

CLIMATE CHANGE IMPACT ON KOKA DAM SAFETY, ETHIOPIA



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DECLARATION

I hereby declare that this Master Thesis entitled “**Climate Change Impact on Koka Dam Safety, Ethiopia**” is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

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I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled “**Climate Change Impact on Koka Dam Safety, Ethiopia**” prepared under my guidance by **Hamid Tsega Nega** submitted in partial fulfillment of the requirements for the degree of Master’s of Science in Water Resources Engineering (Specialization in Hydraulic Engineering). Therefore, I recommend the submission of the revised version of the thesis to the department following the applicable procedures.

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LIST OF ACRONYMS AND ABBREVIATIONS

ARFs	Areal Reduction Factors
CanESM2	Canadian Earth System Model version
CC	Climate Change
CCCma	Canadian Centre for Climate Modelling and Analysis
CGCM2	Second Generation Canadian Coupled Global Climate Model
CMIP5	Climate Model Intercomparison Project Phase 5
CN	Curve Number
CNRM-CM5	Centre National de Recherche Meteorolo-Giques
CORDEX	Coordinated Regional Downscaling Experiment
DEM	Digital Elevation Model
DMC	Double Mass Curve
ECHAM	European Centre Hamburg Model
EEPU	Ethiopian Electric Power Utility
ET	Evapotranspiration
FAO	Food and Agriculture Organization
GCM	General Circulation Models
GIS	Geographic Information System
GLUE	Generalized Likelihood Uncertainty Estimation
HadCM3	Hadley Centre Coupled Model version 3,
HEC-HMS	Hydrologic Engineering Center's- Hydrologic Modeling
HRU	Hydrologic Response Unit
ICOLD	International Commission on Large Dams
ICTZ	The Inter-Tropical Convergence Zone
IPCC	Intergovernmental Panel on Climate Change
LULC	Land Use Land Cover
MCMC	Markov Chain Monte Carlo
MIROC	Model for Interdisciplinary Research on Climate
MoWE	Ministry of Water and Energy
MPI-M-ESM	Max Planck Institute for Meteorology Earth System Model

NASA	National Aeronautics and Space Administration
NEX-GDDP	NASA Earth Exchange Global Daily Downscaled Projections
NMA	National Meteorological Agency of Ethiopia
NSE	Nash-Sutcliffe Efficiency
PBIAS	Percent of Bias
PMF	Probable Maximum Flood
PMP	Probable Maximum Precipitation
PSO	Particle Swarm Optimization
R^2	Coefficient of Determination
RCA4	Rossby Centre regional climate model version 4
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
SCS	Soil Conservation Service
SMHI	Swedish Meteorological and Hydrological Institute
SUFI-2	Sequential Uncertainty Fitting -2
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT Calibration and Uncertainty Programs
US	United State
USACE	United States Army Corps of Engineers
USBR	United States Geological Survey
WGEN	Weather Generator
WRF	Weather Research and Forecasting model

ABSTRACT

Climate change is currently having significant global impacts, affecting both living and nonliving entities. One of the prominent consequences of climate change is the increasing occurrence of floods, which pose a threat to various man-made structures including dams, roads, buildings, bridges, and others. This study focuses on assessing the safety of Koka Dam to climate change, employing future projection scenarios of RCP4.5 and RCP8.5. To achieve this, the distributed hydrological SWAT Model was utilized with input from three distinct Models (CanESM2, CNRM, and MPI) operating under RCP4.5 and RCP8.5 scenarios. As a result, the RCM projection suggests that the average annual maximum precipitation is expected to rise by 34.77%, while the mean annual maximum precipitation is predicted to decline by -22.38%. Additionally, the mean annual maximum and minimum precipitation are projected to increase by 7.2°C and 1.5°C, respectively. The accuracy of the model is assessed based on various indicators, including the R^2 , NSE, and Pbias. The calibration and validation results suggest that the model performed very good and good at both Hombole and Mojo gauging stations, with a good level of correlation and accuracy between the observed and simulated data. In the case of the RCP4.5 scenarios using HEC-HMS, the peak inflow and outflow values for the near, mid, and end-future periods are 7752.03 m³/s, 7240.78 m³/s, and 6510.68 m³/s, and 1354.3 m³/s, 1316.2 m³/s, and 1252.5 m³/s, respectively. Similarly, under the RCP8.5 scenario, the peak inflow values are 10456.6 m³/s, 7224.78 m³/s, and 8000.48 m³/s, respectively. The corresponding outflow values are 1505.9 m³/s, 1315 m³/s, and 1372.3 m³/s. According to the routing analysis, the maximum inflow and outflow during the near future, mid-future, and end future under RCP4.5 and RCP8.5 scenarios exceed the probable maximum flood that the spillway at the Koka Dam was designed to handle. This implies that the dam will be at risk of overtopping. In summary, the results suggest that due to the insufficient capacity of the spillway, the Koka Dam would be considered unsafe and vulnerable to overtopping under the projected outflow.

Keywords: RCM, ArcSWAT, Spillway, Safety, Koka Dam, Climate Change, HEC-HMS

1. INTRODUCTION

1.1. Background

The most important research agenda at the global level is climate change impacts on water resources. The normal hydrological processes are disrupted as a result of climate change, which has a substantial impact on the water resource. One of the commonly mentioned hydrological concerns is the anticipated alterations in the magnitude, variability, and timing of the primary flow event in the future (Frederick, 2002).

Significant changes in the long-term patterns of precipitation and temperature are indicators of climate change, which is connected to accelerated industrial growth and notable greenhouse gas emissions from human-induced activities. Climate change and global warming are responsible for the rise in environmental hazards, including floods, which affect both people and the ecosystem. Extreme droughts and floods are just two examples of climate variations with negative effects that have a substantial influence on rural and urban infrastructure (Fluixá-Sanmartín et al., 2018). Additionally, climate change poses a potential risk, particularly in regions characterized by lower socioeconomic development and elevated poverty rates, where awareness of climate-related safety threats may be insufficient. The most vulnerable rural communities are included in this, where the infrastructure is deteriorating or was not constructed to the highest safety requirements. Along with the constraints of monitoring and management in poor nations, the lack of unifying criteria to conceptualize climate change in the dam's design may increase the hazards to populations downstream, with severe repercussions (Herbozo et al., 2022).

Climate change impacts are becoming a serious problem in Africa. Because the seasonal and decadal climates of several African nations vary greatly. In reality, this affects the overall economy of the countries which depend mostly on hydrological seasonality. For instance, since the economy of Ethiopia is highly intercorrelated to hydrological variability and seasonality, the Ethiopian economy is vulnerable to climate change impact and should implement real mitigation and adaptation measures to reduce the overall impact (Tarekegn et al., 2022).

According to the IPCC's findings, Countries with less economic development, such as Ethiopia, are more vulnerable to the impacts of climate change. Ethiopia is significantly affected by the impacts of climate change as a result of its reliance on agriculture and its limited ability to adapt its economic structure. Therefore, it is important for the country that

the program includes an evaluation of the consequences of climate change (Zeray & Demie, 2015).

Dam safety refers to the measures taken to ensure that dams are designed, constructed, operated, and maintained in a way that minimizes the risks associated with their operation and potential failure. The safety of a dam is critical, as its failure can lead to loss of life, property damage, and other negative consequences. Climate change presents significant challenges to dam safety, including an increase in extreme weather events such as heavy rainfall and floods, which can elevate the risk of dam failure. Furthermore, the stability of dams can be affected by rising temperatures, leading to changes in soil moisture levels, erosion, and ice melting. Alterations in precipitation patterns can also impact the water balance of reservoirs, potentially affecting their storage capacity and resulting in an increased risk of spillway failure or overtopping (Fluixá-Sanmartín et al., 2019).

According to Fluixá-Sanmartín et al. (2018), Dams are vital infrastructure, and it is essential to effectively manage the risk of their potential failure through an ongoing and up-to-date process. Historically, many dam risk assessments operated on the assumption that climate events' variability remained constant when establishing safety standards. However, this assumption of a stable climate baseline is no longer appropriate for ensuring long-term dam safety and guiding decision-making. Consequently, it becomes imperative to reconsider how risk analyses are structured for the long term, considering the influence of new climate change scenarios.

To accurately evaluate the impact of climate change on dam safety, it is necessary to quantitatively analyze the combined effects of various projected factors on each aspect of the dams. Fluixá-Sanmartín et al. (2018), proposed a tool for managing dam safety that enables the assessment of projected climate change impacts using a risk analysis approach. This tool allows for the comprehensive inclusion of all variables related to dam safety and their interconnections, providing a thorough understanding of the potential effects of climate change on dam infrastructure.

The risks of a dam failure are high and might cause significant amounts of harm, including fatalities, property damage, and negative long-term effects. An example from Southeast Asia illustrates the risks associated with dams. In July 2018, the Xepian-Xe Nam Noy hydropower dam in Laos suffered a collapse following a significant rainstorm event, resulting in the release of over 5 billion cubic meters of water. This disaster had a profound

impact, affecting more than 11,000 people in the region. More recently, in May 2020, after two days of rain, a dam in Central Michigan broke in the United States, displacing roughly 10,000 people from downstream areas. Dams can present risks to society by fostering a sense of security that ignores lessons from past mistakes if they are not built with future climate change scenarios in mind (Flores & Peralta Quesada, 2020). Dam safety under the effect of climate change is a problem that requires urgent attention, as mentioned. To assess the vulnerability of dams to climate change and determine future adaptation measures, a holistic analysis may be used as a supporting tool for dam safety management (Fluixá-Sanmartín et al., 2019).

Nowadays in Ethiopia, different irrigation and hydropower projects that range from small-scale to large-scale are being constructed. Among these, the Koka Dam, water storage system is constructed for irrigation development and hydropower generation purposes. To ensure the sustainability of the dam's safety, it should be checked for climate change impact. The Dam was built in Ethiopia in 1960. It was primarily designed for hydropower production. Currently, it is used for irrigation development too. The introduction of irrigation in the area created an opportunity for farmers to enhance their agricultural productivity.

Therefore, it is crucial to conduct research on the impacts of climate change on dam safety to anticipate and respond to potential challenges in the future, either by averting the worst-case scenario or at the very least by being well-equipped and resilient in dealing with potential difficulties. The Upper Awash River has a large watershed area that different varying weather conditions, making it susceptible to the impacts of climate change. As a result, there are changes in the amount of flow and sediment in the basin, as well as fluctuations in flood occurrences. The purpose of this study is to assess how climate change affects the safety of dams in the study area.

1.2. Statement of the Problem

Many studies have focused on assessing climate change impacts on dams, particularly during extreme flood events in the world. due to a lack of understanding of hydrological parameters, capacity of the reservoir, and spillway, dam safety is the most challenging in most countries in the world. These investigations utilize hydrologic models that simulate future scenarios and present conditions by incorporating data on extreme precipitation. However, both ongoing and planned water projects face a significant challenge related to

the uncertainty associated with precipitation, which directly affects the inflow into dam reservoirs. As a result, this uncertainty presents a serious challenge to the sustained functionality and safety of these dams. Substantial scientific evidence supports the reality of climate change, demonstrating that our planet's climate is indeed undergoing significant changes (Nikulin et al., 2018). The adverse effects of climate change, such as extremely low and high temperatures observed worldwide at the beginning of 2019, can be attributed to this phenomenon. Hydrological extreme conditions have the potential to elevate the risk of dam overtopping, thereby endangering the safety of downstream communities through flooding disasters. Remarkably, many feasibility studies and structural designs for water resource projects have neglected to consider the potential effects of climate change (Fluixá-Sanmartín et al., 2019). This neglect represents a significant problem, as it directly impacts the sustainability of such structures. The associated uncertainty arising from increased maximum precipitation can lead to more frequent and severe floods, ultimately resulting in an elevated risk of dam failure. These problems affect the management & performance of Koka Dam in the future. Koka Dam is a concrete gravity dam, which was important for economic development downstream of the Koka Dam such as hydropower plant, irrigation project, and fishery; these activities can be affected if a high flood occurs and the dam is unsafe. there is probable loss of human lives, houses, buildings, and other interesting economic activities if the dam is unsafe. Therefore, we have to give deep attention to the safety of the dam; because the floods resulting from unsafe dams produce huge damage to the downstream areas.

Dam safety must concurrently meet demands for a variety of purposes, including maintaining water security, protecting significant infrastructure investments, protecting human life, and protecting the homes and other property of those who live downstream of the dams. To quantify and suggest suitable mitigation measures for watershed conservation and management of dam spillway safety, it is crucial to properly assess the impact of climate change on the hydrological responses of the catchment.

1.3. Objective

1.3.1. General objective

The main objective of this study is to assess the impacts of climate change on the safety of Koka Dam.

1.3.2. Specific objectives

- To evaluate the SWAT hydrological model performance in simulating the streamflow in the upper awash watershed.
- To assess future climate change of the upper Awash Watershed under the RCP climate scenario
- To predict the time series of streamflow under the influence of climate change.
- To assess the safety of Koka Dam under climate change due to hydrological conditions would be safe or not.

1.4. Research Questions

- How well does the SWAT hydrological model simulate the hydrological processes of the upper awash watershed?
- What are the effects of climate change on rainfall and temperature characteristics of the study area?
- What is the predicted streamflow amount under the future climate change?
- How Koka Dam safety is responding to the changing climate?

1.5. Scope and Limitation of the Study

The scope of this study is limited to the upper awash sub-basin mainly to inflows to the Koka dam and analyzes the dam safety due to climate change. This study focuses only on two representative concentration pathways, RCP4.5 and RCP8.5 when examining the impact of climate change. This choice is made because other concentration emission scenarios have less significant effects compared to these two. It's important to note that the study does not consider the effects of sedimentation in the reservoir, potential dam body failure due to seepage, failure of the spillway, or other natural factors.

1.6. Significance of the Study

The impact of climate change on dams is a crucial and sensitive issue over the entire world today. Therefore, understanding the impact of historical climatic changes on the watershed hydrological system is essential to estimating the potential future effects of climate change on water balance components of river flow. Climate change can have a substantial impact on catchment hydrology, and these effects are often closely interconnected. This study primarily underscores the noteworthy influence of climate change on hydraulic structures,

with a particular focus on its implications for dams. In the study area, climate change has led to two contrasting outcomes: extreme flooding during the rainy season and a scarcity of water during the dry season. To help local governments and policymakers take the necessary actions and implement an effective strategy to mitigate the unfavorable impact of climate changes on dam safety, this study is expected to provide crucial information about the influence of climate change on the hydrological process of the watershed and the safety of the dam constructed.

1.7. Thesis Organization

This thesis is divided into five chapters, which are structured as follows. The first chapter is the introduction of the study, including the background information, statement of the problems, research objectives, research questions, scope, and significance of the study. The second chapter offers a summary of the existing literature on climate change, covering its global, continental, and regional aspects. It also discusses previous studies conducted in the upper Awash basin, and recent climate change scenarios, and provides an overview of the SWAT model. It also discussed the impact of climate change on dam safety over the world. The third chapter offers a description of the study area, data availability, and sources, as well as the methods and materials incorporated in this chapter. Chapter four, considered one of the core sections of this research, presents the results obtained from applying the model to assess the impact of climate change on dam safety. It provides a detailed account of the model setup, sensitivity analysis of model parameters, calibration, validation, flood frequency analysis, reservoir routing, and interpretation of the results. Finally, chapter five provides a conclusion and recommendations.

2. LITERATURE REVIEW

2.1. Climate Change Impact On Rainfall And Temperature

Characteristics

Climate change refers to long-term shifts and alterations in the Earth's climate patterns, primarily resulting from human activities, such as the burning of fossil fuels, deforestation, and industrial processes. The consequences of climate change include rising sea levels, extreme weather events, changes in precipitation patterns, and disruptions to ecosystems and biodiversity. Moreover, there is growing evidence to indicate that global climate change is increasingly apparent through various phenomena, including the rise in global temperatures, changes in rainfall patterns, widespread melting of ice and glaciers, and the resulting rise in sea levels across the planet. These observed changes have been documented for a minimum of three decades according to the Intergovernmental Panel on Climate Change (IPCC, 2007).

Climate change is currently confronting the entire globe. It is widely acknowledged that climate change is already occurring, and additional changes are unavoidable. The compilation of global average temperature data, encompassing both land and ocean surfaces, reveals a warming trend of 0.85°C between 1880 and 2012 (IPCC, 2014). Numerous studies indicate that human activities are largely responsible for the majority of the increase in average global surface temperature over the past 50 years (Broothaerts et al., 2012).

Worldwide research has been conducted by many researchers to assess the climate change impacts. Emiru et al. (2022) studied the Impact of Climate Change on the Hydrology of the Upper Awash River Basin, Ethiopia. Investigations were also carried out regarding hydrological and meteorological drought using metrics such as SPEI (Standardized Precipitation Evapotranspiration Index) and SDI (Standardized Drought Index). Projections suggest that mean annual maximum temperatures are anticipated to rise by approximately 1.16 to 1.73 °C during the period from 2015 to 2100 when compared to a baseline of 1983-2014. These projections are based on the ensemble mean of five global climate models (GCMs). Correspondingly, minimum temperatures are projected to rise by 0.79 to 2.53°C. Precipitation is anticipated to increase by 1.8% in Addis Ababa, while the Hombole region may experience a substantial increase of 45.5%. However, high streamflow (Q5) is expected to decrease at all stations, except for Ginchi. For specific GCMs, some gauging stations such

as Akaki and Hombole may witness a decrease in low flows (Q90), with Q90 reaching 0 m³/s, indicating a 100% reduction.

The SPEI confirmed a significant historical drought pattern, and it predicts that future droughts will occur more frequently and be more severe. Between 1986 and 2005, the basin was subject to a range of weather conditions, from brief dry spells to a particularly severe hydrological drought. Moderately dry to moderately moist conditions are represented by the anticipated SDI. Seasonal changes in the hydrological conditions would be accentuated in the basin by climate change. In the wet seasons, precipitation will decrease and streamflow will increase; in the dry seasons, the opposite will occur.

On the other hand, Abdulahi et al. (2022) studied climate change's impact on future streamflow availability in the Upper Awash River basin, Ethiopia. The results suggested that both RCPs anticipate an overall increase in streamflow following the precipitation enhancement. In the periods of 2021–2040 and 2041–2060, as per the RCP4.5 and RCP8.5 scenarios, it is expected that the average monthly streamflow will experience the following changes: a 40.1% and 29.4% increase for the former period, and a 16.9% and 18.5% increase for the latter, respectively. Under RCP4.5 and 8.5, the annual streamflow would rise by 28.5% and 23.95%, respectively. The outcomes of this research can educate the planners and designers of water resources in framing an acceptable plan and management for the efficient use of water in the future.

2.2. Climate Model

A climate model is a representation of the Earth's climate system, designed to simulate and predict its behavior. It combines various mathematical equations and physical processes to simulate the interactions between the atmosphere, oceans, land surface, ice, and other components of the climate system. When a computer program includes a sufficient representation of the various components of the climate system to accurately simulate climate patterns, it is commonly known as a climate model (IPCC, 2014).

2.2.1. General circulation models

General Circulation Models (GCMs), also known as Global Climate Models, are sophisticated computer-based models used to simulate and predict the Earth's climate system. These models employ complex mathematical equations to represent the behavior of the atmosphere, oceans, land surface, and ice, and their interactions with each other. One of the most effective tools for simulating current and future predictions of climate change

scenarios is a global circulation model (GCM) (Ren et al., 2012). Projections of global climatic variables have primarily relied on General Circulation Models (GCMs), which offer projections at broad spatial scales. However, GCMs have limitations in their suitability for local studies, typically covering areas on the order of 50,000 km², and they struggle to capture critical sub-grid scale features such as topography and clouds due to their coarse spatial resolution (Hay et al., 2002).

2.2.2. Regional climate model

A Regional Climate Model (RCM) is a specialized computer model used to simulate and project the climate of a specific region or smaller geographical area. RCMs are nested within larger-scale Global Climate Models (GCMs) and provide higher-resolution climate information for a particular region of interest. Currently, RCMs act as an important link between local climate and climate change issues and global climate modeling for downscaling. Many studies of the regional effects of different levels of global warming are based on ensembles of coarse-resolution global models, however, high-resolution regional climate data is required for impact assessment and adaptation planning (Osima et al., 2018).

2.2.3. Downscaling

The process of downscaling involves the utilization of models, whether dynamic or statistical, to improve the spatial resolution of Global Circulation Model output, focusing on a particular local or specific area of interest. Downscaling may be used to increase the temporal resolution or the spatial resolution. There are two primary methods for generating localized or regional climate data from global climate scenarios produced by General Circulation Models (GCMs): dynamic and statistical downscaling. Dynamic downscaling entails the use of a regional climate model (RCM) with a finer spatial resolution typically ranging from 10 to 50 kilometers. This process includes incorporating more accurate representations of topography, land use, and vegetation patterns. Techniques of statistical downscaling, which employ a statistical correlation between global climate data and locally derived fluctuations based on historical data. Systematic mistakes caused by RCMs in dynamic downscaling require statistical corrections to provide a realistic output (J. Chen et al. 2012). While several (RCMs) have been employed worldwide, there is a scarcity of dynamic downscaling studies utilizing RCMs in the East Africa region (Endris et al., 2013).

2.3. Climate Change Scenarios

Decision-makers and planners have used scenarios to analyze situations with uncertain outcomes (Bjørnæs, 2015). Climate change scenarios have become a crucial component in climate research, enabling scientists to understand the long-term effects (van Vuuren et al., 2011) and describe realistic pathways of future climatic conditions and related factors (Moss et al., 2010). Over the years, climate studies have utilized different scenarios. These range from SA92, which was used in the initial assessment report of the Intergovernmental Panel on Climate Change (IPCC), to the Special Report on Emissions and Scenarios (SRES) employed in the third and fourth assessment reports. A more recent development is the use of Representative Concentration Pathways (RCPs), which were introduced and applied in the IPCC's fifth assessment report (AR5) released in 2015.

2.3.1. Representative Concentration Pathways (RCPs) scenarios

The Representative Concentration Pathways (RCPs) are a set of scenarios used in climate modeling to project future greenhouse gas (GHG) concentrations and their potential impact on the Earth's climate. They provide a framework for examining potential future climate conditions and their impacts based on different emission pathways. The RCPs are named based on a metric called radiative forcing, which quantifies the energy imbalance caused by greenhouse gases in the Earth's atmosphere. Each RCP represents a different level of radiative forcing and provides a range of future climate projections. There are four main RCP scenarios: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. These scenarios represent a spectrum of possible future emission trajectories and corresponding greenhouse gas concentrations. The RCPs available in the literature include one of the strongest forcing scenarios (RCP8.5), two stabilization scenarios (RCP4.5/RCP6.0), and a mitigation scenario that results in the lowest level of radiative forcing, known as RCP2.6 (IPCC, 2013).

- RCP 2.6; is a pathway where radiative forcing peaks at approximately 3W/m^2 before the 2100 Century and then declines.
- RCP 4.5 and RCP 6.0; are intermediate stabilization pathways in which radiative forcing is stabilized at approximately 4.5W/m^2 and 6.0W/m^2 after 2100 respectively.
- RCP 8.5; is one high pathway for which radiative forcing reaches greater than 8.5W/m^2 by 2100 and continues to rise for some amount of time.

The different findings showed that RCP4.5 and RCP8.5 are more indicated climate variability in East Africa including Ethiopia (Sintayehu et al., 2020; Araro et al., 2020; Getahun & van Lanen, 2016).

2.4. Climate Change Studies in Ethiopia

studies on climate change in Ethiopia have been undertaken to gain insights into the particular effects of climate change on the nation's environment, economy, and society. Ethiopia is particularly vulnerable to the effects of climate change due to its reliance on agriculture, limited infrastructure, and exposure to climate-related hazards. Here are some key areas of study associated with climate change in Ethiopia:

A further study by Musie et al. (2020) used the CORDEX-AFRICA and NEXGDDP datasets for hydrologic forecasts under climate change in the Lake Ziway sub-basin, Ethiopia. In this study, the datasets from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) and the Coordinated Regional Downscaling Experiment (CORDEX-AFRICA) were assessed for their suitability to be used in determining the effects of climate change. Additionally, it considered how climate change would affect the sub-basins. The ensemble average annual stream flows, as modeled using the CORDEX-AFRICA dataset, are anticipated to rise as we approach the end of the century under both climate scenarios. However, during the mid and late parts of the century, there are projected reductions in the ensemble average stream flows specifically during the dry season. These expected declines in stream flow during the dry and pre-wet seasons, combined with increased water extractions from Lake Ziway, are likely to worsen water scarcity issues in the basin.

