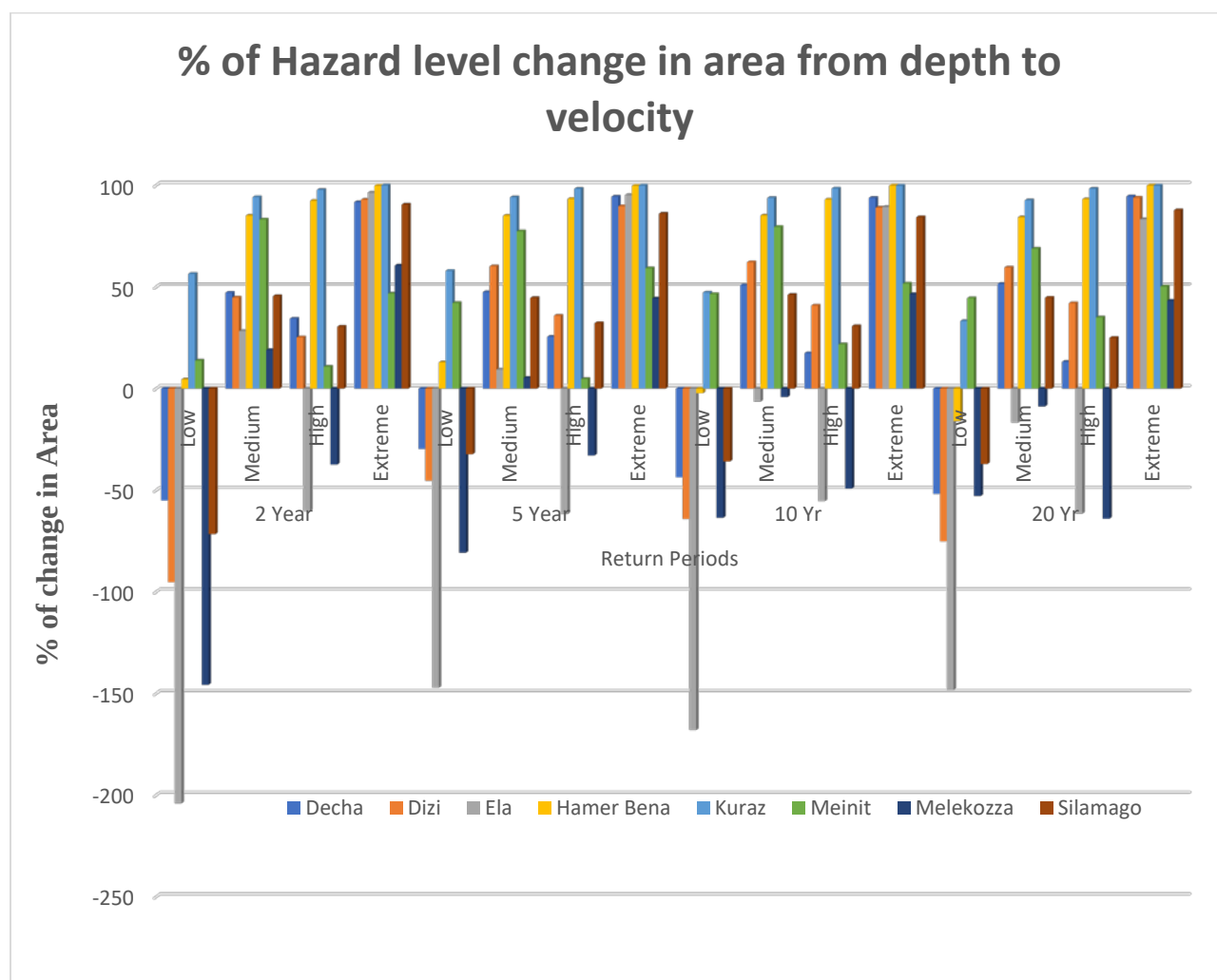


Figure 4. 24 Percent of Hazard level Area change from depth to velocity for return periods (2-20 Years).

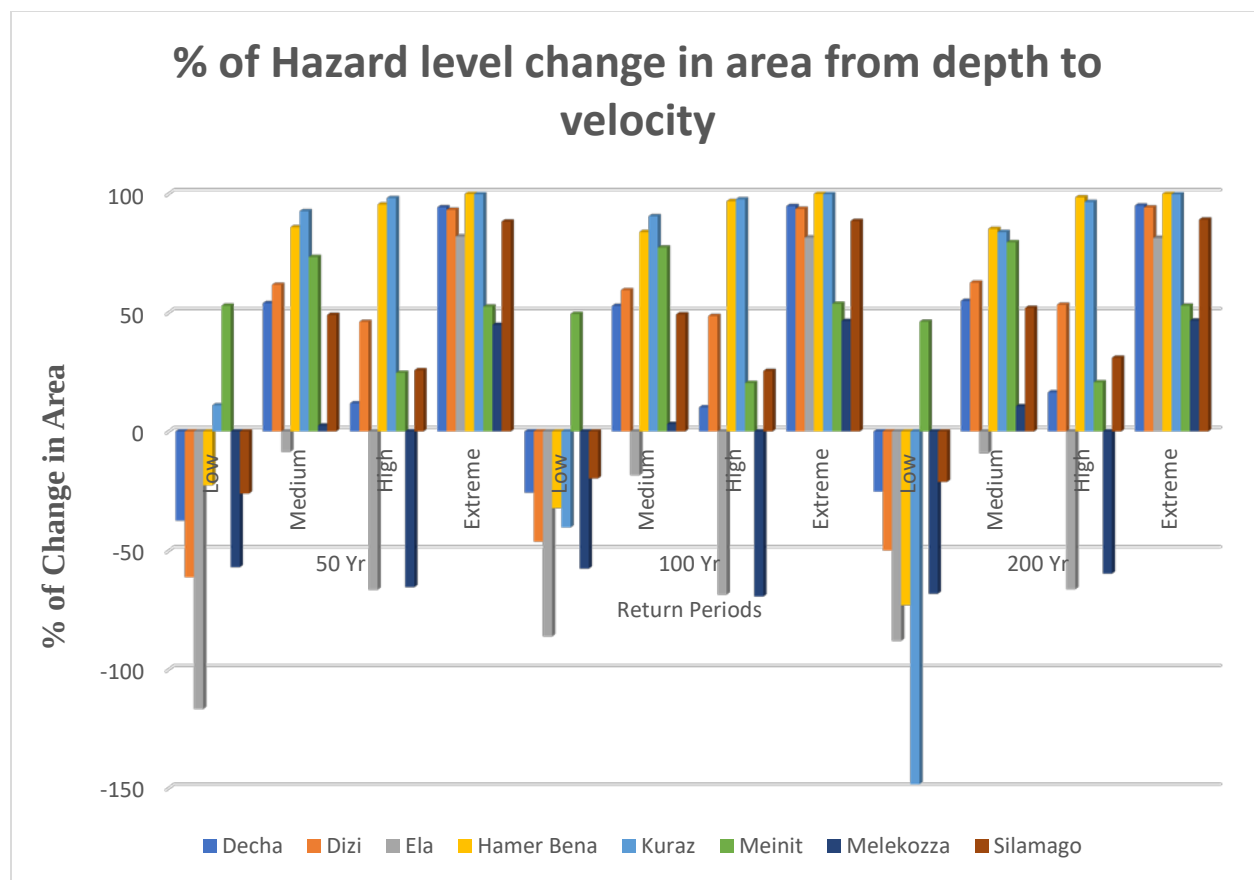


Figure 4. 25 Percent of Hazard level Area change from depth to velocity for return periods (50-200 Years).

4.6 Flood Vulnerability Assessment

The approach followed after the hazard assessment involved evaluating vulnerability. This step focused on identifying and analyzing the factors that increase susceptibility to the assessed hazards, as shown in [Figures 4.20, 4.21, and Appendix F](#). It included examining socio-economic conditions, infrastructure quality, and preparedness levels, which are critical in determining the extent of risk exposure and the ability to recover from potential impacts. Understanding vulnerability enabled the design of more targeted mitigation strategies aimed at reducing risk and enhancing resilience in the most vulnerable areas. The vulnerability assessment of various land use types to flood hazards across multiple return periods highlights significant spatial and temporal patterns that demand attention in risk reduction planning.

