Institute for Water and Energy Sciences (incl. Climate Change)

PAN AFRICAN UNIVERSITY INSTITUTE OF WATER AND ENERGY SCIENCES (Including CLIMATE CHANGE)

# Modelling the Impact of Climate Change on Flood Hazard in Rift Valley Basin of Ethiopia

**Climate Change Engineering Track**

**Dawit Kanito KASSA (BSc. Natural Resources Management)**

**March 2024**

**Tlemcen, Algeria**

**PAN AFRICAN UNIVERSITY INSTITUTE OF WATER AND ENERGY SCIENCES (Including CLIMATE CHANGE)**

# Modelling the Impact of Climate Change on Flood Hazard in Rift Valley Basin of Ethiopia

**A thesis submitted to Pan African University in partial fulfillment of the requirements for the degree of Master of Science in Climate Change Engineering**

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**March 22, 2024**

**Tlemcen, Algeria**

CERTIFICATION

I, as the supervisor, wholeheartedly approve the submission of Dawit Kanito's thesis. I state that this work is the original creation of the student and was conducted under my supervision.

Signature  Date March 14, 2024

Prof. Amos T. Kabo-bah

Senior Lecturer/Head of department

Civil and Environmental Engineering

University of Energy and Natural Resources (UENR)

# DEDICATION

It is with sincere gratitude and warm regard that I dedicate this Thesis to all my beloved family members (KaKa's) and my precious wife Helen Baruda.

# STATEMENT OF AUTHOR

By my signature below, I declare that this thesis is my work. I have followed all ethical principles of scholarship in the preparation, data collection, data analysis, and completion of this thesis. I have given all scholarly matter recognition through accurate citations and references. I affirm that I have cited and referenced all sources used in this document. I have made every effort to avoid plagiarism. I submit this document in partial fulfillment of the requirement for a degree from Pan African University. This document is available from the PAU Library to borrowers under the rules of the library. I declare that I have not submitted this document to any other institution for the award of an academic degree, diploma, or certificate. Scholars may use brief quotations from this thesis without special permission if they make an accurate and complete acknowledgment of the source. The dean of the academic unit may grant permission for extended quotations or reproduction of this document. In all other instances, however, the author must grant permission.

Name: Dawit Kanito KASSA Signature:

Date: March 22, 2024

PAU Institute: Pan Africa University Institute of Water and Energy Science (including Climate Change)

# BIOGRAPHICAL SKETCH

The author was born on September 25, 1994, in Addis Ababa, Ethiopia, from his father Kanito Kassa and his mother Mestawet Tsanga. He attended Selamber Elementary and Primary School in Addis Ababa from 2001 to 2004 for his elementary education, followed by Ezo Primary and Secondary School in Ezo from 2005 to 2010 for his junior and secondary education. He successfully completed his preparatory school education at Chencha Secondary and Preparatory School from 2011 to 2012. In 2013, he joined Wachemo University and graduated in 2015 with a BSc degree in Natural Resources Management.

After his graduation, he was employed in the Chencha District Agricultural Office in the Gamo Zone, where he served as a food security officer from August 2015 to May 2016. In May 2016, he joined Areka Agricultural Research Center (AARC) under the Southern Agricultural Research Institute (SARI) as a junior soil and water conservation researcher. Subsequently, in 2019, he joined Haramaya University to pursue his MSc in Soil Sciences and successfully graduated in February 2022. Finally, he joined the Pan Africa University Institute of Water and Energy Science (including Climate Change) in June 2022 to pursue his second Master's degree in Climate Change Engineering.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank God, the Almighty, who has granted me uncountable blessings, knowledge, strength, and guidance in writing this Thesis. Without him, I would not have had the wisdom or the physical ability to accomplish the Thesis. My sincerest thanks are extended to my advisor Prof Amos T-Kabo Bah for his guidance, encouragement, support, and constructive comments during proposal development, research work, and in improving the quality of this Thesis.

I am grateful for the support and funding provided by the African Union for this research and throughout the academic year. I would also like to express my appreciation to the staff at PAUWES for their assistance and for creating an enriching learning environment.

My thanks are due to my family for their unwavering encouragement and moral support throughout the challenging journey I have undertaken. I extend my heartfelt thanks to Kanito Kassa and Mestawot Tsanga, who have nurtured and guided me along every path I have taken, enabling me to reach this level of accomplishment. I am also immensely thankful to my cherished wife and friends for their constant encouragement, valuable advice, and wholehearted support in countless ways.

# ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| AHP | Analytic Hierarchy Process |
| CCA | Climate Change Adaptation |
| CDFs | Cumulative Distribution Functions |
| CI | Consistency Index |
| CMIP | Coupled Model Intercomparison Project |
| CR | Consistency Ratio |
| DEM | Digital Elevation Model |
| DR | Distance from River |
| DRR | Disaster Risk Reduction |
| EMI | Ethiopian Meteorology Institute |
| FGD | Focus Group Discussion |
| GCMs | Global Climate Models |
| GCP | Ground Control Points |
| GIS | Geographic Information System |
| GPS | Ground Positioning System |
| IPCC | Intergovernmental Panel on Climate Change |
| LULC | Land Use Land Cover |
| MADM | Multi-Attribute Decision-Making |
| MCDM | Multi-Criteria Decision Making |
| MOWIEE | Ministry of Water Irrigation and Energy of Ethiopia |
| PCM | Pair-wise Comparison Method |
| PGIS | Participatory Geographical Information System |
| RCPs | Representative Concentration Pathways |
| RS | Remote Sensing |
| SAGA | System for Automated Scientific Analysis |
| SRTM | Shuttle Radar Topographic Mission |
| SSP | Shared Socioeconomic Pathways |
| TRI | Topographic Roughness Index |
| TWI | Topographic Wetness Index |
| USGS | United States Geological Survey |

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ABSTRACT

The increase of climate change-induced events, such as flooding, has intensified, particularly impacting developing countries over the last few decades. It is essential to develop flood hazard maps to identify and protect vulnerable regions. This will also help establish early warnings system execute both structural and non-structural measures effectively. The study area is the Rift Valley basin of Ethiopia, which has experienced 11 out of 15 recorded flood events in the past. The aim is to forecast the impacts of climate change on flooding, considering both present and future climate scenarios. Through the participatory approach by engaging stakeholders, this study evaluates the reliability of conventional flood risk assessment approaches. Primary and secondary datasets were acquired through field visits and from both non-governmental and governmental organizations. To achieve the objectives of the study, eight flood risk indicators namely, rainfall, DR, land elevation, slope, TRI, TWI, LULC, and soil type were chosen. Two climate scenarios namely SSP245 and SSP585 were used to project the near and far future rainfall based on CMIP6. The study makes use of three standout climate models namely, NoRESM2, CNRM-ESM2-1, and CanESM5. The AHP model and PGIS were used for relative importance analysis, including affected communities from Bilate, Kulfo Gina, Sile-sego, and Lake Hassa sub-basins. The finding revealed that in 2060, both SSP245 and SSP585 scenarios show an increasing trend in high and very high flood-risk areas, with SSP585 indicating a more considerable rise. By 2100, the spatial distribution of very high and high class concentrates in the northern and central parts, emphasizing greater risk under SSP585. Comparison with the baseline period reveals a spatiotemporal change, suggesting climate change's potential contribution to increased flood likelihood and extent in the Rift Valley basin.

**Key words**; Climate modelling, CMIP6, SSP, Near and far future, Flood susceptibility, PGIS, AHP

# 1. INTRODUCTION

Climate change is one of the most significant contemporary challenges to the world (Malhi et al., 2021). The past few decades show that substantial changes in climate at a global level were attributed to heightened anthropogenic activities that changed the composition of Earth's atmosphere on a global scale (Mackay, 2008). This transformation results from the rising level of greenhouse gases in the atmosphere. Pachauri et al. (2014), reported that the concentration of greenhouse gases such as methane ($CH_4$), nitrous oxide ($N_2O$), and carbon dioxide ($CO_2$), have increased by 150%, 20%, and 40%, respectively since the pre-industrial period. Recent researches carried out the Intergovernmental Panel on Climate Change (IPCC) and other scholars projected that climate change and extremes are going to increase in the upcoming future (IPCC, 2023; Krishnan et al., 2020; Lee et al., 2021). Hence, it is imperative to anticipate climate change-related hazards to provide early warning information and enhance preparedness.

The adverse impact of climate change is recognized on various hydrological variables such as evapotranspiration, infiltration, and surface runoff (Nilawar & Waikar, 2019). Research in the domain of climate change points to rising temperatures and increased precipitation (in terms of intensity and duration) as factors contributing to more frequent occurrences of severe floods and prolonged droughts (IPCC, 2018; Nabaei et al., 2019; Xiao et al., 2018). This suggests that climate change may lead to increased frequency, magnitude, and seasonality of flooding, making concurrent flood hazards more common in the future (Huong & Pathirana, 2013; Duan et al., 2015). Besides, flooding is triggered by the nature of topography, river flow, antecedent conditions, weak infrastructure, soil conditions, and land use change, lack of flood response plan, insufficient policy implementation and other manmade and natural factors (Bates et al., 2008).

In recent years, climate change has significantly influenced the entire globe, and there is a growing acceptance that extreme weather-induced hazards and occurrences are becoming the new norm (Chen et al., 2022). Among these hazards, floods stand out as one of the most destructive natural disasters, comprising approximately 33.3% of all global hazards (Adhikari et al., 2010; Smith & Ward, 1998). Floods result in various human and environmental consequences, resulting in human causalities, damage to the environment, property, and infrastructure (Bishaw, 2012; Mamo et al., 2019; Tsakiris, 2014). Uncontrolled floods lead to the inundation of water, causing damage to both infrastructure and agricultural lands. Floods pose a serious threat to human well-being and exert negative impacts on global socioeconomic development (Maskong, 2019; Tanoue et al., 2016). However, its effect extends beyond the socioeconomic sphere in developing countries. A recent research conducted by Alderman et al. (2012) highlighted flooding effect on community health, with epidemiological indication of diseases outbreaks due to extreme events such as post-traumatic and epidemics (physical and mental). Previous studies also demonstrated that floods occurs with varying frequency across various geographical areas, which clearly related to the catchment characteristics and local climate and its impact in the future is expected to rise (Berghuijs et al., 2017; Duan et al., 2017; Smith et al., 2015; Tanoue et al., 2016). According to existing literature, floods pose a significant threat across all African regions. It constitutes a major natural hazard in Africa, resulting in more than 27,000 fatalities between 1950 and 2019 (Azzarri & Signorelli, 2020; Tramblay et al., 2020).

Ethiopia, despite falling within the tropics, continues to experience frequent flood records, leading to casualties and damage to infrastructure and the environment. These events happens at unpredictable intervals and display variations in frequency, duration, magnitude, and affected areas (Mamo et al., 2019). Since 1900, Ethiopia has encountered 47 significant flood events, impacting nearly 2.2 million people (You & Ringler, 2010). The study conducted by Mamo et al (2019) indicated that frequency of floods in the country has risen from one decade to another, notably during the 2001-2010 decade is marked as the decade with the highest frequency of flooding, five out of ten years experienced flooding, closely followed by the 1991-2000.

The spatial pattern of flood occurrences across the 12 main river basins in Ethiopia reveals that out of 15 flood events Awash basin has experienced 13. It is followed by Genale Daa, Rift Valley and Wabishebele with 11, 11, and 12 flood events respectively. According to reports, the Rift Valley basin experiences severe flooding due to heavy rainfall and its topographical characteristics have resulted in many impacts. Previous research conducted in the study area revealed a changing climate particularly torrential rainfall triggering elevated runoff in the wet season leads to the inundation of low-lying areas. Moreover, river flow projections for future periods showed a potential increase in mean monthly river flow (Mamo et al., 2019). This is likely to cause an increase in the magnitude and occurrence of flood in the basin. Therefore, given the pressing need to address the effect of flooding and recognizing the significance of identifying flood prone areas for evidence-based mitigation strategies, it becomes imperative to develop flood risk map for the affected area.

Furthermore, projecting flooding for future is crucial to understand the potential impacts and develop effective mitigation strategies (Pour et al., 2020). Particularly, in recent ever increasing climate change, it is imperative to anticipate flood occurrence for the future. Since this research is critically taking into account the social aspect of affected regions, Shared Socioeconomic Pathways (SSP) was found to be a valuable tool for projecting future climate scenario (O'Neill et al., 2014). These models consider different socio-economic development scenarios and provide insights into potential changes in future temperature, precipitation and extreme weather events. For Rift Valley basin, employing the SSP model allows for a forward-looking approach since the basin under this study lack intensive flood assessment for future using PGIS and conventional method. Therefore, the primary aim of this study was to identify and project flood-prone areas within the study area to provide early warning information.

To assess flood risk, numerous models and methods have been developed by different researchers at various points in time and are currently in use globally. Recently, the prevalent approach for studying flood risk incorporates the integration of space-based technologies such as GIS and RS in conjunction with other methods and models. Among other models and methods, Multi-criteria decision-making (MCDM) has become prominent approach for evaluating complex decision problems, especially those characterized by incomparable criteria or data such as identifying and mapping of flood-prone zones based on multiple contributing factors (Abdelkarim et al., 2020; Allafta & Opp, 2021). Besides, efforts are being made to integrate GIS with participatory techniques, and has gained widespread recognition for its efficacy in participatory decision-making processes and MCDM. Participatory GIS (PGIS) underscores the significance of local experiences and emphasizes a greater focus on pre-flood phases; prevention, preparedness, and mitigation, which prompted the assessment of vulnerabilities leading to floods. The increasing trend of merging participatory methods with GIS underscores the fact that no single approach adequately addresses the evolving information requirements of society. Their integration serves to validate the research process, resulting in a more resilient and comprehensive outcome. However, there has been relatively limited exploration of the usefulness of PGIS, particularly in the context of evaluating the flood risk (Chingombe et al., 2015).

In Ethiopia, various research endeavors have also compared the use of GIS with MCDM for the assessment of present and prospective flood risks. Because of its simplicity in integrating with the rapid emerging GIS and RS technologies, it has significantly advanced hydrological research, including flood assessment and management (Correia et al., 1999). Many models and techniques have since been put forth for MCDM; yet, the Analytic Hierarchy Process (AHP), developed by (Saaty, 1980), is one of the most well-known and frequently applied MCA techniques (Das & Gupta, 2021; Orencio & Fujii, 2013). The AHP method functions on the assumption of complete aggregation across multiple criteria that result in the creation of a linear additive model. Because it can handle uncertainty while maintaining the harmony between subjective and objective evaluation measures, AHP is unique among research methods (Danumah et al., 2016). Therefore, in this study integration of PGIS and RS with analytical hierarchical process is employed to achieve the objectives of the study.

## 1.1. Objectives

### 1.1.1. Main Objective

The overall objective of this research is to model the impact of climate change on flooding under current and future climate scenarios for the Rift Valley basin of Ethiopia.

### 1.1.1. Specific Objectives

2. To develop a flood hazard map for the baseline period in the Rift Valley basin for aiding in the planning and implementation of both structural and non-structural measures.
3. To project a flood hazard map for the near and far future to provide early warning information for the stakeholders
4. To assess the accuracy of conventional flood risk assessment methodologies through stakeholder engagement thereby enhancing the reliability of flood risk management strategies.

### 1.2. Research Questions

This research was directed by the following questions to achieve the objectives.

1. What are the spatiotemporal patterns of flood hazard in the study area under current climate conditions and its expected change under the SSP near and far future climate scenarios?
2. Which areas within the Rift Valley basin are at the highest risk of flooding, both presently and in the future climate scenario under SSP245 and SSP585?
3. How can community engagement and local knowledge be utilized to validate flood hazards within the study area?

### 1.3. Significance of the Study

Climate change poses a critical global challenge, with human activities altering Earth's atmosphere through increased greenhouse gases. This leads to more frequent floods and prolonged droughts, necessitating early warning systems. Ethiopia, despite its tropical location, faces recurring floods. The Rift Valley basin is particularly vulnerable, with substantial damage and displacement. This study identified flood-prone areas within the basin, emphasizing the crucial role of flood mapping in identifying flood-prone areas and planning flood mitigation. It aligns with global flood mitigation efforts using GIS, RS, and MCDM, specifically AHP.

### 1.4. Problem Statement

The problem centers on the ever-increasing flood risks within the Rift Valey basin. The risks are worsened by the impact of climate change, which leads to severe flooding. It has caused in loss of life, damage to infrastructures, and significantly impacted the environmental. Despite the evident risks, the Rift Valley basin still lack a comprehensive and community-engaged flood risk assessment in as a result the community is left unprepared to deal with these escalating threats. Therefore, the pressing problem lies in the inadequacy of compressive flood risk map that delays the development of adaptation strategies and preparing for potential climate change induced flooding.

# 2. LITERATURE REVIEW

## 2.1. Overview of Climate Change

According to IPCC (2007), climate change is defined as alterations in the climate's state, detectable through statistical tests, involving shifts in its mean and/or variability. These changes typically persist for extended periods, often spanning decades or more. Climate change is different from the generally known terms like climatic fluctuations or climatic variability. It results from two fundamental contributors: natural processes, encompassing astronomical and extraterrestrial factors influenced by variations in the Sun's energy (Parikh & Parikh, 2002). On the other hand, the human-induced element of climate change stems from activities that either emit large amounts of greenhouse gases into the atmosphere, contributing to ozone layer depletion, or actions that reduce the amount of absorption of carbon from the atmosphere (Baldwin & Lenton, 2020; Burrell et al., 2020; Zheng et al., 2021).