A study by Serur. (2023) on performance evaluation of hydrological model in simulating streamflow and water balance analysis: spatiotemporal calibration and validation in the upper Awash sub-basin in Ethiopia. The findings of the study indicated that the SWAT model effectively replicated monthly streamflow patterns at the Awash Melka Kunturi, Awash Melka Hombole, and Mojo Upstream of Koka gauge stations within the catchment. The statistical indices (R^2 , NSE, and PBIAS) ranged from 0.80 to 0.74, 0.74 to 0.66, and -3.20 to 14.90, respectively, during the calibration period, and from 0.74 to 0.66, 0.71 to 0.62, and 18.60 to 8.00 during the validation period. The model displayed superior performance during the calibration period when contrasted with its performance during the validation period.

Taye et al. (2018) Also assessed the potential influence of climate change on water availability in various seasons within the Awash basin. This assessment was carried out by utilizing three climate models from the Coupled Models Inter-comparison Project Phase 5 (CMIP5). The forecasts for the upcoming three time interval indicate a rise in water deficit throughout all seasons and in specific areas of the region, owing to the anticipated elevation of temperatures and a reduction in rainfall. Hailemariam, (1999) study, focuses on the Impact of climate change on the water resources of the Awash River Basin, in Ethiopia using GCM (both transient and CO₂ doubling scenarios) and incremental scenarios, various sets of temperature and rainfall scenarios were created. The assessment of the basin's impact revealed a projected decline in the runoff, covering from -10% to -34%, under conditions of doubled CO₂ levels and transient scenarios of CO₂ increase (GFD3, CCCM, GF01). The sensitivity analysis, using incremental scenarios, demonstrated that both drier and warmer climate change scenarios lead to reduced runoff.

2.5. Dam Safety

Dams are constructions used for water control, packing, or diversion that store water in reservoirs upstream. Dams assist in the form of water supply for drinking, agriculture, and industrial purposes, flood control, hydroelectric generation, recreation, and navigation. Dams are also a threat to community safety at the same time. Overtopping is the most frequent failure of the embankment dam. Through the utilization of an analytical conceptual model that integrates physical governing relationships with various scenarios, scientific research has been able to predict the occurrence of overtopping (Lee & You, 2013). Hydrological factors, namely flood features, are causing dam overtopping and dam failure. Typically, hydrologic frequency analysis and engineering designs have relied on the idea that hydrologic patterns exist. When a dam fails, a massive, disastrous flood occurs, with both economic and human costs as a result. In more contemporary earth and earth-rock fill dams, overtopping and dam failure is the most frequent reason for the collapse.

The internal and external threats, failure modes and impacts, operating reliability, and dam reaction should all be included in the safety study of the dam system. The Dam Safety website offers a Hazard and Failure Mode analysis procedure with guidelines to help the review engineer evaluate the safety of the dam.

2.5.1. Probable maximum flood (PMF)

The Probable Maximum Flood (PMF) is the largest flood that might reasonably occur in a given drainage area under a specific set of crucial hydrological and meteorological conditions. If the climate, landscape, and atmospheric moisture constraints at any given location set a finite constraint on the Earth's atmosphere's capacity to create rain, then the weather is considered to be in critical condition. Probable Maximum Precipitation (PMP) is an estimate of the maximum amount of rainfall that could occur in a specific geographical area within a given duration under the most severe meteorological conditions imaginable. PMP is a concept used in hydrology and engineering for designing infrastructure and flood control systems to handle extreme rainfall events.

According to Ouranos. (2015), the PMP exceedance probability and anticipated return periods fall between 1 in 10,000 years and 1 in 1,000,000 years. Without taking into account long-term climatic trends, it is the maximum depth of precipitation that is meteorologically possible for a given storm region or design watershed for a given timeframe. The potential maximum flood caused by PMP would provide the data required for the construction of a specific project in the designated watershed. According to Pothwar et al. (2015), The term "probable maximum flood" can refer to two distinct concepts: either the highest possible flood that arises from an extreme combination of critical hydrological and meteorological conditions, which has no possibility of being exceeded, or a flood specific to a particular catchment area. We can determine the probable maximum flood (PMF) using one of two fundamental methods such as the rational method and the statistical method. In the first approach, rainfall-runoff models are used, while in the second, floods or rains with a set return duration are used. In those, research the chosen rainfall-runoff model to ascertain the likely maximum flood.

2.5.2. Spillway adequacy

Spillway adequacy refers to the capacity of a spillway structure to safely pass the design flood or the maximum probable flood without causing excessive flooding or damage to the dam or surrounding areas. A spillway is an engineered structure designed to control the release of water from a reservoir or dam during high water levels to prevent overtopping and potential dam failure. The adequacy of a spillway is determined by assessing its capacity to handle the expected flow rates and volumes during extreme events. This assessment typically involves hydraulic calculations, hydrological studies, and risk analyses. The goal

is to ensure that the spillway can effectively handle the anticipated inflow and outflow, maintaining the water level within safe limits(Barker et al., 2012).

2.5.3. Spillway discharge capacity

A hydrological analysis is used to calculate the discharge capacity at the maximum reservoir level, with the design flood's hydrograph as the primary determining factor. Achieving absolute accuracy is not feasible; it hinges on the quantity and reliability of historical data related to river flow, flow patterns, and meteorological attributes of significant storms. In the context of the text, the term "spillway design discharge" pertains to a predetermined maximum reservoir level. If the reservoir level is lower than projected due to an underestimated design flood, the dam will not be overtopped, preventing any potentially disastrous consequences (ICOLD, 2014). The spillway's discharge capacity is determined by calculating it according to the inflow design flood derived from the flow hydrograph into the reservoir (Barker et al., 2012). If the reservoir includes both substantial and minimal storage volumes, the spillway capacity could be considerably lower than the peak inflow discharge. When the spillway is unable to accommodate its full capacity, there is an increased likelihood of dam overtopping during more frequent flood occurrences.

2.6. Impact of Climate Change on Dam Safety

Although there are some uncertainties in climate change studies, particularly about future precipitation, most of them are connected to the number of discrepancies between models rather than the projected change's trend. There are very limited uncertainties between different models when it comes to variations in temperature. One approach used in recent studies to account for the impacts of climate change is the utilization of RCPs, which provide projections of how greenhouse gas concentrations in the atmosphere may change over time. As the emission scenario becomes more severe, transitioning from RCP 2.6 to RCP 8.5, it is anticipated that the contributions to discharge and the growth in evapotranspiration due to temperature increases will lead to decreased water levels in reservoirs during dry seasons(Fluixá-Sanmartín et al., 2018), and greater precipitation increases could result in elevated levels during wet seasons. RCPs are valuable tools in climate change studies as they enable the projection of long-term patterns in temperature and precipitation, considering various radiative forcing scenarios that encompass both natural and human-induced factors. The adoption of RCPs is suitable for factoring in the

impacts of climate change when designing water management infrastructure, including evaluations and enhancements in dam design (Fluixá-Sanmartín et al., 2019).

Herbozo et al. (2022) the study conducted an assessment of the risks to dam safety associated with climate change and explored strategies for adapting spillway design to address these challenges. They introduced a general four-phase methodology that involves data collection and the analysis of hydro-climatic, hydrological, and hydraulic factors. This methodology was then applied to the redesign of the Sube y Baja dam's spillway in Ecuador. One significant finding was that, when considering the Representative Concentration Pathway 8.5, the Probable Maximum Precipitation (PMP) increased by approximately 20%. This increase was primarily attributed to a 25% rise in the maximum flow rate through the spillway. The study's results underscored the need to reassess engineering design criteria for hydraulic structures in response to the changing and non-static hydrological conditions associated with climate change. They also emphasized the importance of establishing a consensus regarding design parameters that account for climate change effects. Despite acknowledging limitations in their proposed methodology, the primary objective was to emphasize the critical point that failure to incorporate climate change scenarios into the design or redesign of excess reservoir spillways could have severe and potentially fatal consequences. Therefore, decision makers and authorities responsible for flood hazard and risk assessments should view the study's findings as scientific evidence supporting the necessity of revising policies and regulations. These revisions should mandate the inclusion of climate change scenarios in the planning and execution of hydraulic infrastructure projects to safeguard the well-being of downstream communities.

The risk connected with dams, as well as defensive dikes and levees, must be adequately handled in a continual and updated process. Usually, the management of dam safety has been done in stationary climatic and non-climatic situations. However, the anticipated changes caused by climate change are likely to have an impact on various elements that influence dam risk. Although some reference institutions create guidelines for incorporating climate change into their decision support strategies, the application of this information to particular analyses like dam safety assessments is still difficult due to the vast amount of disparate information that is still available. This article offers an extensive and interdisciplinary examination of the potential impact of climate change on dam safety. By combining the projected impacts on different aspects of risk, including hydrological input and the assessment of flood-induced effects on the population and vulnerable assets, it

enables a comprehensive evaluation of the overall impact. To make decisions, this information will be helpful to dam owners and professionals involved in dam safety. The goal of the evaluation was to evaluate the dam's climate change vulnerability as a supporting tool for dam safety management (Fluixá-Sanmartín et al., 2018).

Similarly, Fluixá-Sanmartín et al. (2019) studied on Quantification of climate change impact on dam failure risk under hydrological scenarios: a case study from a Spanish Dam. This article provides an extensive quantitative assessment of how climate change impacts the safety of a dam in Spain across various hydrological scenarios. The analysis encompasses all anticipated effects affecting each risk factor, starting from hydrological input and extending to the outcomes of the outflow hydrograph. To gauge the dam's risk outlook until the close of the twenty-first century, data from 21 regional climate models spanning three RCP2.6, RCP4.5, and RCP8.5 were specifically employed. Results indicated that the likelihood of dam failure is deteriorating over time for the majority of the instances considered, especially the RCP2.6 and RCP4.5 scenarios. Moreover, the individual analysis of each risk component showed that the alteration in expected inflows has the greatest impact on the final risk. For dam owners and experts in dam safety, the methodology outlined in this study can serve as a valuable guide for investigating similar situations.

The other studies by Morales-Torres et al., (2022) Benefits of incorporating climate change into dam safety risk analysis. the case of the Santa Teresa dam. The Santa Teresa dam study case has been used to apply the suggested methodology. This is the first case in which a thorough examination of the effects of climate change on dam risk under a hydrological scenario has been applied. Previous dam risk studies have offered useful new information. There is no immediate need for adaptation measures given the current scenario. However new adaptation strategies that were not justifiable for the current circumstances have been suggested, and dangers are generally projected to rise over time. The study case has underlined the necessity of taking non-stationarity climate change impacts on dam safety into account to reduce dam risks as effectively as possible over a certain period. Failing to consider the risk evolution can lead us to adopt short-term risk reduction strategies that are ineffective over time.

A Study by Sulistiyono et al. (2023) on the Impact of Climate Change on Dam Safety proposed a procedure for studying how climate change may impact the safety of gated spillway dams. A statistical consistency test, variable selection for global climate change, local climate change modeling, calculating flood discharge due to climate change, and dam

safety assessment make up the approach in the Central Lombok Regency's Batujai Dam. To demonstrate the use of the proposed technique, maximum daily rainfall data from 1998 to 2020 from the Pengadang Station and global climate change data from 1998 to 2100 from the Intergovernmental Panel on Climate Change (IPCC) were both used. The results showed that the proposed methodology can be used to assess how climate change may affect the safety of dams. Additionally, it is well recognized that the tendency for flood discharge into the Batujai Reservoir to increase as a result of climate change is high. The four spillway gates: P₁, P₂, P₃, and P₄ have to be opened 1.0, 1.2, 1.2, and 1.0 m, respectively to anticipate the 1000-year return period of a flood event due to climate change, at a rate of 1833.54 m³/s.

2.7. Hydrological Models

Hydrologic models are conceptual or physical representations of the hydrologic cycle that have been simplified. It is necessary to develop a method of extrapolating rainfall-runoff processes from those of the available measurements, that is, from gauged sites to ungauged sites and from past/current time steps into the future period. This is due to the limited range of hydrological measurements in space and time. Of course, this is the primary purpose of hydrological models for a detailed analysis of water resources.

Numerous hydrological models have been created, and they exhibit various structural resemblances due to their foundational assumptions, although certain models have unique characteristics. As a result, these models are categorized based on diverse criteria. Traditionally, two modeling approaches have been postulated, each with its strengths and limitations: physically-based models and conceptual lumped models.

Models within physical principles, often referred to as theoretical or white box models, establish physical laws through deterministic conservation equations governing mass, momentum, and energy. These equations are computationally solved by dividing the hydrological system into smaller components within a square or polygonal mesh. However, accurate modeling of all hydrologic cycle processes becomes highly difficult, requires a profound understanding of hydrological dynamics, and requires a large amount of data. This property makes it a time-consuming and expensive process (Abbott et al., 1986).

Conceptual lumped models (grey box), provide an alternative to physically-based distributed models and are frequently employed as dependable tools for catchment-scale analyses. These models typically use a series of interconnected reservoirs as the basis for their relatively simple model structure. Additionally, these models serve as invaluable tools

for practical water management tasks, such as reservoir operations and flood prediction. Due to their reliance on readily accessible input and output data, they are predominantly applied in rainfall-runoff modeling. There are different types of hydrological models such as SWAT, HBV, HEC–HMS, MIKE-SHE, and WEAP. In this study, SWAT and HEC-HMS hydrological models are selected for simulation, and HEC-HMS is used for reservoir routing. The choice of SWAT and HEC-HMS for simulation and reservoir routing should align with the specific objectives and scope of the study, as well as the availability of data and resources, respectively.

2.7.1. The Soil and Water Assessment Tool (SWAT)

The Soil and Water Assessment Tool (SWAT) is a widely used computer model developed by the United States Department of Agriculture (USDA) Agricultural Research Service (ARS) that is designed to simulate the hydrology, water quality, and environmental impacts of land use, land management practices, and climate change on watersheds and river basins. SWAT is a powerful tool used for watershed and river basin management, water resource planning, and agricultural land management. A system known as SWAT, which is integrated into a Geographic Information System (GIS), can incorporate diverse spatial environmental data such as soil characteristics, land cover, climatic conditions, and topographical features. This system was created to forecast how land management practices influence the generation of water, sediment, and agricultural chemical runoff in large and intricate watersheds marked by diverse soil types, land usage, and management approaches. This tool empowers users to investigate the long-term repercussions and is thus widely utilized both within the United States and in various regions across the globe for evaluating the consequences of global climate change and water quality (Sl, 2005).

For the study, evaluation, assessment, and estimation of stream flow, sediment yield, agricultural chemicals, and management measures in river basins, SWAT is employed in many countries all over the world. The SWAT model is used in several studies to predict stream flow, sediment yield, and best management strategies for various watersheds. The SWAT model was applied in the upper kharun catchment, India to investigate the impact of land use change on water resources (Kumar et al., 2017); SWAT was also used in the Tennessee River watershed to assess the long-term hydrological impact of land use/ land cover change (Zhu & Li, 2014; Yan et al., 2013), evaluate the impact of land use changes on stream flow and sediment yield at a basin scale using SWAT model. A study by Musie, et al., (2020) for hydrologic forecasts under climate change in the Lake Ziway sub-basin

using the SWAT model. SWAT was also applied in the Rift Valley basin to assess the soil erosion, climate variability, and human activity on water balance (Gadissa et al., 2018b; Ayana et al., 2022; Aliye et al., 2020 and Aga et al., 2018).

2.7.2. HEC-HMS

The utilization of the HEC-HMS rainfall-runoff model, developed by the Hydrologic Engineering Center, represents the earliest research and engineering planning tool employed by scientific institutions, government entities, and engineering firms. This program is a versatile modeling system with the ability to replicate a wide range of watersheds. The Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS) is a computer application designed to emulate precipitation-runoff processes in dendritic watersheds (US Army Corps of Engineers, 2013). HEC-HMS is a semi-distributed deterministic model, allowing for some spatial variability in model parameters by dividing the watershed into smaller sub-basins. It is a physically based model, meaning it considers the physical occurrences, movement, distribution, and storage of water and their variations across both space and time. HEC-HMS can simulate the dynamics of reservoirs, including inflow, outflow, and operational regulations. This functionality is vital for the effective management of water storage and the controlled release of water from reservoirs, serving purposes such as flood control, water supply, and recreational activities.

2.8. Model Selection

2.8.1. Hydrological model selection

Hydrological model selection refers to the process of choosing an appropriate model or set of models to represent and simulate the hydrological processes of a specific study area or watershed. Hydrological models are mathematical representations of the water cycle, incorporating various physical and environmental factors to simulate the movement and transformation of water within a catchment. Determining the model to use for a watershed in any modeling session is an issue in many hydrological investigations. The aim of the modeling task, the time available to develop and apply a model, the level of accuracy required, the requirement for input data, the model's predictive performance, the model's credibility, the modeler's preference and familiarity with using particular models, and the purpose of the study should all be considered before choosing a model (Marshall et al., 2005). The complexity of a hydrological model can vary based on several factors, including its representation of hydrologic processes, the equations employed to simulate these processes, and the model's discretization. Additionally, the model's complexity is influenced

by the estimated data requirements, available resources, time, and costs associated with parameterizing and calibrating the model. Furthermore, the level of expertise and experience necessary to effectively operate these models can also be used as descriptors of their complexity (Dwarakish & Ganasri, 2015; Paul et al., 2021).

Many criteria are used for choosing the correct hydrological model: -

- Study objectives: The model should align with the goals and objectives of the study.
- Data availability of input - The availability and quality of data required by the model are crucial.
- Model complexity: The complexity of the model should be considered.
- Performance and Validation: Assessing the performance and validation of different models is essential.
- User Expertise: Consider the expertise and familiarity of the model users.

Depending upon the above selection criteria for this study Soil and Water Assessment Tool (SWAT) and Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS) model was selected.

3. MATERIALS AND METHODS

3.1. Description of the Study Area

3.1.1. Location

The Koka reservoir is situated within the upper Awash sub-basin in the central part of the Oromia Region, East Shoa zone, Ethiopia. It is positioned approximately 80 kilometers southeast of Addis Ababa, precisely at coordinates (8° 26'N and 39° 02'E) at 1590masl, with an elevation of 1,590 meters above sea level. The Koka Dam, which is the second hydroelectric power facility after the Aba Samuel Dam in Ethiopia, commenced operations in 1960. Originally established for the primary purpose of hydroelectric power generation, it has since evolved into a multifunctional dam. In addition to electricity generation, it now serves various purposes, including downstream irrigation, and it is managed by the Ethiopian Electric Power Utility (EEMU).

Table 3.1 General description of koka dam

Features	Koka reservoir	Features	Koka reservoir
Storage Capacity	43.2 MW	Dam Type	Concrete gravity dam
Installed Capacity	1650 Mm ³	U/S Side Slope	1V:2.1H
Surface Area	236 m ²	Length of the dam	458 m
Dam Hight	47 m	Spillway capacity	1040 m ³ /s

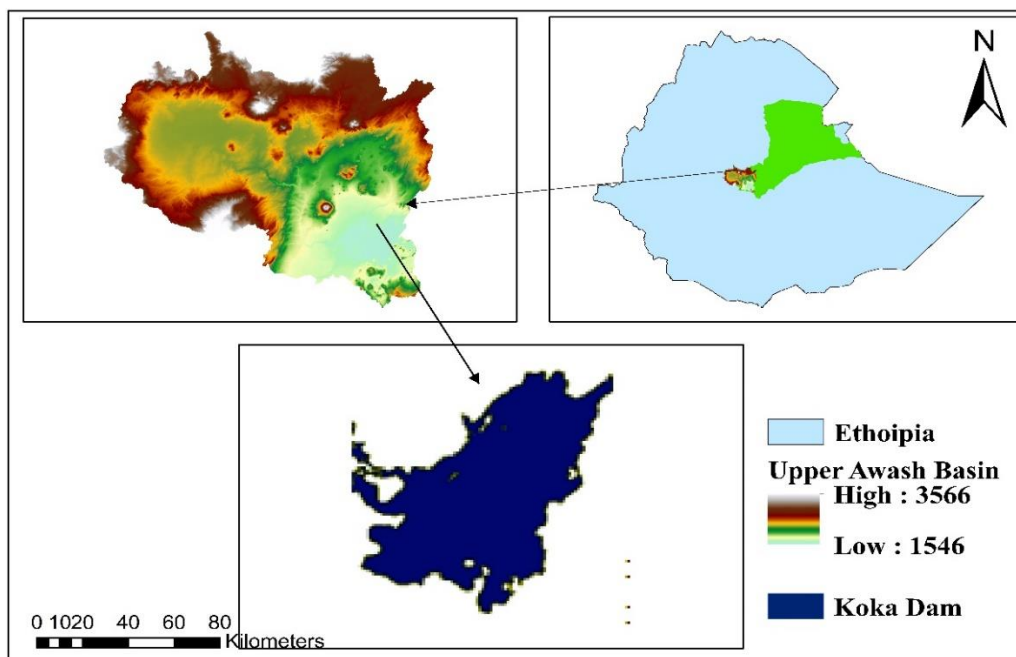


Figure 3.1 Location map of the study area in the Ethiopian Upper Awash Basin

3.1.2. Climate

The Inter-Tropical Convergence Zone (ITCZ), a zone of low pressure that is characterized by the convergence of moist south-easterly and dry tropical easterly winds, affects the climate of the Awash Basin. The ITC migrates annually between May and November when it produces the majority of Ethiopia's rainfall. The ITCZ is located in Northern Ethiopia. The South-East and North-West axis of the weak high-pressure system over Ethiopia depresses the movement of the ITCZ southward from the Upper Awash region and runs parallel to it. As a result, the Middle Awash region receives either rainy or dry winds in July and August, which causes erratic and smaller-than-usual rainfall compared to the rest of Ethiopia.

3.1.3. Rainfall

This pattern is most prominently illustrated by the presence of two well-defined rainy seasons that are frequently observed in the northern plains of the basin, emphasizing the characteristic annual rainfall distribution. While the eastern portion of the basin is mainly dominated by bi-modal rainfall with Belg (short) and Kiremt (long) rainfall peaks, the western part of the basin receives mono-modal rainfall with the highest rainfall occurring from July to August. Thirty-two years from (1990-2021) rainfall records for 7 stations within and adjacent to the study area show an average yearly rainfall between 1205 mm and 827 mm. The climate data for 7 stations from 1990 to 2021 is collected from the Ethiopian National Meteorological Institute.

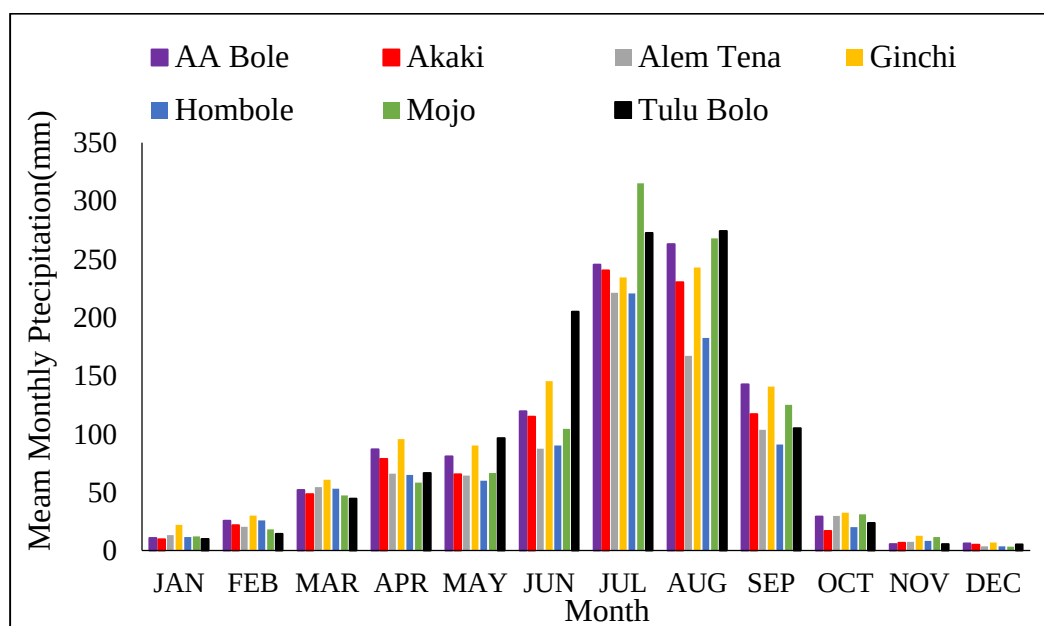


Figure 3.2 Monthly mean rainfall of Upper Awash catchment (1990 – 2021)

3.1.4. Temperature

The temperature within the basin indicates significant variation based on altitude. The average annual maximum temperature ranges from 26.3 to 31.6°C, while the average annual minimum temperature falls between 8.5 and 12.8°C.