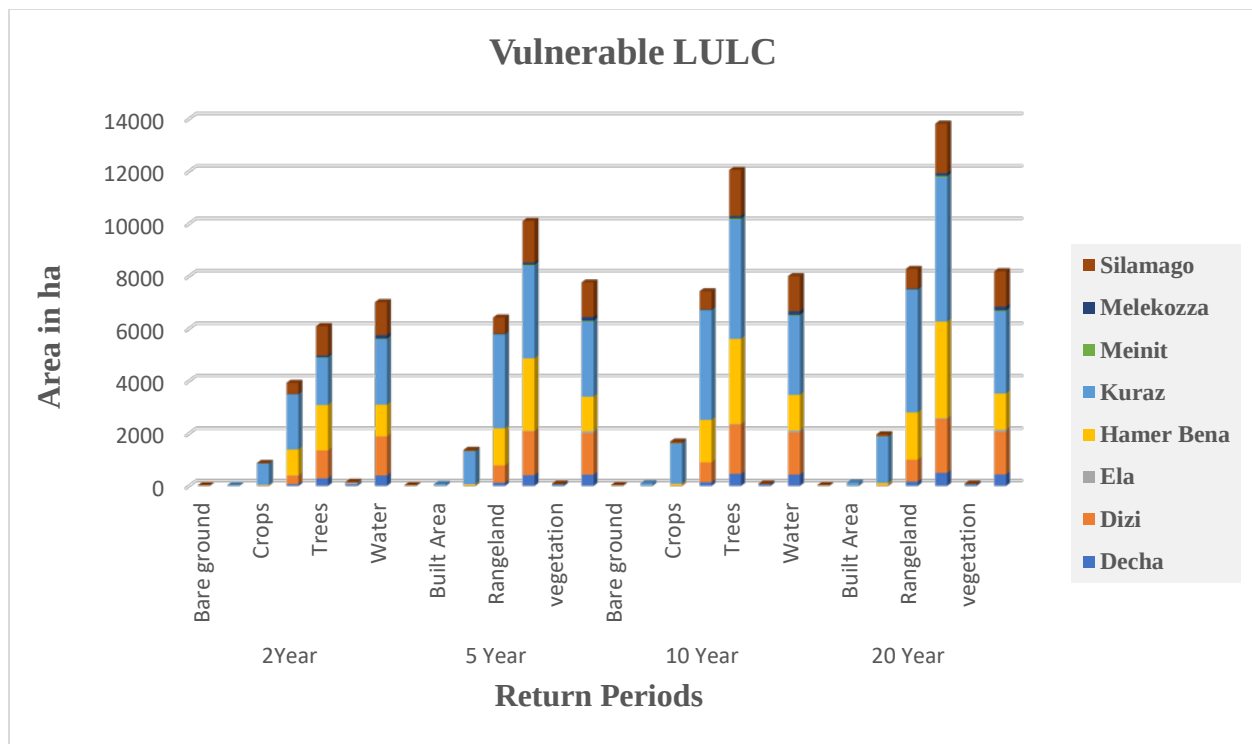


Figure 4. 26 Vulnerable LULC for different Woredas in different return periods from (2-20 Year)

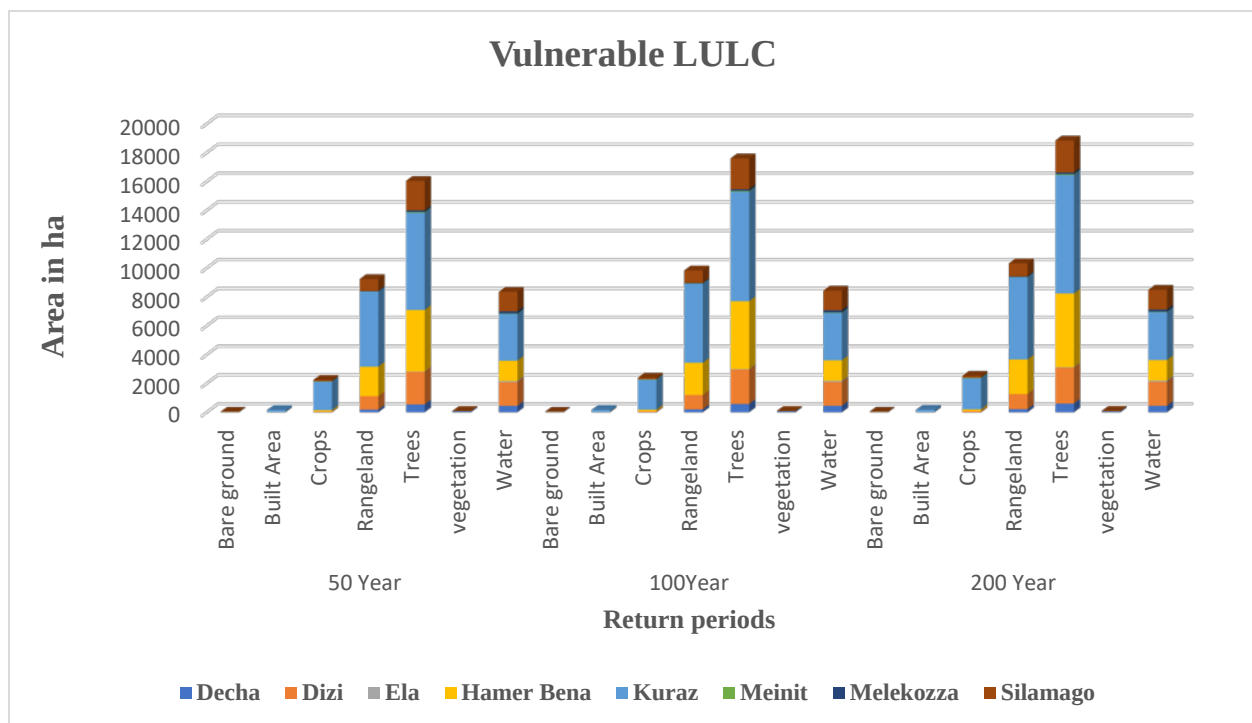


Figure 4. 27 Vulnerable LULC for different Woredas in different return periods from (50 - 200 Year).

4.7 Discussions

4.7.1 Flood Inundation Analysis by Return Periods

The progression of total flood inundation area across different return periods clearly illustrates the growing severity of flood hazards in the study area as the recurrence interval increases. At the 2-year return period, the total inundation area is approximately 16,483.84 hectares, which represents flooding from relatively frequent and less intense events. As the return period increases, so does the extent of inundation, reflecting a strong correlation between flood magnitude and area impacted. Between the 2-year and 5-year events, there is a significant rise of over 5,700 hectares, indicating the sensitivity of the landscape to moderately intense floods. The trend continues with consistent increases through the 10-year and 20-year return periods, reaching over 30,683 hectares. The most substantial jumps are observed between the 10-year to 20-year (an increase of about 3,858 ha) and from 20-year to 50-year (about 3,440 ha) as shown in [Figure 4.12](#).

The inundation area reaches approximately 36,056 hectares during the 100-year return period, and further expands to 38,009 hectares in the extreme 200-year event. While the rate of increase slows slightly between the 100-year and 200-year events, the area still grows by about 1,952 hectares, indicating that even very rare events have the potential to cause significant additional flooding. Flood inundation extent varies significantly across the studied woredas under different return periods, ranging from 2-year to 200-year events. The data demonstrates both spatial and temporal dynamics of flood hazards, essential for risk assessment and mitigation planning. The flood inundation data across various return periods reveals important insights into the spatial extent and progression of flood risk in the studied woredas. Generally, the data shows a clear trend of increasing inundated area as the return period increases, indicating a higher risk of widespread flooding during more extreme events.

Kuraz is the most severely impacted woreda across all return periods, with flood-affected areas increasing from 6,910.42 hectares during the 2-year flood to a peak of 18,173.28 hectares in the 100-year flood, followed by a slight decline to 17,243.29 hectares at the 200-year return period. This slight drop may reflect natural limitations in floodplain spread or model-related adjustments. Similarly, Hamer Bena exhibits a significant increase in flood extent, rising from 3,490.89 hectares to 8,324.24 hectares between the 2-year and 200-year events, as tried to show in Table 4.9,

reflecting the woreda's vulnerability due to expansive flood-prone zones or insufficient drainage infrastructure.

4.7.2 Flood hazard level analysis across different return periods

In general, **all woredas experience an increase in flood hazard levels with longer return periods**, meaning rarer and more intense floods inundate larger areas and reach more severe hazard categories. For example, in **Kuraz**, the area exposed to extreme hazard increases from about 1,368 ha at the 2-year return period to over 5,933 ha at the 200-year return period, indicating a dramatic escalation in vulnerability with extreme events. Similarly, **Hamer Bena** shows a steady increase in all hazard levels, particularly in the extreme hazard category, which grows from 759 ha (2-year) to over 3,358 ha (200-year). This suggests that the woreda is highly sensitive to intense flooding and should be prioritized for robust flood mitigation and response strategies.

Dizi also follows a similar pattern, with the area under extreme hazard expanding from 1,048 ha at the 2-year return period to 1,452 ha at 200 years. Interestingly, even the high hazard zone shows considerable growth, reflecting widespread inundation under both medium and extreme events. **Silamago**, **Melekozza**, and **Ela** demonstrate a more balanced distribution across hazard levels but still show steady increases, especially in the medium and high categories. **Ela**, though smaller in area, sees extreme hazards increase from 39.97 ha to over 55 ha, indicating growing vulnerability even in relatively less affected regions.

On the other hand, **Meinit**, while having lower absolute flood hazard areas, consistently shows incremental growth in all hazard categories. The presence of measurable extreme hazard even in the 2-year return period (about 18 ha) suggests some localized vulnerability that could worsen with time and climate shifts.

Decha, the first woreda in the list, experiences a gradual increase in all hazard zones, with the extreme hazard area rising from approximately 288 ha (2-year) to over 320 ha (200-year). Notably, the high hazard zone grows from 121 ha to 260 ha across the return periods, reflecting a marked increase in threat to moderately vulnerable zones.

4.7.3 Discussion on Vulnerable Land Use and Land Cover to Flood Inundation

The assessment of land use/land cover (LULC) vulnerability under different flood return periods (2-year to 200-year) provides critical insight into the spatial distribution and exposure of key land categories to flood hazards across the study areas. The results reveal both spatial and temporal variability in flood impacts, which are essential for disaster risk reduction, land-use planning, and climate resilience strategies.