Human activities responsible for significant greenhouse gas emissions include fossil fuel combustion, industrialization, agriculture, gas flaring and urbanization (Raihan & Tuspekova, 2022; Wadanambi et al., 2020). Conversely, actions that reduce carbon sinks involve deforestation, agricultural practices, alterations in land usage and water pollution. These human-related factors have been proven to be responsible for the ongoing and unequivocal global warming and climate change. The escalation in ambient temperatures and associated processes directly correlates with the mounting concentrations of anthropogenic greenhouse gases in the atmosphere (IPCC, 2007). While no region across the globe will remain untouched, the adverse negative impacts are anticipated to disproportionately affect poor nations in the tropical region. Available evidence indicates that while climate change will be global, its harshest effects will be felt more by developing countries, particularly those in Africa, due to their limited coping capacities (Jagtap, 2007). The following main causes of climate change are;

### 2.1.1. Greenhouse Gases and Greenhouse Effect

The greenhouse effect serves as a warming process that counterbalances Earth's cooling process (Clancy et al., 2007). During this natural process, incoming sunlight enters Earth's atmosphere as short-wave radiation and is absorbed by the planet's surface. As the Earth's surface warms, it releases long-wave radiation into the atmosphere. Within the atmosphere, specific gases known as greenhouse gases absorb a portion of this long-wave radiation (Xu & Cui, 2021). Greenhouse gases include carbon dioxide ($CO_2$), methane ($CH_4$) chlorofluorocarbons (CFCs), and nitrous oxide ($N_2$) among others (IPCC, 2023; Lee et al., 2021). Every molecule of greenhouse gas absorbs energy from the long-wave radiation, becoming energized. Subsequently, these energized gas molecules release heat energy in various directions. Through the emission of heat energy toward the earth, greenhouse gases contribute to an increase in the Earth's temperature. While carbon dioxide ($CO_2$) is the most abundant greenhouse gas, its warming potential is relatively modest. For instance, a gram of methane ($CH_4$) has an impact approximately 23 times greater than the equivalent volume of $CO_2$, and a gram of sulfur hexafluoride ($SF_6$) released into the atmosphere is roughly 22,000 times more impactful than $CO_2$ in terms of tropospheric ozone depletion. The duration of $CO_2$ in the atmosphere varies, but noticeably less than ten years, while that of $N_2O$, $SF_6$, CFCs and $CH_4$ 120, 3200, 50-1700, and 12.2 years respectively. This implies that whereas a $CO_2$ molecule may affect stratospheric ozone for a limited duration, other greenhouse gases have the potential to cause damage to the ozone layer over a much longer timeframe, ranging from decades to thousands of years.

### 2.1.2. Black Carbon and Sulfate Aerosol

Black carbon and sulfate aerosol are two important examples of human-induced forcing. Black carbon is soot generated from the burning of coal, industrial pollution, biomass fuels, outdoor fires, and traffic. Soot particles absorb sunlight, warming the air and diminishing the sunlight that reaches the ground (Sims et al., 2003). Sulfate aerosols, naturally released into the atmosphere during volcanic eruptions, are minuscule airborne particles that reflect sunlight away from the Earth. These sulfate aerosols, stemming from volcanic activity, persist for 1 to 3 years in the stratosphere, where they scatter sunlight. This leads to an overall negative radiative forcing at the top-of-the-atmosphere (TOA) and subsequent surface cooling. Recent industrial activities have increased their presence in the atmosphere, primarily due to the combustion of sulfur-containing fossil fuels (Zhong et al., 2020). The anthropogenic emission of sulfate aerosols has been associated with an overall cooling impact.

## 2.2. Impacts of Climate Change

The frequency and severity of extreme climate events are on the rise, driven by the impacts of climate change. Since the latter half of the nineteenth century, extreme weather events have steadily become more norm. These changes in extreme weather patterns contribute to the growing incidence of climate-related natural disasters like droughts and floods (Yisehak & Zenebe, 2021). Climate change also alters streamflow patterns, potentially leading to more severe flood events. Notably, the impacts of climate change on food security are particularly pronounced in Sub-Saharan African countries and Eastern Asia, as highlighted by Adhikari et al. (2015). Extreme precipitation events play a significant role in triggering natural disasters. Consequently, the increasing frequency and duration of intense extreme rainfall events, including landslides, floods, and water scarcity after rain-on-snow events, will likely contribute to a rising number of hydro-meteorological disasters (Clifton et al., 2018; Zisopoulou & Panagoulia, 2021). Under climate change scenarios, extreme rainfall events are expected to become more frequent, significantly increasing the risk of flooding.

The change in climate has also resulted in widespread shifts in pressure patterns, rainfall patterns, and sea surface temperatures, impacting various facets of life on Earth. One of the most prominent consequences of these changes is the global temperature rise. Numerous studies conducted across the globe have documented substantial alterations in precipitation and evaporation patterns associated with this temperature increase (Ghasemian et al., 2020; Hodgkins et al., 2017). According to reports from the IPCC, climate change has induced hydrological changes worldwide in recent years, heightening the likelihood of extreme weather events. Hydrological extremes, are intrinsic features of the climate and can occur in virtually all climatic regions, irrespective of their historical precipitation levels. Given that human societies, ecosystems, and physical infrastructure have adapted to prevailing climatic conditions, they often lack the resilience to withstand extreme climatic events. Consequently, such deviations can have adverse impacts on ecosystems and communities, resulting in substantial economic and social consequences.

## 2.3. Historical Studies of Climate Change and Flooding in Ethiopia

Climate change is the most serious threat to our planet today. However, its impact is more intense in agrarian peoples of developing countries, which are economically unprivileged, face technology inaccessibility, and have a lower capacity to adapt to climate change-induced shocks (Thomas et al., 2019). Its projections in East Africa show an increase in temperature as well as high variability in rainfall (Gebrechorkos et al., 2019; Girvetz et al., 2019). Climate change and variability in Ethiopia, like that of the rest of the world, have been detected by several studies. Forest-dependent, smallholder and subsistence farmers and pastoralist households are the most hit by climate-related hazards (Mekonnen et al., 2018). The study conducted on long-term (1988-2017) trends of temperature and rainfall for different agro-ecological zones of Ethiopia revealed the following results (Table 1);

Table 1.Seasonal and annual trend of rainfall and temperature in Ethiopia

| Place | Variables | *Belg* | | *Kiremt* | | Annual | |
|---|---|---|---|---|---|---|---|
| | | MK | Slope | MK | Slope | MK | Slope |
| Lowland | Tmin | 0.016 | 0.003 | 0.269 * | 0.039 | 0.154 | 0.023 |
| | Tmax | 0.615 *** | 0.090 | 0.384 | 0.060 | 0.616 *** | 0.068 |
| | Tavr | 0.333 ** | 0.032 | 0.366 ** | 0.044 | 0.438 *** | 0.042 |
| Midland | Tmin | 0.306 * | 0.023 | 0.223 | 0.015 | 0.407 * | 0.027 |
| | Tmax | 0.145 | 0.022 | 0.315 * | 0.027 | 0.320 * | 0.025 |
| | Tavr | 0.319 * | 0.021 | 0.255 * | 0.019 | 0.434 ** | 0.030 |
| Highland | Tmin | 0.497 *** | 0.129 | 0.453 ** | 0.078 | 0.409 * | 0.065 |
| | Tmax | 0.044 | 0.006 | - 0.159 | - 0.028 | - 0.009 | - 0.001 |
| | Tavr | 0.269 * | 0.057 | 0.347 * | 0.044 | 0.241 | 0.033 |
| Lowland | | 0.103 | 0.661 | - 0.002 | - 0.028 | - 0.039 | - 0.344 |
| Midland | Rainfall | 0.379 * | 4.538 | 0.591 ** | 15.443 | 0.621 *** | 24.784 |
| Highland | | - 0.136 | - 0.707 | - 0.021 | - 0.699 | - 0.062 | - 2.022 |

Source: adapted from Etana et al. (2020)

Flooding is one of the most common and devastating natural disasters today, killing thousands of people and causing incalculable property damage. Over the years, in nearly every region of the world, excessive rainfall due to climate change has caused flooding, claiming lives and properties (Olanrewaju et al., 2019). In Ethiopia, flood is one of the most recurrent natural disasters caused by extreme weather events (UNDRR, 2022). Currently, Ethiopia is facing its worst flood experience since a decade ago. More than 2.2 million people have been affected by over 47 significant flood events. This situation has caused a range of risks and impacts including displacement, death and injury, pollution of drinking water, distraction of houses and livelihood, and distraction of the community and wildlife (Mamo et al., 2019). The flood disaster of 2006 in Ethiopia remains intense in our collective memory (Figure 1). This catastrophic event was widespread, affecting nearly every corner of the country. The southern and eastern regions, in particular, face the devastation, resulting in significant loss of human and animal lives, as well as substantial property damage (Semu, 2007).

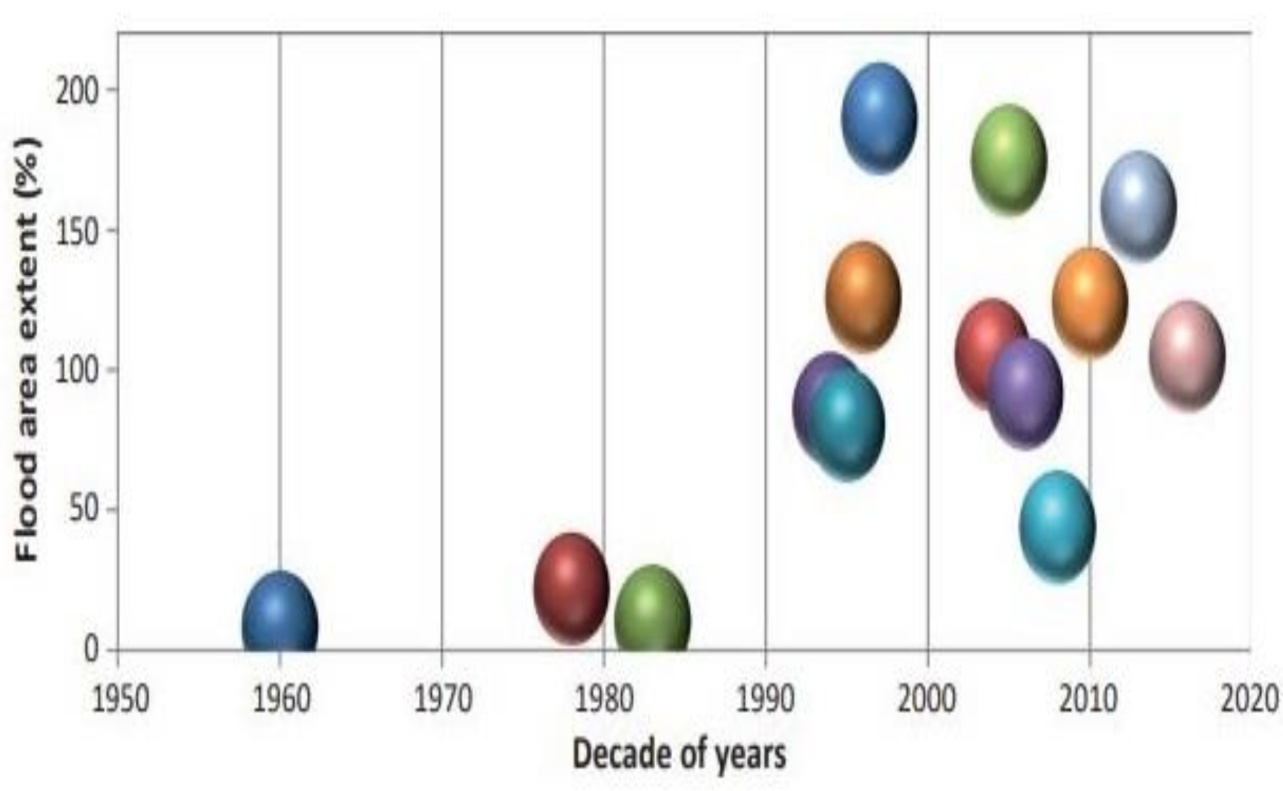



Figure 1. Frequency and area extent of flood events in Ethiopia (Source: Mamo et al., 2019)

## 2.4. Methods for Assessing Flood Risk

In recent years, there has been a notable shift in global focus from merely controlling flood hazards to conducting comprehensive assessments of flood impacts and risks. The UNDRR defines risk as the combination of the likelihood of an event occurring and the adverse outcomes it could entail (UNDRR, 2009). Various methodological approaches have emerged in this regard. These include statistical and mathematical methods, remote sensing and geographic information system techniques, and a combination of methods such as GIS-modeling-simulation, as well as GIS-machine learning. Additionally, survey and interview-based approaches, modeling and simulation techniques, evaluation methods, and machine-learning methods have gained prominence in assessing flood risks.

Initially, mathematical theories were among the pioneering approaches employed to analyze flood patterns, predominantly utilizing hydrological data. Building upon existing data, new models were developed for areas sharing similar characteristics (Bocanegra & Stamm, 2021; Popa et al., 2019). The hydrological model serves as a mathematical representation of the simplified form of hydrological processes within a river basin. Its primary purposes include understanding and explanation of hydrological processes, as well as hydrological forecasting. These models can assume different forms depending on their approach, whether deterministic or stochastic. A hydrological model is considered deterministic when it represents the physical processes within a river basin without accounting for randomness. On the other hand, it assumes a stochastic nature when it incorporates random mathematical representations of variables and their associated probability distributions within the parameter space. One widely utilized hydrological modeling system is the HEC-RAS. The Hydrologic Engineering Center – Hydrologic Modelling System (HEC-HMS) stands as a comprehensive modeling system designed to simulate precipitation-runoff processes in dendritic river basin systems, demonstrating versatile applicability.

Statistics were introduced as soon as databases allowed effective processing with promising results. With the development of GIS techniques, these methodologies underwent spatialization, leading to hybrid approaches. Statistical analysis primarily played a role in estimating flood frequency. Until 1966, the prevailing distribution for flood frequency analysis was the Type I extreme value distribution, commonly known as the Gumbel distribution, followed by the lognormal distribution. These are still widely employed today, recognized in hydrology as Pearson Type III and log-Pearson Type III. They began with remote sensing techniques and subsequently extended to encompass GIS techniques, modeling, simulation, and more recently, machine learning methods. The advancement of data processing capabilities, coupled with the utilization of an extensive array of parameters, paved the way for the development of highly precise methodological approaches aimed at mitigating the impacts of floods. The spatialization of these methodologies using GIS techniques has not only facilitated the refinement of existing methods but also encouraged the fusion of algorithms, giving rise to the creation of hybrid algorithms (Costache et al., 2020).

However, when considering the multitude of models along with their individual precision and suitability, it becomes evident that there is no single best model due to the inherent complexities of environmental predictions. Each model can provide only an approximation of the reality it attempts to represent (Galavi et al., 2013). Instead, numerous feasible solutions exist, contingent upon the intended purpose and required level of complexity. Often, the choice of a model leans more toward one's familiarity with it rather than its absolute appropriateness.

### 2.5.Multi Criteria Decision Modeling

Multi-criteria decision-making (MCDM) is the most suitable method adopted to address multi-objective (criteria) problems and various computational multi-criteria decision tools have been designed to support decision-makers in fields such as environmental protection, water allocation, land allocation, energy production, forest management, and project management (Mardani et al., 2015; Veintimilla-Reyes et al., 2019). It is an effective tool used to address conflicting and complex decision problems, accommodating both qualitative and quantitative evaluation factors. The MCDA method is employed to overcome the limitations of hydrodynamic models, and thus, it has gained widespread acceptance for assessing intricate choice issues. MCDM is a broad term encompassing methods for solving complex problems, which can be classified into two primary categories: Multi-Attribute Decision-Making (MADM) and Multiple-Objective Decision-Making (MODM).

MCDA technique is applicable in different domains and fields such as; (i) water resources and energy management; (ii) agriculture, land use, forestry and construction (iii) recycling management; (iv) transportation, manufacturing, logistics and supply management (v) emissions, remediation and abatement strategies; (vi) tourism and events management; (vii) policy planning and sustainability. Given its multidisciplinary character, multi-criteria decision analysis (MCDA) has emerged as a widely used approach for tackling such issues. In this context, MCDA provides methodologies to facilitate decision-making in situations where numerous conflicting criteria are involved. The most widely used MCDA methods are Analytical hierarchy process (AHP), Analytic network process (ANP), Data envelopment analysis (DEA), Weighted sum model (WSM), Weighted product model (WPM), Goal programming (GP), Elimination and choice translating reality (ELECTRE), Multi-attribute utility theory (MAUT), Simple multi-attribute rating technique (SMART), Preference ranking organization method for enrichment of evaluations (PROMETHEE), Technique for order preferences by similarity to ideal solutions (TOPSIS) and Simulated uncertainty range evaluations (SURE). The choice of MCDA techniques may depend on the complexity of the problem and the objective of the study. Decision-makers should consider factors such as the decision goal, type of problem, data volume, consistency, ease of use, number of criteria, and type of analysis during MCDA technique selection. It has gained recognition as an approach, for evaluating complex decision problems. These problems often involve data or criteria that are difficult to compare like mapping and identification of flood areas using multiple factors. Among the methods used in multi-criteria decision making the analytical hierarchy process (AHP) is widely employed (Abdelkarim et al., 2020; Karymbalis et al., 2021).