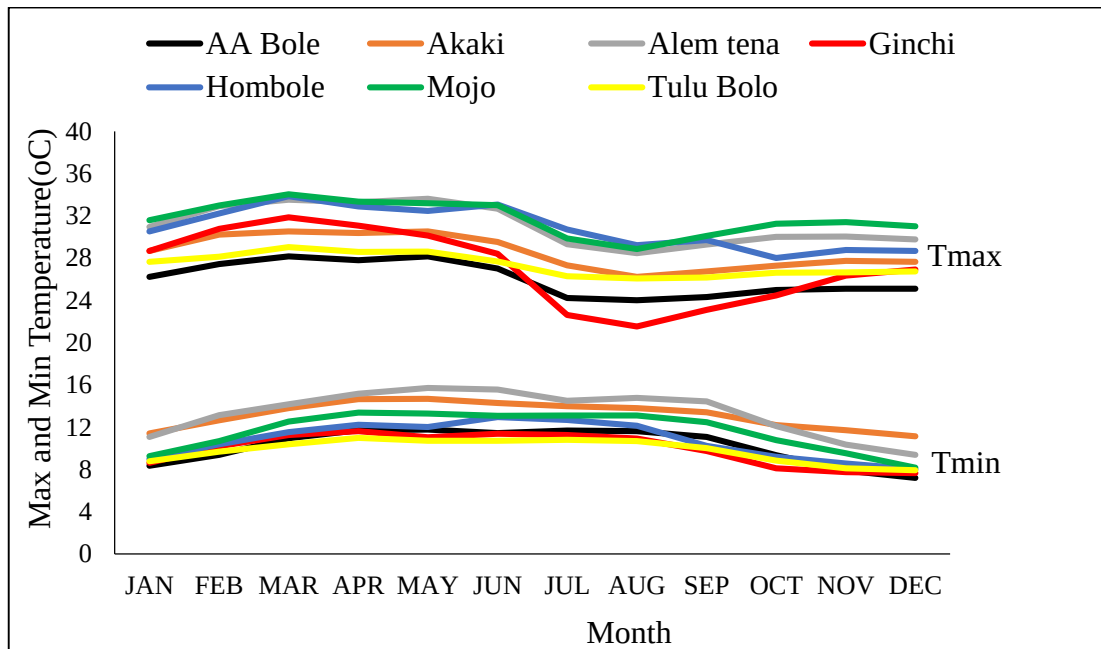


Figure 3.3 Mean monthly temperature maximum and minimum of the upper Awash catchment (1990 – 2021)

3.1.5. Topography, geology and soil type

The topography of the Upper Awash region is characterized by a combination of highlands, plateaus, and valleys. The slope of the Upper Awash region ranges from steep slopes in mountainous and hilly areas to relatively flat or gently sloping terrain in plateaus, flat areas, and some valleys. The varied slope conditions in the region influence factors such as land use, agricultural practices, and water drainage patterns. The altitude in the Upper Awash region ranges from around 1,546 meters to over 3,566 meters above sea level. The geology of the Upper Awash region is primarily influenced by the Ethiopian Rift Valley system. The region is situated on the African Plate, which is being pulled apart by tectonic forces, resulting in the formation of rifts (AAWSA et al., 2000). The geology of the area includes volcanic formations, sedimentary rocks, and basaltic lava flows. Volcanic activity has played a significant role in shaping the landscape, and there are several dormant and extinct volcanoes in the region. The soils in the Upper Awash region are diverse and vary depending on factors such as topography, climate, and parent material. In general, soils can be

classified into several categories, including vertisols, nitisols, and fluvisols. Vertisols are clay-rich soils that have a high capacity to shrink and swell with changes in moisture content. The soils of the Upper Awash region have varying agricultural potential, with some areas being highly fertile and suitable for cultivation, while others may have limitations such as steep slopes or poor drainage. The region is known for its agricultural activities, including the cultivation of crops such as teff, barley, wheat, and various fruits and vegetables (OWWDSE 2015).

3.2. Materials

Many materials and software were used to achieve the objective of the study to assess climate change impacts on the dam safety of Koka Dam. The study utilized CORDEX-Africa data from the Coupled Model Inter-comparison Project Phase 5 (CMIP5) to examine the upper Awash watershed. Additionally, a hydrological model was employed to assess changes in streamflow and their impact on the flow of water into the Koka Dam, all in the context of climate change. The hydrological components of the watershed and streamflow prediction were simulated using the Soil and Water Assessment Tool (SWAT) hydrological model. Software such as Geographic Information System (GIS) 10.4 was used for processing the spatial data such as Land use data, and soil map used as an interface for the SWAT hydrological model. The Rainbow software was used for checking the homogeneity of weather data. The sequential uncertainty Fitting -2 (SUFI-2) algorithm which is one of the five uncertainty analysis techniques incorporated in SWAT Calibration and Uncertainty Program (SWAT-CUP) software was used for model sensitivity analysis, calibration, validation, and uncertainty analysis of SWAT model simulation. The Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS) was employed for reservoir routing, allowing for comprehensive analysis and management of water flow within the reservoir system.

3.3. Hydrological Models Data Input and Sources

3.3.1. Weather data

Weather data is an important input for the SWAT hydrological model, which simulates the hydrology of a watershed. Daily precipitation, along with the highest and lowest recorded temperatures, relative humidity, wind speed, and solar radiation data were gathered from seven meteorological stations situated within and around the study area. These stations, specifically Addis Ababa (Bole), Akaki, Alem Tena, Ginchi, Hombole, Mojo, and Tulubolo

meteorological stations, provided data from 1990 to 2021. The data was sourced from the National Meteorological Institute of Ethiopia (NMI).

Table 3.2 Historical meteorological data of the study area

No	Station Name	Lat	Long	Elv (m)	Parameters						Year
					PCP	Tmax	Tmin	RHD	SLR	WS	YR
1	AA Bole	8.98	39.79	2354	✓	✓	✓	✓	✓	✓	1990-2021
2	Akaki	8.87	38.79	2057	✓	✓	✓	✗	✗	✗	1990-2021
3	AlemTena	8.29	38.91	1656	✓	✓	✓	✗	✗	✗	1990-2021
4	Ginchi	9.02	38.13	2132	✓	✓	✓	✓	✗	✗	1990-2021
5	Hombole	8.37	38.78	1743	✓	✓	✓	✓	✗	✗	1990-2021
6	Mojo	8.61	38.21	1771	✓	✓	✓	✓	✗	✗	1990-2021
7	Tulu Bole	8.66	38.21	2190	✓	✓	✓	✓	✗	✗	1990-2021

PCP is Precipitation, Tmax and Tmin represent the maximum and minimum temperatures, RHD stands for Relative Humidity, SLR denotes Solar Radiation, and WS represents Wind Speed.

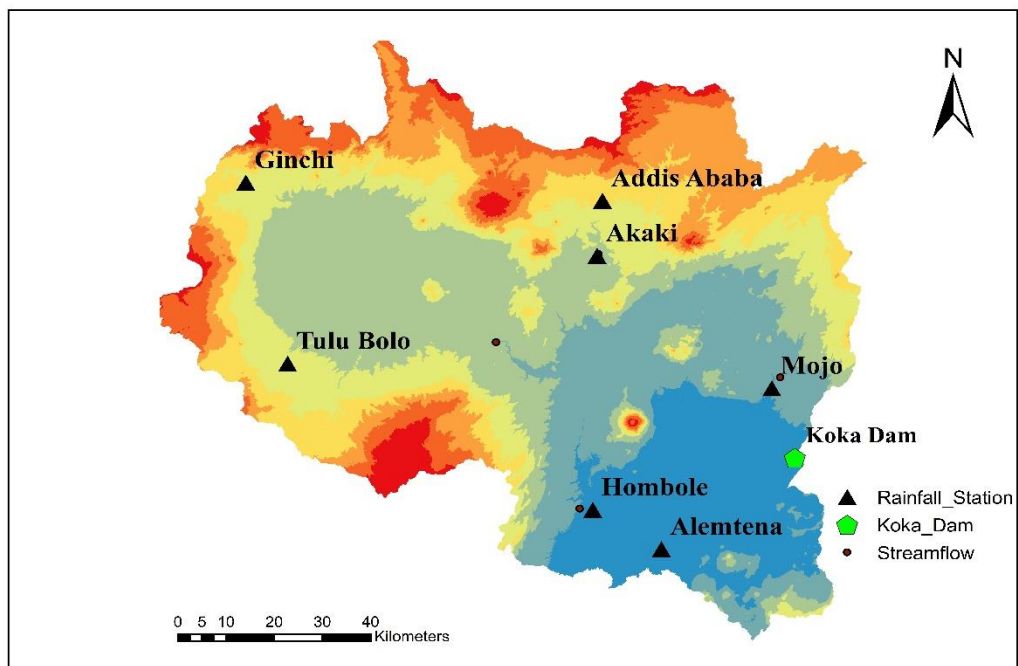


Figure 3. 4 Location of meteorological station of upper Awash watershed

3.3.2. Hydrological data

3.3.2.1. Streamflow data

Hydrological data plays a crucial role in conducting sensitivity analysis, calibration, and validation of hydrological models. The daily streamflow information for the upper Awash watershed, specifically from the Hombole and Mojo areas, spanning the years 2000 to 2015, was obtained from the Ministry of Water and Energy of Ethiopia (MoWE). The maximum discharge occurs from June to September (Figure 3.5).

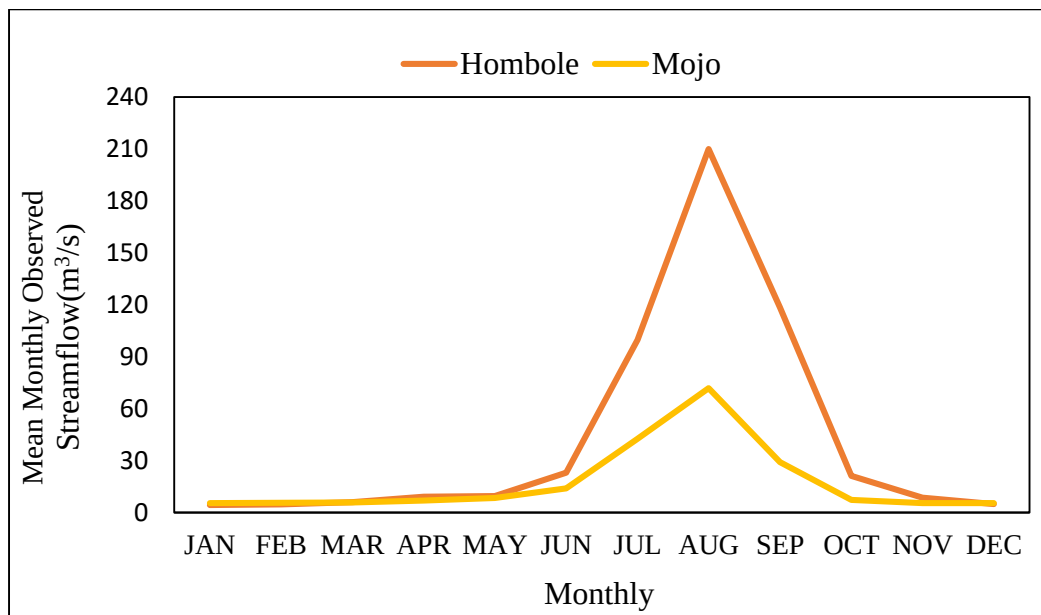


Figure 3.5 Mean monthly observed streamflow of Hombole and Mojo station (2000-2015)

3.3.3. Digital elevation model (DEM)

The GIS Department of the Ministry of Water and Energy (MoWIE) provided Digital Elevation Model (DEM) data at a 30m by 30m resolution. This DEM information is utilized in conjunction with soil and land use/land cover data within the SWAT model. It serves the purpose of delineating the watershed and subsequently dividing it into sub-watersheds and hydrologic response units (HRUs). The upper Awash watershed was classified into four land slope classes 0-10%, 10-20%, 20-40%, and > 40% as indicated in Figure 3.6 below. The slope class indicates that 87.96% of the watershed of the area is between the slope class of 0-10%, 9.30% between 10-20%, 2.69% between 20-40% and the remaining is in the class of >40%.

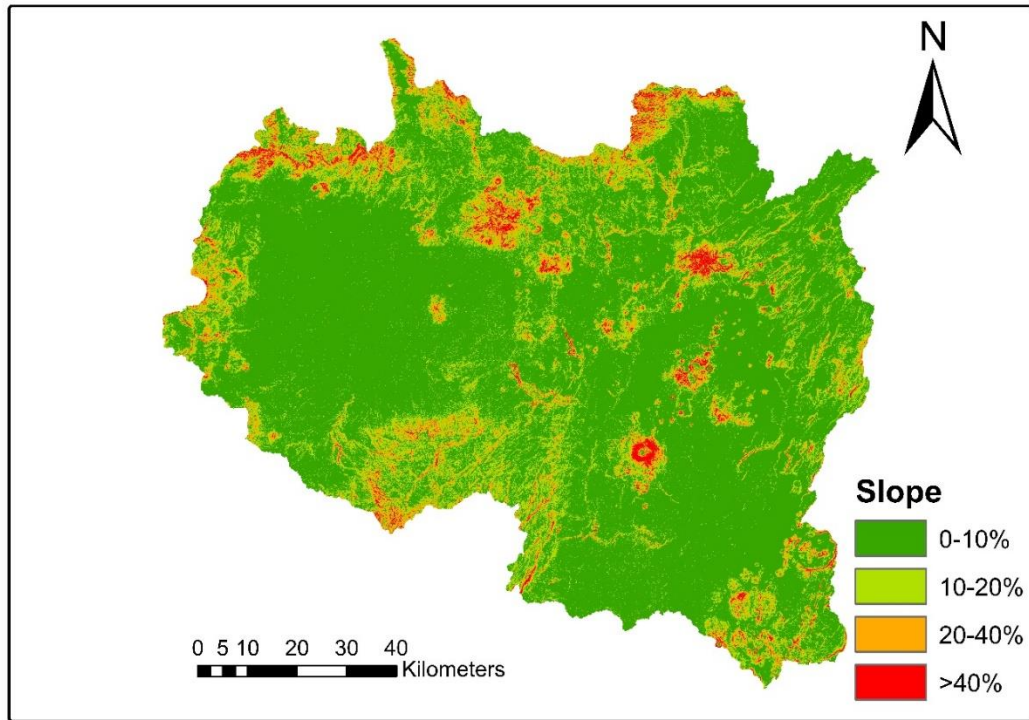


Figure 3.6 Slope class of the study area

3.3.4. Soil data

Soil data is one of the spatial input data required for the modeling of stream flow and sedimentation in the physical-based hydrological models. The hydrological model necessitates both a soil map and a database table containing various soil attributes. These attributes encompass factors such as soil hydrologic group, the maximum rooting depth of the soil profile, moist bulk density, soil texture, saturated hydraulic conductivity, grain size distribution, texture classification, and soil available water content across different soil layers (Zhang et al., 2020). Soil maps and properties play an important role in hydrological modeling. The soil data for the upper Awash watershed was downloaded from the Food and Agriculture Organization (FAO). According to the FAO/Globe soil categorization system (FAO/UNESCO), the soils in the study watershed are categorized. According to FAO, the study area has six major soil types, which are shown in Figure 3.7 below. Eutric Cambisols (clay), LithosolsEutric Gleysols (sandy-clay loam), Eutric Nitosols (clay), Pellic Vertisols(clay), Haplic Xerosols (silt loam) are found in the study area.

Table 3.3 Soil Types of upper Awash watershed

No	Soil Group Name	SNAME	Soil Group	Area (km ²)	% area coverage
1	Eutric Cambisols	Be9-3c-26	C	703.01	6.2
2	LithosolsEutric Gleysols	I-Re-3a-83	C	413.84	3.6
3	Eutric Nitosols	Ne10-3b-154	C	587.52	5.2
4	Eutric Nitosols	Ne13-3b-158	C	3772.97	33.2
5	Pellic Vertisols	Vp14-3a-286	C	4894.89	43.0
6	Haplic Xerosols	Xh16-a-309	C	815.49	7.2
7	Water	WATER-1972	D	184.85	1.6
Total				11372.58	100

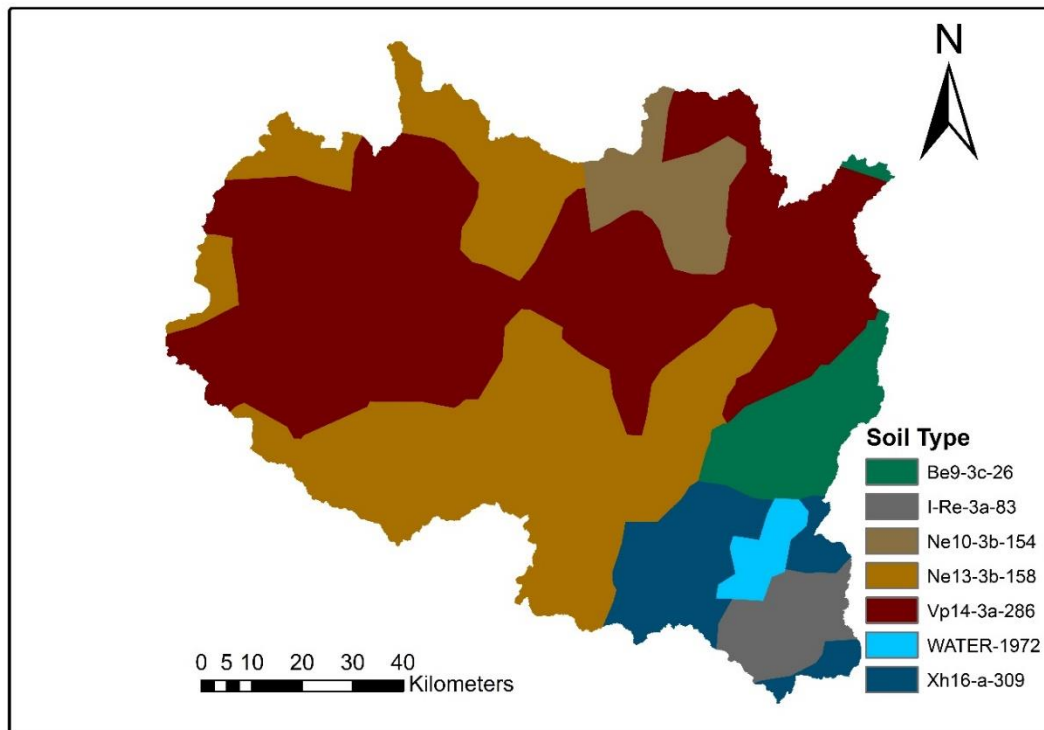


Figure 3.7 Soil map of the study area

3.3.5. Land use land cover

The Ministry of Water and Energy (MoWE) provided the land use/land cover (LULC) map and all associated datasets in shape file format. To align with specific LULC types and the corresponding crop parameters for the SWAT database, we performed a reclassification of the land use map. Furthermore, we created a lookup table that associates the SWAT land use code with various LULC categories. Below, you can find Figure 3.8, which displays the land use/cover in the study area as of 2015.

Table 3.4 Land use Types of Upper Awash Watershed

LULC	SWAT Code	Area(Km²)	Area (%)	Description
Agricultural Land	AGRR	10018.62	88.09	Land areas utilized for growing crops and dispersed rural settlements are linked to the category of cultivated land.
Forest Land	FRST	172.2	1.51	land areas covered with a high density of trees which include deciduous broadleaf forests, evergreen forests, mixed forests, and plantations.
Grass Land	RNGE	557.52	4.90	Land areas are covered predominantly by grassland with a cover density of over 10%.
Built-Up	URBN	272.85	2.40	Areas used for permanent building and other man-built artificial structures such as transportation facilities, industrial and commercial.
Shrub Land	RNGB	14.09	0.12	The land area is covered with shrubs and the cover density is over 30%.
wetland	WETL	5.75	0.05	The land area is covered by lands of land and water area, which is constantly covered by biogas or hygrophite plants and shallow water or wet soils.

Water Body	WATR	181.16	1.59	It refers to a liquid water-covered region in the land area. River, lake, reservoir, pit-pond, etc.
Bare Land	BARR	150.38	1.32	It refers to naturally covered lands with a cover density lower than 10%. Desert, sand, gravel ground, bare rocks, saline and alkaline lands.
Wetland for Non-Forest	WETN	0.01	0.0001	The land area is covered by lands of non-forest and water area, which is constantly covered by Freshwater Marshes, Salt Marshes, Bogs, and Ponds and Lakes.

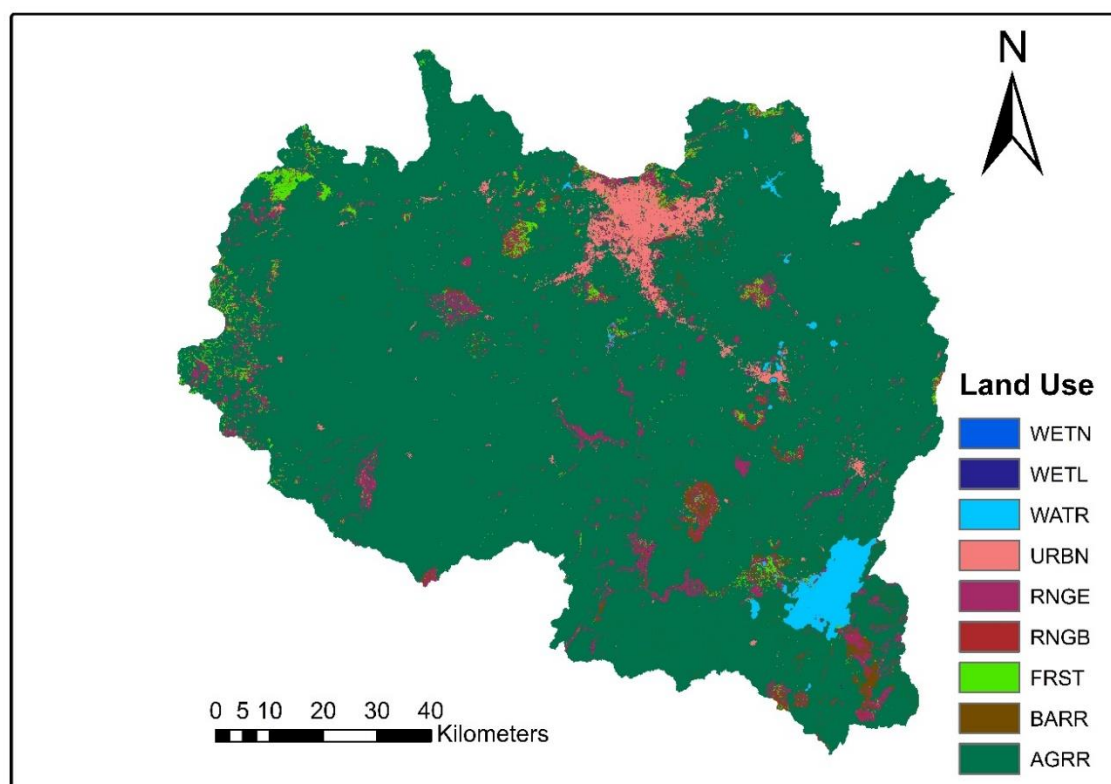


Figure 3.8 LULC of upper Awash (Koka Dam) watershed

3.4. Regional Climate Model Data

For this study, we acquired future climate projection data from the Coordinated Regional Downscaling Experiment (CORDEX) dataset available on the Earth System Grid Federation (ESGF) website at <https://esgf-data.dkrz.de/projects/esgf-dkrz/>. CORDEX comprises

regionally downscaled climate models established under the World Climate Research Program (WCRP). It's important to note that the choice of Regional Climate Models (RCMs) can influence the future projections within the study area. Therefore, in this study, the choice of RCMs was based on their ability to accurately represent past and present climate conditions, this includes variables such as rainfall, maximum temperature, and minimum temperature. Additionally, the models' resolution and insights from related studies on climate change impacts in the Awash River Basin and adjacent basins were considered during the selection process. The RCA4 simulations conducted within the CORDEX-Africa domain have an approximate spatial resolution of $0.44^{\circ} \times 0.44^{\circ}$, which translates to a grid cell size of approximately $50 \text{ km} \times 50 \text{ km}$.

For this study, the selected representative concentration pathways (RCPs) were RCP4.5 and RCP8.5 based on their ability to represent a spectrum of emissions trajectories, their policy relevance, their wide applicability in climate research, and their capacity to inform policy decisions related to climate change mitigation and adaptation. RCP4.5 corresponds to an intermediate emissions scenario with a relatively moderate stabilization outlook, resulting in a radiative forcing of 4.5 W/m^2 by the end of the 21st century. On the other hand, RCP8.5 represents a high-end emission scenario that projects a significant increase in greenhouse gases, leading to a radiative forcing of 8.5 W/m^2 above pre-industrial levels by the year 2100 (Stocker et al., 2013). The latest version of the regional climate model (RCA4), developed by the Swedish Meteorological and Hydrological Institute (SMHI), was selected for this study (Chokkavarapu and Mandla, 2019). The data from the Regional Climate Model (RCM) is categorized for analysis into distinct periods: historical (1951-2005), near future (2024-2048), mid-future (2049-2074), and end future or late 21st century (2075-2100).

Table 3.5 details of CORDEX-Africa regional climate model (RCA4) considered in this study.