1. Trends Across Return Periods

As expected, the **area of land affected increases consistently with longer return periods** across all Woredas. For instance:

- In **Decha**, cropland affected increases from **~71 ha (2-year)** to **~215 ha (200-year)**.
- In **Hamer Bena**, cropland impact grows from **25 ha** to over **115 ha**, with similar trends seen in rangelands and built-up areas.
- **Kuraz** shows a striking increase in all LULC types, especially in **cropland, rangeland, and built-up areas** as the return period lengthens.

This indicates that **more extensive and intense flood events threaten larger areas of all LULC classes**, emphasizing the compounding nature of flood risks over time.

2. Most Vulnerable Land Use Types

Across all woredas:

- **Rangelands and croplands** are the most vulnerable, consistently showing the **largest inundated areas** in all scenarios.
- This poses a significant risk to **pastoralism and agricultural livelihoods**, which dominate rural economies.
- **Vegetation and tree covers** also exhibit considerable exposure, which could lead to **ecosystem degradation and loss of biodiversity** if not managed sustainably.

- **Built-up areas**, while affected to a smaller extent numerically, represent **critical infrastructure and settlements**; even minor inundations here can lead to high socio-economic losses.

3. Spatial Highlights by Woreda

- **Dizi and Kuraz** stand out with **very high flood exposure**, especially in agricultural and rangeland categories. For example, Kuraz sees over **2000 ha of rangeland** and **7000+ ha of vegetation** affected in the 200-year event.
- **Hamer Bena and Silamago** also show increasing exposure to crops and rangelands, highlighting the vulnerability of agro-pastoral communities.
- **Ela and Melekozza**, while smaller in total affected area, experience steady increases in cropland and vegetation exposure, calling for attention to localized flood control measures.

4. Built-up Areas and Infrastructure Risk

Although the values for **built-up areas** remain relatively low in comparison to natural land covers, their **socio-economic significance** cannot be overstated. For example:

- In **Kuraz**, built-up area exposure rises from **26.8 ha (2-year)** to **over 21.7 ha (200-year)**.
- The potential for **loss of homes, public services, and economic facilities** calls for **targeted flood protection and urban planning** in vulnerable towns.

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

The findings of this study clearly demonstrate the increasing severity and spatial extent of flood inundation across the Lower Omo-Gibe Basin under various return period scenarios ranging from 2 to 200 years. By integrating hydrodynamic modeling (HEC-RAS) with geospatial analysis, the research offers a robust framework for understanding flood behavior and its impacts on diverse land use and land cover types. The simulation results indicate a marked expansion of flooded areas with increasing return periods, with the 200-year event exhibiting the highest levels of inundation across all woredas. Kuraz, Hamer Bena, and Dizi emerge as the most critically affected districts in terms of both area coverage and intensity of flooding. Notably, Kuraz woreda alone accounts for more than 35% of the total area under high flood hazard, identifying it as an extreme risk zone where both the natural and built environment face substantial threat.

The land use/land cover (LULC) vulnerability analysis further reveals that croplands and rangelands are the most susceptible to recurrent flood events. These land covers not only occupy large portions of the study area but are also key to the local agricultural economy and food security. For instance, in Decha woreda, the cropland area affected increases significantly—from 70.97 ha in the 2-year flood to over 215 ha in the 200-year event—indicating a growing vulnerability of subsistence farming to climate-induced hydrologic extremes. Similarly, rangelands and tree-covered areas are increasingly exposed, particularly in Dizi, Silamago, and Melekozza, threatening biodiversity, livestock production, and forest ecosystems. Built-up areas, while occupying relatively smaller proportions of land, are also at risk of flooding, especially in expanding settlements within Kuraz and Hamer Bena. These regions show a steady increase in inundation over time, which could lead to long-term infrastructural damage and displacement of local populations.

From a flood hazard perspective, the delineated hazard zones reveal a complex spatial distribution of risk. High hazard zones are primarily concentrated along river corridors and in low-lying plains, coinciding with areas of high agricultural productivity and population density. Kuraz, Dizi, and

Hamer Bena stand out with the largest high hazard extents, whereas Decha and Silamago are dominated by moderate hazard zones. Ela and Meinit, although showing relatively limited inundation, still exhibit upward trends in flood exposure, indicating latent risks that could escalate under future climate scenarios. Water bodies and floodplains themselves also expand under higher return periods, suggesting prolonged periods of surface water retention, backwater effects, and potential waterlogging, which can disrupt farming cycles and damage infrastructure.

The implications of these findings are far-reaching. They highlight the urgent need for proactive flood risk reduction strategies and sustainable land use planning in the Lower Omo-Gibe Basin. Priority should be given to establishing community-based early warning systems, enforcing zoning regulations that restrict development in high-risk floodplains, and promoting nature-based solutions such as wetland restoration and reforestation. Additionally, adaptive agricultural practices, including flood-resilient crop varieties and improved drainage systems, should be introduced to mitigate the vulnerability of farming communities. The integration of hazard maps into regional planning can further assist policymakers, NGOs, and stakeholders in targeting their interventions more effectively. Ultimately, this study reinforces the necessity of adopting an integrated, ecosystem-based flood management approach that balances development with environmental conservation to ensure the long-term resilience and sustainability of the basin.

5.2 Recommendations

Based on the findings of this study and the methodological framework applied, the following recommendations are proposed to improve future flood risk assessments, enhance data quality, and support evidence-based decision-making in flood-prone regions like the Lower Omo-Gibe Basin:

1. Strengthening Hydrodynamic Modeling with HEC-RAS

The HEC-RAS model has proven to be an effective tool for simulating flood extents and depths under varying return period scenarios. However, to improve model accuracy, future studies should incorporate higher-resolution topographic and bathymetric data, field-measured flow parameters, and more refined boundary conditions. Calibration and validation with observed flood events, including water levels and inundation maps, are

essential for improving the model's predictive reliability and should be prioritized in subsequent research and practical applications.

2. Improving the Quality and Resolution of Digital Elevation Models (DEMs)

The accuracy of flood simulation and hazard mapping is highly sensitive to the resolution and quality of the DEM used. While this study utilized freely available SRTM or similar DEM data, future assessments would benefit significantly from the use of high-resolution LiDAR, photogrammetric DEMs, or drone-based elevation data. These can better capture micro-topographic variations and drainage features, leading to more realistic floodplain delineations.

3. Addressing Data Availability and Accessibility Challenges

One of the primary limitations encountered during this study was the limited availability of high-quality and up-to-date hydrological, meteorological, and land use data. To overcome this, it is recommended that relevant national institutions (e.g., Ethiopian Ministry of Water and Energy, Ethiopian Meteorological Institute, Basin Authorities) enhance their data archiving, digitization, and public accessibility. Furthermore, collaborative data-sharing platforms should be established among universities, research centers, and government agencies to support more comprehensive and integrated water resource assessments.

4. Enhancing Land Use and Land Cover (LULC) Monitoring

The integration of land use data with flood modeling demonstrated that croplands and rangelands are particularly vulnerable to flood hazards. Regular LULC monitoring using remote sensing tools like Google Earth Engine (GEE), Sentinel, and Landsat imagery should be institutionalized for early detection of encroachments into flood-prone areas. Planners and local governments must use such information to guide land allocation, agricultural planning, and disaster preparedness strategies.

5. Utilizing the Obtained Results for Planning and Disaster Risk Reduction

The flood extent and hazard maps produced in this study are valuable resources for guiding urban planning, emergency response, and infrastructure development. Regional governments, disaster risk management offices, and NGOs should integrate these outputs into spatial planning tools and flood contingency plans. Critical areas such as Kuraz, Dizi, and Hamer Bena, identified as high-hazard zones, should be prioritized for the

implementation of flood mitigation structures, resettlement planning, and public awareness campaigns.

6. Promoting Ecosystem-Based Flood Management

In addition to structural measures, the study recommends the adoption of nature-based solutions to reduce flood risks. Reforestation of degraded uplands, preservation of wetlands, and sustainable rangeland management can naturally attenuate flood peaks and restore watershed health. These strategies should be supported through community-based natural resource management initiatives and integrated into basin-wide flood resilience planning.

7. Capacity Building and Technical Training

Finally, capacity building at both local and institutional levels is crucial for sustaining flood modeling and hazard mapping efforts. Training programs should be offered on hydrodynamic modeling tools (like HEC-RAS), GIS and remote sensing, and flood risk communication to empower local authorities, researchers, and students.

8. Invest in Flood-Resilient Infrastructure:

Construct or reinforce embankments, levees, and floodways in overtopping-prone areas. Incorporate climate-resilient design standards into the construction of bridges, culverts, and roads in vulnerable zones.

9. Implement Nature-Based Solutions:

Promote watershed management, wetland restoration, and afforestation in the upper catchments to reduce peak flows and enhance natural flood retention in the Lower Omo Basin.