## 2.6.Analytical Hierarchical Method

The Analytic Hierarchy Process (AHP), developed by Saaty in 1980, stands as one of the most renowned, powerful, and broadly used MCDM approaches (Gebre et al., 2021). It is a decision-making method that involves structuring multiple-choice criteria hierarchically (Wind & Saaty, 1980). The AHP is a good software support and simple to understand. It finds applications across a wide spectrum of multi-criteria decision-making problems, with its pairwise comparison matrix effectively calculating the weights for each considered criterion. Within the AHP method, deriving the weights or priority vector for alternatives or criteria is a crucial step. To facilitate this, Saaty (1980) introduced the Pair-wise Comparison Method (PCM). Moreover, AHP analyzes the alternatives at the lowest level of the hierarchy to identify the most suitable option. This approach enables experts to transform subjective judgments into objective metrics (Sipahi & Timor, 2010).

The decision-making procedure starts with the segmentation of the problem into distinct issues, which can optionally be further subdivided to structure a hierarchical of issues. These issues encompass the aspects that require consideration when addressing the problem. This hierarchical order serves the purpose of simplifying the problem and making it more comprehensible. At each level within this hierarchy, the weights of the elements are computed (Kordi, 2008). The AHP has been a favorite tool of decision-makers and research experts from various fields such as technology, engineering, production, manufacturing, social sciences, and more. It has proved to be a reliable and efficient decision-making tool. The uniqueness of applying it in various studies helps in modelling situations of uncertainty while preserving both subjectivity and objectivity in the evaluation process.

Saaty devised this method with the aim of establishing a systematic approach to establishing priorities and facilitating complex decision-making processes (Saaty, 1980). Essentially, the hierarchical framework of the AHP methodology is able to synthesize and measure the various facets of a complex decision-making process in a hierarchical fashion, simplifying to combine the parts in a whole. Therefore, the three primary functions of the AHP methodology are as follows: structuring complexity, synthesis, and measurement (Saaty, 1980). Regarding the initial function, Saaty sustains that to deal with the intricacy of a decision-making procedure we need to classify all the different factors that affect the decision and organize them in a hierarchical structure of homogenous groups. Measurement in a ratio scale is achieved through pairwise comparisons of these factors. The weight of each factor in the hierarchy is determined through a process in which each factor is compared with its parent factor. Priorities across the hierarchy are found by multiplying the priority of one factor at each level by the priority of the factor to which it is linked. Although the AHP method has its limitations, such as its rejection of certainties in spatial decision-making processes, it remains a viable choice for flood susceptibility studies (Singh et al., 2021).

### 2.7. Future Climate Projection

Future climate projection is a critical aspect of climate science that allows us to anticipate the potential impacts of climate change and develop strategies for adaptation and mitigation. It involves utilizing climate models and scenarios to estimate potential changes in Earth's climate in the coming decades and centuries. These projections rely on factors such as greenhouse gas emissions scenarios, atmospheric and oceanic processes, and feedback mechanisms. Climate models, including those employed by the Intergovernmental Panel on Climate Change (IPCC), simulate intricate interactions between the atmosphere, ocean, land surface, and ice, incorporating various physical, chemical, and biological processes to project future climate conditions. These models are run under different scenarios representing diverse socio-economic trajectories and greenhouse gas emissions levels. In recent years, there has been a transition from using Representative Concentration Pathways (RCPs) to Shared Socioeconomic Pathways (SSPs) as the foundation for climate modeling and projection (Hewitt et al., 2021).

The shift from RCPs to SSPs reflects the evolving understanding of climate change as a complex interplay between greenhouse gas emissions and socioeconomic factors. SSPs capture this complexity by providing a more comprehensive set of scenarios that incorporate not only emissions but also broader socioeconomic contexts. This inclusion of socioeconomic narratives is particularly significant, as it acknowledges that climate change is not solely driven by emissions, but also by human choices and policies. One key advantage of SSPs is their flexibility and adaptability to a broader range of policy and development scenarios. The SSP framework includes a set of narratives that describe a spectrum of possible future socioeconomic conditions. These narratives allow researchers to consider various development pathways, including sustainability and inequality, providing a richer context for climate projection. This makes SSPs more suitable for exploring a diverse range of future scenarios and understanding the implications of different policy decisions and socioeconomic choices (Riahi et al., 2017). By integrating detailed information about demographics, technology, and policy, SSPs offer a more realistic and comprehensive foundation for climate models. Another critical reason for favoring SSPs is that they enable the exploration of multiple dimensions of climate change, including adaptation and mitigation efforts. With SSPs, researchers can assess the effectiveness of various climate policies and adaptation strategies in different socioeconomic contexts.

### 2.8. Application of GIS and RS in Flood Risk Assessment

Renowned experts worldwide have emphasized the significance of cost and time-effective decision-making strategies based on geographic information systems (GIS) techniques for flood mapping. The role of geospatial technologies, encompassing remote sensing (RS) and GIS, has marked a significant advancement in flood forecasting, modeling, and hazard assessment. Geospatial techniques, which encompass GIS, global positioning systems (GPS), RS, and spatial analysis, have consistently demonstrated their potential in natural hazard management over the years (Dewan, 2013). Flood modeling necessitates the acquisition, maintenance, and extensive utilization of a spatial database, where remote sensing and GIS emerge as outstanding methods capable of fulfilling these demands. Recent research endeavors have notably leveraged Digital Elevation Models (DEMs) through RS and GIS technology to extract geomorphological statistics, aiding in tasks such as flood monitoring, flood mapping, and flood risk assessment.

Remote sensing plays a pivotal role in acquiring critical data for mapping flood inundation, while the power of geographic information systems (GIS) comes to the forefront in effective flood risk management (Wang & Xie, 2018). Consequently, the precise mapping and management of flood risk are of paramount importance, necessitating the use of state-of-the-art technologies like remote sensing, GIS, and geostatistics. In flood inundation mapping and risk management, remote sensing and GIS are indispensable. Remote sensing offers a cost-effective and time-efficient alternative to on-site data collection, which is essential for building the necessary databases in hazard management. On the other hand, GIS provides a comprehensive toolkit for flood risk management, including the identification of flood-prone areas, vulnerability mapping, and the setup of hydrologic models. It serves as a versatile platform for processing input data, conducting output analysis, and visualizing results. Remote sensing's role in river basin hydrologic modeling is primarily attributed to its capacity to offer continuous spatial data, measurements of hydrological variables that are beyond the scope of traditional techniques, and notably, access to long-term global data. Modeling and simulation techniques, in this context, pertain to the process of converting precipitation data into a flood hydrograph.

The GIS has increased the significance of RS by improving spatial modeling efficiency. This process has increased the ability to estimate hydrological models. This synergy has improved the capability to estimate hydrological models. GIS offers an extensive array of tools for managing flood risk, enabling the identification of flood-prone areas and mapping vulnerability. It is a dynamic modeling system providing spatial analysis, data management, visualization, and processing. At every stage of flood risk assessment, GIS tools are now integral, from data preparation to floodplain delineation. The combination of GIS and remote sensing serves as a potent tool for analyzing and identifying flood zones and assessing their impact on affected areas, greatly saving time and streamlining the analysis of geomorphological data (Ding et al., 2021).

### 2.9. Participatory Geographic Information System

Recent efforts to integrate GIS with participatory techniques have given rise to concepts like participatory GIS (PGIS). According to Quan et al. (2001), PGIS refers to the integration of local knowledge and stakeholders' viewpoints in a GIS framework. The PGIS approach emerged around the 1980s when the practitioners were inclined to adopt Participatory Rural Appraisal (PRA) techniques rather than doing a time-consuming process of scale mapping. The core principle of the PGIS approach lies in its structured, systematic, and cross-cutting and back referenced manner of local spatial knowledge, external scientific insights from environmental experts, satellite imagery, and maps. PGIS has gained widespread recognition for its efficacy in participatory decision-making processes. However, there has been relatively limited exploration of the usefulness of PGIS, particularly in the context of flood risk assessment (Chingombe et al., 2015).

PGIS integrates local and community experts with well-established knowledge derived from conventional scientific sources and experts in various fields. As highlighted by McCall (2008), PGIS can be used in both human-induced and natural hazards, long and short return time and environmental hazards (floods, landslides and volcanic eruptions). Disaster experts and researchers maintain that adopting a collaborative approach, coupled with community-based methodologies, geospatial techniques, and earth observation data, enhances the ability to pinpoint threatening events in a particular community and identify vulnerable groups (Peters-Guarin, 2008). PGIS excels in capturing, representing, and validating spatial knowledge (indigenous knowledge) which rarely exists on official maps. The essence of PGIS lies in its combination of traditionally top-down GIS and bottom-up participatory mapping methods. This combination is driven by scientific investigations with the grassroots participatory mapping methods driven by the experiences and insights of local individuals, results in a GIS that reflects both the scientific reality of a location and the local perceptions of truth within that location.

The application of PGIS is effective and common in regions where local people possess the capacity to accumulate experience and knowledge. It integrates quantitative data with qualitative information (public opinions and mental maps). Participatory PGIS endeavors to empower marginalized communities and citizens with GIS technologies within their specific contexts. PGIS boasts several key strengths, including its capacity for spatial precision, sensitivity to social dynamics, integration of local and external knowledge, images as spatial narratives and multi-sourcing and enhancing public involvement in community-based decision-making processes. This approach facilitates the extraction of local and indigenous knowledge, as well as the articulation of environmental issues and hazards from the lay perspective (McCall, 2008; Sieber, 2006). On the other hand, PGIS and P-mapping excel in needs assessment, problem analysis, exploration of local perceptions and priorities, and understanding adaptive measures and people's coping strategies. They also serve as effective for communicating these to planners, policy makers and scientists. PGIS emerges as an invaluable tool for harnessing indigenous knowledge and capturing the local perspective on environmental challenges and hazards, subsequently facilitating communication with environmental scientists and local authorities.

## 2.10. Climate Change Adaptation and Disaster Risk Reduction

Climate change and disaster risk are serious global concerns that have caused a number of events and have been rising over the last decades. Nowadays, climate change and climate-sensitive disasters are impacting finance, increasing the risk of disease, death, and injury (Banwell et al., 2018; Heazle et al., 2013). However, the impact is unevenly distributed across the world and has been boldly affecting developing countries. As a result, to address climate-sensitive disasters and climate change, a large number of researchers have suggested an increase well planned, appropriate and effective risk reduction and adaptation measures (Watts et al., 2018). Consequently, various scientific and indigenous CCA and DRR measures have been undertaken at different levels.

Man-made and natural hazards and the vulnerability of society to these are reduced through appropriate measures including disaster management policies, materials, lessening vulnerability of property and people, improving preparedness for extreme events, reducing exposure to hazards, and sustainable management of land and environment. Failures to implement or sustain disaster management policies and practices are likely to increase disaster risk and losses in the case of hazardous systems (Burns & Machado, 2008). Climate change is characterized by uncertainty about its future trajectory, phases, and timing, as well as potential impacts and non-containability within existing jurisdictional borders (Lundqvist, 2016). Infrastructure introduction or development in a given environment to reduce climate change-associated peak flows and flooding, development of more effective drainage systems, smart irrigation, and integrated water management are some examples of climate change adaptation.

According to Busayo and Kalumba (2020), DRR and CCA have a common goal and wide range of crossover, where the first addresses issues with all hazards (man-made) including either hydro meteorological or geophysical hazards, while the latter involves dealing with variability in climate conditions and climate hazards. However, CCA, on the other hand, deals exclusively with communities' long-term coping mechanisms to changing climatic conditions, including the benefits this can provide, whereas DRR is specifically concerned with extreme events that cause disaster.

# 3. METHODOLOGY

## 3.1. Description of the Study Area

### 3.1.1. Location

The geographical focus of this research is the Rift Valley basin, one of the twelve main basins in Ethiopia. It is located in Southern Ethiopia, spanning from 4.37° to 8.47° N latitude and 36.59° to 39.41° E longitude (Figure 2b). The total area coverage of the basin is about 53,054.1 square kilometers. It is bounded to the north by the Awash, to the west by the Omo-Gibe, to the southeast by the Genale Dawa, and to the east by the Wabi Sheble basins.

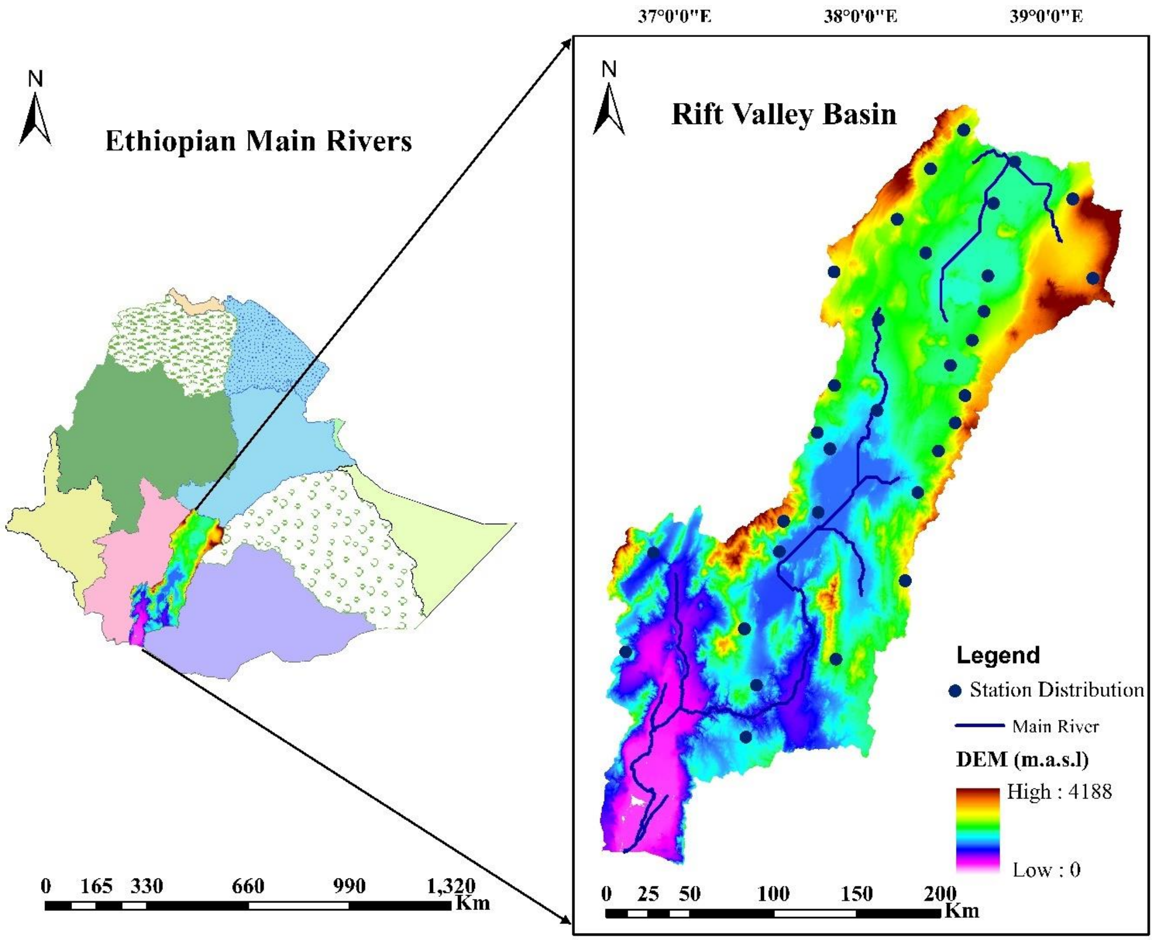



Figure 2. Shows the location map of Rift Valley basin

### 3.1.2. Hydrology and Drainage

The study area is characterized by diverse and complex hydrological systems. It includes a chain of lakes including Lake Abiyata, Lake Abaya, Lake Langano, Lake Chamo, Lake Shalla, Lake Ziway, Lake Hawassa, and Lake Beseka among others. These lakes, which differ in size and hydrological properties, add to the area's great biodiversity and ecological significance.

The topography of the study area is rugged, elevation ranging from 0 at the valley floor up to 4188 meters above sea level (Figure 2b). This terrain affects the way water flows, with rivers and streams winding through the area to create a vast system of waterways.

### 3.1.3. Climate and Vegetation

The climate of the basin is characterized by moderate tropical semi-arid with bimodal rainfall patterns. The '*Belg*' or short rainy season takes place from March to May, while the '*Kiremt*' or long rainy season takes from June to September (extending to October in the most southern regions) (Mohammed & Yimam, 2021). The main economic activity is agriculture, which is dominated in the highlands by mixed farming, rain-fed cereal crops, and agroforestry-driven perennial crop cultivation. The principal crops farmed in the study area are *enset* (Ensete ventricosum), maize (Zea mays), wheat (Triticum), *teff* (Eragrostis tef), and arabica coffee (Coffea arabica). Conversely, the lowlands support pastoral livelihoods due to minimal rainfall (Tesfamariam et al., 2019).