Institution	Name	Country	GCM Resolution
Canadian Centre for Climate Modelling and Analysis	CanESM2	Canada	$2.8^{\circ} \times 2.8^{\circ}$
Centre National de Recherches Meteorolo-Giques	CNRM-CM5	France	$1.4^{\circ} \times 1.4^{\circ}$
Max Planck Institute for Meteorology	MPI-ESM-LR	Germany	$1.9^{\circ} \times 1.9^{\circ}$

3.5. Data Quality Analysis

It is important to first gather the data and arrange them in a geospatial database for proper management before analyzing the available data for dam safety. After the collection of relevant hydrological and meteorological data of the study area, it is important to check the quality of the data before further analysis and simulation. This enables us to identify whether either of the data is homogeneous, accurate, sufficient, and fully inclusive without any gaps in the data. Errors resulting from inadequate data processing procedures are significant as they introduce bias into the ultimate outcomes (Vedula et al., 2005). In this study, hydro-meteorological data was processed through data quality tests such as filling in the missing, adjusting for inconsistency and non-homogeneity.

3.5.1. Filling missing data

Due to regular equipment failure or observer absence, most of the collected data is not always maintained. The missing value breaks the continuity of the data that has been recorded, so it is crucial to fill in the missing data to prevent this. The meteorological data collected from the seven stations (Addis Ababa (Bole), Akaki, Alem Tena, Ginchi, Hombole, Mojo, and Tulu Bolo for this study have missing data for some time. There exist methods for addressing missing data, such as the arithmetic mean approach, the normal ratio technique, and the inverse distance weighting method, among others. The arithmetic mean method, for instance, is suitable for data reconstruction when the annual precipitation closely aligns with the gauge or station's values, typically within a 10% margin. If the annual precipitation at an index station differs by more than 10% from that of the precipitation station, the normal ratio method is applied. When the average annual rainfall data for the stations is unavailable, the missing data can be estimated using the inverse distance weighting method. In this study, we employed both the arithmetic mean and normal ratio methods, and the specific formulas for these approaches are described below, following Richard H.'s (1998) guidance.

Arithmetic mean method

$$Px = \frac{1}{n} \sum_{i=1}^n Pi \quad (3.1)$$

Where n represents the total number of stations, Pi is the recorded precipitation at the ith station and Px is the missing precipitation.

Normal ratio method

$$Px = \frac{1}{n} \sum_{i=1}^n \frac{Nx}{Ni} Pi \quad (3.2)$$

Where P_x is the missing precipitation for any storm at the interpolation station x , P_i represents the precipitation during the same time frame for the same storm at the i^{th} station of a group of index stations, N_x is the annual average precipitation for station x , N_i indicates the annual average precipitation value for the i^{th} station.

3.5.2. Data consistency

Hydro-meteorological data time series could be inconsistent and non-homogeneous. The study area stations' precipitation time series data may contain outliers as a result of the replacement of a rain gauge, shifting the instrument to a new location, errors in the observation of precipitation, etc. The presence of an outlier within the rainfall time series disrupts the data's integrity. To assess the consistency of rainfall time series data in this study, a double mass curve (DMC) was employed.

A double mass curve (DMC) is a graphical representation that illustrates the cumulative values of one quantity plotted against the cumulative values of another quantity over the same timeframe. This graph typically forms a straight line when the data maintains a proportional relationship, with the slope of the line indicating the constant of proportionality between the two quantities (Searcy & Hardison, 1960). If the double mass curve exhibits a linear trend, it indicates the accuracy of the rainfall data. The change in the constant of proportionality between two variables is indicated by a break in the slope of the DMC. Plotting all stations against the pattern allows us to test for consistency; any inconsistent records should be eliminated from the analysis. The DMC is plotted by taking the summation of the rainfall series for the rain gauge station whose consistency is to be checked against the summation of the average rainfall of the remaining rainfall gauge station in the area under consideration (Searcy & Hardison, 1960). In this study, as indicated in Appendix C, the graphical inspection showed no significant inconsistency in all stations used in the upper Awash watershed.

3.5.3. Homogeneity test

The technique employed to detect significant alterations in the statistical characteristics of time series data is referred to as homogeneity analysis. Spatial homogeneity should ideally be present in rainfall data for various periods at nearby stations (Seleshi & Camberlin, 2006).

Both natural and man-made factors will have an impact on the data, including changes in land use and the placement of the observation gauging station.

Homogeneity tests are used to evaluate the effects of non-climatic elements such as changes to instruments, methods of observation, relocation of rain gauge stations, and station environment on climate time series data (Khalil, 2021). RAINBOW software was used to carry out the homogeneity test for this study. RAINBOW Software was created at K.U. Leuven's Institute for Land and Water Management. The program is made to do a frequency analysis of rainfall and evaporation data as well as test the homogeneity of hydrologic records. According to Garcia et al., (2007), the homogeneity test within the RAINBOW software relies on adjusted partial sums or cumulative deviations from the mean as its foundation. According to (Buishand, 1982)), one homogeneity test relies on cumulative departures from the mean:

$$S_k = \sum_{i=1}^k (X_i - \bar{X}) \quad (3.3)$$

$K = 1, 2, \dots, n$:

Where X_i represents the values in the series $X_1, X_2, \dots, X_n$, and $\bar{X}$ is the mean of these values. The initial value of S_k is set to 0, and the final value, $S_k=n$, is also set to 0. When visualizing the S_k values (sometimes referred to as a residual mass curve), it becomes easy to identify shifts in the mean. When a record X_i is higher than the normal, the S_k value for i increases, while for a record below the normal, the S_k value for i decreases. In the case of a homogeneous record, one would anticipate that the S_k values oscillate around zero since there is no consistent pattern in how the X_i values deviate from their average, $\bar{X}$.

According to Ren et al., (2012), the dataset's homogeneity is deemed not valid with probabilities of 90%, 95%, and 99%, respectively, when the cumulative deviation surpasses any of the specified horizontal lines. The datasets' homogeneity was assessed for this study, as shown in Figure 3.9 for the meteorological station in question and in Appendix C for the remaining stations, The cumulative deviation of the representative stations did not cross the horizontal line with 90%, 95%, or 99% probability, respectively.

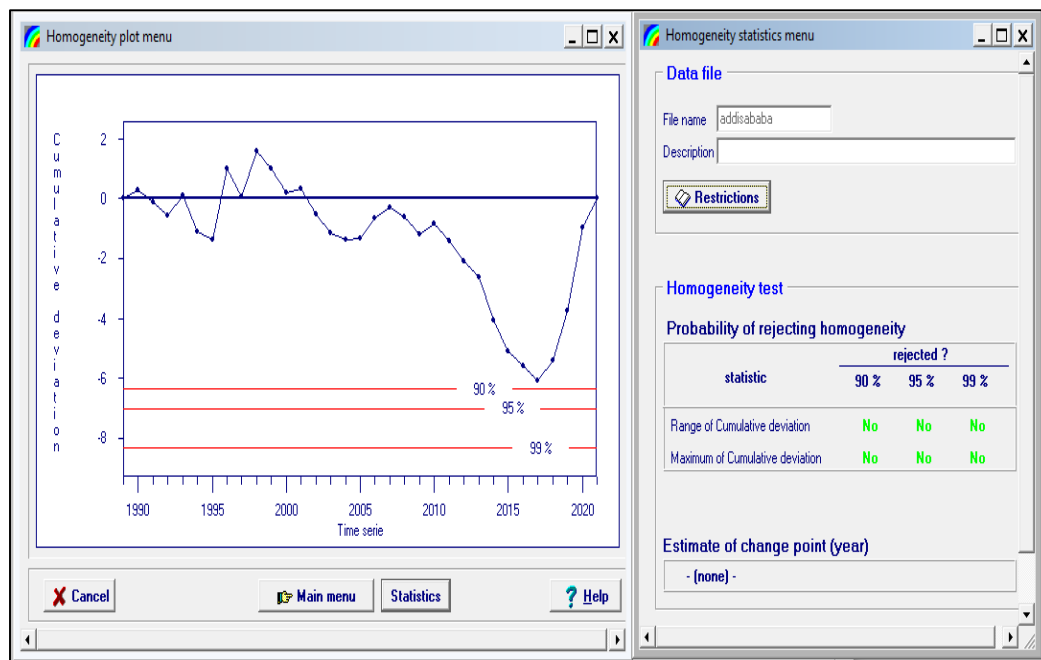


Figure 3.9 Homogeneity test of AA Bole rainfall station

3.5.4. Bias correction

Bias correction is a technique used in climate science and meteorology to adjust climate model outputs or observational data to remove systematic errors or biases. There are various methods for bias correction, and the choice depends on the specific characteristics of the biases and the data. Several commonly used methods encompass Linear Scaling, Delta Change, Precipitation Local Intensity Scaling, Power Transformation of Precipitation, Variance Scaling of Temperature, and Distribution Mapping. In this study, the process of extracting and bias-correcting the outputs of the RCA4 model involved utilizing the distribution mapping approach implemented in the program known as CMhyd, which is designed for utilizing climate model data in hydrological modeling. Specifically, the precipitation and temperature data were subjected to bias correction using this method. The distribution mapping approach implemented in CMhyd involved comparing the probability distributions of the model data with the corresponding observed data. Through this comparison, systematic biases or discrepancies in the model outputs were identified and adjusted to align with the observed data. The bias correction of precipitation and temperature data was performed systematically, ensuring that the corrected values better represented the actual climate conditions. This step aimed to reduce any systematic errors or biases in the model outputs and improve their reliability for further analysis and interpretation. Notably, upon comparing the graphical representations of bias-corrected techniques, Distribution Mapping emerges as the optimal selection.

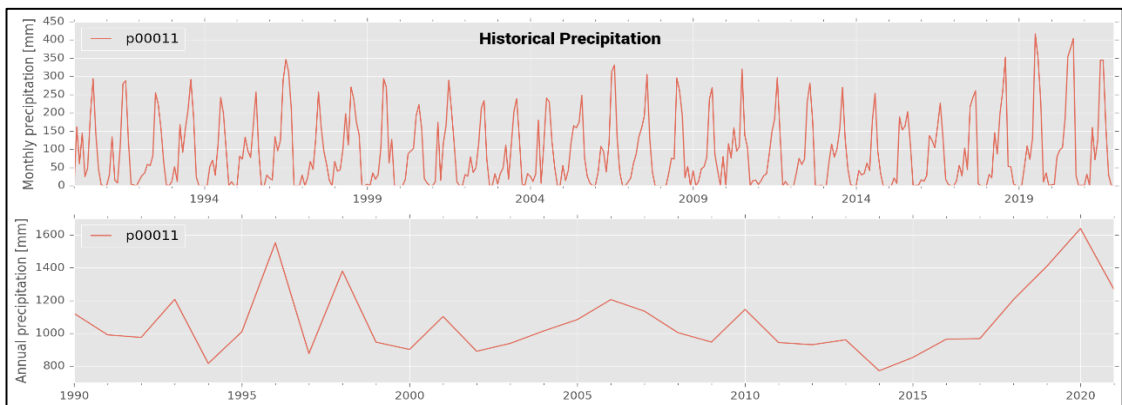
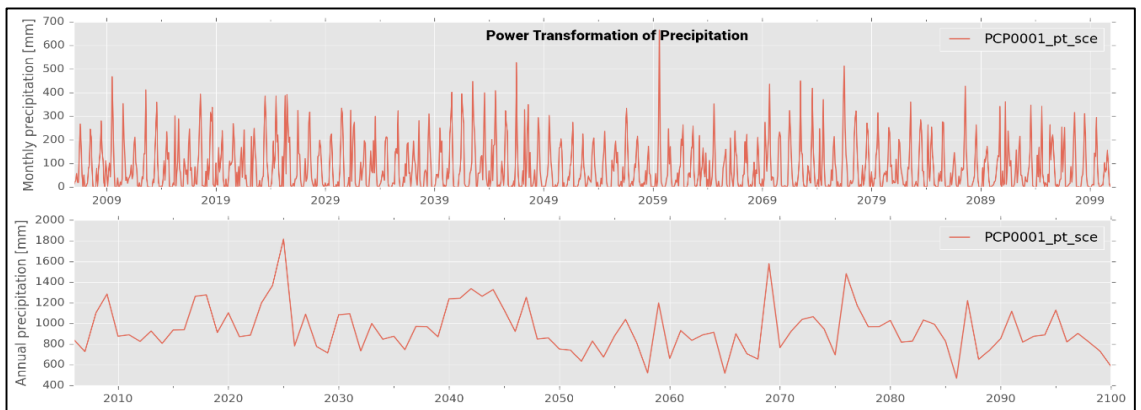
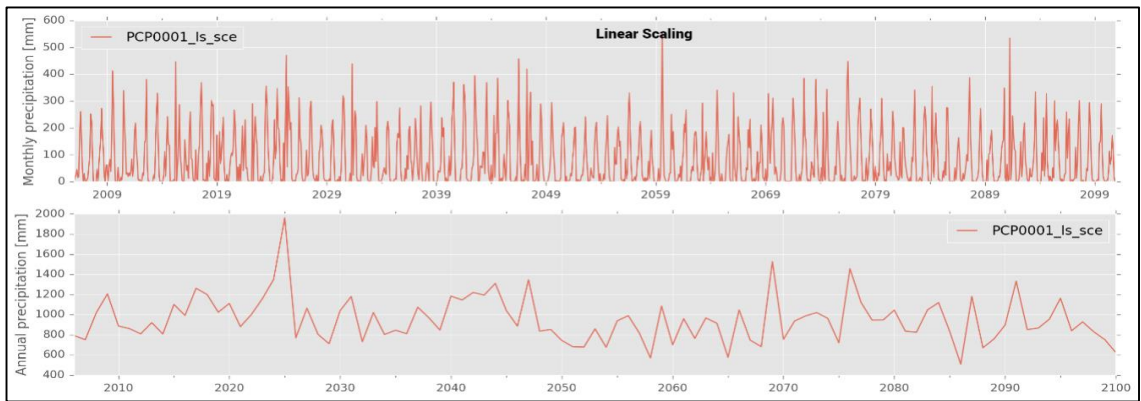
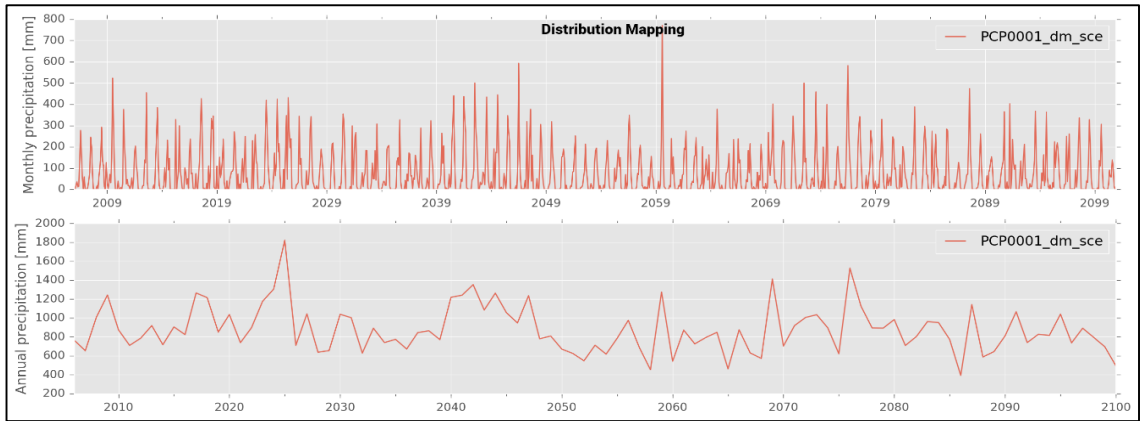


Figure 3.10 Graphical representations of bias-corrected techniques

The distribution mapping method is employed in the context of bias correction to adjust the output data of the Regional Climate Model (RCM). Its primary objective is to align the statistical characteristics of climate variables with the observed data, enhancing the overall similarity between the two. This adjustment procedure involves several parameters, such as the average, standard deviation, variance, and the distribution of higher moments of the climate variable.

Specifically, the distribution mapping method utilizes the Gamma distribution, which is frequently applied in representing precipitation distributions. This distribution takes into account essential computing parameters, namely the shape parameter (α) and scale parameter (β). These parameters play a crucial role in the bias correction process, ensuring a more accurate representation of the observed precipitation data.

$$f(p; \alpha, \beta) = p^{\alpha-1} \frac{\exp\left(-\frac{p}{\beta}\right)}{\Gamma(\alpha)\beta^\alpha} \quad p, \alpha, \beta > 0 \quad (3.4)$$

Where: Γ represents the gamma function, and P stands for the simulated daily precipitation from the RCM. The parameters α and β are computed separately for each grid box and each month. This estimation is achieved through the method of moments.:

$$\alpha = \left(\frac{\bar{p}}{\sigma p} \right)^2 \quad (3.5)$$

$$\beta = \frac{\sigma_p^2}{\bar{p}} \quad (3.6)$$

Where: σp and $\bar{p}$ denote the sample standard deviation and mean of the variable P , respectively.

The correction method for daily precipitation in this study involves the application of local intensity scaling, which allows for the simultaneous adjustment of both precipitation intensity and frequency. The correction process is performed as follows

$$P_{cor, m, d} = Fr^{-1} (Fr (P_{LOCI, m, d} / \sigma_{LOCI, m}, \beta_{LOCI, m}) / \sigma_{obs, m}, \beta_{obs, m}) \quad (3.7)$$

Where: $P_{cor, m, d}$ corrected precipitation, Fr represents the cumulative distribution function, while Fr^{-1} represents the inverse of the cumulative distribution function.

By utilizing the Gaussian distribution and adjusting the values of μ and σ , the temperature time series can be bias-corrected to better align with observed data. The location parameter

μ allows for shifting the distribution to match the observed mean temperature, while the scale parameter σ allows for adjusting the spread of the distribution to match the observed standard deviation.

$$fN\left(\frac{x}{\mu}, \sigma^2\right) = \frac{1}{\sigma\sqrt{2\pi}} * e^{-\frac{(x-\mu)^2}{2\sigma^2}}; x \in \mathbb{R} \quad (3.8)$$

The corrected temperature is

$$T_{cor, m, d} = F_N^{-1} \left(F_N(T_{raw, m, d} / \sigma_{raw, m} \mu_{raw, m}) / \mu_{obs, m} \sigma_{obs, m} \right) \quad (3.9)$$

Where: F_N represents the Gaussian Cumulative Distribution Function and F_N^{-1} is its inverse, $\mu_{raw, m}$, and $\mu_{obs, m}$ refers to the observed means of the raw and observed precipitation data for a specific month denoted as "m.", and $\sigma_{raw, m}$, and $\sigma_{obs, m}$ indicates the respective standard deviations for the raw and observed precipitation data, also for the same month "m."

3.5.5 Areal Precipitation

Area rainfall analysis is used to obtain the areal representation of the point rainfall. Thiessen polygon method was selected for the determination of areal rainfall for this study for its sound theoretical basis and availability of computational tools. However, the method requires a good network of representative rain gauges. The Thiessen polygon method was chosen for calculating areal precipitation in this study due to its sound theoretical foundation and the accessibility of computational tools for its implementation. The Thiessen polygon method assigns weights to individual precipitation gauges relative to the area they encompass within the entire basin, and this allocation is made without taking into account the topographical or other physical characteristics of the basin. This approach is chosen for its ability to capture the spatial distribution of rainfall effectively. By dividing the region into polygons based on proximity to precipitation measurement stations, the Thiessen polygon method considers the influence of nearby gauges on the estimated precipitation at a given location. This makes it particularly valuable in engineering applications where accurate knowledge of rainfall patterns is crucial.

$$P_X = \frac{\sum_{i=1}^n A_i P_i}{A} \quad (3.10)$$

Where: P_X represents the average rainfall, P_i stands for the rainfall recorded at station i , A_i signifies the area of the sub-region associated with station i , and A represents the total area of the sub-basin.

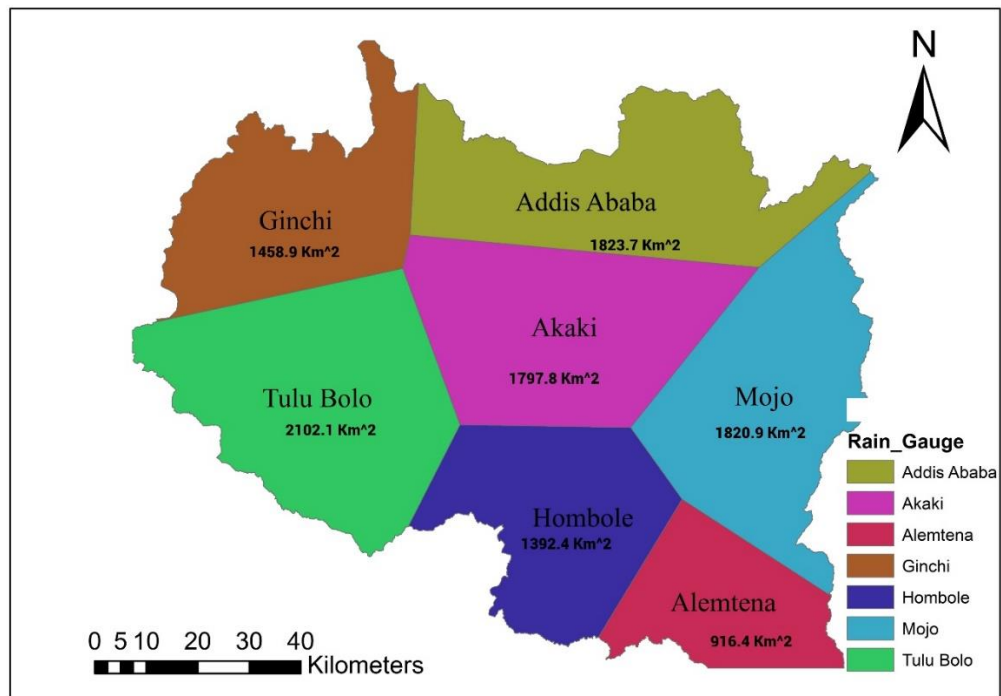


Figure 3.11 Areal coverage of each station

3.6. Hydrological Model Setup and Simulation

3.6.1. Hydrological components of SWAT

The semi-distributed physical model known as SWAT proves to be highly proficient in predicting changes in hydrology and sediment yield resulting from shifts in climate patterns. SWAT is specifically engineered for forecasting the impact of land management practices on water quality, sediment accumulation, and the release of agricultural chemicals within extensive and intricate watersheds characterized by diverse soil types, land use patterns, and management factors (Arnold et al., 2013). In the SWAT model, the water balance equation links together a range of elements, including soil moisture, surface runoff, interception, daily rainfall, evapotranspiration, percolation, lateral subsurface flow, return flow, snowmelt, transmission losses, and pond dynamics. When it comes to hydrological modeling in SWAT, only two components are considered for percolation and return flow or base flow: percolation from the vadose zone to the shallow aquifer and base flow from the shallow aquifer to the channel. Since it is assumed that water entering the deep aquifer will contribute to streamflow somewhere else outside the watershed, the groundwater flow from the deep aquifer is not taken into consideration. (Arnold et al., 1993) claims that surface runoff, lateral flow from soil profiles, and return flow/base flow from shallow aquifers all contribute to the water in the stream. According to Neitsch et al. (2011), the water that

seeped into the deep aquifer is presumed to have been lost from the watershed system. It is not included in the water balance. Equation 3.11 serves as the method for calculating the soil water content within the watershed.

$$SW_t = SW_o + \sum_{k=0}^n (R_{day} - Q_{surf} - Ea - W_{seep} - Q_{gw}) \quad (3.11)$$

Where SW_t is used to compute the final soil water content in mm, SW_o represents the initial soil water content (mm), t is the time in days, R_{day} is the daily precipitation amount in mm, Q_{surf} is the surface of runoff on day i (mm), Ea is the evapotranspiration on day i (mm), W_{seep} is the water inflow into the vadose zone from the soil profile on day i (mm), and Q_{gw} is the return flow on day i (mm).

3.6.1.1. Surface runoff

SWAT calculates surface runoff volumes and peak runoff rates for each Hydrologic Response Unit (HRU) using daily or sub-daily rainfall data. The model offers two approaches to estimating surface runoff volume: the SCS curve number method and the Green & Ampt infiltration method. While the latter method provides more accurate runoff volume estimates, its need for sub-daily time step data poses challenges to its applicability in our country's context. As a result, we opted for the SCS curve number method. Equation 3.12 represents the general equation for this method.

$$Q_{surf} = \frac{[(P - Ia)]^2}{((P - Ia) + S)} \quad (3.12)$$

Where Q_{surf} represents the cumulative rainfall excess runoff in millimeters, P is the daily rainfall depth in millimeters, Ia is the initial abstraction in millimeters and S is the potential maximum water retention capacity within the watershed.