REFERENCES

- Afzal, M. A., Ali, S., Nazeer, A., Khan, M. I., Waqas, M. M., Aslam, R. A., Cheema, M. J. M., Nadeem, M., Saddique, N., Muzammil, M., & Shah, A. N. (2022). Flood Inundation Modeling by Integrating HEC–RAS and Satellite Imagery: A Case Study of the Indus River Basin. *Water*, 14(19), 2984. <https://doi.org/10.3390/w14192984>
- Al Jazeera English (Director). (2024, August 25). *Southern Ethiopia flooding: Efforts to save town after river Omo bursts banks* [Video recording].
<https://www.youtube.com/watch?v=16JOGolmiC4>
- Albu, L.-M., Enea, A., Iosub, M., & Breabăn, I.-G. (2020). Dam Breach Size Comparison for Flood Simulations. A HEC-RAS Based, GIS Approach for Drăcșani Lake, Sitna River, Romania. *Water*, 12(4), Article 4. <https://doi.org/10.3390/w12041090>
- Anadolu Ajansı, T. (2024, August 20). *79,000 displaced as Omo river overflows in southern Ethiopia*. <https://www.aa.com.tr/en/africa/79-000-displaced-as-omo-river-overflows-in-southern-ethiopia/3308892>
- Asare-Kyei, D., Forkuor, G., & Venus, V. (2015). Modeling Flood Hazard Zones at the Sub-District Level with the Rational Model Integrated with GIS and Remote Sensing Approaches. *Water*, 7(12), Article 12. <https://doi.org/10.3390/w7073531>
- Baky, M. A. A., Islam, M., & Paul, S. (2019). Flood Hazard, Vulnerability and Risk Assessment for Different Land Use Classes Using a Flow Model. *Earth Systems and Environment*, 4(1), 225–244. <https://doi.org/10.1007/s41748-019-00141-w>
- Bates, P. D., & De Roo, A. P. J. (2000). A simple raster-based model for flood inundation simulation. *Journal of Hydrology*, 236(1–2), 54–77. [https://doi.org/10.1016/S0022-1694\(00\)00278-X](https://doi.org/10.1016/S0022-1694(00)00278-X)

- Benameur, S., Benkhalel, A., Meraghni, D., Chebana, F., & Necir, A. (2017). Complete flood frequency analysis in Abiod watershed, Biskra (Algeria). *Natural Hazards*, 86(2), Article 2. <https://doi.org/10.1007/s11069-016-2703-4>
- Bhandari, M., Nyaupane, N., Mote, S. R., Kalra, A., & Ahmad, S. (2017). 2D Unsteady Flow Routing and Flood Inundation Mapping for Lower Region of Brazos River Watershed. *World Environmental and Water Resources Congress 2017*, 292–303. <https://doi.org/10.1061/9780784480625.027>
- Brunner, G. W. (2016). HEC-RAS River Analysis System: Hydraulic Reference Manual, Version 5.0. *US Army Corps of Engineers–Hydrologic Engineering Center*, 547.
- Chen, Y.-W., Tsai, J.-P., Chang, L.-C., Ho, C.-C., & Chen, Y.-C. (2014). The development of a real-time flooding operation model in the Tseng-Wen Reservoir. *Hydrology Research*, 45(3), Article 3. <https://doi.org/10.2166/nh.2013.301>
- Cirella, G., & Iyalomhe, F. (2018). Flooding Conceptual Review: Sustainability-Focalized Best Practices in Nigeria. *Applied Sciences*, 8(9), Article 9. <https://doi.org/10.3390/app8091558>
- Daba, M. H., Ayele, G. T., & You, S. (2020). Long-Term Homogeneity and Trends of Hydroclimatic Variables in Upper Awash River Basin, Ethiopia. *Advances in Meteorology*, 2020, 1–21. <https://doi.org/10.1155/2020/8861959>
- Dandapat, K., & Panda, G. K. (2017). Flood vulnerability analysis and risk assessment using analytical hierarchy process. *Modeling Earth Systems and Environment*, 3(4), 1627–1646. <https://doi.org/10.1007/s40808-017-0388-7>

- Dasallas, L., & Lee, S. (2019). Topographical Analysis of the 2013 Typhoon Haiyan Storm Surge Flooding by Combining the JMA Storm Surge Model and the FLO-2D Flood Inundation Model. *Water*, 11(1), Article 1. <https://doi.org/10.3390/w11010144>
- Desalegn, H., & Mulu, A. (2021). Mapping flood inundation areas using GIS and HEC-RAS model at Fetam River, Upper Abbay Basin, Ethiopia. *Scientific African*, 12, e00834. <https://doi.org/10.1016/j.sciaf.2021.e00834>
- Dewan, T. H. (2015). Societal impacts and vulnerability to floods in Bangladesh and Nepal. *Weather and Climate Extremes*, 7, 36–42. <https://doi.org/10.1016/j.wace.2014.11.001>
- DHI. (2020). *MIKE FLOOD User Manual*. DHI Water & Environment. Retrieved from <https://www.mikepoweredbydhi.com/>
- Drissia, T. K., Jothiprakash, V., & Anitha, A. B. (2019). Flood Frequency Analysis Using L Moments: A Comparison between At-Site and Regional Approach. *Water Resources Management*, 33(3), 1013–1037. <https://doi.org/10.1007/s11269-018-2162-7>
- Farooq, M., Shafique, M., & Khattak, M. S. (2019). Flood hazard assessment and mapping of River Swat using HEC-RAS 2D model and high-resolution 12-m TanDEM-X DEM (WorldDEM). *Natural Hazards*, 97(2), Article 2. <https://doi.org/10.1007/s11069-019-03638-9>
- FloodList. (2020, September 11). *Ethiopia – 300,000 Displaced by Floods, Says UN – FloodList*. <https://floodlist.com/africa/ethiopia-floods-update-september-2020>
- FloodList. (2021, May 14). *Ethiopia – Thousands Displaced by Floods in Afar, SNNP and Somali Regions – FloodList*. <https://floodlist.com/africa/ethiopia-floods-afar-snnp-somali-may-2021>

- Gao, Y., Merz, C., Lischeid, G., & Schneider, M. (2018). A review on missing hydrological data processing. *Environmental Earth Sciences*, 77(2), Article 2.
<https://doi.org/10.1007/s12665-018-7228-6>
- Gashaw, W., & Legesse, D. (2011). Flood Hazard and Risk Assessment Using GIS and Remote Sensing in Fogera Woreda, Northwest Ethiopia. In A. M. Melesse (Ed.), *Nile River Basin* (pp. 179–206). Springer Netherlands. https://doi.org/10.1007/978-94-007-0689-7_9
- Getahun YS, G. S. (2015) G. (2015). Flood Hazard Assessment and Mapping of Flood Inundation Area of the Awash River Basin in Ethiopia using GIS and HEC-GeoRAS/HEC-RAS Model. *Journal of Civil & Environmental Engineering*, 05(04).
<https://doi.org/10.4172/2165-784X.1000179>
- Ghimire, E., Sharma, S., & Lamichhane, N. (2022). Evaluation of one-dimensional and two-dimensional HEC-RAS models to predict flood travel time and inundation area for flood warning system. *ISH Journal of Hydraulic Engineering*, 28(1), Article 1.
<https://doi.org/10.1080/09715010.2020.1824621>
- Gurmu. (2018). *FLOOD MODELING AND MAPPING OF LOWER OMO GIBE RIVER*.
<https://core.ac.uk/download/pdf/199939045.pdf>
- Haddad, K. (2021). Selection of the best fit probability distributions for temperature data and the use of L-moment ratio diagram method: A case study for NSW in Australia. *Theoretical and Applied Climatology*, 143(3–4), 1261–1284. <https://doi.org/10.1007/s00704-020-03455-2>
- Hagen, E., & Lu, X. X. (2011). Let us create flood hazard maps for developing countries. *Natural Hazards*, 58(3), Article 3. <https://doi.org/10.1007/s11069-011-9750-7>

- Heidarpour, B., Saghafian, B., Yazdi, J., & Azamathulla, H. M. (2017). Effect of Extraordinary Large Floods on at-site Flood Frequency. *Water Resources Management*, 31(13), Article 13. <https://doi.org/10.1007/s11269-017-1739-x>
- Horritt, M. S., & Bates, P. D. (2002). Evaluation of 1D and 2D numerical models for predicting river flood inundation. *Journal of Hydrology*, 268(1–4), 87–99. [https://doi.org/10.1016/S0022-1694\(02\)00121-X](https://doi.org/10.1016/S0022-1694(02)00121-X)
- Hosking, J. R. (1990). L-moments: Analysis and estimation of distributions using linear combinations of order statistics. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, 52(1), 105–124.
- Jacobs. (2020). *Flood Modeller User Guide*. Jacobs Engineering Group. Retrieved from <https://www.floodmodeller.com/>
- Kamal, V., Mukherjee, S., Singh, P., Sen, R., Vishwakarma, C. A., Sajadi, P., Asthana, H., & Rena, V. (2017). Flood frequency analysis of Ganga river at Haridwar and Garhmukteshwar. *Applied Water Science*, 7(4), Article 4. <https://doi.org/10.1007/s13201-016-0378-3>
- Kamboh, S. A., Sarbini, I. N., Labadin, J., & Eze, M. O. (2016). Simulation of 2D Saint-Venant equations in open channel by using MATLAB. *Journal of IT in Asia*, 5(1), Article 1. <https://doi.org/10.33736/jita.47.2015>
- Namara, W. G., Damisse, T. A., & Tufa, F. G. (2022). Application of HEC-RAS and HEC-GeoRAS model for Flood Inundation Mapping, the case of Awash Bello Flood Plain, Upper Awash River Basin, Oromiya Regional State, Ethiopia. *Modeling Earth Systems and Environment*, 8(2), 1449–1460. <https://doi.org/10.1007/s40808-021-01166-9>
- NDRMC. (2018). *Federal Democratic Republic of Ethiopia National Disaster Risk Management Commission, Early Warning and Emergency Response Directorate*.