The vegetation distribution is influenced by elevation, with deciduous Acacia woodlands and wooded grasslands dominating the rift valley floor, gradually transitioning into deciduous woodlands at higher elevations. The study basin is rich in biodiversity, containing lakes, wetlands, forests, grasslands, and savannahs. It serves as a living environment for a diverse range of bird species, wildlife, fishes, and with over 500 bird species and 33 fish species identified. Many lakes in the region are important for waders, and wildfowl as well as endangered species, recognized globally by BirdLife International (Ayalew et al., 2022).

## 3.2. Methods

### 3.2.1. Data Sources and Collection Process

To accomplish the goals of this research both primary and secondary datasets were collected. Primary data was generated through field observation using Geographic Positioning Systems (GPS) to verify ground truth. Besides, a focus group discussion (FGD) was conducted to collect relevant data to verify the flood-prone areas identified during the field visit.

Both digital and non-digital secondary data sets such as; rainfall, elevation, slope, distance from river (DR), and soil type were collected from the relevant organizations to carry out this research endeavor. The soil map was acquired from the Ministry of Water Irrigation and Energy of Ethiopia (MOWIEE). The Living Atlas provided the Esri Land Cover 2020 dataset, which was then processed to create the basin's LULC map. With a 10-meter resolution, this open-source dataset depicts a nine-class worldwide LULC map for 2020 that was produced using Esri Sentinel-2 Land Cover Explorer (https://livingatlas.arcgis.com/landcoverexplorer). This was subjected to application and recommendations made by several scholars in various parts of the world and Ethiopia specifically (Ahmed et al., 2022; Chaaban et al., 2022; Venter et al., 2022). Shuttle Radar Topographic Mission (SRTM) DEM with 30 meters by 30 meters spatial resolution was sourced from the USGS (https://earthexplorer.usgs.gov). It is used to delineate the stream lines and generate slope map of the basin. Meteorological data was acquired from the Ethiopian Meteorology Institute (EMI) for 39 years (1981-2020).

### 3.2.2. Softwares Used

The processing and analysis of data involved digitization, calculation, and classification of essential information for every thematic layer in the ArcGIS 10.8. Before conducting an overlay analysis, all the thematic layers were resampled to 30m resolution. Locations were marked during fieldwork using the Garmin handheld Global Positioning System (GPS). The research created the Topographic Wetness Index (TWI) and Topographic Ruggedness Index (TRI) using the System for Automated Scientific Analysis (SAGA) GIS. Additionally, a chart and several statistical analyses were produced using Microsoft Office tools.

### 3.2.3. Data Processing

To assess flood risk in the Rift Valley basin, eight factors influencing flood were taken into account including soil type, land use land cover, rainfall, elevation, slope, TWI, TRI, and distance from river (DR). In this process, digital spatial layers were generated for each factor using the geospatial software (ArcGIS and SAGA GIS). The overall methodology employed the use of the AHP model in the ArcGIS 10.8 environment. Prior to joint processing, the diverse data layers underwent re-projection to a geographic projection with the UTM zone 37 N.

The following land use land cover map was obtained from ESRI, reclassified and resampled in ArcGIS 10.8 environment. Namely; water bodies, forest land, wetland, agricultural land, built-up, bare land, and range land. The descriptions are stated below (Table 2).

Table 2. Land use land cover categories and their corresponding descriptions

| No. | LULC | Description |
|---|---|---|
| 1 | Water body | Areas having year-round water; may not include areas with intermittent or ephemeral water; little to no sparse vegetation, no rock outcrop, and no built-up features |
| 2 | Forest land | Any notable collection of tall (~1.4 meters or more) dense vegetation, usually with a closed or thick canopy |
| 3 | Wetland | 3. Any sort of vegetation in areas where water is clearly mixed during most of the year |
| 4 | Agricultural land | Crops, grasses, and cereals grown by humans that are not at tree height |
| 5 | Built-up | Man-made buildings, significant highway and train systems |
| 6 | Bare land | 6. Huge stretches of sand and deserts with little to no flora, as well as regions of rock or soil with extremely little to no vegetation throughout the year |
| 7 | Range land | Areas characterized by uniform grass cover with sparse taller vegetation, patches of wild cereals and grasses devoid of human cultivation, scattered individual plants or small clusters interspersed across exposed soil or rocky terrain, and clearings with low shrubs within densely wooded areas, all without surpassing the height of surrounding trees |

Source; Modified from ESA (2020)

## 3.2. Climate Data Projection

### 3.2.2. Data Types and Sources

This study utilized the daily rainfall of observed station data, gridded data, and climate projections from the CMIP6 models. The observed station and gridded data were sourced from the Ethiopian Meteorology Institute (EMI). EMI generated the gridded data with technical assistance from the International Research Institute (IRI) at Columbia University and Reading University in the United Kingdom (Dinku et al., 2014). The gridded data in this study was used to fill the missing values in the observed station data. It combines locally calibrated satellite data with quality-controlled station data from the National Observation Network (Mena et al., 2023). The observed datasets were gathered for 33 weather stations located inside the study basin.

The state-of-the-art CMIP6 models were used in this work to forecast future climate conditions. These CMIP6 models globally developed collaboratively by climate modeling centers by incorporating complicated interactions between the earth's atmosphere, land, oceans, and ice. Using two distinct CMIP6 scenarios (SSP245 and SSP585), the future climate conditions for the period 2021 to 2100 based on various emission scenarios were projected. SSP245 signifies a pathway with moderate greenhouse gas emissions and policies aiming to limit climate change whereas, SSP585 signifies a high-emission scenario with limited mitigation efforts.

Out of the CMIP6 suite, five global climate models namely CanESM5, CNRM-ESM2-1, MIROC6, MRI-ESM2, and NoRESM2-were carefully selected because they performed better in earlier evaluations conducted in Ethiopia and the Horn of Africa (Balcha et al., 2022; Feyissa et al., 2023; Sime & Dibaba, 2023). In order to confirm the applicability and trustworthiness of these chosen models, an extra evaluation was carried out especially throughout the Ethiopian Rift Valley basin, taking into account the spatial variability of model performance.

### 3.2.2. Model Performance Evaluation

Climate model outputs usually have uncertainties due to various influences such as model structure, parameterization, assumptions, and calibration processes (Randall et al., 2003).

Therefore, careful performance evaluation is imperative prior to application of climate models (Frederiksen et al., 2016; Worku et al., 2018). In this study, the outputs from five GCMs were assessed using three performance metrics namely, root mean square error (RMSE), Pearson correlation coefficient (r), and bias (Equation 1, 2, 3). Since the historical values of the CMIP6 models only extend to 2014, the assessment concentrated on the historical climate variables in the study area from 1981 to 2014.

The metrics are calculated based on the guidelines developed by Ayehu et al. (2018). The defining variables expressed as O (gauge rainfall observations), M (model rainfall estimates), $\bar{O}$ (average gauge rainfall observations), $\bar{M}$ (average satellite rainfall estimates), and n (number of data pairs).

$$r = \frac{\sum(O-\bar{O})(M-\bar{M})}{\sqrt{\sum(O-\bar{O})^2}\sqrt{\sum(M-\bar{M})^2}} \quad 1$$

$$Bias = \frac{\sum(M)}{\sum(O)} \quad 2$$

$$RMSE = \sqrt{\frac{\sum(O-M)^2}{n}} \quad 3$$

### 3.2.3. Bias Correction

Employing climate models like Global Climate Models (GCMs) should be done with caution because they frequently show differences between projected and actual data for variables like temperature and rainfall (Teutschbein & Seibert, 2012). Thus, to improve their applicability in projections additional post-processing steps found to be paramount important. Accordingly, this research uses the well-known quantile-mapping technique, which is regarded as one of the most important techniques for bias correction (Enayati et al., 2021; Li et al., 2010). Specifically, the Empirical Quantile Mapping (EQM) variant of quantile mapping is chosen for its ability to map between observed and simulated Cumulative Distribution Functions (CDFs). When correcting rainfall bias in GCM data, EQM proves to be a highly effective method as it builds CDFs based on actual data from a historical timeframe (Enayati et al., 2021).

The following equation is utilized to transform distribution functions of modeled variables into observed ones is stated as following (Mena et al., 2023):

$$V_{corr} = V_{m-f} + E_{o-c}^{-1}\left(F_{m-f}\left(V_{m-f}\right)\right) - F_{m-c}^{-1}\left(F_{m-f}\left(V_{m-f}\right)\right) \quad 4$$

here F is Cumulative Distribution Function (PDF) of either the model (m) or observations (o) for a future (projection) period (f) or historical (calibration) period (c), and V_corr is the time series of the corrected variable. V_(m-f) is the original time series of the variable (Equation 4). The empirical nature of F is a critical feature in this bias correction process. Bias coefficients computed during the historical period are subsequently applied to correct future periods under the assumption of consistent model error.

### 3.3. Analytical Hierarchy Process

AHP is a method of decision-making that considers the relative value of several factors (Németh et al., 2019). It uses the hierarchical structures to model a problem and to establish priorities for alternatives based on user discretion. The process creates a hierarchical structure for multiple-choice criteria, analyzes a large number of possibilities for each criterion, evaluates each option's relative worth, and comes up with a final evaluation of each option's affordability, value, and risk. This approach is highly effective in identifying potential flooding causes. Consequently, AHP was used in this work to estimate the weights for each input variable in the flood risk mapping. It was discovered that the pairwise comparison matrix was crucial in determining these weight values. The normalized matrix was then created by dividing each element in the pairwise comparison matrix by the sum of its corresponding column. The average value of each row was used to get the final weight value for each equivalent parameter. The relative importance of factors were assessed using a rating scale as shown in Table 3. This study used multi-objective decision analysis developed by Saaty (1977) which utilizes a pair-wise comparison approach, constructing a judgment matrix with absolute numbers on a scale from 1 to 9 to evaluate the relative significance among criteria, where 1 signifies equal importance, and 9 indicates significantly greater importance.

Table 3. Fundamental scales of compared parameters

| Intensity of importance on an absolute scale | Definition | Explanation |
|---|---|---|
| 1 | Equal importance | Two activities contribute to the objective |
| 3 | Moderate importance of one over another | Experience and judgment strongly favor one activity over another |
| 5 | Essential or strong importance | Experience and judgment strongly favor one activity over another |
| 7 | Very strong importance | An activity is strongly favored and its dominance demonstrated in practice |
| 9 | Extreme importance | The evidence favoring one activity over another is of tile highest possible order of affirmation |
| 2, 4, 6, 8 | Intermediate values between the two adjacent judgments | When compromise is needed |

Adopted from (Saaty, 1990)

The AHP methodology involves several key phases (Saaty & Vargas, 2012): (i) choosing the multi-criteria parameters; (ii) organizing the parameters in a hierarchical fashion; (iii) determining the relative relevance by giving each parameter a subjective value; and (iv) combining the ratings to determine priorities. The following procedures was implemented to generate the flood risk map of Rift Valley basin (Figure 3).

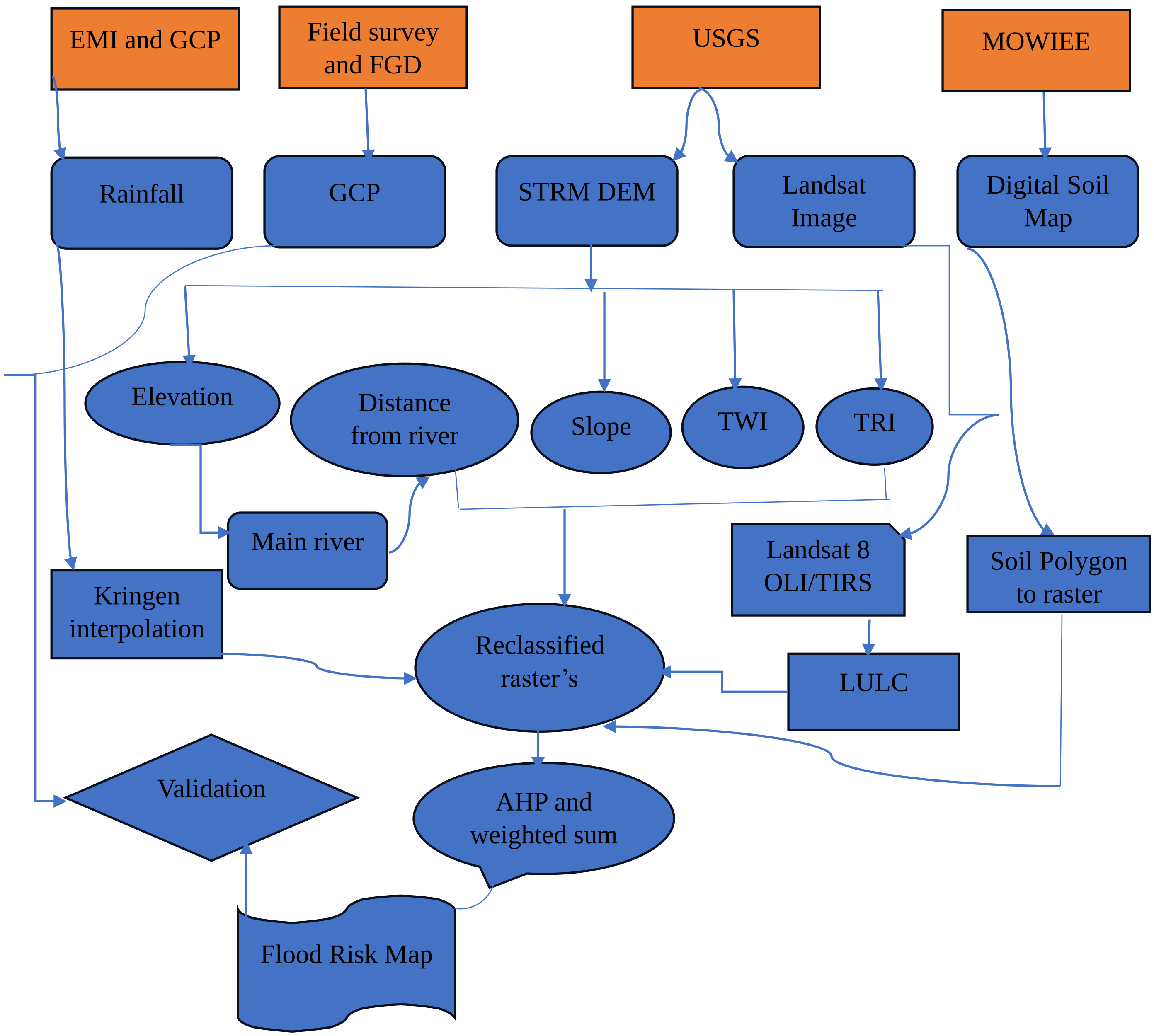



Figure 3. Flowchart of an overall methodology

### 3.3.2. Consistency Ratio

The determination of pairwise comparative weights has high dependence on expert opinion and needs to meet the consistency ratio (CR) requirements. Weights allocated to each parameter were normalized using the eigen vector, and the eigen vector was then put through a consistency check using the CR algorithm (Equation 5). The CR value to be obtained must not exceed 0.1, this threshold ensures that any subjectivity involved in prioritizing one factor over another is minimized. Conversely, if the CR equals or exceeds 0.10, it signifies inadequate consistency in the pairwise comparisons, necessitating a repetition of the comparison process until a CR value below 0.10 is achieved (Aslan, 2023; Saaty, 1987).

$$CR = {}^{CI}/_{RI} \qquad 5$$

Where, CI stands for the Consistency Index and RI stands for the Random Consistency Index, and its value depends on the number of factors, denoted as n. The specific values of RI corresponding to various numbers of factors can be found in Table 4 as presented by Saaty (1990).

Table 4. The index of random consistency

| n | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| I | 0 | 0 | 0.58 | 0.9 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |

Adopted from Saaty (1990)

Following the computation of weights for each factor influencing flood control, the consistency check was employed. This process is executed by applying equation (6) to ensure the validity and consistency of the comparisons. The Consistency Index (CI) was calculated using the formula provided in the following equation (Equation 6), originally proposed by Saaty (1987).

$$CI = \frac{\lambda max}{n-1} \qquad 6$$

Where CI denotes the Consistency Index, n represents the number of factors compared within the matrix, and λmax stands for the highest eigen value of the pairwise comparison matrix. As recommended by Saaty (1987), the determination of the maximum eigen value (λmax) for the comparison matrix involved the following steps:

1. Multiplying each value in the column (from the non-normalized matrix table) by the weight assigned to the criteria
2. Summing up the scaled values in each row to compute the weighted sum
3. Finding the ratio of each weighted sum to its corresponding criteria weight
4. Determining the average of these ratios of the weighted sum to the criteria weight

### 3.2. Flood Zone Identification

The selected flood distribution features; land use/land cover, soil type, rainfall, elevation, slope, TWI, TRI, and DR, were converted into raster format and reclassified. Subsequently, they were assigned weights obtained from the AHP (Equation 7) in the ArcGIS environment to produce a flood hazard map for the Rift Valley basin.

$$FH = \sum_{i=1}^{n} R_i * F_i \qquad 7$$

Where the flood risk is represented by FH, the appropriate weights are Ri, and the flood-generating variables are Fi. Following the future rainfall projection under different scenarios, the flood hazard map for both near and far future was developed using the same procedures.