The parameter S , which relates to retention, can be determined through the following equation

$$S = 24.5 \left(\frac{1000}{CN} - 10 \right) \quad (3.13)$$

Where CN is the curve number for the day. The initial abstractions, Ia are commonly approximated as $0.2 S$.

$$Q_{surf} = \frac{[(P - 0.2S)]^2}{(P + 0.8S)} \quad (3.14)$$

SCS defines the three antecedent moisture conditions:

AMC-I: This moisture level includes the lowest runoff potential; because the soils are dry enough for satisfactory cultivation to take place.

AMC-II: The moisture level is an average condition regarding the runoff potential.

AMC-III: This moisture level includes the highest runoff potential of the soil, which practically happens when the area of the watershed is saturated from antecedent rains. The curve numbers for moisture conditions I and II are calculated as follows

$$CN_I = CN_{II} - \frac{20(100 - CN_{II})^2}{(100 - CN_{II} + \exp[2.533 - 0.0636(100 - CN_{II}]))} \quad (3.15)$$

$$CN_{III} = CN_{II} \cdot \exp[0.00673(100 - CN_{II})] \quad (3.16)$$

3.6.1.2. Flow routing

The rate and velocity of flow are determined using Manning's equation for uniform flow in a channel (Neitsch et al. 2011). After the model determines flow to the main channel, SWAT incorporates two methods, such as variable storage and Muskingum routing methods, to move water through the channel network. The storage volume in a channel length is represented by the Muskingum routing method as a combination of wedge and prism storage. The variable storage routing method, initially formulated by Williams (1969), has been applied in this study, drawing on its utilization in the HYMO (Williams & Hann, 1973) and ROTO (Arnold et al., 1995). The variable storage routing is based on the continuity equation:

$$V_i - V_{out} = \Delta V_{stored} \quad (3.17)$$

where V_i represents the inflow volume during the specified time step (m^3), V_{out} stands for the outflow volume during the same time step (m^3), and ΔV_{stored} represents the change in storage volume over that time step (m^3).

3.6.1.3. Evapotranspiration

Evapotranspiration is a comprehensive term encompassing all the mechanisms through which water on the Earth's surface is transformed into water vapor. This encompasses evaporation occurring from the plant canopy, transpiration, sublimation, as well as soil evaporation. Penman, (1956) defined PET as "the quantity of water transpired by a short green crop, which fully covers the ground, maintains a consistent height, and is never limited

by water availability" and noted that several vegetative surface features had a significant impact on the evapotranspiration rate. To calculate PET (Potential Evapotranspiration), various techniques have been developed, and in the case of SWAT, three of these methods have been integrated, including the Penman-Monteith method ((Monteith, 1965; Allen, 1986; Allen et al., 1989), the Priestley-Taylor method (Priestley & Taylor, 1972), and the Hargreaves (Hargreaves & Allen, 2003). The Penman-Monteith approach necessitates data on solar radiation, air temperature, relative humidity, and wind speed. In contrast, the Priestley-Taylor method relies on solar radiation, air temperature, and relative humidity, while the Hargreaves method only requires air temperature. Given the data inputs available, the Penman-Monteith method was utilized to calculate the potential evapotranspiration (PET) for the study area.

3.6.1.4. Base flow estimation

The amount of streamflow that emerges from the ground is known as baseflow. SWAT simulates two aquifers within each sub-basin. The primary channel or reach in the sub-basin receives water flow from the shallow aquifer, which is unconfined. In addition, there is a confined aquifer, known as the deep aquifer, in the sub-basin. According to Arnold et al., (1993), it is believed that water entering the deep aquifer contributes to streamflow outside of the watershed. The water balance for the shallow aquifer is:

$$Aqsh,i = Aqsh,i - 1 + Wrchrg,sh - Qgw - Wrevap - Wpump,sh \quad (3.18)$$

where $Aqsh,i$ represents the water storage in the shallow aquifer on day i in mm, $Aqsh,i-1$ is the water storage in the shallow aquifer on the previous day $i-1$ (mm), $Wrchrg,sh$ is the recharge entering the shallow aquifer on day i in mm, Qgw is denoting the groundwater flow or base flow into the primary channel on day i in mm, $Wrevap$ indicates the water movement into the soil zone due to water deficiencies on day i in mm, and $Wpump,sh$ represents the water extraction from the shallow aquifer through pumping on day i in mm.

The shallow aquifer provides base flow to the primary channel or reaches in the sub-basin. The groundwater flow response to recharge follows the steady-state model developed by Hooghoudt in 1940:

$$Qgw = \frac{8000 * Ksat}{Lgw} * hwtbl \quad (3.19)$$

where Qgw represents the base flow or groundwater flow into the primary channel on day i (mm), $Ksat$ is the hydraulic conductivity of the aquifer (mm), Lgw denotes the distance from

the ridge or subbasin divide to the main channel for the groundwater system (m), and hwtbl is the height of the water table (m).

The variations in the water table resulting from the non-steady-state reaction of groundwater flow to cyclic recharge are computed (Smedema & Rycroft, 1983):

$$\frac{dhwtbl}{dt} = \frac{wrchrg,sh - Q_{gw}}{800 * \mu} \quad (3.20)$$

where $\frac{dhwtbl}{dt}$ represents the rate of change in water table height over time in mm/day, wrchrg,sh is the recharge entering the shallow aquifer on day i in mm, Q_{gw} is the groundwater flow into the primary channel on day i in mm, and μ denotes the specific yield of the shallow aquifer, measured in m/m.

The water balance equation for the deep aquifer is as follows:

$$A_{qdp,i} = A_{qdp,i-1} + W_{deep} - W_{pump,dp} \quad (3.21)$$

where $A_{qdp,i}$ represents the water storage in the deep aquifer on day i in mm, $A_{qdp,i-1}$ is the water storage in the deep aquifer on the previous day (i-1) in mm, W_{deep} denoting the water percolating from the shallow aquifer into the deep aquifer on day i in mm, and $W_{pump,dp}$ is the water extracted from the deep aquifer through pumping on day i in mm.

3.6.2. SWAT model setup

The most effective physical model for forecasting hydrological and sedimentary changes in response to climate fluctuations is the SWAT model. Designed for extensive and intricate watersheds characterized by diverse soil types, land usage, and management practices over extended timeframes, SWAT aims to predict the influence of climate management strategies on water, sediment, and agricultural chemical yields (Arnold et al., 2012). A basin is divided into several sub-basins. Hydrological response units (HRUs) are based on the homogeneity of soil types, land-use types, and slope classes. To simulate hydrological processes, the SWAT model (Arnold et al., 2012) needs input data such as topography, soil, and land use in addition to hydro-meteorological data.

The SWAT model setup incorporates components such as Watershed delineation, Hydrologic Response Unit (HRU), Sensitivity analysis, and calibration and Validation of the model. In this study, the SWAT-2012 interface compatible with Arc GIS 10.4 (Arc SWAT 2012) was used to set up a SWAT model for the upper Awash watershed to assess the impact of climate change on dam safety. We determined potential evapotranspiration

using the Penman-Monteith method, while surface runoff was estimated by applying the modified Soil Conservation Service (SCS) curve number method to aggregated precipitation data covering all Hydrologic Response Units (HRUs) within a sub-watershed. The simulation of channel runoff routing was performed using the variable storage method.

3.6.2.1. Watershed delineation

Arc SWAT employs digital elevation model (DEM) information to autonomously partition the watershed into interconnected sub-watersheds. The initial stage of watershed delineation involved loading the correctly projected DEM. To expedite the GIS processes, a mask was generated to encompass the study area within the DEM. After the preparation of spatial input data such as DEM, soil data, and land use data and project into the UTM zone 37 projection to assure map overlapping in Arc GIS 10.4 software, the watershed was delineated in Arc SWAT in which the Arc GIS is an interface. A 30-meter resolution digital elevation model (DEM) was employed to delineate the watershed and its sub-watersheds. The delineation process encompassed several steps, including DEM setup, stream definition, inlet-outlet identification, selection and specification of the watershed outlet, and the calculation of sub-basin parameters. Initially, the stream network and sub-basin outlets were determined based on a drainage area threshold derived from the DEM. A smaller threshold yielded a more detailed drainage network with a larger number of sub-basins and Hydrologic Response Units (HRUs), while a larger threshold had the opposite effect. Subsequently, the final configuration of the stream network and outlets used for modeling was fine-tuned. Consequently, the upper Awash watershed was partitioned into 35 sub-basins, as illustrated in Figure 3.12.

3.6.2.2. Hydrologic response unit analysis

The smallest operational unit for streamflow routing in the model, known as the Hydrological Response Unit (HRU), was created through the process of reclassifying land use, soil maps, and slope classes, and then overlaying them. The HRU analysis within SWAT involves the delineation of HRUs by overlaying spatial data sets representing slope classes, land use, and soil types. Conducting hydrological simulations at the HRU level allows for a detailed examination of the spatial variability in water balance components within the watershed, focusing on relatively smaller areas, which is essential for planning interventions in the watershed (Shawul & Chakma, 2019).

The delineated watershed, along with the land use and soil maps, exhibited complete overlap, with 100% coverage. Subsequently, multiple criteria were employed for defining Hydrological Response Units (HRUs) in most applications. This study considered four classes of the slope, 0-10%, 10-20%, 20- 40%, and $\geq 40\%$ in Figure 3.5. The land use/land cover (LULC), soil, and slope maps underwent reclassification to align with the parameters specified in the SWAT database. Subsequently, the reclassified LULC, soil, and slope maps were superimposed to delineate Hydrological Response Units (HRUs). The distribution of HRUs was established by applying various HRU definition criteria. In the context of this particular study, HRUs were defined using a 5% threshold for land use, 10% for soil, and 15% for slope. The 2015 land use data were utilized to define these HRUs, resulting in the division of the Upper Awash watershed into 158 HRUs based on the 2015 land use map.

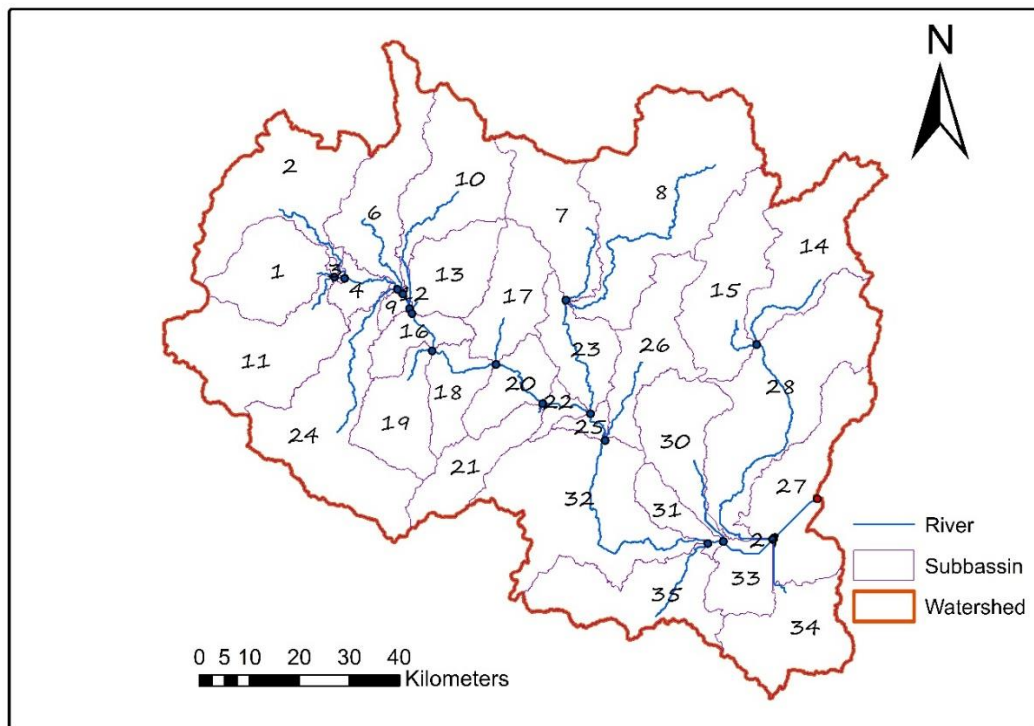


Figure 3.12 Sub-basins of the study area

3.6.2.3. Weather data

The maximum and minimum temperatures, precipitation, wind speed, relative humidity, and solar radiation are only some of the input files used by the Arc SWAT model, an ArcGIS interface. To fill in the gaps, SWAT incorporates an integrated weather generator named WGEN, initialized with the value -99. After generating weather parameters using WGEN, these parameters were imported into the SWAT database to complete the weather data for the remaining meteorological stations.

3.7. Sensitivity Analysis, Calibration, and Validation

Sensitivity analysis, calibration, validation, and uncertainty analysis of the SWAT model were conducted using the SWAT Calibration and Uncertainty Programs (SWAT-CUP) in combination with the Sequential Uncertainty Fitting version-2 (SUFI-2) algorithm, as described by (K. C. Abbaspour et al., 2009).

3.7.1. Sensitivity analysis

The process estimates the rate at which a model's output will change when its inputs change. This model has accurate values for determining the important parameters and evaluating the model's applicability. Sensitivity analysis explains how a given input variable's range impacts model output. Several parameters make sensitivity analysis and calibration difficult, according to some researchers. The primary objective of parameter sensitivity analysis is to potentially reduce the number of parameters that need to be estimated, thereby decreasing the computational time needed for model calibration. Which parameters that impact the output variance caused by the input variability are revealed by a parameter sensitivity analysis (Holvelt et al., 2005). Sensitivity analysis was conducted to determine how a set of parameters influences total flow prediction (Shawul & Chakma, 2019). In this analysis, the parameter is considered more sensitive when its t-statistic has a greater absolute value and its p-value is smaller (K. Abbaspour et al., 2007). Two sensitivity analysis approaches are permissible: Global Sensitivity Analysis and One-at-a-time Sensitivity Analysis.

For sensitivity analysis and model calibration, the SWAT Calibration and Uncertainty Program (SWAT-CUP) software package, as developed by (Abbaspour et al., 2007) employed the global sensitivity analysis method. This global sensitivity analysis can be conducted following each iteration. The determination of parameter sensitivities involves performing a multiple regression analysis, where the parameters generated through Latin hypercube sampling are regressed against the values of the objective function.

$$g = \alpha + \sum_{i=1}^m \beta_i b_i \quad (3.22)$$

A t-test is subsequently employed to assess the relative significance of each parameter denoted as 'b_i.' The sensitivities described above represent estimated average variations in the objective function when each parameter changes, while all other parameters remain in flux. These relative sensitivities are based on linear approximations and, therefore, offer only partial insights into how the objective function responds to alterations in model parameters.

The simulated, and observed data and sensitive parameters are considered as input for sensitivity analysis.

3.7.2. Calibration and Validation

Model calibration involves the task of establishing model parameters by comparing the model's predictions for a specific set of conditions with the corresponding observed data. The calibration process is based on the assumption that a linear relationship exists between the observed and simulated data. This means that the measured data are error-free and that all of the error variances are contained in the simulated values. But, the measured values are not error-free in reality (Moriassi et al., 2007). The Arc SWAT model can undergo calibration through both manual and automatic methods.

Manual calibration entails a visual comparison of observed and simulated data, where the process is carried out manually. On the other hand, automated calibration involves defining one or more objective functions to guide the calibration process (Balascio et al 2007). In this study, the calibration and validation of the model were conducted using the software package known as SWAT Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour et al., 2013). By mitigating potential sources of modeling and calibration errors, SWAT-CUP offers a range of calibration and uncertainty analysis techniques to minimize uncertainty in modeling. It integrates methods such as Markov Chain Monte Carlo (MCMC), Sequential Uncertainty Fitting version 2, Generalized Likelihood Uncertainty Estimation (GLUE), and Particle Swarm Optimization (PSO) with the SWAT model ((Arnold et al., 2012; Khalid et al., 2016)). In this study, a semi-automated sufi-2 algorithm which is one of the uncertainty analysis techniques incorporated in SWAT-CUP was used for streamflow calibration and validation at the upper Awash station.

The resulting calibrated parameter values were added to the SWAT model for validation and other applications when the calibration exercise was completed. Hydrologic model validation is the process of matching simulated and actual values without altering the calibrated parameters. The process of running a model using parameters that were established through calibration and then comparing the model's results with observed data, which were not utilized during the calibration phase, is known as validation. The SWAT model simulation was executed for the period spanning from 2000 to 2021, with the first 3 years (2000 to 2002) designated as a warm-up phase for model initialization. The data from

2003 to 2011 was employed for calibration, while data from 2012 to 2015 was set aside for validation.

3.7.3. Uncertainty analysis

Watershed modeling, analysis, and assessment are challenging tasks due to uncertainties such as model input uncertainty, model parameter uncertainty, model structure uncertainty, and model response uncertainty. There are many uncertainty analysis methods developed such as (SUFI-2, GLUE, ParaSol, and PSO) included in the SWAT-CUP (SWAT Calibration and Uncertainty Programs).

The assessment of model performance and its ability to address uncertainties can be evaluated through the utilization of the Sequential Uncertainty Fitting, version 2 (SUFI-2) program (SWAT CUP), employing the two aforementioned metrics, namely the P-factor and R-factor. The P-factor measures the extent to which all uncertainties are considered, representing the percentage of observed data falling within the 95% prediction uncertainty (95PPU) range. Conversely, the R-factor serves as an indicator of calibration quality, quantifying the width of the 95PPU band and the average width of this band relative to the standard deviation of the observed data (K. Abbaspour, Vajdani, et al., 2007). In SUFI-2, parameter uncertainty encompasses various sources of uncertainty, including uncertainties in driving variables like precipitation, the conceptual model, model parameters, and measured data. Evaluating the percentage of data encompassed by prediction uncertainty serves as a valuable metric for gauging the robustness of our uncertainty analysis. The 95% Prediction Probability Uncertainty (95PPU) is computed based on the 2.5% and 97.5% percentiles of the cumulative distribution of an output variable, determined through Latin hypercube sampling, with the exclusion of the worst 5% of simulations. In theory, the P-factor ranges from 0 to 1, while the R-factor ranges from 0 to infinity. A P-factor of 1 and an R-factor of 0 indicate a simulation that perfectly matches observed data. Deviations from these values can be used to assess the quality of our calibration. Typically, a P-factor exceeding 0.7 and an R-factor less than 1.5 are recommended for discharge data (Abbaspour et al., 2015).

3.8. Model Performance Evaluation

During the calibration and validation periods, observed data and simulated data are frequently compared using graphical and statistical techniques. An initial assessment of model performance and a visual comparison between simulated and observed constituent

data is conducted using graphical methods. The SWAT model's statistical performance will be evaluated using metrics such as the coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), and Percent Bias (PBIAS) (N. Moriasi et al., 2007). The coefficient of determination (R^2) is calculated as the squared ratio between the covariance and the product of the standard deviations of observed and predicted values.

The coefficient of determination quantifies the proportion of the variability observed in the measured data that is mirrored in the simulated model outcomes. The observed and simulated data cannot fit the model if the R^2 is 0. An R^2 value of 1 indicates that there is no difference between the measured value and the simulated value. If the R^2 is between 0 and 1, the model can be used. When R^2 values fall outside the range of 0 to 1, it indicates that the model's data does not align with the observed data. According to de Vos & Rientjes, (2008), the range of values for R^2 is 1.0 (best) to 0.0 (worst). It is estimated by:

$$R^2 = \frac{(\sum_{i=1}^n [Q_{o_i} - \bar{Q}_o][Q_{s_i} - \bar{Q}_s])^2}{\sum_{i=1}^n [Q_{o_i} - \bar{Q}_o]^2 \sum_{i=1}^n [Q_{s_i} - \bar{Q}_s]^2} \quad (3.23)$$

Where Q_o represents the observed flow, Q_s is the Simulated flow, $\bar{Q}_o$ stands for the average of observed flow and $\bar{Q}_s$ is the average of simulated flow.

The Nash-Sutcliffe Efficiency (NSE) is an efficiency metric that quantifies the relationship between the model's goodness-of-fit and the variance of observed data. NSE can range from negative infinity to 1, where a value of 1 signifies a perfect agreement between observed and simulated discharges. When NSE is zero, simulations are as poorly fitted as they would be for a constant value prediction. Moreover, a model performs very well when its NSE value is between 0.75 and 1, whereas values between 0.6 and 0.75 indicate a model that performs fairly well (G. Chen et al., 2016; Roth et al., 2016). The NSE efficiency, proposed by Nash & Sutcliffe, (1970), is defined as

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{o_i} - Q_{s_i})^2}{\sum_{i=1}^n (Q_{o_i} - \bar{Q}_o)^2} \quad (3.24)$$

Where: Q_o represents the observed flow, Q_s is the Simulated flow, $\bar{Q}_o$ stands for the average of observed flow

The Percent Bias (PBIAS) calculates the average disparity between simulated and observed values for a specific data quantity throughout the entire calibration or validation period in

the study. It quantifies the average inclination of simulated data toward their observed counterparts.

$$Pbias = 100 \left(\frac{\sum_{i=1}^n (Q_{obs_i} - Q_{sim_i})}{\sum_{i=1}^n Q_{obs_i}} \right) \quad (3.25)$$

Where, Q_o = Observed value, Q_s = Simulated value

Table 3-1 General performance ratings for recommended statistics in SWAT

Performance rate	R^2	NSE	PBIAS
Very good	$0.75 < R^2 \leq 1.0$	$0.75 < NSE \leq 1.0$	$PBIAS \leq \pm 10$
Good	$0.60 < R^2 \leq 0.75$	$0.60 < NSE \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$
Satisfactory	$0.36 < R^2 < 0.60$	$0.36 < NSE \leq 0.60$	$\pm 15 \leq PBIAS < \pm 25$
Bad	$0.25 < R^2 \leq 0.50$	$0.00 < NSE \leq 0.36$	$\pm 25 < PBIAS \leq \pm 50$
Unsatisfactory	$R^2 < 0.00$	$NSE < 0.00$	$\pm 50 \leq PBIAS$

3.9. Dam Safety Evaluation

Determining the safety of a dam involves assessing its ability to withstand the potential maximum inflow of water into the reservoir. This maximum inflow is anticipated to result from the highest projected precipitation levels in future scenarios. The assessment of this inflow considers data from climate change simulations, specifically those corresponding to the RCM model's projections for scenarios like RCP4.5 and RCP8.5. Within this future context, the evaluation aims to predict the peak flow or maximum flood occurrence over the next century, including the present, mid-term, and end future. Subsequently, the adequacy of the dam's spillway is examined to determine its overall safety.

3.9.1. Reservoir routing

Reservoir routing or reservoir inflow routing, is a hydrological concept and modeling technique used in the field of water resources engineering and hydrology. It involves the analysis and prediction of how water flows into and out of a reservoir over time, often considering factors like rainfall, evaporation, runoff, and other inflows. The primary purpose of reservoir routing is to simulate and understand the movement of water through a reservoir system, which could be a natural lake, an artificial dam, or a combination of natural and

engineered components. This analysis is crucial for various reasons, including flood control, water supply management, hydropower generation, and ecological studies.

Because of the influx of a flood wave into a reservoir, the reservoir's elevation and the discharge of water from it change as time progresses. Consequently, it is crucial to grasp the connection between the reservoir's water volume and its elevation, particularly concerning the outflow through the spillways. The outflow hydrograph is calculated using the inflow hydrograph and storage outflow parameters that are provided as part of the reservoir level pool method (Seleshi & Camberlin, 2006) The level pool method is calculated as follows:

$$(\text{Average inflow rate} \times \Delta t) - (\text{average outflow rate} \times \Delta t) = \text{change of storage (S)}$$

or

$$\left(\frac{I_1+I_2}{2}\right) \Delta t + \left(S_1 - \frac{Q_1 \Delta t}{2}\right) = \left(S_2 - \frac{Q_2 \Delta t}{2}\right) \quad (3.26)$$

Where: - I_1 is the initial time, I_2 is the inflow at a subsequent time, Q_1 is the outflow at the initial time, Q_2 is the outflow at a second time, S_1 is the initial storage at the start, S_2 is the storage at the second and Δt is a time interval.

Estimation of Inflow Hydrograph

The inflow hydrograph is derived from the maximum recorded rainfall or precipitation within the RCM dataset, considering both RCP4.5 and RCP8.5 scenarios, for the near, mid, and end future periods. In this study, the MPI climate model was selected because the MPI model's projections of mean monthly precipitation and temperature are closer to the historical values compared to the other models. Probable Maximum Precipitation (PMP) represents the maximum achievable depth of precipitation at a specific geographical location and time of year, considering the largest possible storm area. Consequently, the maximum precipitation value is chosen for each of these periods (near, mid, and end future) under both RCP4.5 and RCP8.5 scenarios. Subsequently, the PMP is calculated using the Hershfield, 1965 method. The mathematical expression for the Hershfield method for one day in a catchment is as follows:

$$\text{PMP} = P_{\text{ave}} + K_m \delta_n \quad (3.27)$$

Where; - PMP represents the maximum expected precipitation over a one day, P_{ave} is the average of the annual maximum rainfall observed over one day, δ_n is the standard deviation

of these annual one-day maximum rainfall and K_m is a frequency factor influenced by the number of observations and is determined as follows:

$$K_m = \left(\frac{P_{\max} - P_{\text{ave}(n-1)}}{\delta_{n-1}} \right) \quad (3.28)$$

Where: - $P_{\max}$ is the maximum value within a sequence of annual daily maximum rainfall, $P_{\text{ave}}(n-1)$ represents the average of the annual maximum rainfall observed over one day, calculated from $n-1$ data points after excluding the highest rainfall value, $\delta_{(n-1)}$ is the standard deviation of the annual maximum rainfall observed over one day, computed from $n-1$ data points after excluding the highest rainfall value.