- OCHA. (2024, August 23). *Several regions are reeling from the impact of floods that occurred in July and August*. <https://reports.unocha.org/en/country/ethiopia/card/2ET9B3qeCz/>
- Ongdas, N., Akiyanova, F., Karakulov, Y., Muratbayeva, A., & Zinabdin, N. (2020). Application of HEC-RAS (2D) for Flood Hazard Maps Generation for Yesil (Ishim) River in Kazakhstan. *Water*, 12(10), Article 10. <https://doi.org/10.3390/w12102672>
- Orkodjo, T. P., Kranjac-Berisavijevic, G., & Abagale, F. K. (2022). Impact of climate change on future availability of water for irrigation and hydropower generation in the Omo-Gibe Basin of Ethiopia. *Journal of Hydrology: Regional Studies*, 44, 101254. <https://doi.org/10.1016/j.ejrh.2022.101254>
- Papaioannou, G., Loukas, A., Vasiliades, L., & Aronica, G. T. (2016). Flood inundation mapping sensitivity to riverine spatial resolution and modelling approach. *Natural Hazards*, 83(S1), 117–132. <https://doi.org/10.1007/s11069-016-2382-1>
- Patakamuri, S. K., Muthiah, K., & Sridhar, V. (2020). Long-Term Homogeneity, Trend, and Change-Point Analysis of Rainfall in the Arid District of Ananthapuramu, Andhra Pradesh State, India. *Water*, 12(1), Article 1. <https://doi.org/10.3390/w12010211>
- Psomiadis, E., Diakakis, M., & Soulis, K. X. (2020). Combining SAR and Optical Earth Observation with Hydraulic Simulation for Flood Mapping and Impact Assessment. *Remote Sensing*, 12(23), Article 23. <https://doi.org/10.3390/rs12233980>
- Rehman, S., Sahana, M., Hong, H., Sajjad, H., & Ahmed, B. B. (2019). A systematic review on approaches and methods used for flood vulnerability assessment: Framework for future research. *Natural Hazards*, 96(2), 975–998. <https://doi.org/10.1007/s11069-018-03567-z>
- Sahana, M., & Sajjad, H. (2019). Vulnerability to storm surge flood using remote sensing and GIS techniques: A study on Sundarban Biosphere Reserve, India. *Remote Sensing*

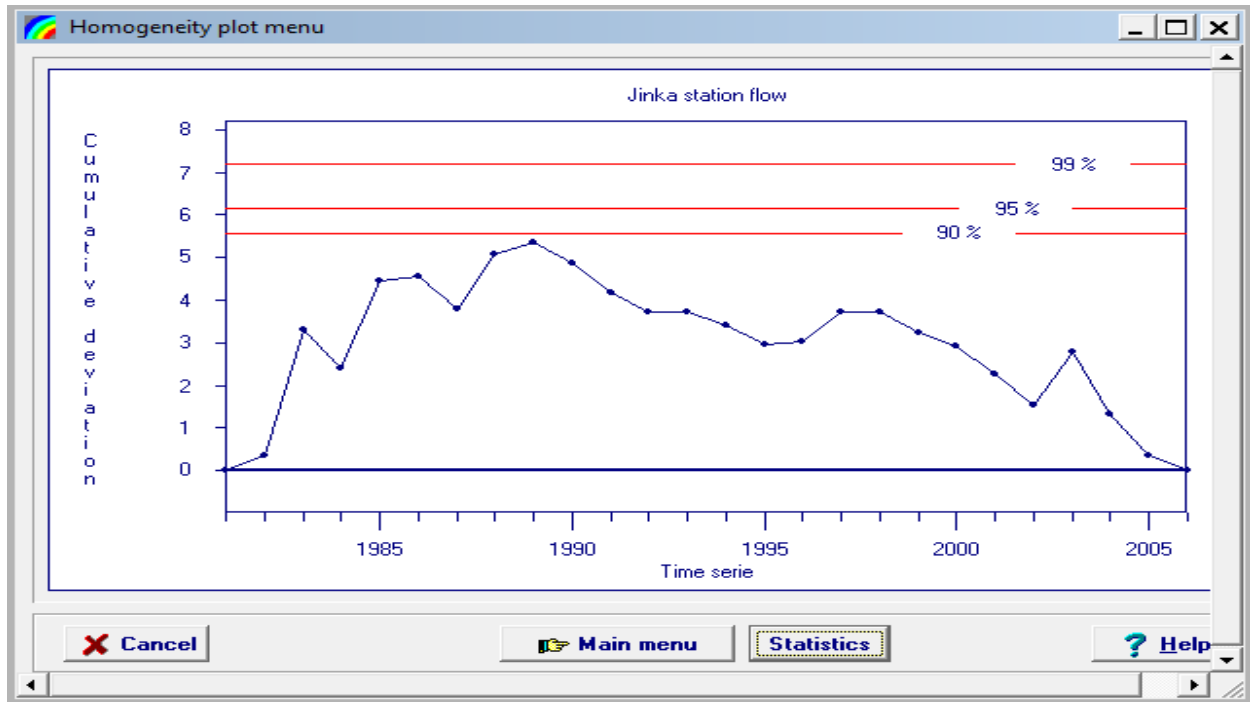
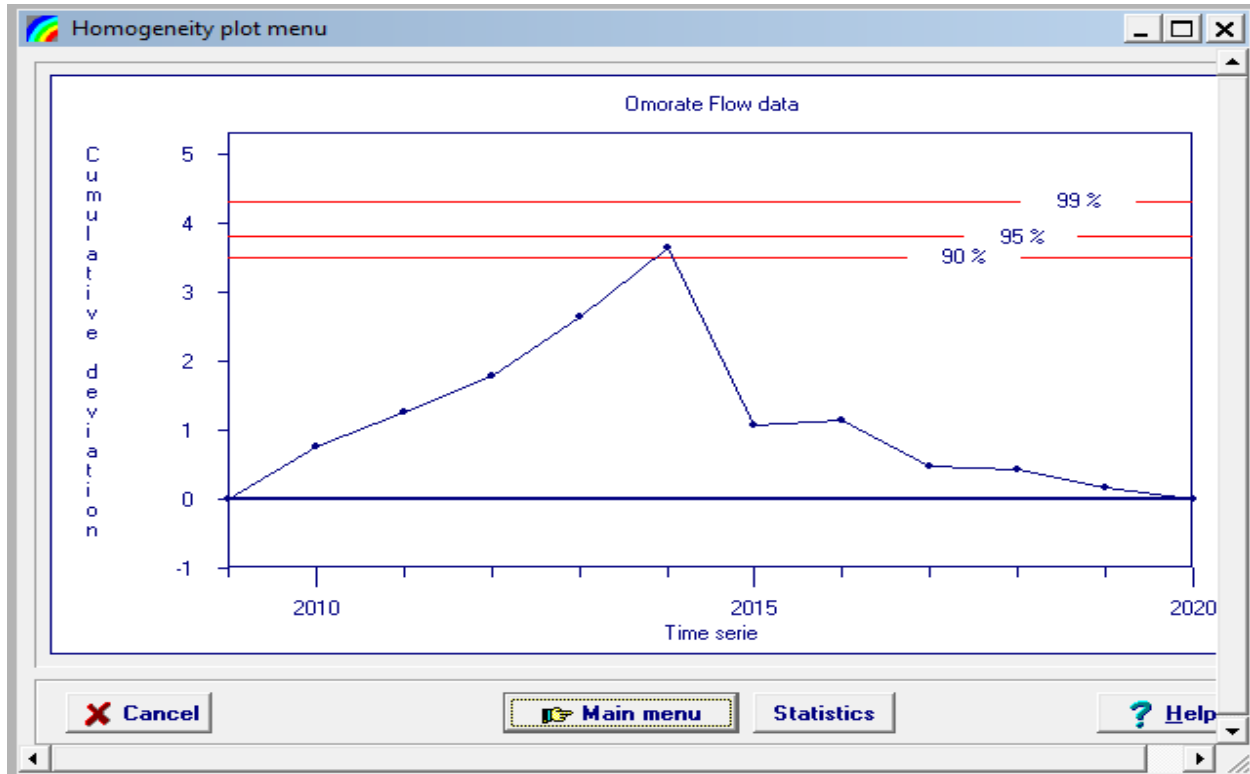
- Applications: Society and Environment*, 13, 106–120.
<https://doi.org/10.1016/j.rsase.2018.10.008>
- Sajjad, A., Lu, J., Chen, X., Chisenga, C., Saleem, N., & Hassan, H. (2020). Operational Monitoring and Damage Assessment of Riverine Flood-2014 in the Lower Chenab Plain, Punjab, Pakistan, Using Remote Sensing and GIS Techniques. *Remote Sensing*, 12(4), Article 4. <https://doi.org/10.3390/rs12040714>
- Santillan, J. R., Marqueso, J. T., Makinano-Santillan, M., & Serviano, J. L. (2016). Beyond Flood Hazard Maps: Detailed Flood Characterization With Remote Sensing, Gis And 2D Modelling. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLII-4/W1, 315–323. <https://doi.org/10.5194/isprs-archives-XLII-4-W1-315-2016>
- Shadmehri Toosi, A., Doulabian, S., Ghasemi Tousi, E., Calbimonte, G. H., & Alaghmand, S. (2020). Large-scale flood hazard assessment under climate change: A case study. *Ecological Engineering*, 147, 105765. <https://doi.org/10.1016/j.ecoleng.2020.105765>
- Subramanya, K. (2008). *Engineering hydrology*. McGraw-Hill.
- Syme, W. J. (2008). *TUFLOW – A Two-Dimensional / One-Dimensional Hydrodynamic Modelling System*. BMT WBM Pty Ltd. Retrieved from <https://www.tuflow.com/>
- Tamiru, H., & Dinka, M. O. (2021). Application of ANN and HEC-RAS model for flood inundation mapping in lower Baro Akobo River Basin, Ethiopia. *Journal of Hydrology: Regional Studies*, 36, 100855. <https://doi.org/10.1016/j.ejrh.2021.100855>
- Thiemig, V., De Roo, A., & Gadain, H. (2011). Current status on flood forecasting and early warning in Africa. *International Journal of River Basin Management*, 9(1), Article 1. <https://doi.org/10.1080/15715124.2011.555082>