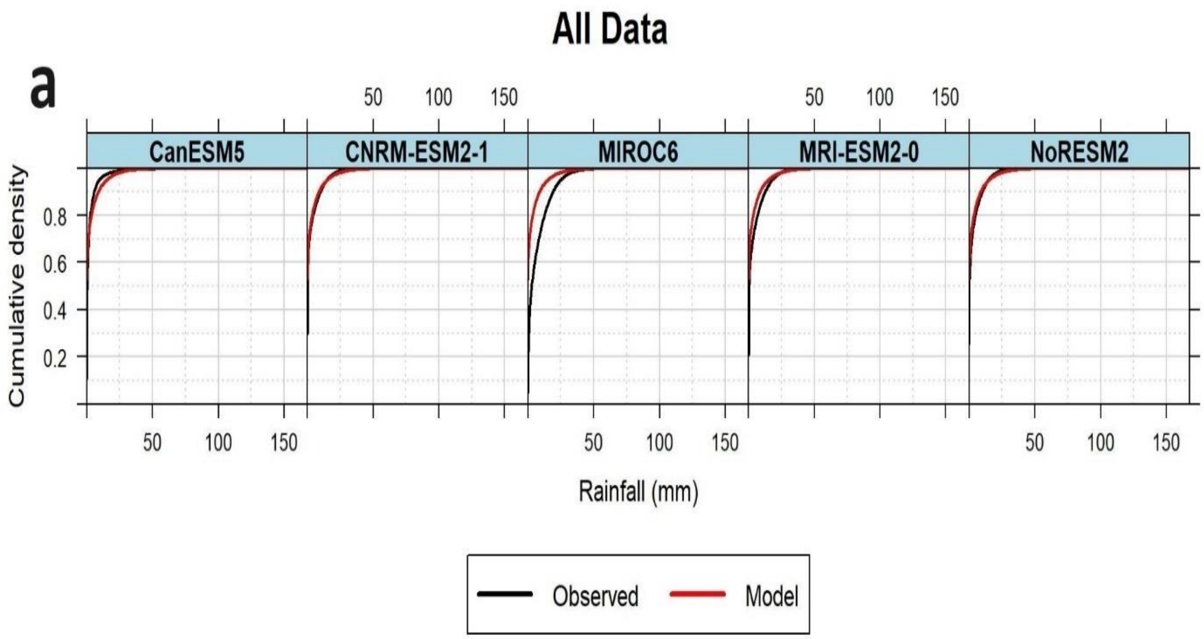
### 3.3. Validation of Flood Hazard Map

There is currently no specific quantitative method available for validating the accuracy of spatial flood risk maps. However, a qualitative validation approach, as employed by Mishra & Sinha (2020), involves an extensive field survey to evaluate the accuracy of the generated vulnerability, hazard, and risk maps. During this survey, X and Y coordinates for flood-prone areas including flooded farmlands, towns, infrastructures, and notable features such as bridges, irrigation farms and dams were collected using GPS. The visit included comprehensive field observations and discussions with local people and experts to get their feedback on the susceptible areas. Additionally, the history of past flood events, their severity and extent were explored through discussion with stakeholders and the local community and successfully integrated with the GIS environment to comply with the principles of PGIS.

# 4. RESULT AND DISCUSSION

## 4.1. Model Performance and Selection

Following the criteria explained in the methods section, the research assessed five models in the study region to see how well they could simulate daily rainfall. After careful evaluation, the study picked the three models that performed the best for more in-depth examination. These standout models are NoRESM2, CNRM-ESM2-1, and CanESM5 (Figure 4a and 4b). Consequently, the research took the average of these three models to thoroughly analyze the anticipated rainfall patterns. This approach helps ensure a robust and reliable assessment of the projected rainfall characteristics in the study.



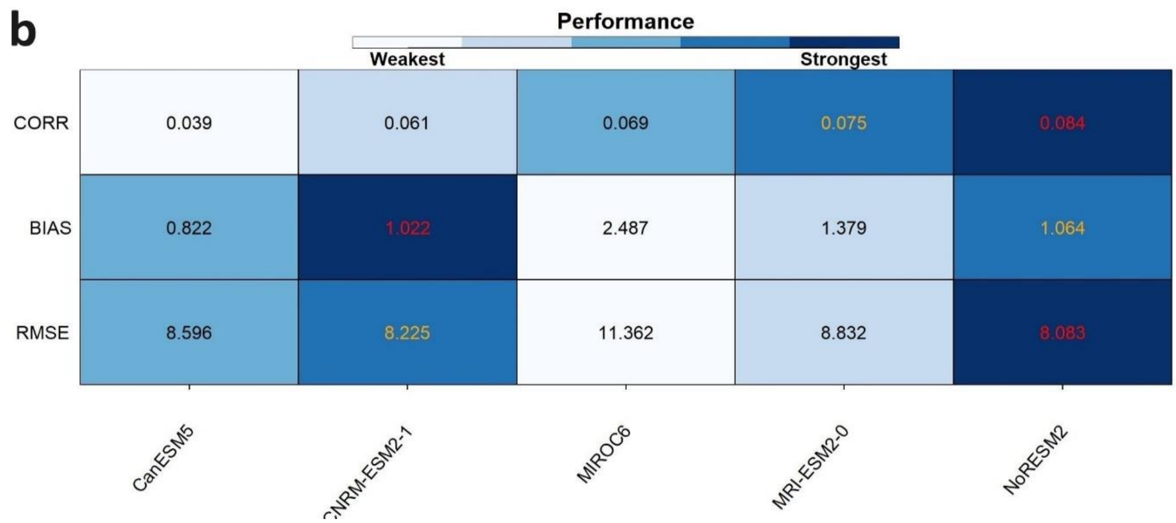


Figure 4. a) Model performance b) Performance rank

### 4.2. Indicators of Flooding Risk

In the current research, flood hazard signifies the likelihood of flood events occurring in a specific area, determined by the geomorphological and hydrological variables of the region (Mishra & Sinha, 2020). This research purposely selected particular flood-indicative parameters based on hydrological and geomorphological attributes namely; rainfall, elevation, DR, slope, TRI, TWI, LULC, and soil type. All the parameters were reclassified into five flood susceptibility classes: very high, high, moderate, low, and very low (Appendix Table 1).

#### 4.2.2. Rainfall

The study has examined the spatiotemporal variations of rainfall over the Rift Valley basin for the base and two future periods (2020-2060 and 2061-2100) under two SSP scenarios (SSP245 and SSP585). The basin experiences a mean annual rainfall ranging from 629 to 1484mm for the base period (1981-2020), with high values in the central and southwestern regions (Figure 5). Notably, these regions receive the highest mean annual rainfall, heightening the risk of flooding.

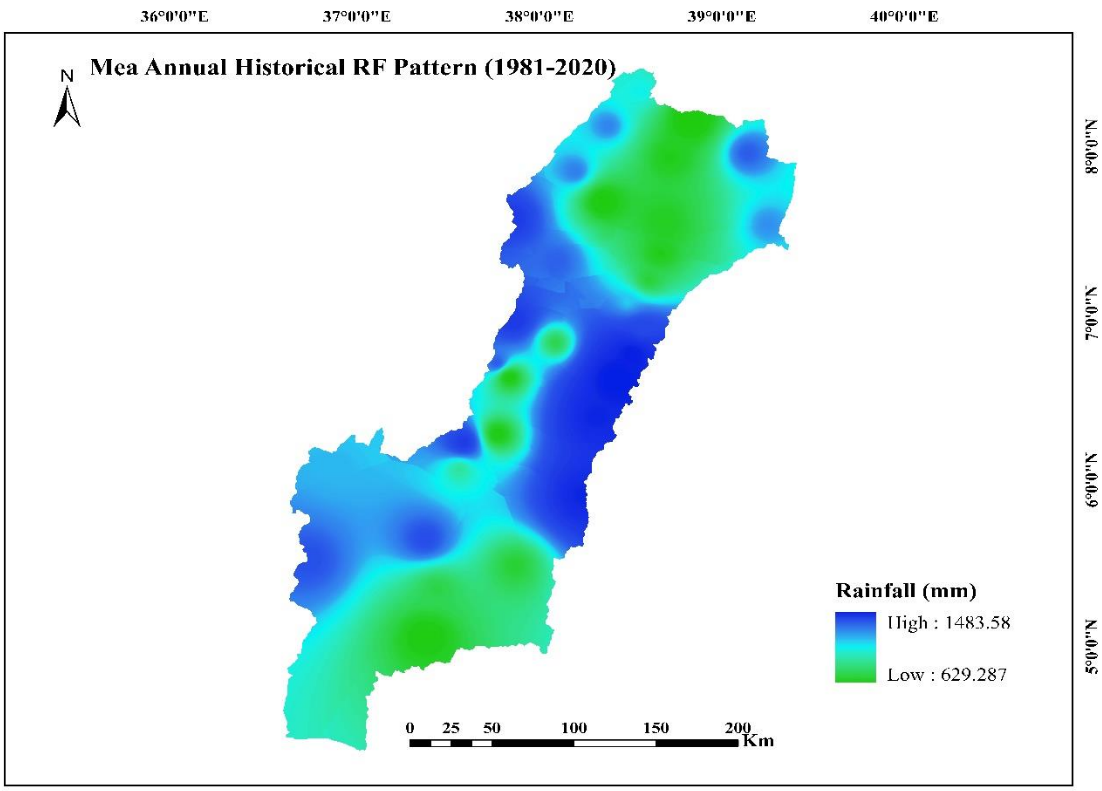



Figure 5. Rainfall pattern of the base period (1981-2020*)*

The future scenarios indicate that the upper parts of the basin receive high annual rainfall, while the lower parts receive less annual rainfall. Figure 6 shows the varied rainfall values under each scenario: SSP245 near future (899.84 to 1380.07 mm), SSP245 far future (838.62 to 1563.92 mm), SSP585 near future (833.98 to 1573.23 mm), and SSP585 far future (967.51 to 1803.01 mm) with the mean values of 1116, 1158.3, 1172.3, and 1371.3 mm respectively. This suggests an overall increase in rainfall in all future scenarios over the base period which has a mean value of 908.7 mm.

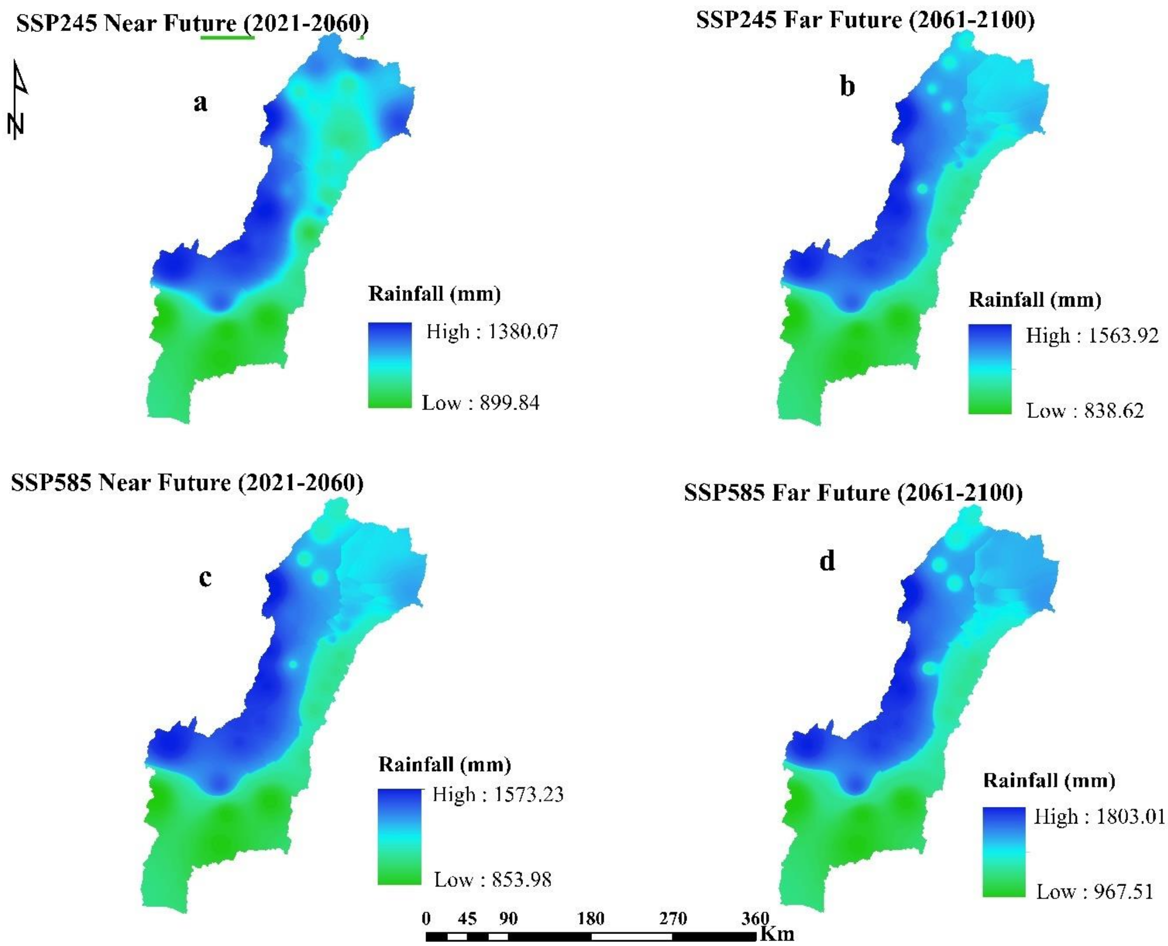



Figure 6. Spatiotemporal distribution of projected average rainfall

### 4.2.3. Elevation

The elevation of a watershed plays a crucial role in influencing flood hazards within the area (Adnan et al., 2019). In this study, the highest point in the watershed reaches 4188m, while the lowest point is at 0m (Figure 7). During reclassification, the lowest elevation classes assigned a very high susceptibility class, while the highest elevation class assigned a very low susceptibility class. The result signifies those areas with lower elevations, particularly in the southern part of the basin, show a higher susceptibility to floods.

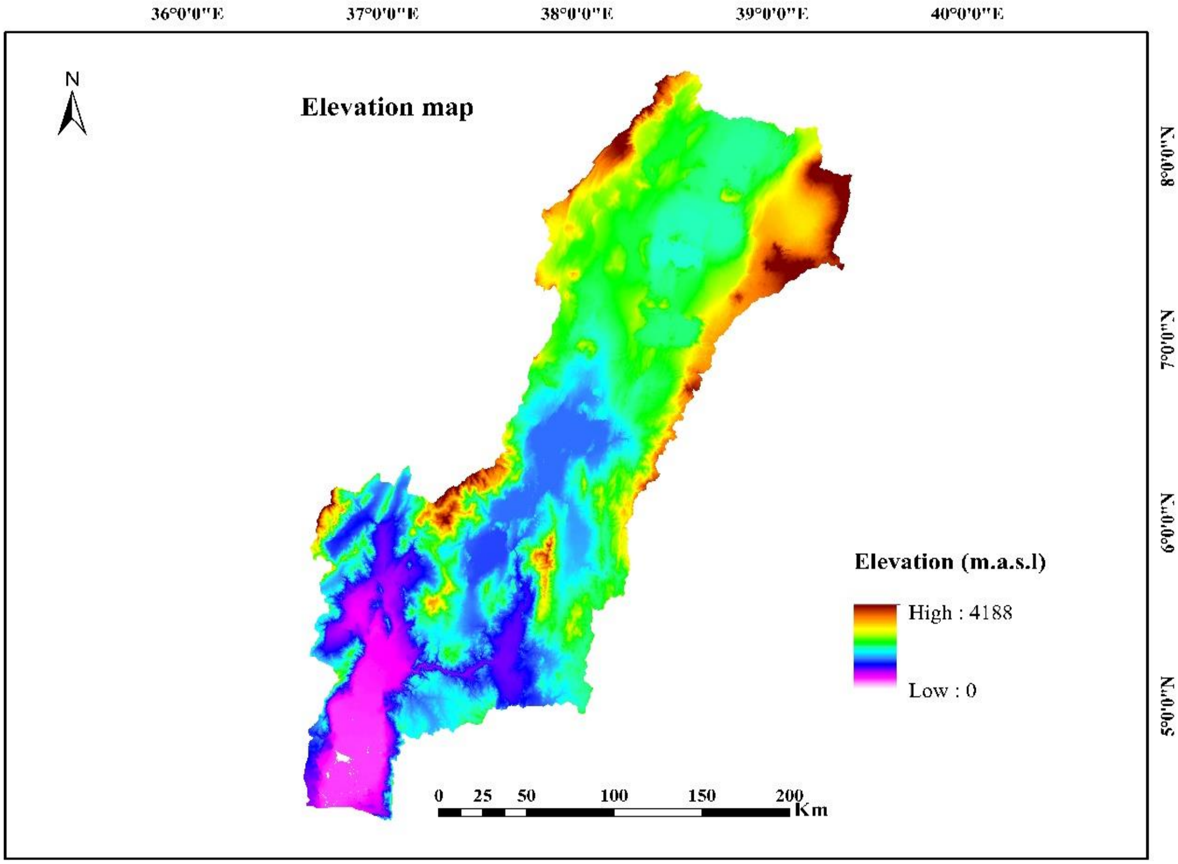



Figure 7. Elevation map of Rift Valley basin

### 4.2.4. Distance from River

Proximity to the river plays a significant role in identifying areas that are susceptible to flooding. It serves as a crucial indicator of flood hazard, as regions in proximity to the river encounter more frequent floods compared to those situated farther away (Ali et al., 2022). Being situated at a considerable distance from river lowers the probability of flooding and reduces the potential risks associated with inundation. In the study basin the distance from river ranges from 0 and 58190 m. As shown in Figure 8 below, the distances were reclassified into five classes; 0-8215 m, 8215-16886 m, 16886-25786 m, 25786-36967 m, and 36967-58190 m. The spatial map of flood risk revealed that the areas near the river are more prone to flooding (Figure 8 and associated flood maps). The PGIS result also confirmed that the areas near to river are more frequently affected by floods and experiencing high flood extent.