Table 3.6 Probable maximum precipitation for RCP4.5 and RCP8.5 in mm

MPI-ESM-LR (2024-2100)						
Parameters	RCP4.5			RCP8.5		
	Near	Mid	End	Near	Mid	End
P_{max}	158.65	141.18	145.02	170.34	144.09	152.87
P_{ave}	56.20	47.91	51.60	51.78	46.44	46.85
δ_n	32.14	26.01	28.90	30.48	27.14	29.03
P_{ave (n-1)}	51.93	44.18	47.86	46.84	42.53	42.60
δ_(n-1)	24.55	17.36	22.18	18.24	18.81	19.77
k_m	4.35	5.59	4.38	6.77	5.40	5.58
PMP_{24 Hr}	195.93	193.27	178.21	258.13	192.95	208.79

In this study area, the maximum Probable Maximum Precipitation (PMP) over 24 hours is determined for two scenarios from the Representative Concentration Pathway (RCP): RCP4.5 and RCP8.5. For RCP4.5, the PMP values are 195.93mm, 193.27mm, and 178.21mm in the near, mid, and end, respectively. In the case of RCP8.5, the corresponding PMP values are 258.13mm, 192.95mm, and 208.79mm for the near, mid, and end future, respectively.

The calculated point-based probable maximum precipitation (PMP) needs to be converted into the mean areal rainfall depth calculated through the application of an areal reduction factor. This conversion is necessary to represent the PMP over the entire catchment area, as stated in the study (Haile & Awass, 2016). Areal reduction factors (ARFs) are generally derived through empirical or analytical techniques. In several nations, including Ethiopia,

the prevailing methods for establishing ARFs predominantly depend on empirical approaches, which encompass storm-centered or geographically centered approaches. However, in the case of Ethiopia, specific area reduction factors were not calculated. Instead, a uniform area reduction factor of 0.6 was applied to represent a large area of the watershed in East Africa, as indicated by (Haile & Awass, 2016).

The HEC-HMS Rainfall-Runoff Hydrograph Models are employed to determine the inflow and outflow hydrographs within the river basin of the Koka Dam. HEC-HMS (Hydrologic Engineering Center's Hydrologic Modeling System) is a hydrological modeling software extensively employed and created by the Hydrologic Engineering Center, a division of the U.S. Army Corps of Engineers. It's designed to simulate the hydrological processes within a watershed, helping engineers and hydrologists analyze and predict the behavior of rivers, streams, and other water bodies in response to rainfall events. The software can simulate the routing of water through reservoirs and channels, allowing for the analysis of water storage, release, and movement in these systems.

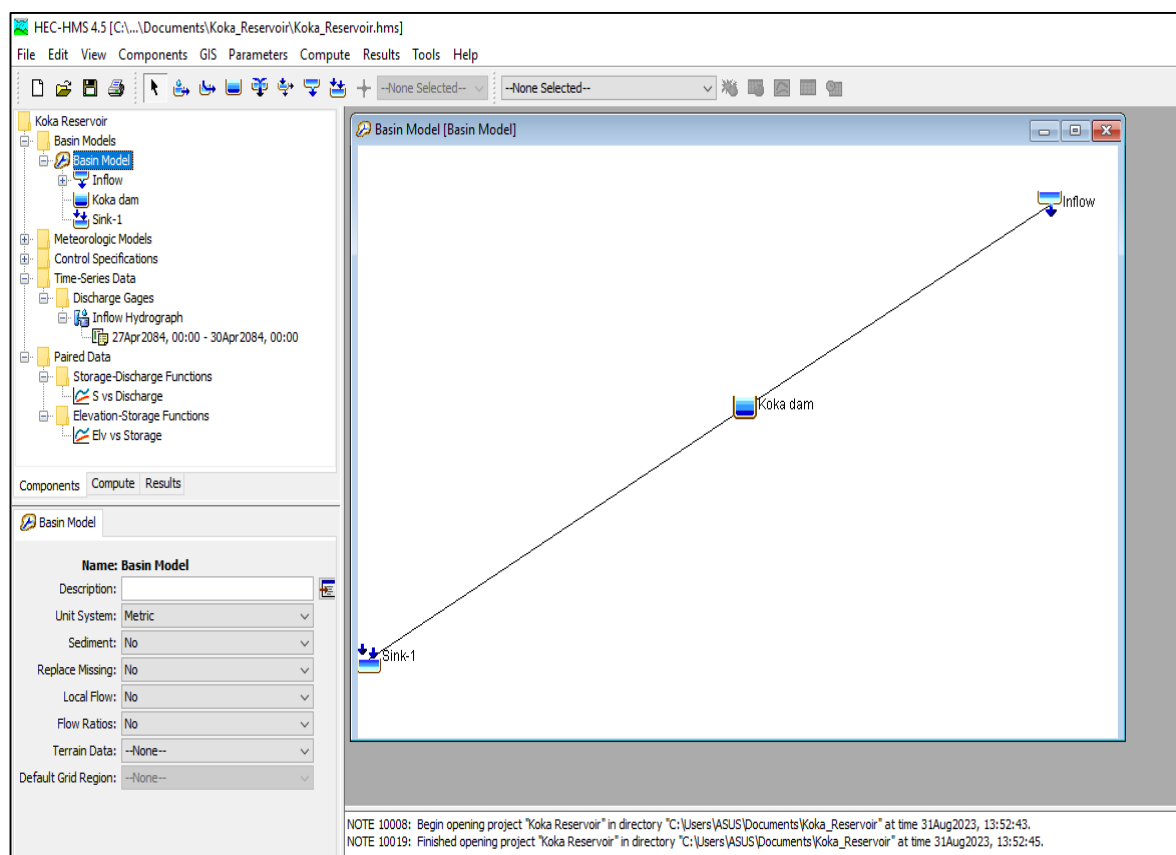


Figure 3. 13 Screen Capture of HEC-HMS

3.10. Flow Chart for the Methodology

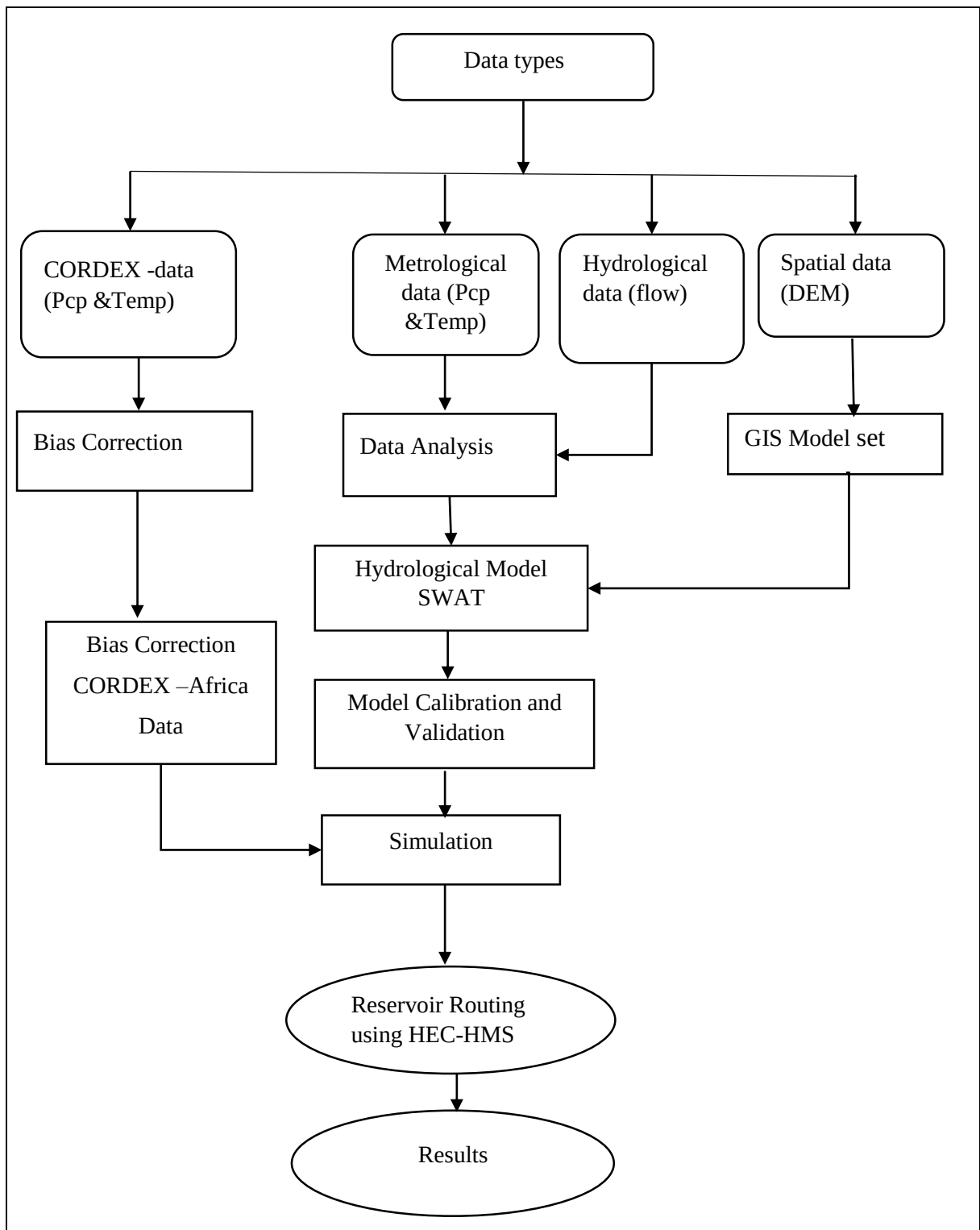


Figure 3.14 Conceptual framework of the study methodology

4. RESULT AND DISCUSSION

4.1. Climate Change Impact Analysis

4.1.1. Changes in projected precipitation

The upper Awash catchment region examined daily precipitation data from climate models, specifically focusing on RCP scenarios, notably RCP4.5 and RCP8.5, to project climate changes at a regional level for the next century. However, to facilitate the evaluation process, the daily precipitation changes were converted to average monthly precipitation. According to projections from CanESM2, the average annual precipitation is expected to undergo slight changes. Specifically, under RCP4.5 scenarios, the end period is projected to experience a 23.63% increase, while the near and mid periods are anticipated to decrease by -9.13% and -9.31% respectively as shown in Figures 4.1, 4.2, and 4.3. On the other hand, under RCP8.5, the near, mid, and end periods are expected to witness an increase of 1.75%, 14.43%, and 34.77% respectively. For CNRM, the mean annual precipitation is projected to increase by 1.66% and 9.82% during the near and end periods under RCP4.5 scenarios. However, the mid period is anticipated to experience a decrease of -2.87%. Under the RCP8.5 scenarios, the near, mid, and end periods are projected to see an increase of 6.85%, 2.19%, and 8.42% respectively. Regarding MPI, the mean annual precipitation is expected to increase by 6.24% during the near period, while the mid and end periods are projected to decrease by -14.44% and -5.27% respectively under RCP4.5 scenarios. However, under RCP8.5, the near, mid, and end periods are expected to see a decrease of -12.71%, -8.00%, and -22.38% respectively.

The analysis of future rainfall patterns indicates that there will be both increases and decreases in rainfall over different periods and under different scenarios. When considering the RCP4.5 scenario, the projected average monthly rainfall percentage change varies from -124.6% to +61.3%, -108.73% to 42.8%, and -97.4% to +26.6% for CanESM2, CNRM, and MPI, respectively, during the near term (2024-2048) compared to the observed period. Under the RCP8.5 scenario, the projected changes range from -154.5% to +87.7%, -44.02% to +44.2%, and -130.7% to +28.27% for CanESM2, CNRM, and MPI, respectively, during the same near-term period as indicated in figure 4.1, 4.2 and 4.3. Looking at the mid-term period (2049-2074), the projected changes in rainfall vary from -168% to +50.4%, -68.8% to +14.9%, and -141.8% to +37.4% under RCP4.5, and -121.87% to +92%, -82.23% to +45.33%, and -100.23% to +32.18% under RCP8.5 for CanESM2, CNRM, and MPI,

respectively, when compared to the historical period (1990-2021). Similarly, for the end term (2075-2100), the projected changes in rainfall range from -148.4% to +93.3%, -70.1% to +37.5%, and -165.9% to +39.6% under RCP4.5, and -169.2% to +95.2%, -123% to +36.8%, and -111.9% to +42.54% under RCP8.5 for CanESM2, CNRM, and MPI, respectively, compared to the historical period. In summary, the future rainfall patterns indicate a mix of increasing and decreasing trends across various time horizons and scenarios, with substantial variations in the projected changes depending on the specific climate model and scenario used. Similar patterns have been documented in earlier research. For example, Abdulahi et al., (2022) investigated the Upper Awash River basin and found that, across all scenarios, they anticipate an increase in rainfall during February, June, July, August, and November, coupled with a decrease in March, April, May, October, September, December, and January. Furthermore, they project an overall annual rainfall increase of 11.97% and 20.67% under RCP4.5 and RCP8.5, respectively.

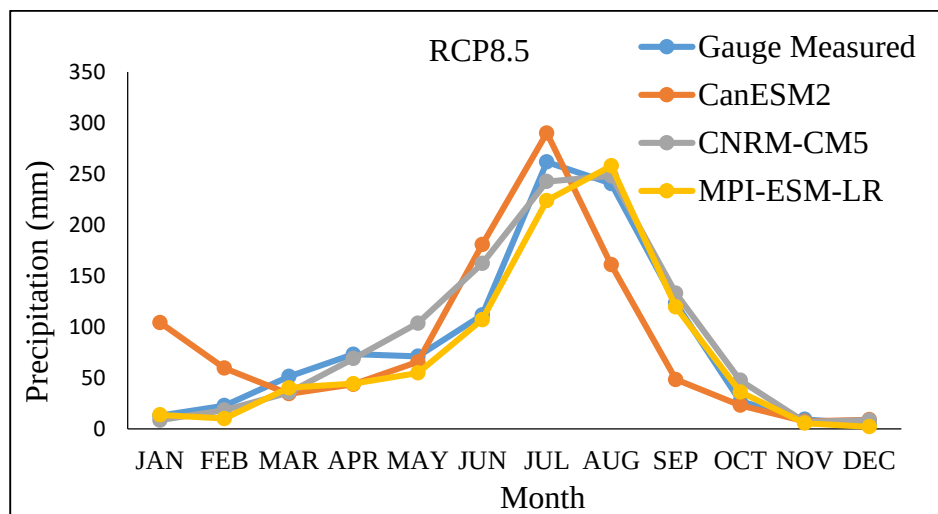
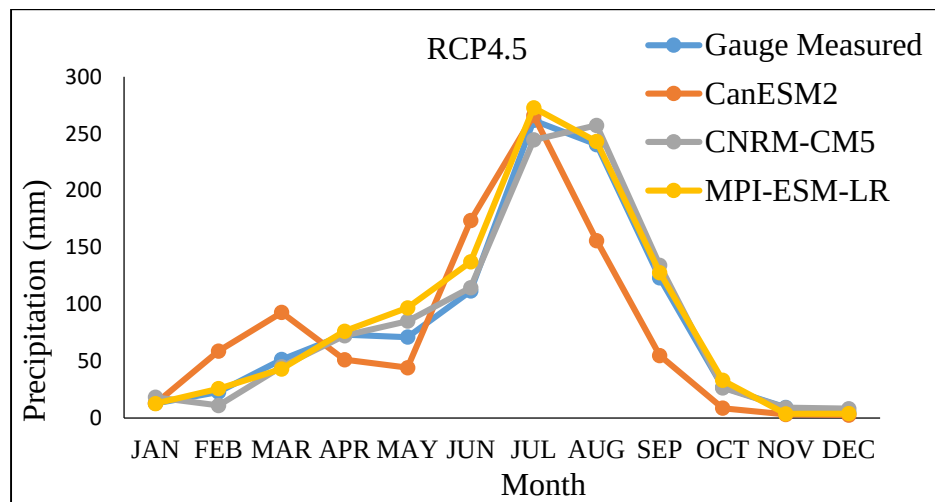


Figure 4.1 Average monthly precipitation of upper Awash catchment projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected near-future period.

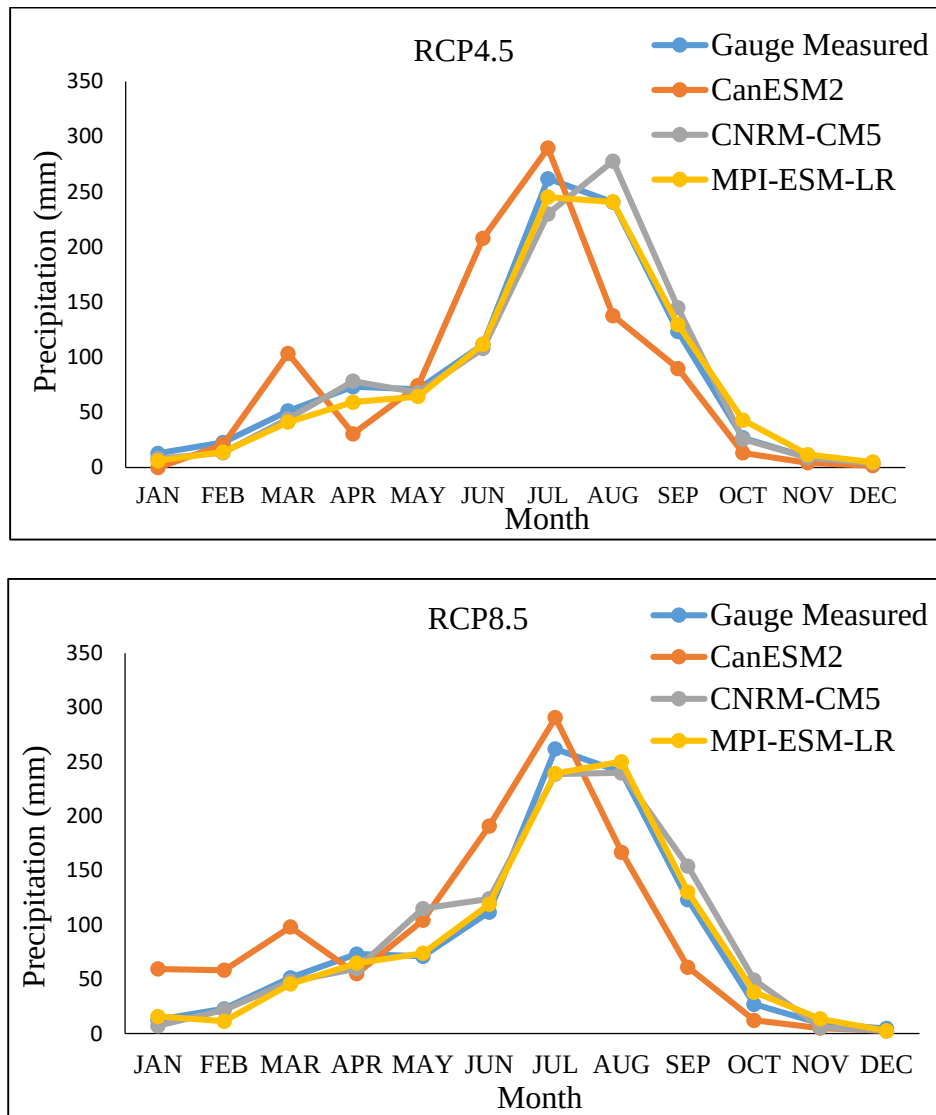


Figure 4.2 Average monthly precipitation of upper Awash catchment projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected mid-future period.

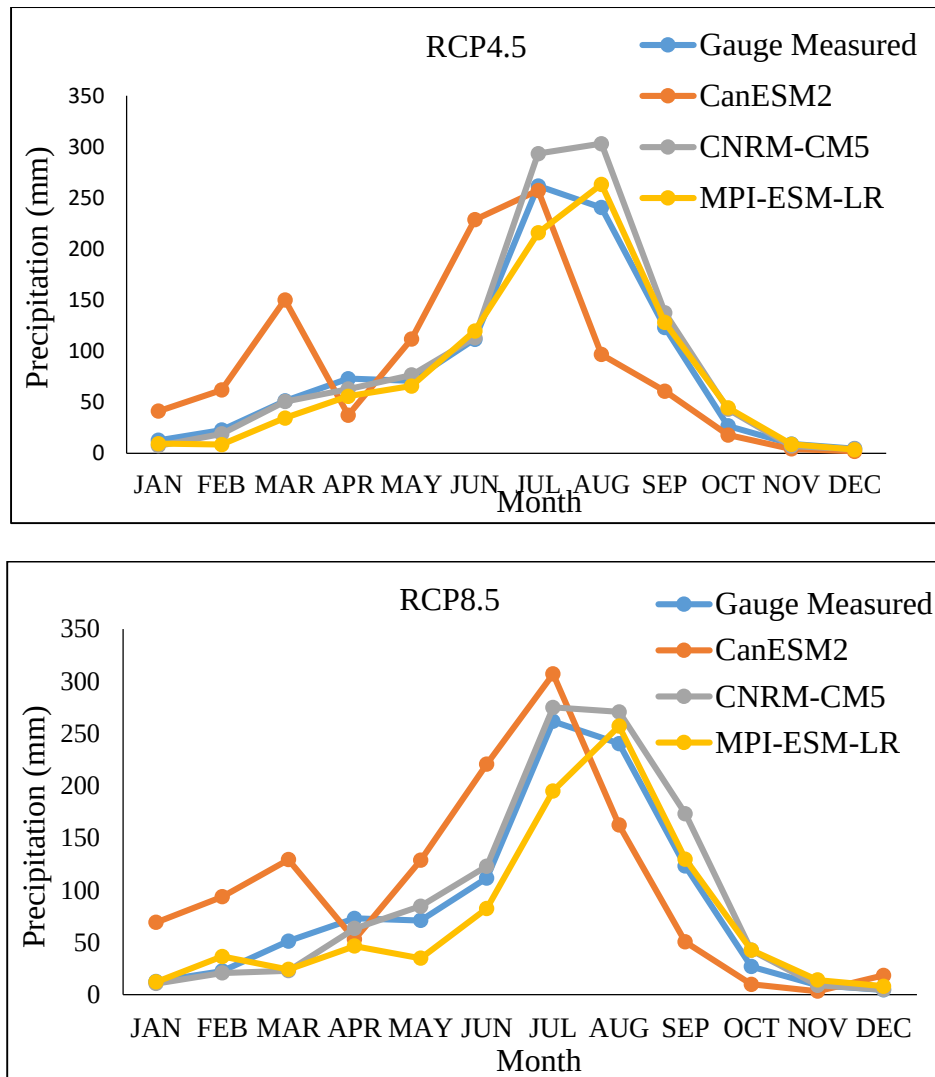


Figure 4.3 Average monthly precipitation of upper Awash catchment projected by the selected climate models, under RCP4.5 and RCP8.5 projected end of the century

The CanESM2 model forecasts a higher mean monthly precipitation of 307 mm in July under the RCP8.5 scenario. Similarly, both the CNRM and MPI models project the highest mean monthly precipitation in July and August, with values of 303 mm and 273 mm, respectively, under the RCP4.5 scenario. Based on the provided information, it appears that the MPI model's projection of mean monthly precipitation is closer to the historical values compared to the other models.

4.1.2. Seasonal changes in projected precipitation

We also examined the variations in rainfall patterns for each of the Representative Concentration Pathways (RCPs) across different seasons, including summer (June - Aug), autumn (Sep to Nov), winter (Dec to Feb), and spring (Mar to May), as well as annually for all specified future periods. The projected data indicates that there will be a generally non-

significant increase in annual rainfall across all time frames for both RCPs, as simulated by all Regional Climate Models (RCMs). The highest increase, reaching up to +72.51%, is projected for the near century (2024-2048) for the CanESM2 model under RCP8.5. Similarly, the changes in autumn reveal a minimum trend, with the most substantial decrease being -89.78%. Furthermore, the projected rainfall patterns exhibit varying trends for all RCMs during the winter, summer, and spring seasons, respectively, under both RCPs across all periods.