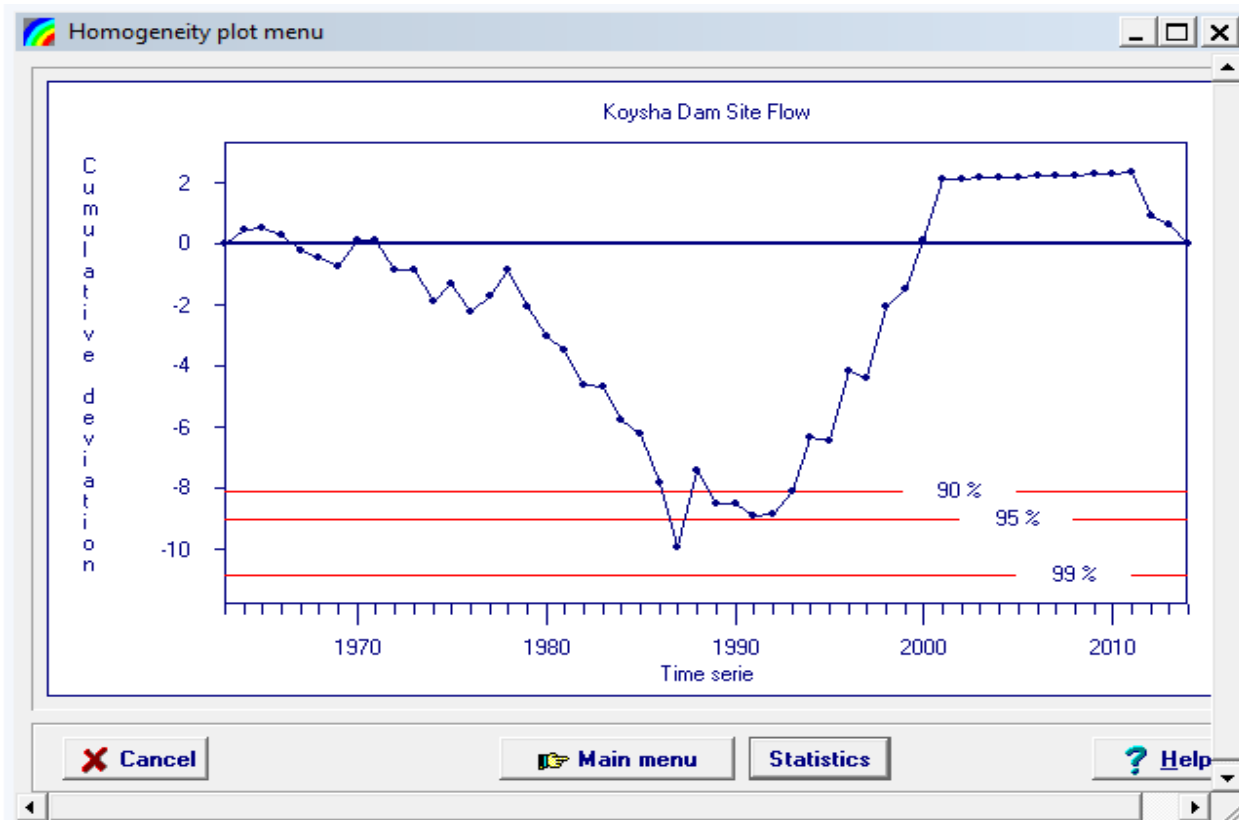
- Timbadiya, P. V., Patel, P. L., & Porey, P. D. (2011). Calibration of HEC-RAS Model on Prediction of Flood for Lower Tapi River, India. *Journal of Water Resource and Protection*, 03(11), 805–811. <https://doi.org/10.4236/jwarp.2011.311090>
- Trambadia, N. K., Patel, D. P., Patel, V. M., & Gundalia, M. J. (2023). *Flood inundation assessment in the data-scarce region using hydrodynamic models and google earth engine -A case of Ghed region, Ozat River basin, Gujarat, India* [Preprint]. In Review. <https://doi.org/10.21203/rs.3.rs-2321703/v1>
- Ukumo, T. Y., Abebe, A., Lohani, T. K., & Edamo, M. L. (2022). Flood hazard mapping and analysis under climate change using hydro-dynamic model and RCPs emission scenario in Woybo River catchment of Ethiopia. *World Journal of Engineering*, 20(3), Article 3. <https://doi.org/10.1108/WJE-07-2021-0410>
- Ul Hassan, M., Hayat, O., & Noreen, Z. (2019). Selecting the best probability distribution for at-site flood frequency analysis; a study of Torne River. *SN Applied Sciences*, 1(12), Article 12. <https://doi.org/10.1007/s42452-019-1584-z>
- Vojtek, M., & Vojteková, J. (2016). Flood hazard and flood risk assessment at the local spatial scale: A case study. *Geomatics, Natural Hazards and Risk*, 7(6), 1973–1992. <https://doi.org/10.1080/19475705.2016.1166874>
- Woldegebrael, S. M., Kidanewold, B. B., & Melesse, A. M. (2022). Development and Evaluation of a Web-Based and Interactive Flood Management Tool for Awash and Omo-Gibe Basins, Ethiopia. *Water*, 14(14), Article 14. <https://doi.org/10.3390/w14142195>

Woldegebrael, S. M., Kidanewold, B. B., Zaitchik, B., & Melesse, A. M. (2020). *Rainfall and Flood Event Interrelationship—A Case Study of Awash and Omo-Gibe Basins, Ethiopia*. 11(1).

APPENDICES

Appendix A: Homogeneity test for stream flow stations using Rainbow software





Appendix B: Quantile Water Level for Omorate Station

Quantile Water level for Omorate River station 123031.4 for $n = 0.043$					
Observed			Simulated		
Return period	WL Observed	QT	Min Cha El (m)	W.S Elev (m)	WL (Simulated)
2	6.2	258.4	355.71	362.37	6.66
5	7.9	776.6	355.71	364.18	8.47
10	8.1	1263	355.71	365.06	9.35
20	11.1	1896.9	355.71	365.91	10.2
50	11.4	3106.5	355.71	367	11.29
100	11.5	4472.4	355.71	367.94	12.23
200	11.6	6458.7	355.71	369	13.29
Quantile Water level for Omorate River station 123031.4 for $n = 0.04$					
Observed			Simulated		