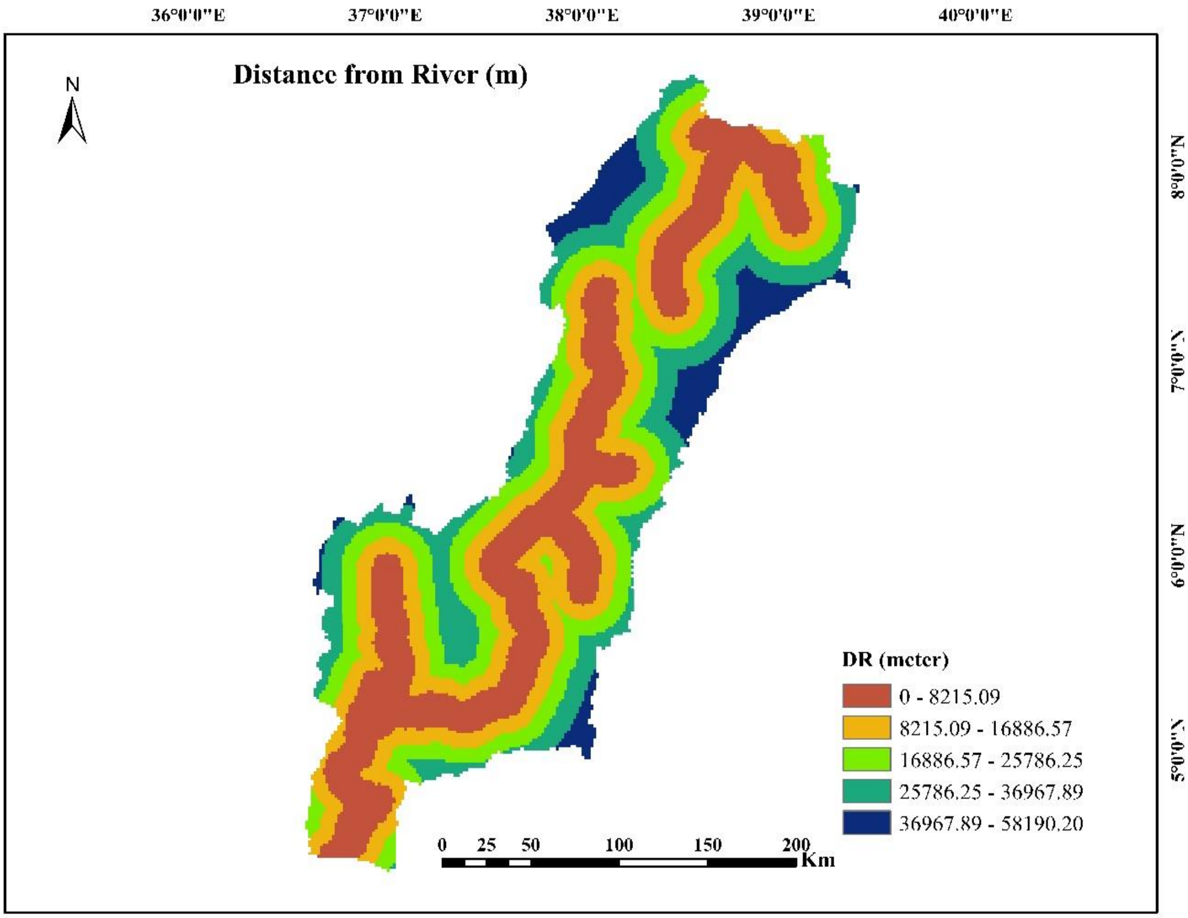



Figure 8. Distance from River in the Rift Valley basin

#### 4.2.5. Slope

Flooding of an area depends on the steepness and length of its slope (Bajabaa et al., 2014). The slope of a given area determines the intensity and quantity of percolation and water accumulation. Since water moves from high to low altitude, the quantity of infiltration and overland flow is affected by the slope. The slope of the Rift Valley basin ranges from a minimum of 0° to a maximum of 85.4° (Figure 9). It is worth noting that the southern tip, central and northern regions of the basin are dominated by a flat slope which increases the susceptibility to flooding events whereas higher slope values are prevail at the southeast and southwest part of the basin, indicating less susceptibility to flooding.

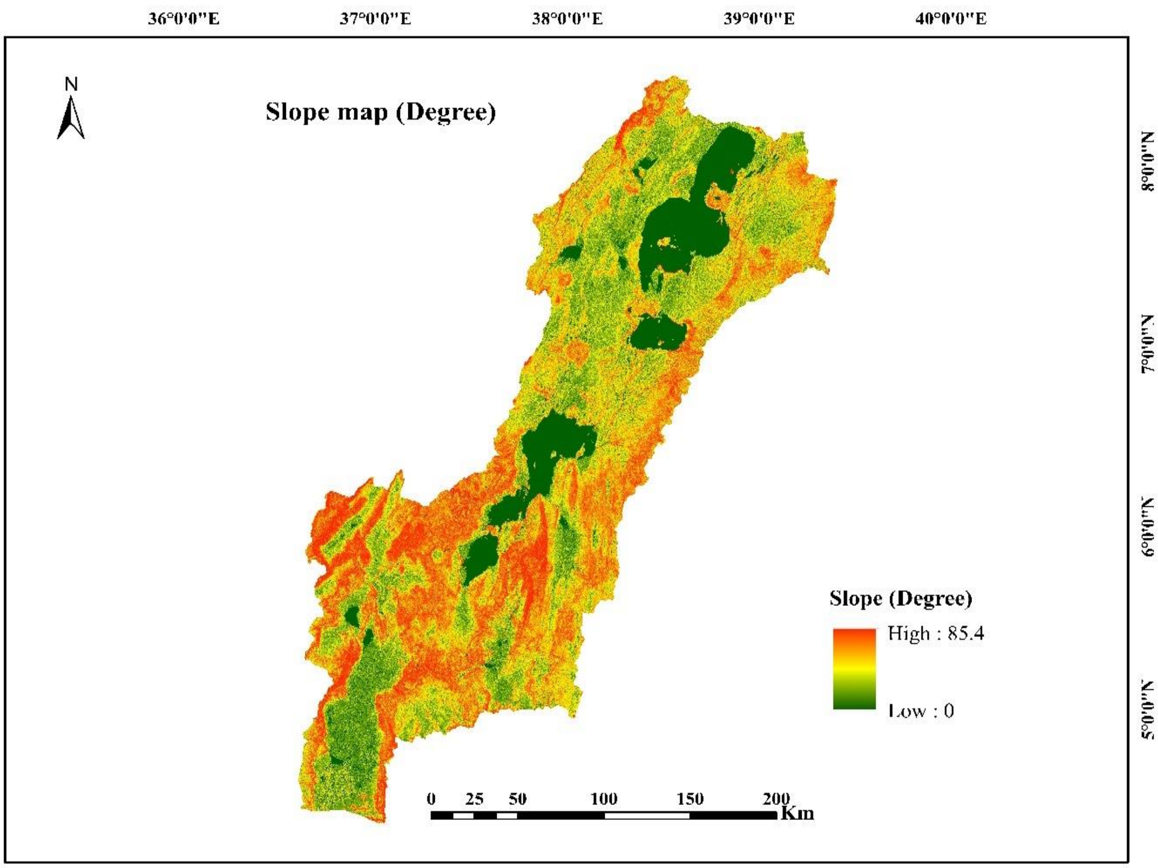



Figure 9. The slope map of the study area

### 4.2.6. Terrain Ruggedness Index

The Terrain Ruggedness Index (TRI) of an area is the elevation difference between nearby cells in a digital elevation grid. It measures the uniformity in the terrain distribution of elevation and is crucial to determine whether an area is rugged or level ground (Das, 2021; Riley et al., 1999). The lower TRI value designates a flat terrain which is more prone to flooding whereas higher values indicates less susceptibility of the area to flooding (Ali et al., 2020). The TRI value of the study basin varies from 0.11 to 0.89 (Figure 10).

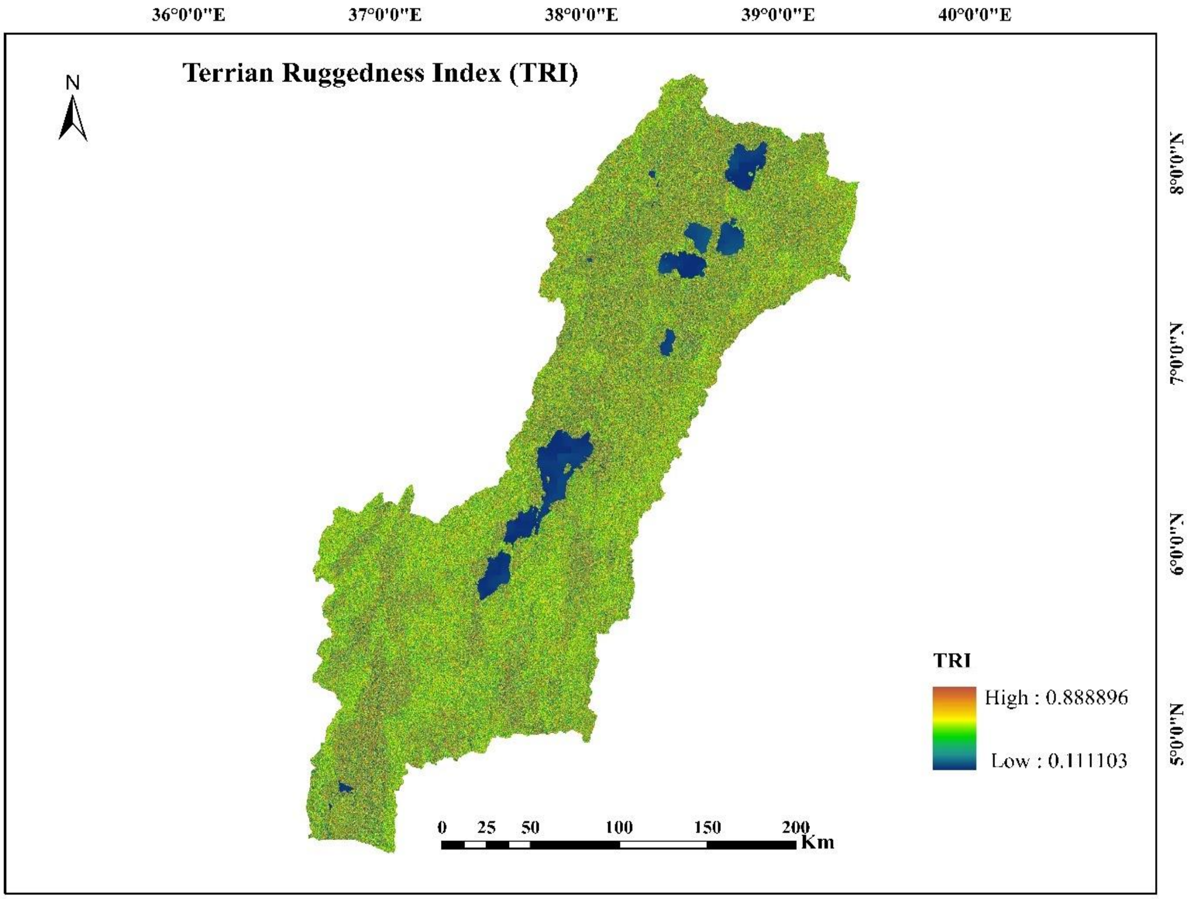



Figure 10. The TRI map of the study basin

### 4.2.7. Topographic Wetness Index

It is a crucial parameter for assessing the effect of topography on flow accumulation and overflow generation (Ali et al., 2020). Because of their lower elevated area, regions with high TWI values like the study area's active floodplain are found to be more vulnerable to floods. This research has assigned higher weight for areas with high TWI values and lower weight for areas with low TWI value. The TWI of the study area varies from -10.7 to 16.2 (Figure 11).

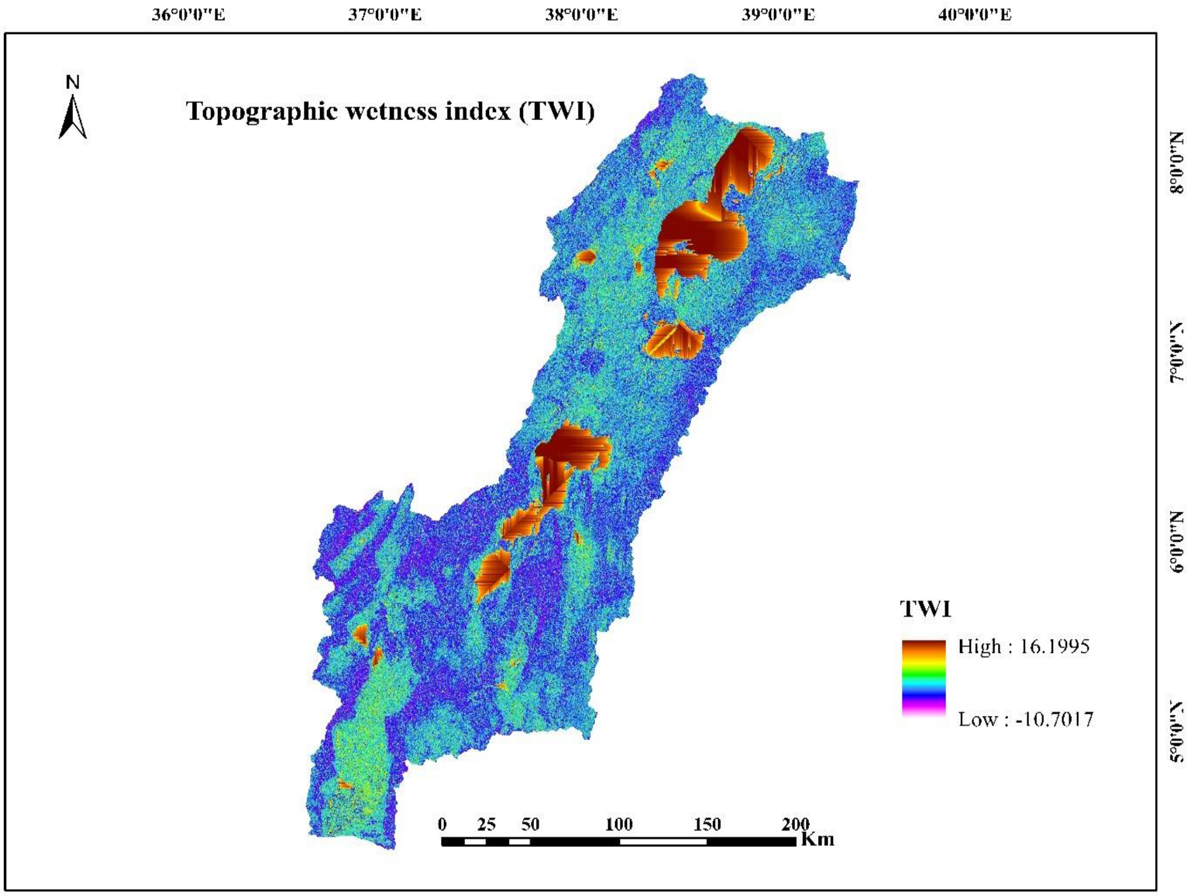



Figure 11. TWI map of the study area

### 4.2.8. Land use land cover

The LULC is one of the prominent parameter in determining regions that are susceptible to flooding and is a key spatial indicator essential for assessing the severity of floods (Ghosh & Kar, 2018). Research has established a negative correlation between flooding and vegetation cover. An area with good vegetation cover reduces runoff intensity and enhances the infiltration process. On other hand, built-up area strongly impedes infiltration into the ground and hastens the surface runoff (Hammami et al., 2019). The Rift Valley basin is predominantly characterized by agricultural land, constituting 35.2% of the total area, followed by forest land, which makes up 27.04% of the basin. The remaining portions of the basin are dominated by range land (25.07%), water bodies (5.2%), built-up areas (5.03%), bare land (2.08%), and wetlands (0.38%) as illustrated in Figure 12. The LULC classification is reassigned on a scale from 1 to 5, considering their economic value and their capacity to mitigate flooding.