Table 4.1 Percentage change of Mean seasonal precipitation of Upper Awash catchment for RCMs during future periods

Time		Near future (2024-2048)					
RCM		CanESM2		CNRM		MPI	
Scenario		RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Season	Winter	35.38%	25.10%	-31.12%	-39.84%	-3.04%	-49.17%
	Spring	-22.70%	-12.62%	6.00%	18.78%	16.44%	-58.62%
	Summer	-59.04%	-54.39%	2.60%	0.85%	2.94%	-4.38%
	Autumn	-70.90%	1.75%	12.95%	15.37%	-33.98%	-12.71%

Time		Mid future (2049-2074)					
RCM		CanESM2		CNRM		MPI	
Scenario		RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Season	Winter	10.48%	55.03%	-48.21%	-29.42%	-67.18%	-60.42%
	Spring	-29.71%	29.11%	-0.50%	1.23%	-51.83%	-39.67%
	Summer	-34.18%	-45.34%	1.33%	3.35%	-5.57%	-0.04%
	Autumn	-89.78%	-60.59%	-8.75%	-32.57%	20.81%	-8.24%

Time		End future (2075-2100)					
RCM		CanESM2		CNRM		MPI	
Scenario		RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Season	Winter	52.80%	72.51%	-30.26%	-50.10%	-82.84%	-26.00%
	Spring	26.42%	38.52%	-2.48%	3.41%	-10.61%	-65.09%
	Summer	-84.04%	-58.86%	13.97%	14.97%	-2.96%	-7.52%
	Autumn	-70.49%	-54.62%	1.03%	13.83%	2.56%	38.09%

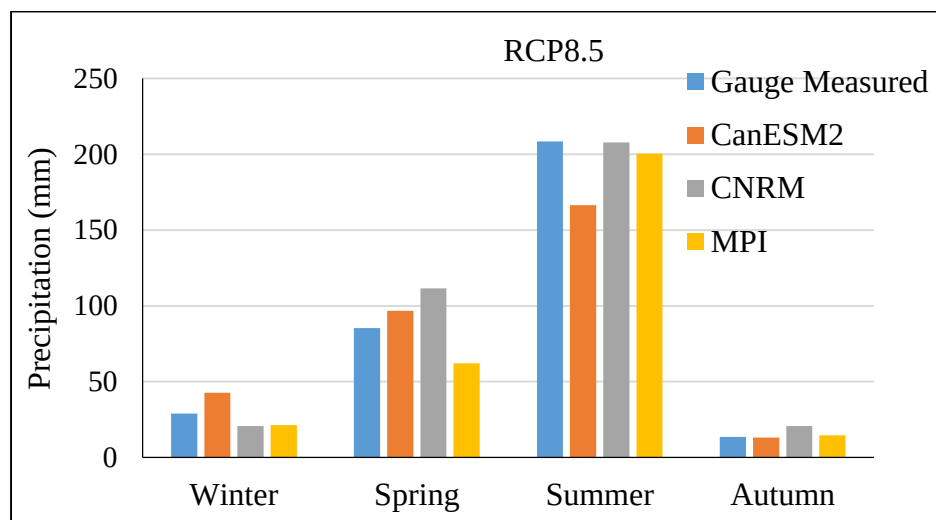
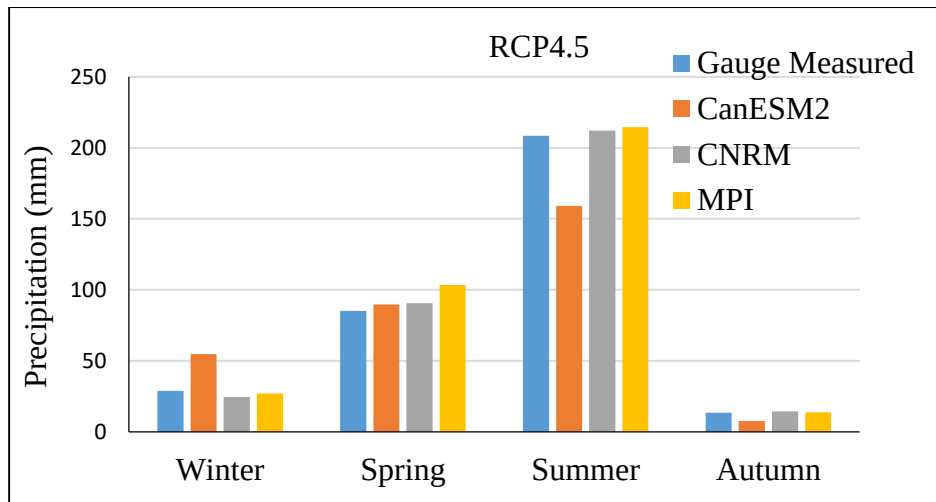
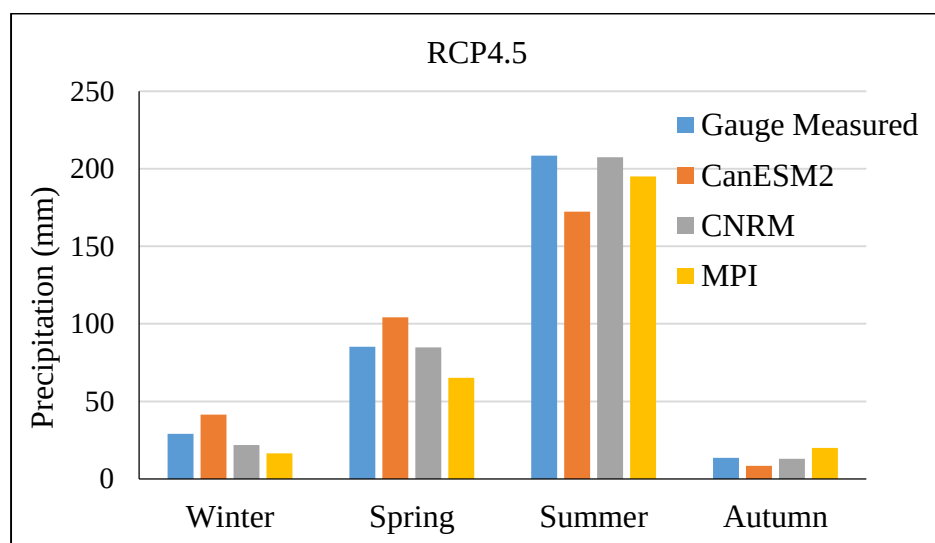


Figure 4.4 Average seasonal precipitation of upper Awash catchment projected by the selected climate models, under RCP4.5 and RCP8.5 projected near the century



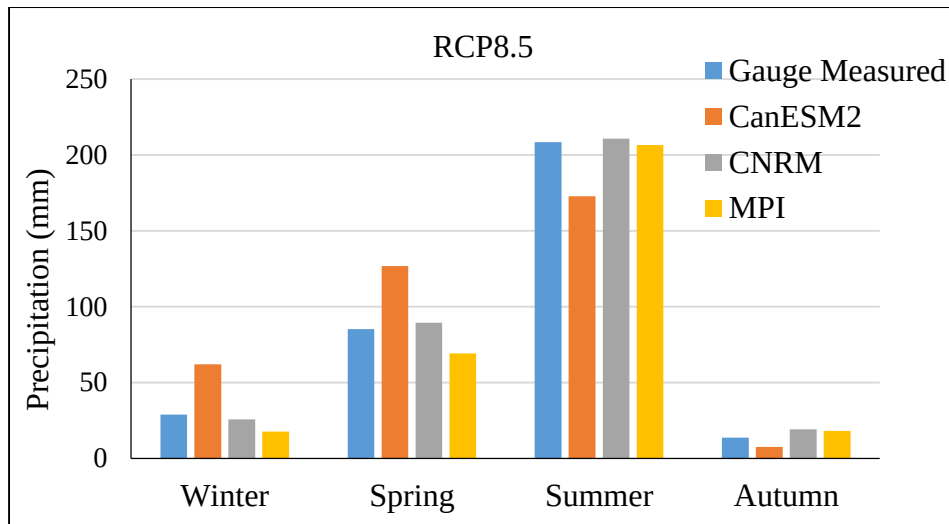


Figure 4.5 Average seasonal precipitation of upper Awash catchment projected by the selected climate models, under RCP4.5 and RCP8.5 projected mid of the century

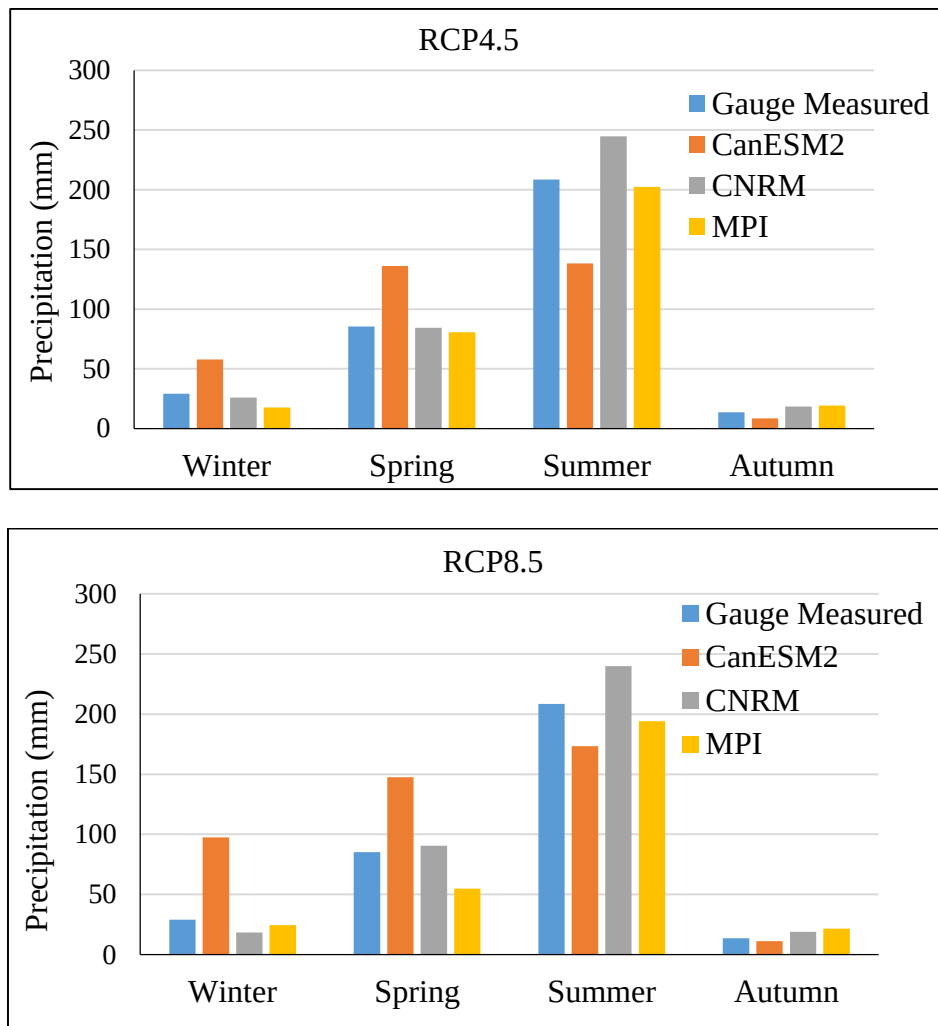


Figure 4.6 Average seasonal precipitation of upper Awash catchment projected by the selected climate models, under RCP4.5 and RCP8.5 projected end of the century

4.1.3. Changes in projected temperature

The RCM in simulation offers the average monthly temperature projections for the upper Awash catchment under various RCP scenarios in the upcoming century. The values obtained for the near years (2024-2048), mid years (2049-2079), and end-future years (2075-2100) under the RCP4.5 scenarios show an increase across all months. Furthermore, for the RCP8.5 scenarios, there is an observed increase throughout the year in the near, mid, and end future periods. CanESM2 experienced the greatest increase in maximum temperature during various periods. In January, the near future and mid-future exhibited temperature increases of +2.8°C and +4°C respectively. In June, a rise of +3.9°C was observed in the end future saw an increase under the RCP4.5 scenario. Similarly, the minimum temperature change showed a significant rise in February for all future periods. In the near future, the increase was +4.8°C, while the mid-future and end future experienced changes of +5.8°C and +6.9°C respectively under RCP4.5. Under the RCP8.5 scenarios, CanESM2 displayed the maximum temperature increases. In January, the mid-future and end future experienced increases of +5°C and +7.04°C respectively. However, the maximum change in minimum temperature occurred in February for all three future periods.

For the CNRM RCM model, the maximum temperature change peaked in May (+1.5°C) and June (+2.2°C and +2.7°C) in the near, mid, and end future respectively. The maximum change in minimum temperature occurred in May for the near future and end future (+1.5°C and +2.7°C respectively), while in January it was observed for the mid-future (+2.2°C) under RCP4.5. In the case of RCP8.5, the CNRM RCM model showed maximum temperature changes in March, December, and April (+1.6°C, +3°C, and +4.6°C) for the near future, mid-future, and end future respectively. Finally, the MPI model exhibited the greatest increase in maximum temperature during various periods. In January, the near future experienced a change of +2.5°C, while July saw increases of +3.9°C and +1.7°C in the mid-future and end future respectively under RCP4.5. For RCP8.5, the near future showed a change of +2.2°C in May, while July experienced increases of +4.4°C and +7.2°C in the mid-future and end future respectively. These results were also reported by Abdulahi et al., (2022) in the upper Awash watershed. They indicated that both maximum and minimum temperatures are likely to increase in both scenarios. On average, the projected minimum temperature is expected to rise by approximately 9.6% under RCP4.5 and around 11.7% under RCP8.5. As for the maximum temperature, the changes may reach approximately +6.3% and +7.6% for both scenario as shown in the figure 4.7, 4.8 and 4.8.

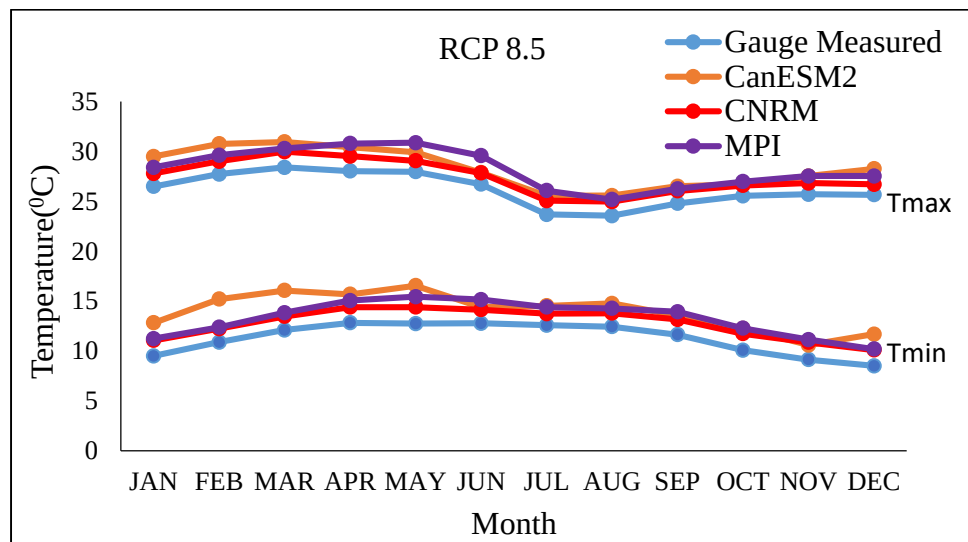
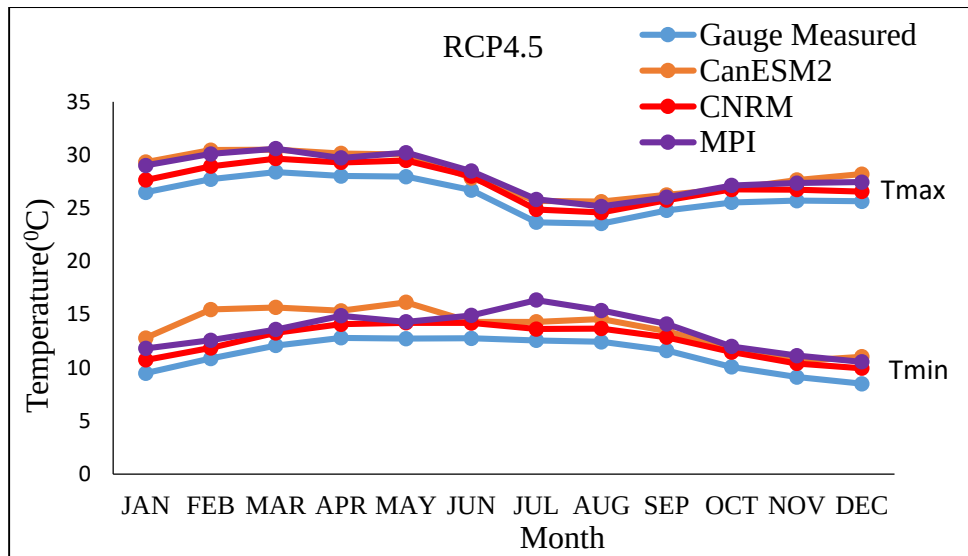
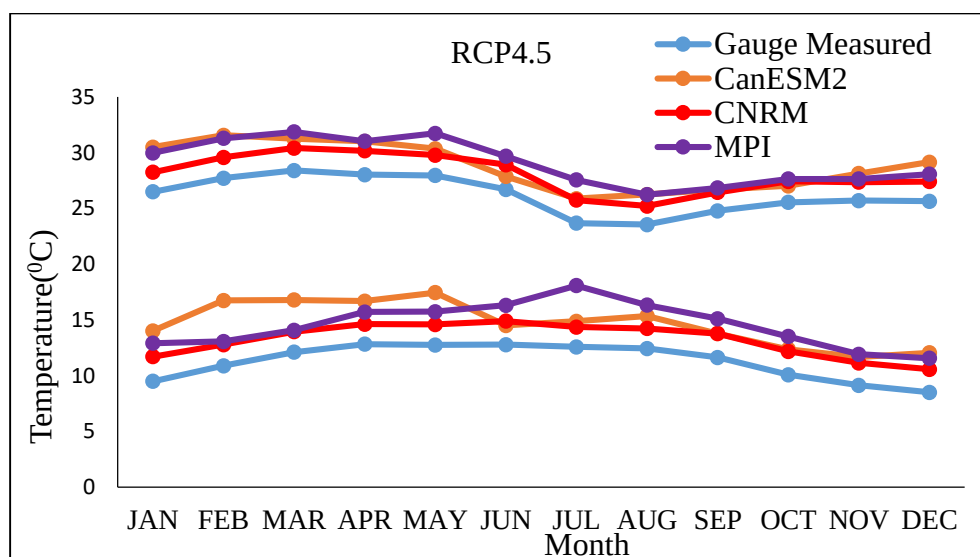


Figure 4.7 Average monthly temperature of upper Awash catchment projected by the selected climate models, under RCP 4.5 and RCP 8.5. projected near-future period



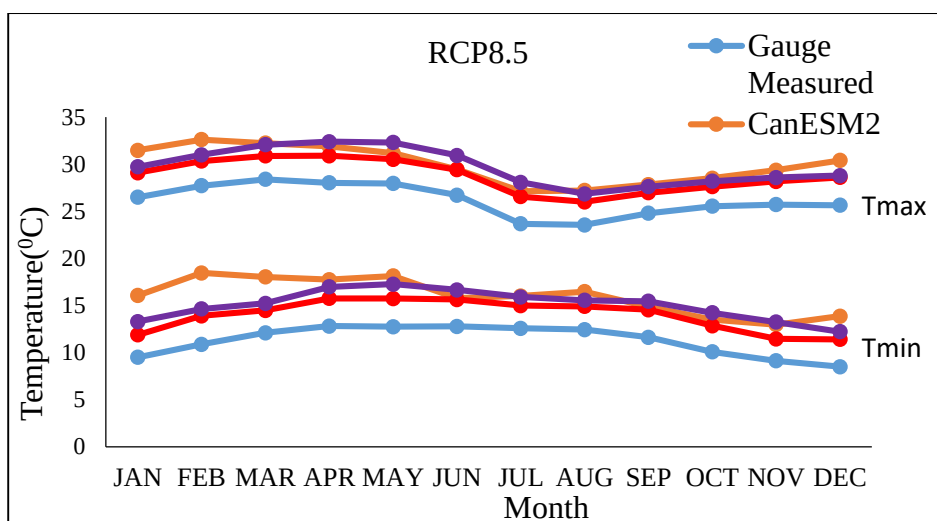


Figure 4.8 Average monthly temperature projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected mid-future period

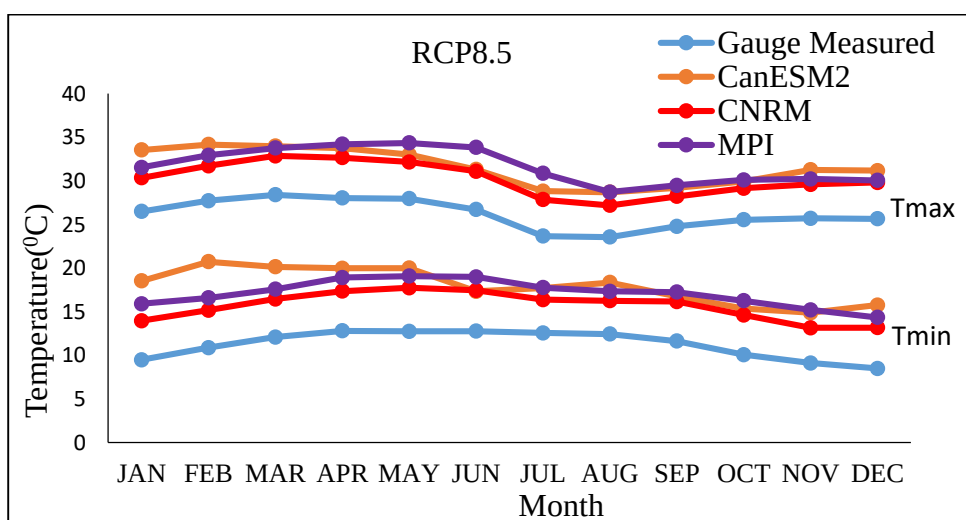
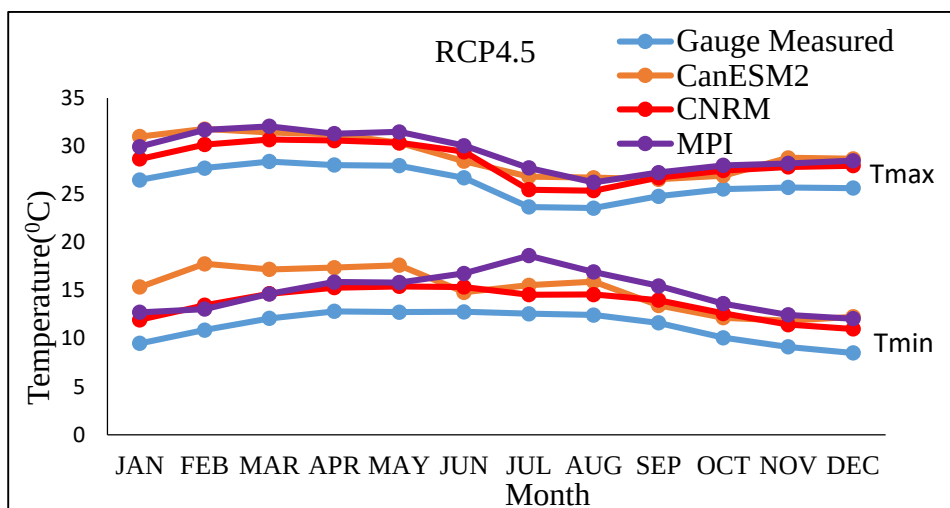


Figure 4.9 Average monthly temperature projected by the selected climate models, under RCP 4.5 and RCP 8.5. projected end of the century

4.2. Hydrological Modelling Output

4.2.1. Sensitive analysis

Through numerous iterations and simulations utilizing the SWAT-CUP program and employing the global sensitivity method, the most influential parameters for flow were successfully determined. Recognizing these critical parameters enables us to concentrate our attention on those with the most significant impact on the model's results throughout the simulation. Sensitivity analysis was performed by utilizing the SUFI-2 algorithm in conjunction with SWAT-CUP, using mean monthly observed data, to identify the key parameters that exert a notable influence on the model's results. The identification of sensitive parameters for upper Awash catchments was achieved through a literature review of relevant research works (Serur, 2023; Tolera et al., 2018; Guder et al., 2023; Daba & You, 2020) to decrease the substantial quantity of parameters needed for the calibration of the ArcSWAT model. Following a sequence of simulations, SWAT-CUP evaluates parameter sensitivity by ordering them based on their t-statistic and p-value. A higher absolute value of the t-stat and a lower p-value were accepted as a more sensitive parameter (K. Abbaspour, Vejdani et al., 2007). The sensitive Streamflow parameters were selected for calibration and validation processes as given below in Figure 4.7.