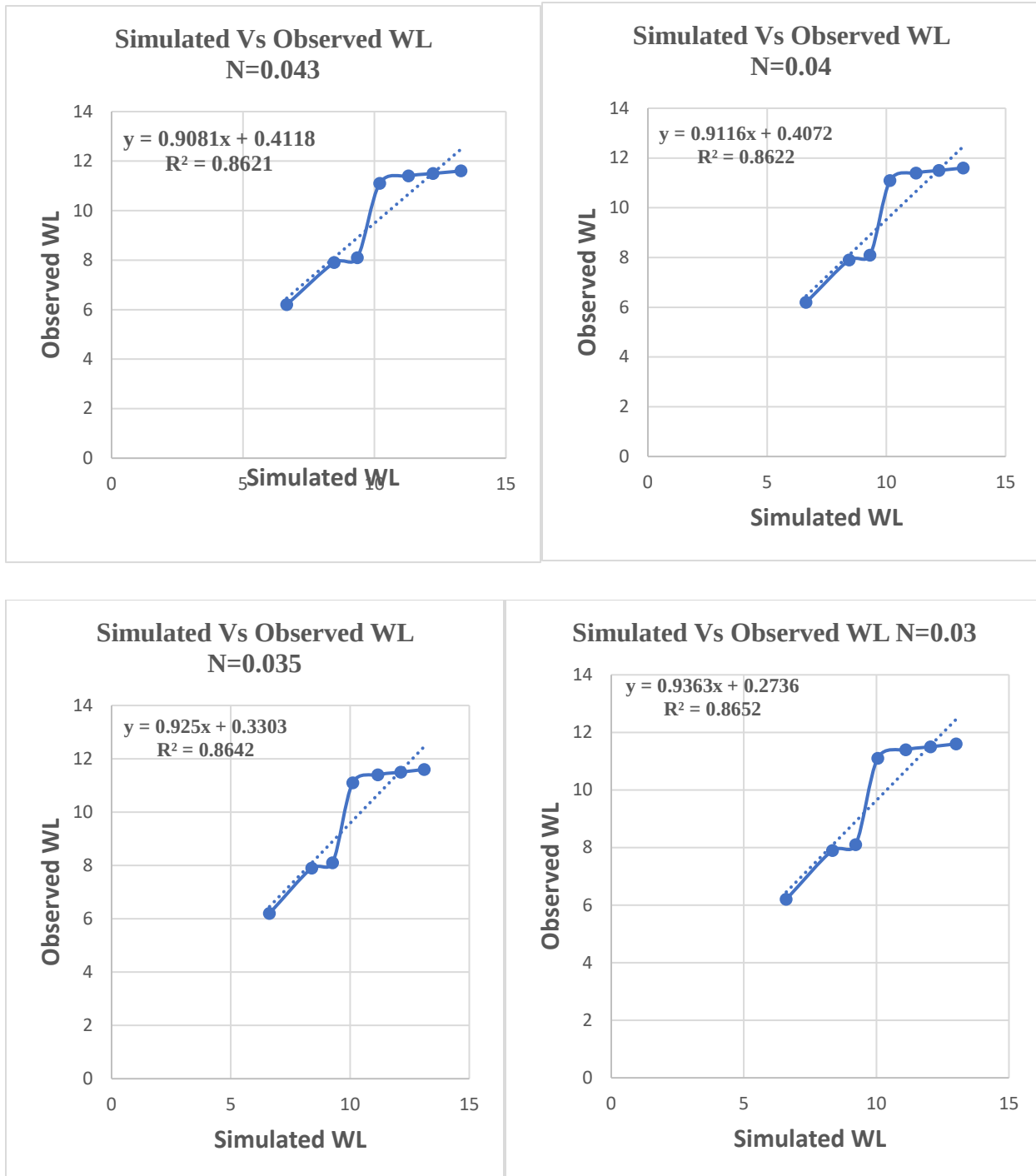
Return period	WL Observed	QT	Min Cha El (m)	W.S Elev (m)	WL (Simulated)
2	6.2	258.4	355.71	362.35	6.64
5	7.9	776.6	355.71	364.15	8.44
10	8.1	1263	355.71	365.03	9.32
20	11.1	1896.9	355.71	365.87	10.16
50	11.4	3106.5	355.71	366.96	11.25
100	11.5	4472.4	355.71	367.92	12.21
200	11.6	6458.7	355.71	368.94	13.23
Quantile Water level for Omorate River station 123031.4 for n = 0.035					
Observed			Simulated		
Return period	WL Observed	QT	Min Cha El (m)	W.S Elev (m)	WL (Simulated)
2	6.2	258.4	355.71	362.33	6.62
5	7.9	776.6	355.71	364.1	8.39
10	8.1	1263	355.71	364.98	9.27
20	11.1	1896.9	355.71	365.82	10.11
50	11.4	3106.5	355.71	366.88	11.17
100	11.5	4472.4	355.71	367.84	12.13
200	11.6	6458.7	355.71	368.82	13.11
Quantile Water level for Omorate River station 123031.4 for n = 0.03					
Observed			Simulated		
Return period	WL Observed	QT	Min Cha El (m)	W.S Elev (m)	WL (Simulated)
2	6.2	258.4	355.71	362.31	6.6
5	7.9	776.6	355.71	364.05	8.34
10	8.1	1263	355.71	364.93	9.22
20	11.1	1896.9	355.71	365.76	10.05
50	11.4	3106.5	355.71	366.82	11.11
100	11.5	4472.4	355.71	367.75	12.04
200	11.6	6458.7	355.71	368.72	13.01

Appendix C: Omorate Station Output Profile Generated From HEC-RAS

Profile Output Table - Standard Table 1												
File Options Std. Tables Locations Help												
HEC-RAS Plan: 01 River: Omo Main River Reach: Omorate Reach												Reload Data
Reach	River Sta	Profile	Q Total (m3/s)	Min Ch El (m)	W.S. Elev (m)	Crit W.S. (m)	E.G. Elev (m)	E.G. Slope (m/m)	Vel Chnl (m/s)	Flow Area (m2)	Top Width (m)	Froude # Chl
Omorate Reach	132874.0	50 Yr	3106.50	362.75	367.93		367.98	0.000254	0.97	3606.12	1106.30	0.20
Omorate Reach	132874.0	100	4472.40	362.75	368.83		368.89	0.000251	1.18	4641.45	1180.05	0.21
Omorate Reach	132874.0	200 Yr	6458.70	362.75	369.80		369.88	0.000263	1.43	5805.28	1200.00	0.22
Omorate Reach	127952.7	2 Yr	258.40	361.96	362.98	362.98	363.33	0.014007	2.99	110.79	166.34	1.18
Omorate Reach	127952.7	5 Yr	776.60	361.96	364.43		364.67	0.002558	2.55	458.34	420.49	0.60
Omorate Reach	127952.7	10 Yr	1263.00	361.96	365.48		365.59	0.001144	1.95	1193.98	1015.00	0.41
Omorate Reach	127952.7	20 Yr	1896.90	361.96	366.37		366.43	0.000578	1.49	2190.45	1181.31	0.30
Omorate Reach	127952.7	50 Yr	3106.50	361.96	367.46		367.52	0.000353	1.48	3490.46	1200.00	0.25
Omorate Reach	127952.7	100	4472.40	361.96	368.41		368.47	0.000292	1.57	4626.14	1200.00	0.23
Omorate Reach	127952.7	200 Yr	6458.70	361.96	369.37		369.45	0.000294	1.79	5778.70	1200.00	0.24
Omorate Reach	123031.4	2 Yr	258.40	355.71	362.31		362.32	0.000044	0.58	469.35	149.38	0.09
Omorate Reach	123031.4	5 Yr	776.60	355.71	364.05		364.12	0.000122	1.16	803.20	344.36	0.16
Omorate Reach	123031.4	10 Yr	1263.00	355.71	364.93		365.03	0.000181	1.51	1173.68	470.52	0.19
Omorate Reach	123031.4	20 Yr	1896.90	355.71	365.76		365.90	0.000233	1.81	1613.55	564.14	0.22
Omorate Reach	123031.4	50 Yr	3106.50	355.71	366.82		367.01	0.000309	2.23	2364.42	804.12	0.26
Omorate Reach	123031.4	100	4472.40	355.71	367.75		367.92	0.000443	2.27	3334.83	1155.81	0.30
Omorate Reach	123031.4	200 Yr	6458.70	355.71	368.72		368.89	0.000467	2.33	4483.34	1200.00	0.31
Omorate Reach	118110.2	2 Yr	258.40	357.66	362.25		362.26	0.000041	0.40	951.47	466.47	0.08
Omorate Reach	118110.2	5 Yr	776.60	357.66	363.96		363.97	0.000061	0.62	1860.06	591.40	0.10
Omorate Reach	118110.2	10 Yr	1263.00	357.66	364.81		364.83	0.000082	0.77	2388.66	653.99	0.12
Omorate Reach	118110.2	20 Yr	1896.90	357.66	365.61		365.64	0.000106	0.93	2940.87	725.53	0.14
Omorate Reach	118110.2	50 Yr	3106.50	357.66	366.59		366.64	0.000156	1.22	3755.50	896.55	0.17
Omorate Reach	118110.2	100	4472.40	357.66	367.38		367.45	0.000204	1.52	4505.26	1015.53	0.20
Omorate Reach	118110.2	200 Yr	6458.70	357.66	368.23		368.34	0.000266	1.90	5411.89	1105.38	0.24
Omorate Reach	113188.9	2 Yr	258.40	359.05	361.36	361.36	361.98	0.007275	3.71	78.39	60.14	0.97
Omorate Reach	113188.9	5 Yr	776.60	359.05	362.74	362.74	363.59	0.007956	4.28	196.42	121.31	1.04
Omorate Reach	113188.9	10 Yr	1263.00	359.05	363.54	363.54	364.36	0.006543	4.36	338.70	227.84	0.97
Omorate Reach	113188.9	20 Yr	1896.90	359.05	364.25	364.25	365.08	0.005530	4.54	541.24	386.98	0.92
Omorate Reach	113188.9	50 Yr	3106.50	359.05	364.82	364.82	365.85	0.008264	5.20	794.83	512.35	1.11
Omorate Reach	113188.9	100	4472.40	359.05	365.66	365.66	366.56	0.005217	5.10	1368.73	867.78	0.93

Critical water surface elevation. Water surface corresponding to the minimum energy on the energy versus depth curve.

Appendix D: Observed Vs simulated WL for Omorate Station 123031.4 from different Manning's Roughness coefficients.



Appendix E: Flood Hazard Affected Woredas in different return periods.