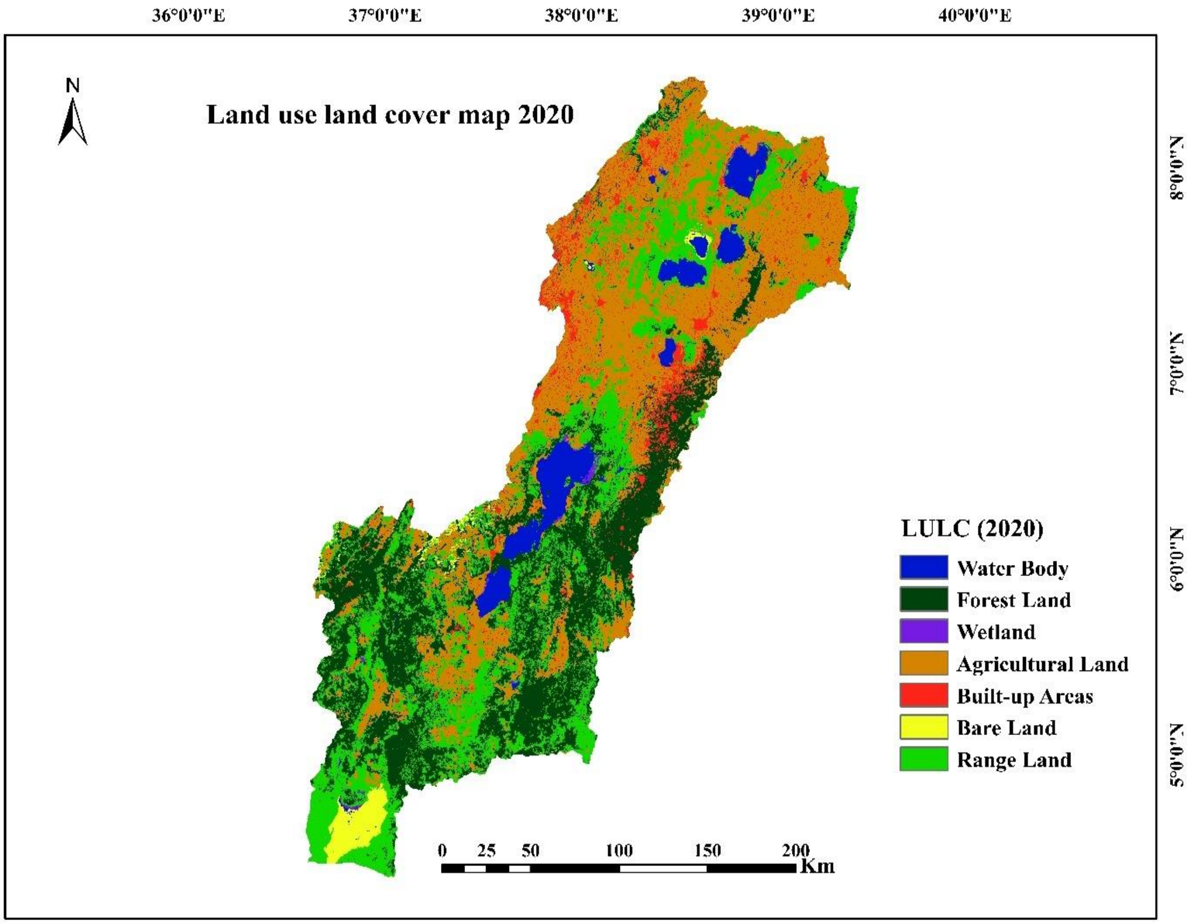



Figure 12. Land use/land cover map of Rift Valley basin

### 4.2.9. Soil type

The nature of the soil in a specific region plays a crucial role in regulating flood levels and infiltration capacity. Soil data proves invaluable in determining excess precipitation and infiltrations. The clay content within the soil emerges as an important factor in flood control. Soils with minimal clay content exhibit high infiltration rates, leading to reduced surface runoff and lower flood susceptibility of the region. The study area is characterized by 29 distinct soil types as shown in figure 13.

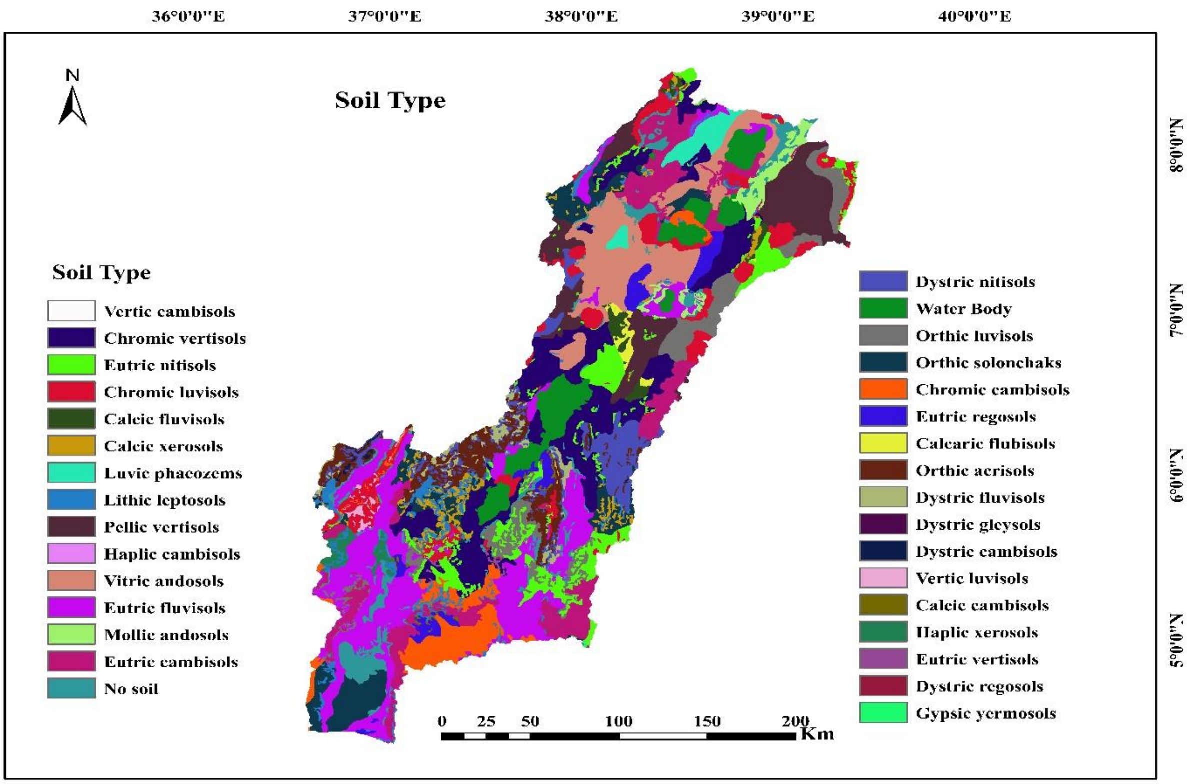



Figure 13. Soil type of Rift Valley basin

### 4.3. Weights of Flood Influencing Factors

Employing various flood conditioning factors proves valuable in assessing the effectiveness of flood risk management in flood-prone areas, given the regional variability in flood causes. This study used AHP which considers both subjective and objective factors to choose the finest alternatives. For pairwise comparison and calculation of the weights and CRs, the research employed AHP Excel Template Version 2022.07.08 developed by Goepel (2013). A pairwise comparison matrix was developed to define the appropriate weight signifying the influence of every factor that affect flooding. In this matrix for pairwise comparisons, the significance of every factor is determined by evaluating each factor against every others using a comparative scale introduced by Saaty (1980), which spans from1 and 9.

The results of flood influencing factor analysis in the Rift Valley basin showed that rainfall (17%), distance from river (14%), elevation (14%), slope (12%), TRI (12%), LULC (11%), TWI (11%) and soil type (9%) weighted consecutively (Figure 14). The CR and CI values of 0.056 and 0.02 are obtained from the study area which is less than 10% denoting a level of consistency that is acceptable (R. W. Saaty, 1980). A similar study conducted by Rimba et al. (2017) discovered that rainfall was the most flood-triggering parameter in Okazaki City, Japan. This implies that rainfall has more influence and contribution to flooding occurrences in the Rift Valley basin than other factors.

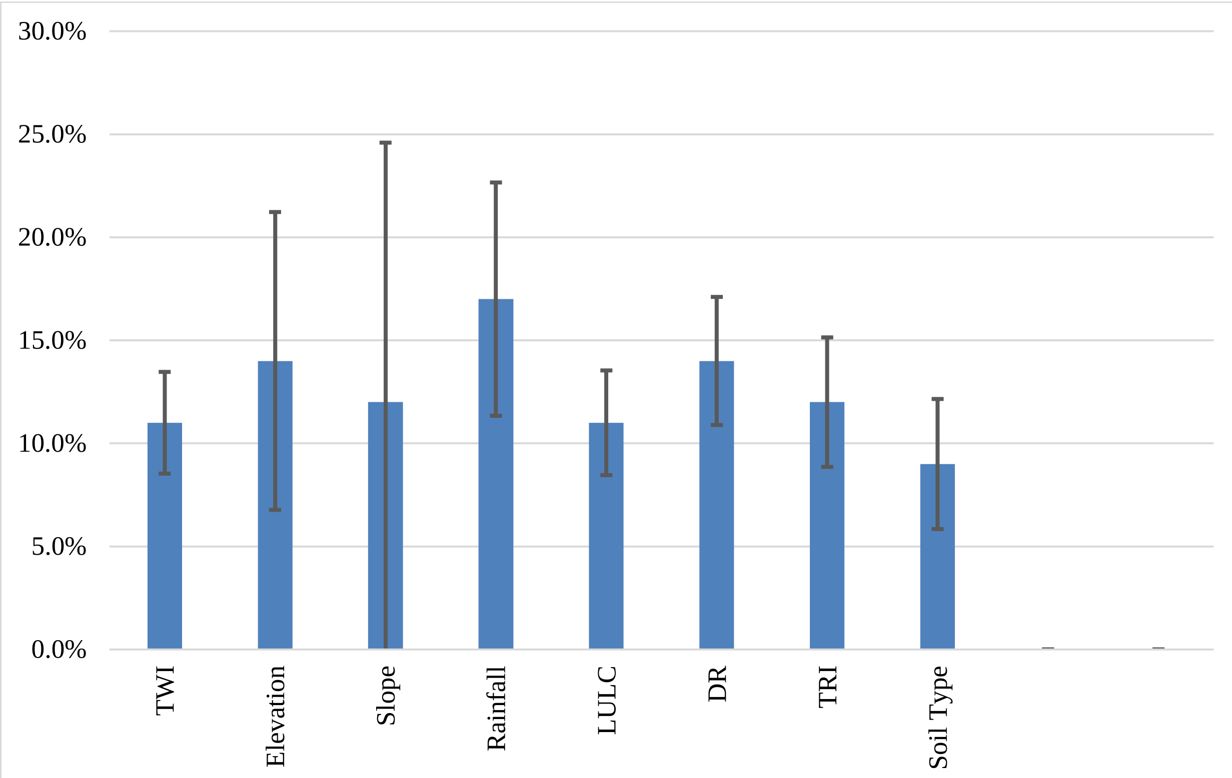



Figure 14. Weight for flood hazard indicators

### 4.4. Projected Flood Hazard Map

In this study the flood risk in the Rift Valley basin was assessed for the baseline period (1981-2020) and for the near future (2021-2060) and far future (2061-2100) under SSP245 and SSP585 scenarios. The study has categorized the level of flood susceptibility into five groups: very low, low, moderate, high, and very high.

#### 4.4.1. Flood Hazard for Baseline Period (1981-2020)

The baseline flood hazard map of the basin outlines five levels of hazard classes spanning from very low to very high flood hazards (Figure 15). The high and very high flood classes constitute 9259.92 $km^2$ (18.43%) and are mainly distributed in central and southern parts with a comparatively small proportion in northern parts of the basin. High and very high hazards were evident in areas near rivers and areas where high rainfall values were recorded. This result is in agreement with the research review conducted by Merz et al. (2021). It is also in line with a study conducted by Mamo et al. (2019) in Ethiopia, who stated heavy rainfall and increase in river flow trigger increased runoff in the wet season leads to the flooding of low lying areas in the rift valley basin of Ethiopia. Besides, this might be attributed to the dominance of bare lands in the southern part of the basin and higher TWI in the central part of the basin (Erena & Worku, 2019; Riadi et al., 2018). Moreover, the moderate hazard class covers about 35120.1 Km$^2$ (69.89%) of the basin. However, low-risk areas are dominant in areas with good vegetation cover and areas far from rivers. They are distributed in the entire body of the study area and cover about 5866.2 Km$^2$ (11.67%) of the basin (Table 5). This finding is in agreement with studies concluding that areas with good vegetation cover, low elevation, and distance from rivers are less susceptible to flooding (Dalu et al., 2018; Rahman et al., 2021).

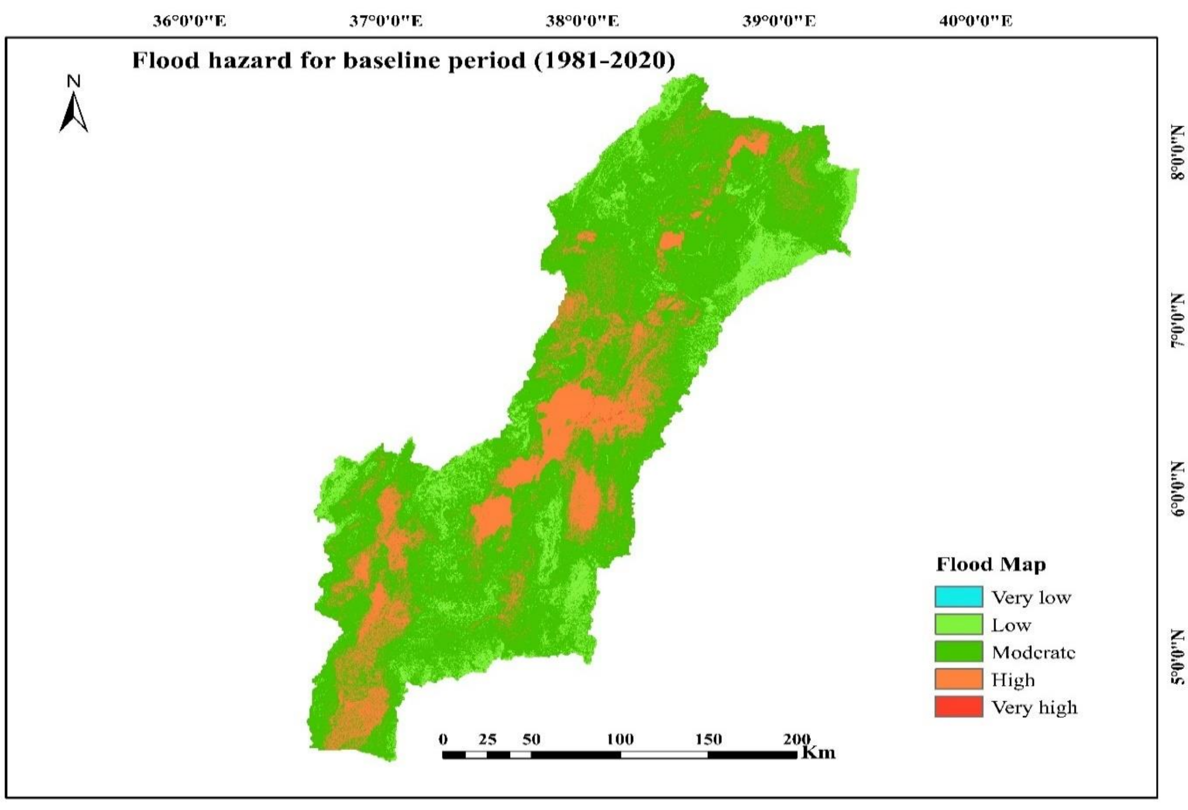



Figure 15. Flood hazard map for the baseline period (1981-2020)

### 4.4.2. Flood Hazard under SSP245 and SSP585 Scenarios (2021-2060)

Flood-prone zones were projected for the 2060s using the SSP245 and SSP585 scenarios based on climate data (Figure 16). According to the SSP245 near future climate scenarios, the next 40 years will see a notable increase in flood susceptible areas compared to the baseline period (Figure 15). Besides, the spatial pattern of flood hazard in the study area exhibits slight variations, with an expanded coverage under both SSP245 and SSP585. This implies a changing flood risk level in the Rift Valley basin. SSP585 shows an increasing trend over SSP245 which is the moderate to high-risk class increases from 31806.1 to 32308.2 and 12165.8 to 13001.6 $Km^2$ respectively. Whereas, the low and very high flood classes show a decline from 6167.7 to 4861.9 and 109.6 to 77.7 $Km^2$ respectively with no significant change in the very low class (Table 5). Compared to the baseline, in both SSP245 and SSP585 scenarios, the risk of flooding in the Rift Valley basin showed an increasing trend, except at the moderate class level. Specifically, in the SSP245 scenario, very high risk has shown a significant increment, increasing from 9,247.36 $km^2$ to 12,166.58 $km^2$ (Table 5).