Affected Area	Return Periods							
	2 Year				5 Year			
	Low	Medium	High	Extreme	Low	Medium	High	Extreme
Decha	181.8429	198.0218	121.3071	287.809	227.12	255.95	175.03	337.80
Dizi	522.61	461.57	383.06	1047.86	786.25	786.72	528.42	851.94
Ela	10.76	12.33	11.86	39.97	14.56	14.96	13.94	48.31
Hamer Bena	935.08	997.84	799.01	758.96	1282.82	1255.86	1112.50	822.91
Kuraz	2220.07	2119.50	1203.20	1367.65	3244.40	3062.12	2289.05	1879.06
Meinit	17.79255	13.92014	9.025111	17.96999	29.39213	22.72746	11.54002	21.33207
Melekozza	28.64318	36.08953	31.29927	89.51398	36.84688	39.5721	38.95621	80.88601
Silamago	531.107	602.8572	475.7351	949.5957	703.6769	755.9425	625.9134	856.8776
Affected Area	Return Periods							
	2 Year				5 Year			
	Low	Medium	High	Extreme	Low	Medium	High	Extreme
Decha	181.8429	198.0218	121.3071	287.809	227.12	255.95	175.03	337.80
Dizi	522.61	461.57	383.06	1047.86	786.25	786.72	528.42	851.94
Ela	10.76	12.33	11.86	39.97	14.56	14.96	13.94	48.31
Hamer Bena	935.08	997.84	799.01	758.96	1282.82	1255.86	1112.50	822.91
Kuraz	2220.07	2119.50	1203.20	1367.65	3244.40	3062.12	2289.05	1879.06
Meinit	17.79255	13.92014	9.025111	17.96999	29.39213	22.72746	11.54002	21.33207
Melekozza	28.64318	36.08953	31.29927	89.51398	36.84688	39.5721	38.95621	80.88601
Silamago	531.107	602.8572	475.7351	949.5957	703.6769	755.9425	625.9134	856.8776
Affected Area	Return Periods							
	10 Yr				20 Yr			
	Low	Medium	High	Extreme	Low	Medium	High	Extreme
Decha	226.3971	278.4899	203.5677	308.1149	226.1004	286.6321	227.0705	388.5396
Dizi	778.2076	886.9906	640.4452	905.3084	765.9188	930.6558	711.6787	1745.975
Ela	15.0324	15.97552	15.31237	51.06113	16.00846	17.07528	15.08204	52.98205
Hamer Bena	1356.549	1423.694	1225.019	1898.98	1357.858	1561.871	1306.147	2243.841
Kuraz	3484.113	3538.616	2894.942	3215.385	3399.205	3949	3237.683	4303.261
Meinit	34.11302	27.46614	13.31637	22.59012	34.7676	28.99987	16.54509	23.72351
Melekozza	38.48699	40.70071	42.18804	88.65922	38.39324	42.56852	41.52021	92.98815
Silamago	711.4948	822.1442	700.1327	921.2071	710.2015	849.8096	716.5729	1344.347
Affected Area	Return Periods							
	50 Yr				100 Yr			

	Low	Medium	High	Extreme	Low	Medium	High	Extreme
Decha	269.9954	313.8663	234.333	323.1162	292.9573	325.1593	243.9714	334.1953
Dizi	884.808	1021.864	766.9198	1411.705	978.1861	1011.363	837.0934	1475.861
Ela	19.40185	19.44909	15.79041	54.09714	22.46541	19.11079	17.07447	55.61905
Hamer Bena	1489.507	1764.594	1490.899	2855.16	1495.441	1717.433	1648.967	2990.439
Kuraz	3554.458	4389.496	3736.388	5266.334	3105.869	4415.463	4068.784	6583.165
Meinit	42.80732	35.57178	16.91038	24.75951	49.82617	37.97194	18.58362	25.63005
Melekozza	42.11346	47.77722	42.69246	98.35867	43.05655	49.58913	44.09602	102.6512
Silamago	815.3522	942.0686	745.8429	1386.763	860.8296	955.7386	785.8088	1444.034
Affected Area	Return Periods							
	200 Yr							
	Low	Medium	High	Extreme				
Decha	322.7958	348.124	259.9477	320.3813				
Dizi	1031.2	1104.602	897.5964	1452.042				
Ela	23.08229	21.70245	18.27098	55.28645				
Hamer Bena	1377.378	1811.457	1776.782	3358.622				
Kuraz	2455.833	4366.859	4486.864	5933.739				
Meinit	56.93846	41.83456	19.64734	25.00524				
Melekozza	44.57609	53.59292	47.68056	101.7585				
Silamago	915.1188	1020.573	844.6071	1415.271				

Appendix F: Vulnerable Land use Land Cover.

Affected Areas	2Year						
	Bare ground	Built Area	Crops	Rangeland	Trees	vegetation	Water
Decha	0.224915		0.068296	70.97349	284.335	56.29127	398.8832
Dizi	8.403965		7.859546	314.801	1067.3		1485.009
Ela				11.0751		70.77633	
Hamer Bena	5.954955	1.100539	25.26847	989.7216	1731.498	0.545493	1210.08
Kuraz	8.384188	26.81849	817.5606	2103.87	1798.226	1.055298	2489.97
Meinit			4.342163	3.889296	24.16384		29.64138
Melekozza				12.25056	64.09044		136.0113

Silamago	3.026035		16.5089 8	420.6823	1122.34 9	23.36085	1256.86 5
Affected Areas	5 Year						
	Bare ground	Built Area	Crops	Rangelan d	Trees	vegetatio n	Water
Decha	0.417617		0.19928 8	118.989	409.246 9	61.89189	425.285 2
Dizi	8.403966		13.3491 4	658.7472	1666.18 3		1578.50 4
Ela				0.037271	19.7665 9		79.4536 4
Hamer Bena	7.104217	1.83451 7	46.0340 4	1415.003	2766.35 7	1.034673	1315.39
Kuraz	10.74245	68.9723 6	1256.44 7	3582	3529.39 5	1.528284	2865.19 1
Meinit			10.7366 2	6.798908	39.2434		31.3879 8
Melekozza				19.4966	86.7826		143.378
Silamago	3.026034		43.0116 1	616.6371	1587.80 7	23.64796	1319.58 5
Affected Areas	10 Year						
	Bare ground	Built Area	Crops	Rangelan d	Trees	vegetatio n	Water
Decha	0.567227		0.23533 3	139.1773	456.987 2	63.58078	432.403 5
Dizi	8.403966		19.5568	757.1444	1879.19 3		1603.15 3
Ela				0.086198	23.6430 3		82.0007 9
Hamer Bena	7.139883	2.38458 4	62.0856 7	1617.522	3245.63	1.767985	1351.93 6
Kuraz	12.65977	98.8632 5	1534.85 1	4181.534	4543.21 8	1.629875	3014.86 6
Meinit			13.4906 5	9.263317	46.4430 3		32.4123 2
Melekozza				23.18114	96.6748		146.517 8
Silamago	3.026034		55.3493 8	694.5259	1756.13 6	23.67485	1335.55 5
Affected Areas	20 Year						
	Bare ground	Built Area	Crops	Rangelan d	Trees	vegetatio n	Water
Decha	0.632894		0.28765 2	159.6302	495.123 3	64.16631	437.081 3

Dizi	8.403966		29.0396 4	833.9865	2054.45 6		1620.05 8
Ela				0.188497	27.5457 5		84.0152 1
Hamer Bena	7.139884	3.45418 9	79.4023 6	1808.277	3688.09 1	2.207846	1380.26 5
Kuraz	14.29245	126.144 1	1766.97	4680.584	5502.82 1	1.77828	3133.37 7
Meinit			16.3457 7	10.6123	49.5404		32.8581 2
Melekozza				26.20118	104.434 2		148.869 2
Silamago	3.026034		72.4801 2	751.6005	1889.55 4	23.70141	1347.42 8
Affected Areas	50 Year						
	Bare ground	Built Area	Crops	Rangelan d	Trees	vegetatio n	Water
Decha	0.815289		0.31463 3	179.6501	545.725 7	64.39933	443.196 2
Dizi	8.403965		44.0633 6	928.3667	2249.98 8	0.0051	1636.58 2
Ela				0.379334	32.8448 5		86.1094 9
Hamer Bena	7.139884	4.93700 3	99.2806 2	2052.593	4259.25 4	3.047211	1407.22 8
Kuraz	17.4537	146.281 3	1982.68 4	5204.658	6739.36 1	2.905696	3235.18 4
Meinit			21.7322 9	13.47705	56.3462 1		33.6574
Melekozza				30.53685	112.852 1		151.203 2
Silamago	3.026035		93.6952 3	821.895	2044.28 9	23.7305	1357.93 7
Affected Areas	100Year						
	Bare ground	Built Area	Crops	Rangelan d	Trees	vegetatio n	Water
Decha	0.87044		0.34176 8	199.5983	575.228 5	64.5551	446.704 3
Dizi	8.40397		62.4155 2	999.5465	2382.19 8	0.03	1646.31 6
Ela				0.618824	36.8188 9		87.3660 3
Hamer Bena	7.139882	5.49804 1	110.936 1	2231.302	4702.28 4	3.239545	1419.44 6

Kuraz	19.38095	156.213 4	2087.36 2	5483.024	7585.51 1	3.399808	3283.84 5
Meinit			27.2714 2	15.52362	60.2417 5		34.1091 1
Melekozza				33.344	118.458 2		152.134
Silamago	3.02603		111.182 4	864.9452	2140.59 1	23.74631	1363.81 6
Affected Areas	200 Year						
	Bare ground	Built Area	Crops	Rangelan d	Trees	vegetatio n	Water
Decha	0.921356		0.35525 6	215.1207	605.532 2	64.64883	450.044 9
Dizi	8.403967		84.2439 7	1052.058	2480.40 5	0.03	1654.43 9
Ela				0.812636	39.7721 1		88.3055 9
Hamer Bena	7.139883	6.20285 8	115.498 5	2387.305	5107.03 4	3.337564	1426.44 5
Kuraz	21.69559	162.798 7	2161.29 3	5708.15	8203.51 2	4.777508	3315.24 1
Meinit			32.824	17.36254	63.1178 9		34.3931 5
Melekozza				36.20534	123.541		152.939 5
Silamago	3.026033		132.596 3	909.3927	2215.22 3	23.79739	1368.13 8

Appendix G: Flood inundation Area coverage in different woredas for different return periods