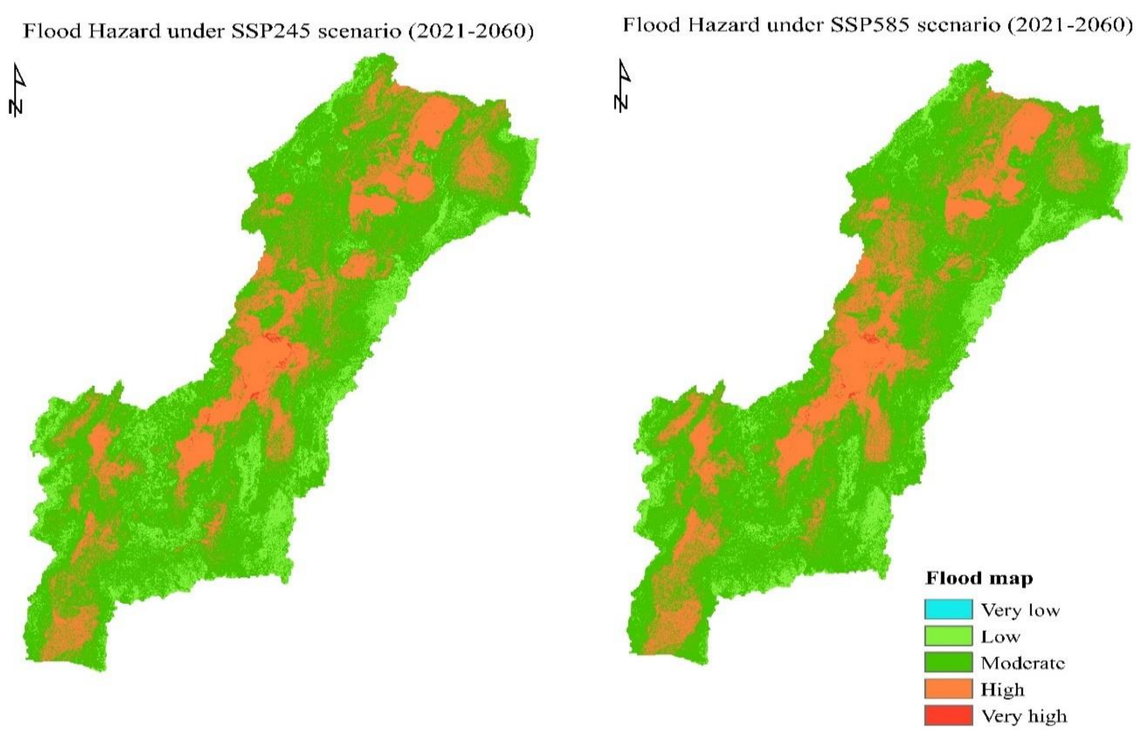



Figure 16. Flood hazard map for the 2060s under a) SSP245 and b) SSP585

### 4.4.3. Flood Hazard under SSP245 and SSP585 Scenarios (2061-2100)

The spatial distribution of flood risk in Rift Valley basin signifies that, under both scenarios, the high to very high-risk areas are mainly concentrated in the central and northern parts and slightly in the southern regions of the study area (Figure 17). The results also suggest that under SSP585, there is a greater risk of flooding, especially moderate and very high flood classes prevail. This is likely due to more extreme weather events which can result in more severe flooding. Conversely, under SSP245, the risk of flooding is lower, with smaller areas being affected overall (Table 5).

Table 5. Projected flood areas under ensembles of SSP245 and SSP585

| Flood hazard class | Description | Baseline period | SSP245 near future | SSP245 far future | SSP585 near future | SSP585 far future |
|---|---|---|---|---|---|---|
| | | Area ($Km^2$) | Area ($Km^2$) | Area ($Km^2$) | Area ($Km^2$) | Area ($Km^2$) |
| 1 | Very low | 3.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| 2 | Low | 5866.21 | 6167.71 | 10.63 | 4861.73 | 4547.16 |
| 3 | Moderate | 35120.10 | 31806.10 | 64.38 | 32308.20 | 33262.00 |
| 4 | High | 9247.36 | 12165.80 | 24.90 | 13001.60 | 12365.90 |
| 5 | Very high | 12.56 | 109.61 | 0.09 | 77.73 | 74.12 |

Comparing the baseline period with the flood risks under the SSP245 and SSP585 far-future scenarios revealed potential spatiotemporal variation in flood risk due to climate change. In both scenarios, the flood classes generally signified an increase in area coverage compared to the baseline (Table 5). This indicates that climate change may contribute to a higher likelihood and extent of flooding in the future.

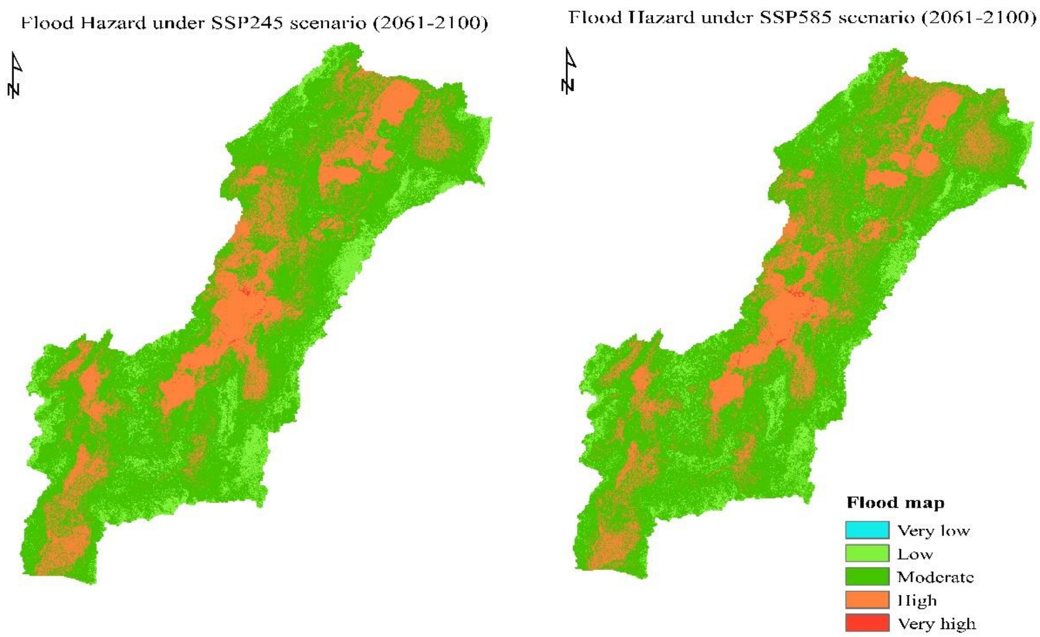



Figure 17. Shows the flood hazard from 2061-2100 under a) SSP245 and b) SSP585

## 4.5. PGIS and Flooding

This study involved stakeholders during primary data collection through community participation. Areas for stakeholder involvement were deliberately selected based on suggestions from previous studies, literature reviews, and the time and resources the researcher had. The chosen areas for PGIS are Bilate, Kulfo Gina, Sile-sego, and Lake Hassa sub-basins, located in the central and southern parts of the study basin. From their past experiences and exposures, stakeholders identified flood susceptible areas which were subsequently georeferenced using GPS. Following the generation of the flood risk map by overlaying all factor maps in the ArcGIS 10.8 environment, the georeferenced points were overlaid and checked. Additionally, Google Maps were also used to navigate flood-prone areas.

In the study area, spatial awareness of the flood event within the community was found to be variable, as revealed in field visit and FGD assessing flood-prone areas. The community emphasized recurrent flood-prone zones and the associated consequences, including the loss of lives and properties. Notably, residents mentioned various adverse impacts resulting from flooding. The PGIS results corroborate the community's concerns, indicating a consistent yearly increase in flooding frequency and extent. This research underscores the significance of PGIS, not just for engaging local communities in research but also as a crucial tool for comprehending the evolving spatial characteristics of hazards in flood-prone areas. This research has triangulated the results and revealed a high level of alignment between the perceptions of flood-affected communities and the conventional flooding assessment.

# 5. CONCLUSION AND RECOMMENDATION

## 5.1. Conclusion

Given the increasing concentrations of greenhouse gases, climate change and climate change-induced hazards become one of the biggest world problems in the 21$^{st}$ century. Its impact is more severe in developing countries due to various reasons. Hence, it is essential to anticipate these challenges, providing early warning information and enhancing preparedness. Ethiopia is among the ones that contend with frequent and increasing climate change-induced flooding with the recent decade being the most inundated posing significant risks to both people and infrastructure. Despite the research being conducted in a limited number of watersheds and sub-basins, there is a notable absence of studies covering the entire basin, which is recognized as one of the top three flood-prone basins in Ethiopia. Moreover, the previous research was carried out using conventional methods without incorporating PGIS. Therefore, this study addresses this gap by conducting a comprehensive flood assessment of the entire basin, by integrating both conventional research and PGIS method. It is mainly aimed at projecting the impact of climate change under current and future climate scenarios.

This study used field visits, and governmental and non-governmental organizations as sources of primary and secondary data. These datasets were used to develop thematic layers of flood indicators namely; rainfall, land use land cover, slope, elevation, TWI, TRI, DR, and soil type. Daily rainfall data from 33 observed stations and gridded data and climate projections from CMIP6 models were incorporated, with Enactus gridded data utilized to fill missing rainfall data. The study harnessed state-of-the-art CMIP6 models, employing two emission scenarios (SSP245 and SSP585) to predict future climate conditions. Five global climate models that have performed well in East Africa and Ethiopia were carefully selected namely, CanESM5, CNRM-ESM2-1, MIROC6, MRI_ESM2, and NoRESM2. All the models underwent bias correction and model performance evaluation. Additionally, the AHP model was utilized to calculate the weights for all input variables in flood risk mapping. From the pairwise comparison matrix, CR and CI were calculated. Finally, the projected flood hazard zones were validated using georeferenced data collected during field surveys. The overall analysis was conducted using the AHP Excel Template Version 2022.07.08, ArcGIS, and SAGA GIS.

After careful evaluation, the study picked the three models that performed the best for more in-depth examination. These standout models are NoRESM2, CNRM-ESM2-1, and CanESM5. The analysis revealed that the basin experiences a mean annual rainfall ranging from 629 to 1484mm for the base period. Whereas, the projected rainfall for SSP245 and SSP585 scenarios in the near and far future resulted in mean values ranging between 899.8 to 1308.1, 838.6 to 1563.9, 854 to 1573.2, and 967.5 to 1803 mm, respectively. In the Rift Valley basin, seven LULC classes were identified, namely water bodies, forest land, wetland, agricultural land, built-up areas, bare land, and range land. It is predominantly characterized by agricultural land (35.2%), followed by forest land, covering 27.04% of the total basin area. In this study, rainfall emerged as the most influential factor contributing 17% to flood events in the Rift Valley basin followed by distance from the river (14%), elevation (14%), slope (12%), TRI (12%), LULC (11%), TWI (11%), and soil type (9%). The result of this finding also shows that the values of CR and CI were found to be 0.056 and 0.02, respectively.

In the baseline flood hazard map, the Rift Valley basin exhibits high and very high flood classes covering 18.43% (9259.92 km²) of the area, primarily in the central and southern regions. This might be attributed to factors such as proximity to rivers, high rainfall, bare land dominance, and higher TWI. The low-risk areas covering 11.67% of the basin align with studies emphasizing the protective role of good vegetation cover. In projections for 2060 under SSP245 and SSP585 scenarios, the high and very high flood-risk areas exhibited an increasing trend. Particularly, under SSP245, the high and very high flood classes show a significant increment, increasing from 9,247.36 to 12,166.58 km² and 12.56 to 109.61 km². Meanwhile, under SSP585, the high class experienced a more considerable rise, reaching 32,308.2 km² and the very high class reached 77.3 km², respectively. Under the SSP245 and SSP585 scenarios (2061-2100), the spatial distribution of flood risk in the study area indicates a concentration of high to very high-risk areas in the central and northern parts, with a greater risk under SSP585, especially in moderate and very high flood classes. Comparing the baseline period with the flood risks under both scenarios reveals spatiotemporal changes, indicating climate change's potential contribution to higher flood likelihood and extent in the future in the Rift Valley basin. Stakeholders pinpointed flood-prone areas and their insights aligned with conventional results and highlighted an over-year increase in flooding extent.

## 5.2. Recommendations

Based on the result of the findings of this study, the following suggestions are forwarded;

- ✓ Establish and enhance community-based early warning systems in flood vulnerable regions to empower local communities with timely and accurate information to better prepare for and respond to flood events.
- ✓ Prioritize targeted afforestation and implement climate resilient initiatives particularly in moderate to very high flood risk areas under baseline and future climate scenarios.
- ✓ Seriously integrating flood measures into development plans can contribute to flood risk reduction in Ethiopia and other regions facing similar challenges.
- ✓ This research underscores the importance of conducting comprehensive flood assessments across entire Rift Valley basin using CMIP6 climate model alongside PGIS. This integrated approach provides valuable insights into flood risk dynamics and support informed decision-making and adaptation strategies in flood vulnerable areas.

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# 7. APPENDICES

Appendix Table 1. Flood hazard assessment criteria and sub-criteria ranges

| Flood Causative criterion | Unit | Class | Hazard class ranges | Hazard ratings | Weight |
|---|---|---|---|---|---|
| TWI | level | -10.596159 - -5.215932 | Very low | 1 | 11 % |
| | | -5.215932 - -3.000544 | Low | 2 | |
| | | -3.000544 - 0.058801 | Moderate | 3 | |
| | | 0.058801 - 3.329135 | High | 4 | |
| | | 3.329135 - 16.093987 | Very high | 5 | |
| Elevation | m | 0 - 974 | Very high | 5 | 14 % |
| | | 974 - 1514 | High | 4 | |
| | | 1514 - 2032 | Moderate | 3 | |
| | | 2032 - 2625 | Low | 2 | |
| | | 2625 - 4188 | Very low | 1 | |
| Slope | degree | 0 - 4.019583 | Very high | 5 | 12 % |
| | | 4.019583 - 9.846934 | High | 4 | |
| | | 9.846934 - 17.549152 | Moderate | 3 | |
| | | 17.549152 - 27.531113 | Low | 2 | |
| | | 27.531113 - 85.039452 | Very low | 1 | |
| Rainfall (His) | mm/yr | 629.2701 - 800.1360 | Very low | 1 | 17 % |
| | | 800.1360 - 893.9447 | Low | 2 | |
| | | 893.9447 - 1001.1547 | Moderate | 3 | |
| | | 1001.1547 - 1168.670 | High | 4 | |
| | | 1168.6703 - 1483.599 | Very high | 5 | |
| Rainfall SSP245 (Near) | mm/yr | 899.8432 - 999.6561 | Very low | 1 | |
| | | 999.6561 - 1076.8698 | Low | 2 | |
| | | 076.8698 - 1154.0835 | Moderate | 3 | |
| | | 1154.0835 - 1229.4140 | High | 4 | |
| | | 1229.4140 - 1380.0749 | Very high | 5 | |
| Rainfall SSP245 (Far) | mm/yr | 838.6196 - 995.0579 | Very low | 1 | |
| | | 995.0579 - 1114.519 | Low | 2 | |
| | | 1114.519 - 1233.9818 | Moderate | 3 | |
| | | 1233.9818 - 1339.2221 | High | 4 | |
| | | 1339.2221 - 1563.9244 | Very high | 5 | |
| Rainfall SSP585 (Near) | mm/yr | 853.9796 - 1000.6506 | Very low | 1 | |
| | | 1000.6506 - 1116.295 | Low | 2 | |
| | | 1116.2950 - 1231.939 | Moderate | 3 | |
| | | 1231.9394 - 1333.4809 | High | 4 | |
| | | 1333.4809 - 1573.2315 | Very high | 5 | |
| Rainfall SSP585 (Far) | mm/yr | 967.5109 - 1141.1646 | Very low | 1 | |
| | | 1141.1646 - 1298.435 | Low | 2 | |
| | | 1298.4359 - 1449.1543 | Moderate | 3 | |
| | | 1449.1543 - 1547.4488 | High | 4 | |

| | | | | | |
|---|---|---|---|---|---|
| | | 1547.4488 - 1803.01 | Very high | 5 | |
| | | | | | |
| LULC | level | Water body (1) | Very high | 5 | 11 % |
| | | Forest land (2) | Low | 2 | |
| | | Wetland (4) | Moderate | 3 | |
| | | Agricultural land (5) | High | 4 | |
| | | Built-up areas (7) | Moderate | 3 | |
| | | Bare land (8) | High | 4 | |
| | | Range land (11) | Very low | 1 | |
| DR | m | 0 - 7342.940918 | Very high | 5 | 14 % |
| | | 7342.940 - 16501.207 | High | 4 | |
| | | 16501.207 - 25700.293 | Moderate | 3 | |
| | | 25700.293 - 37043.664 | Low | 2 | |
| | | 37043.664 - 58190.203 | Very low | 1 | |
| TRI | level | 0.111084 - 0.378049 | Very low | 1 | 12 % |
| | | 0.378049 - 0.466948 | Low | 2 | |
| | | 0.466948 - 0.540966 | Moderate | 3 | |
| | | 0.540966 - 0.6325 | High | 4 | |
| | | 0.6325 - 0.888916 | Very high | 5 | |
| Soil types | level | Calcic Xerosols, Haplic Cambisols, Vitric Andosols, Dystric Gleysols | Very low | 1 | 9 % |
| | | Luvic Phaeozems, Chromic Cambisols, Orthic Acrisols | Low | 2 | |
| | | Eutric Nitisols, Lithic Leptosols, Mollic Andosols<br>Dystric Nitisols, Orthic Luvisols, Chromic Luvisols<br>Orthic Solonchaks, Eutric Regosols, Haplic Xerosols, Dystric Regosols, Utric cambisols, Dystric cambisols, Calcic cambisols<br>Eutric vertisols, No Soil | Moderate | 3 | |
| | | Calcic Fluvisols, Eutric Fluvisols, Calcaric Flubisols<br>Dystric Fluvisols | High | 4 | |

| | | | | | |
|---|---|---|---|---|---|
| | | Vertic Cambisols, Chromic Vertisols, Pellic Vertisols, Vertic Luvisols, Gypsic Yermosols | Very high | 5 | |
| | | Water bodies | Very high | 5 | |
| Total | | | | | 100 |