After multiple iterations within the calibration and validation processes, the parameters with the most sensitivity were identified and assigned rankings. These parameters, which played a significant role in influencing the flow, were determined from a set of 11 parameters used during the iterations. Among the parameters considered were Curve number (CN₂), Alpha factor for base flow (ALPHA_BF) and the minimum water depth in the shallow aquifer needed to initiate return flow (GWQMN), Average slope length (SLSUBBSN), Threshold depth of water in the shallow aquifer for "revap" to occur (REVAPMN), Manning's "n" value for surface runoff (OV_N), the capacity for available water in the soil (SOL_AWC), soil evaporation compensation factor (ESCO), Groundwater delay (GW_DELAY), soil hydraulic conductivity (SOL_K), channel effective hydraulic conductivity (CH_K2), were more sensitive parameters for this study.

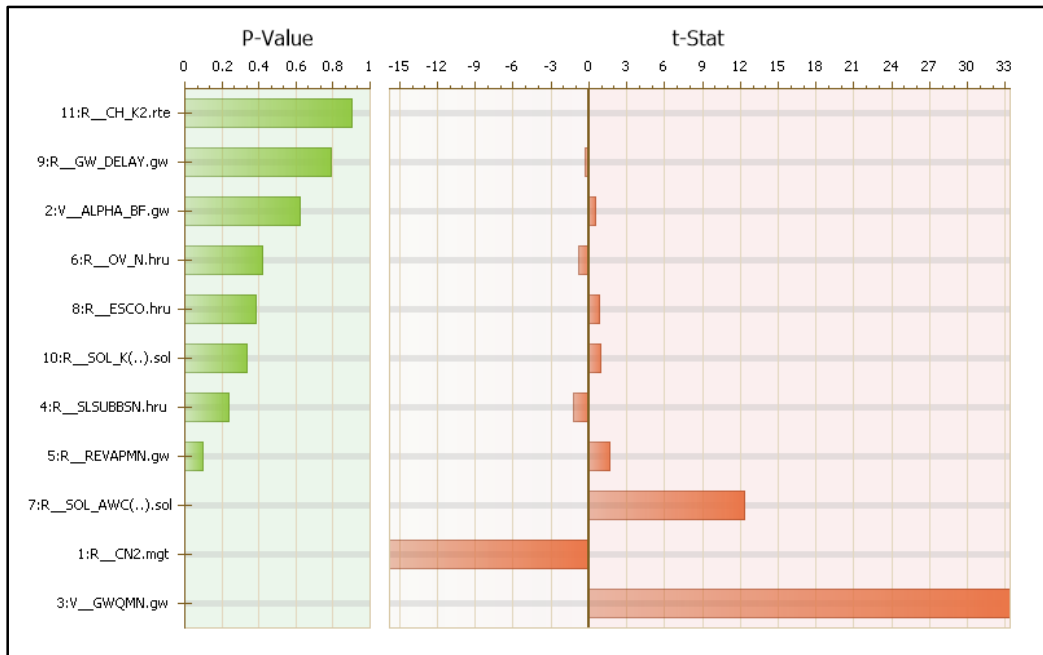


Figure 4.10 Streamflow sensitive parameters of Hombole gauge station

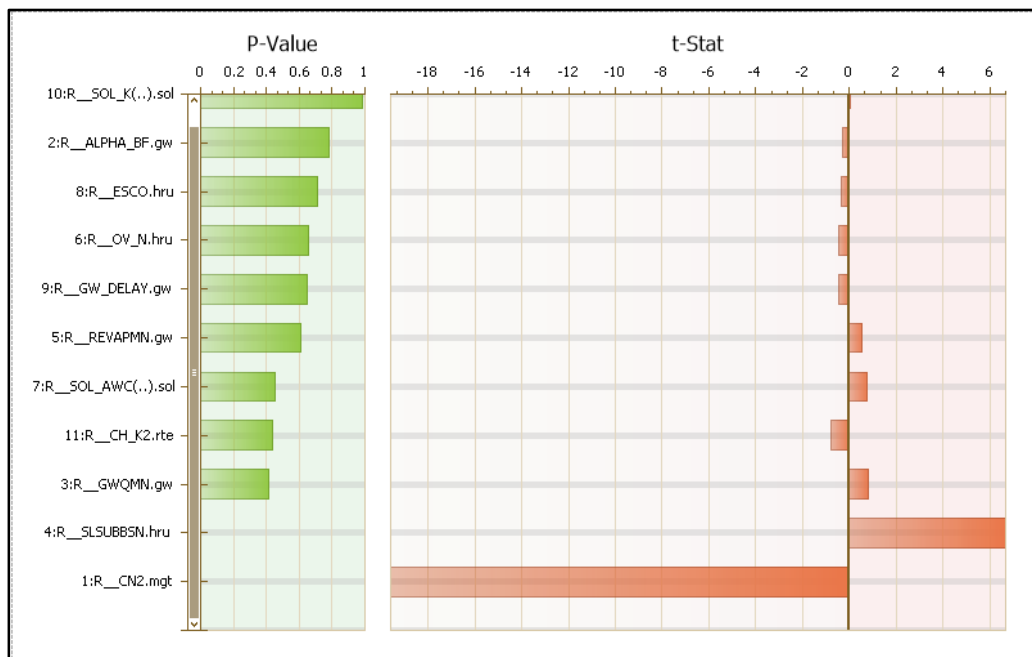


Figure 4.11 Streamflow sensitive parameters of Mojo gauge station

The more effective surface runoff parameters to influence streamflow were CN2.mgt, SOL_K.sol, CH_K2.rte, and SOL_AWC.sol. For this study area, the baseflow parameters ALPHA_BF.gw, GW_DELAY.gw, and REVAPMN.gw were more sensitive parameters.

Table 4.2 Streamflow sensitivity parameter rank of Hombole and Mojo streamflow, respectively

S.No	Parameter Name	Min Value	Max Value	fitted Value	t-Stat	P-Value	Rank
1	CN ₂	-0.25	0.25	-0.0196	-15.80	0.00	1
2	ALPHA_BF	0	1	0.502	0.49	0.62	2
3	GWQMN	0	5000	3385.4	33.37	0.00	3
4	SLSUBBSN	10	150	148.96	-1.18	0.24	4
5	REVAPMN	0	500	117.86	1.64	0.10	5
6	OV_N	-0.22	-0.07	-0.015	-0.81	0.42	6
7	SOL_AWC	-0.25	0.25	1.6	12.36	0.00	7
8	ESCO	0	1	0.49	0.87	0.39	8
9	GW_DELAY	0	500	175.12	-0.27	0.79	9
10	SOL_K	-0.25	0.25	-0.002	0.97	0.33	10
11	CH_K2	50	160	129.12	-0.12	0.91	11

S.No	Parameter Name	Min Value	Max Value	fitted Value	t-Stat	P-Value	Rank
1	CN ₂	-0.25	0.25	-0.02	-19.6	0.00	1
2	ALPHA_BF	0	1	0.512	-0.282	0.778	2
3	GWQMN	0	1200	1056.87	0.819	0.413	3
4	SLSUBBSN	10	150	27.93	6.673	0.00	4
5	REVAPMN	20	450	438.39	0.515	0.607	5
6	OV_N	-0.22	-0.07	-0.155	-0.451	0.653	6
7	SOL_AWC	-0.25	0.25	0.74	0.750	0.453	7
8	ESCO	0	1	0.27	-0.371	0.711	8
9	GW_DELAY	20	350	265.35	-0.452	0.652	9
10	SOL_K	-0.03	0.077	0.0027	0.017	0.987	10
11	CH_K2	56	160	145.54	-0.779	0.436	11

4.2.2. Model calibration and validation

The model calibration and validation procedures utilize the SUFI-2 algorithm within the SWAT-CUP software. Once the sensitive parameters are identified, the model undergoes calibration and validation processes.

The calibration of the SWAT model for streamflow involves selecting the Hombole and Mojo gauging stations and utilizing 9 years (2003-2011) of recorded flow data. The SWAT-CUP model incorporates a three-year warm-up period spanning from 2000 to 2002. This time frame is used to establish hydrological processes and attain equilibrium, serving as the initial phase for model simulation. During the calibration process, the daily time-series data is transformed into a monthly format. Selected parameters were adjusted during the calibration process to minimize the disparity between the observed and simulated flow data. The calibration period involved evaluating the model's performance using criteria that assess the agreement between the simulated and observed flow data. The aim was to achieve an acceptable range of goodness-of-fit criteria. After the calibration of the model was completed, the next step was model validation. This validation process evaluates the model's precision in replicating periods that were not part of the initial calibration stage. This process entails the comparison of the model outputs with an external dataset, and no further modifications are made. The outcomes of the model validation affirmed the suitability of the hydrological parameters obtained for the watershed during the calibration phase.

During the model validation, data from a period of four years (2012-2015) was utilized for analysis through the SWAT-CUP program. The results of the model validation fell within the acceptable range according to the evaluation criteria for model performance. These criteria included an R^2 , a Nash-Sutcliffe, and a percent bias, which are recommended values for assessing model performance (Moriassi et al., 2007).

Table 4.3 SWAT model performance for streamflow during the calibration and validation periods

Model performance evaluation index	Gauged stations			
	Hombole		Mojo	
	Calibration	Validation	Calibration	Validation
R²	0.84	0.77	0.74	0.67
NSE	0.81	0.68	0.72	0.63
PBIAS	- 6.1	1.5	4.5	-10.17

During the calibration period, the model demonstrated very good performance at the Hombole gauging station, as indicated by high values of R^2 (0.84), NSE (0.81), and PBIAS (-6.1). During the validation period, the model performed very good in terms of R^2 (0.77) and PBIAS (1.5), and good in terms of NSE (0.68), as shown in Table 4-2.

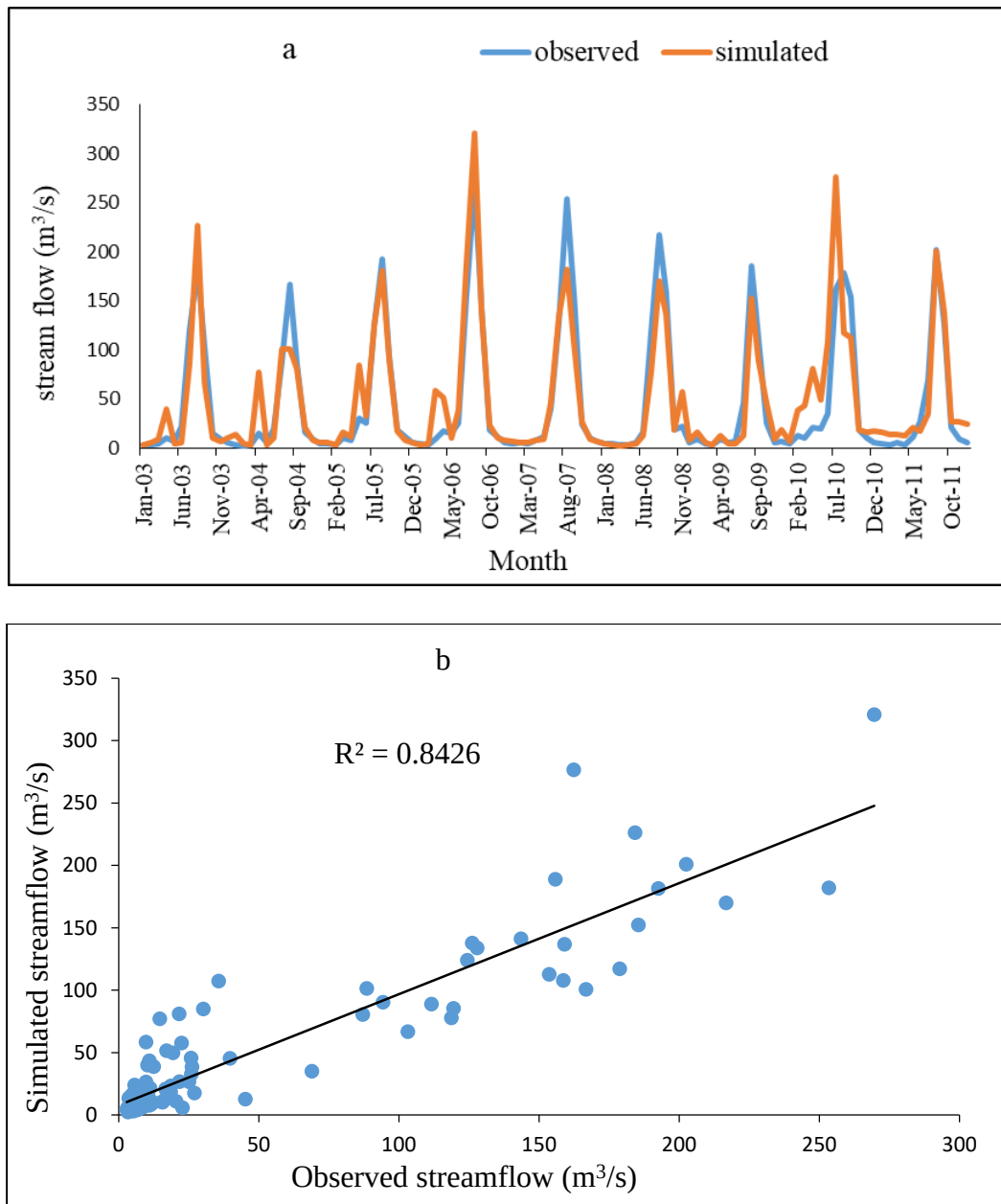


Figure 4.12 observed and simulated streamflow hydrographs, along with a scatter plot, at the Hombole gauging station: **a** hydrograph during calibration, **b** scatter plot during calibration

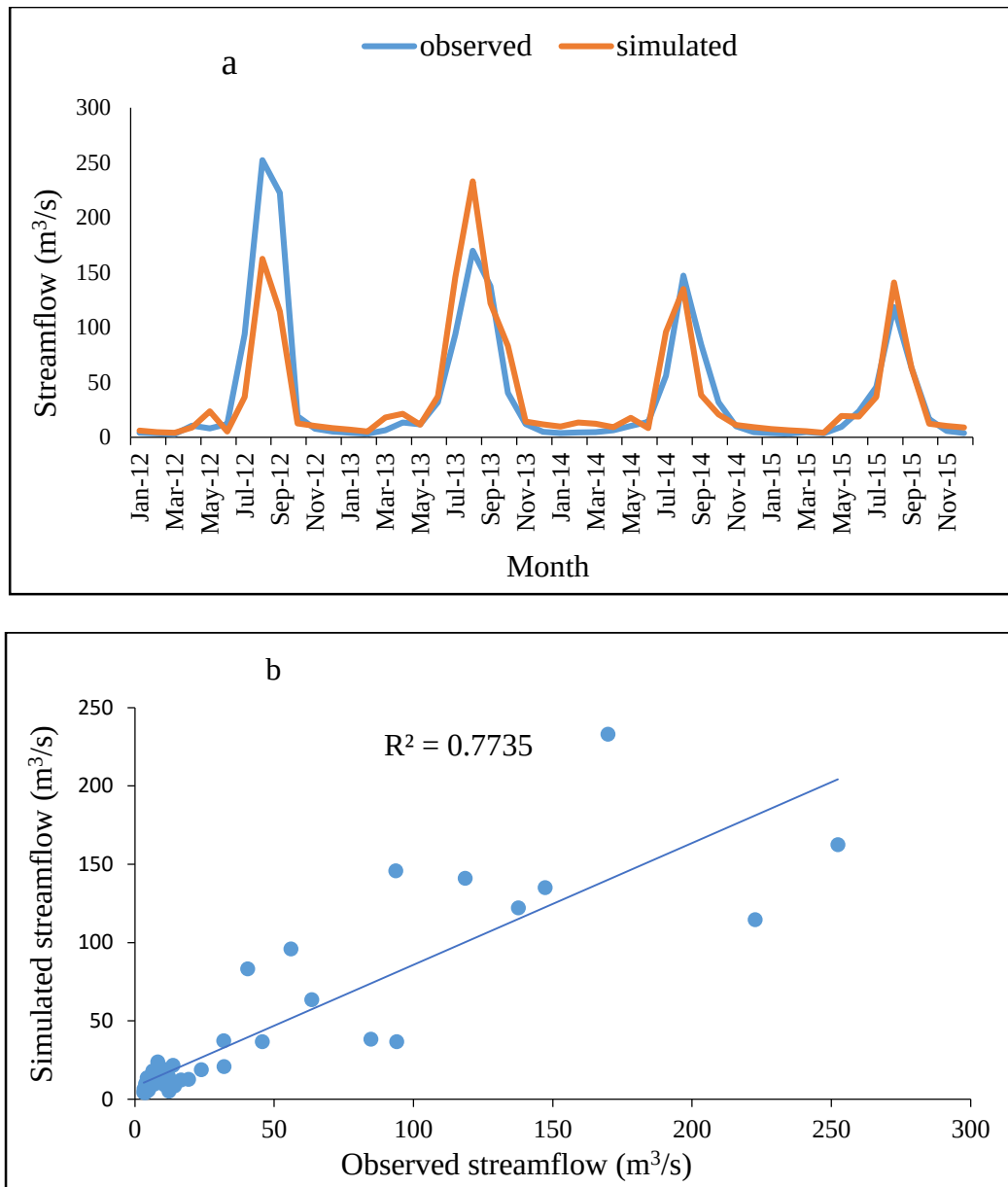


Figure 4.13 observed and simulated streamflow hydrographs, along with a scatter plot, at the Hombole gauging station: a hydrograph during validation, b scatter plot during validation

The model performance at the Mojo gauge station, with an R^2 value of (0.74) and NSE of (0.72). Furthermore, it performed very good with a PBIAS value of (4.5) during the calibration period. During the validation period, the model continued to perform good achieving an R^2 value of (0.67) and very good results with a PBIAS value of (-10.2). However, it showed satisfactory performance in terms of NSE with a value of (0.63), as shown in Table 4-2 and Figure 4.11. According to the assessment conducted by Moriasi et al., (2007) on the streamflow simulation, the performance of the SWAT model is evaluated and rated positively at all the gauged stations.

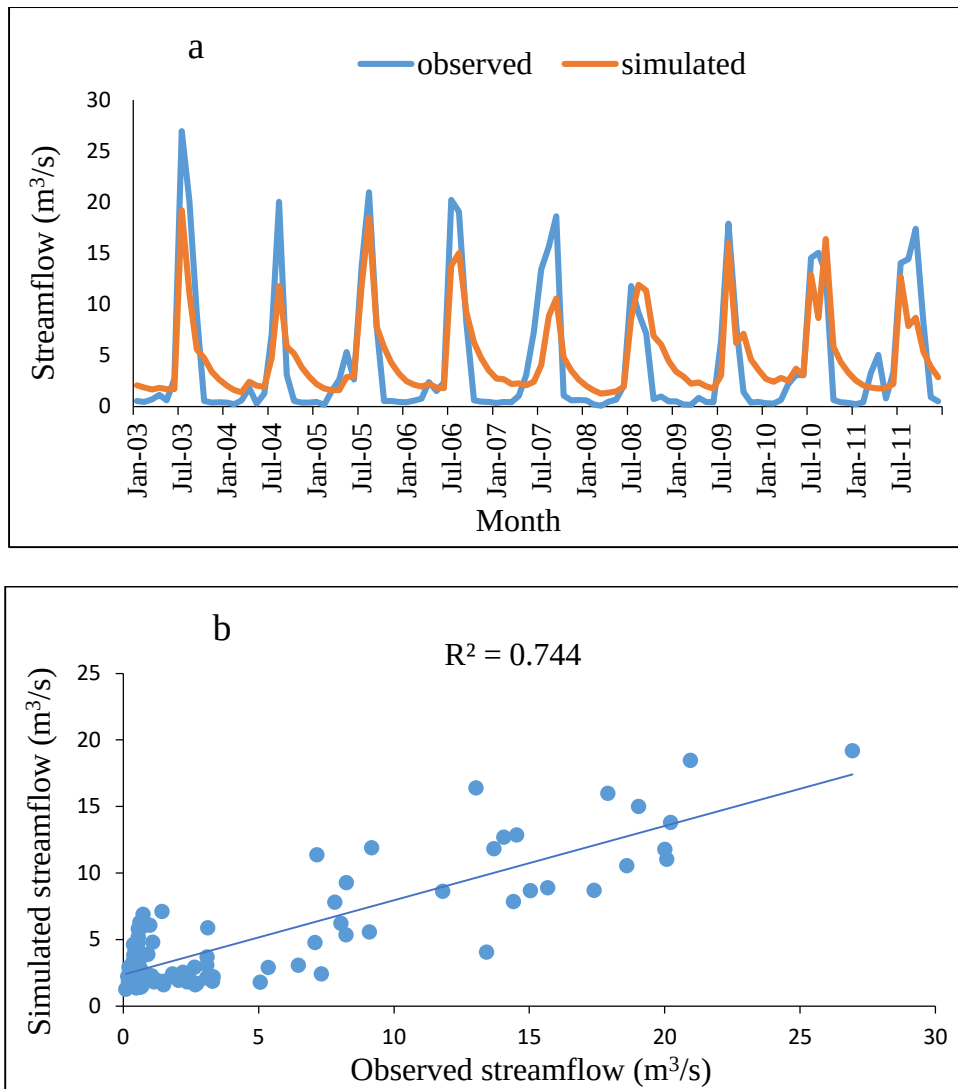
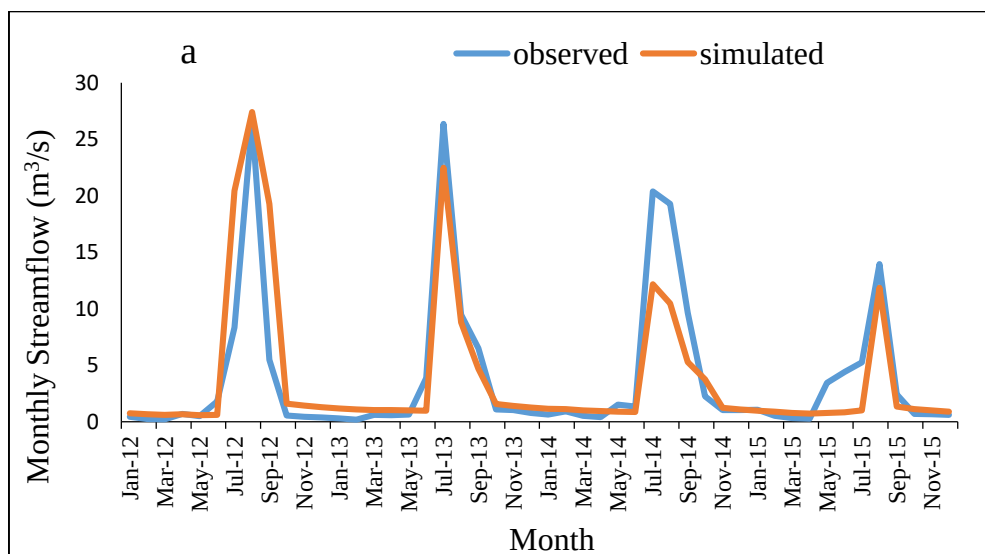


Figure 4.14 Observed and simulated streamflow hydrograph as well as a Scatter plot at Mojo gauging station: **a** hydrograph during calibration, **b** scatter plot during calibration



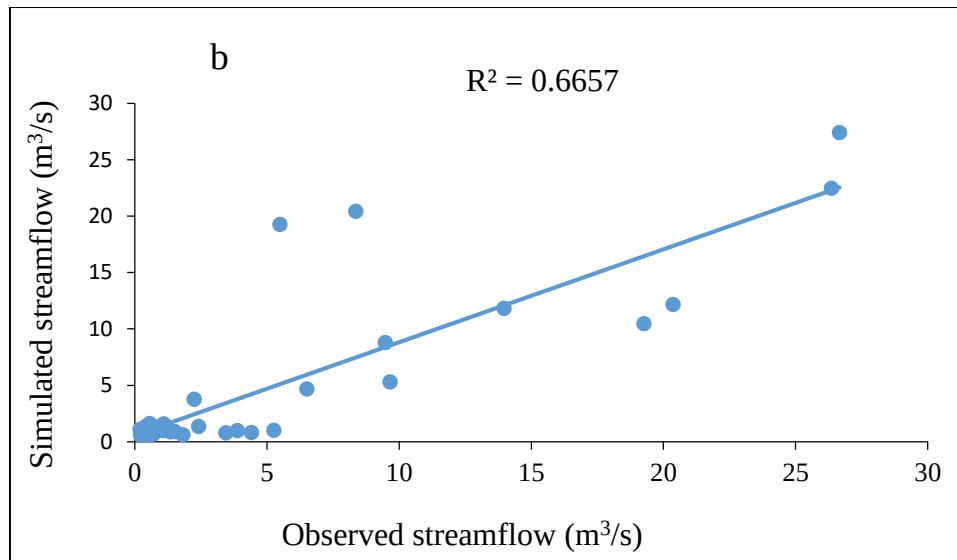
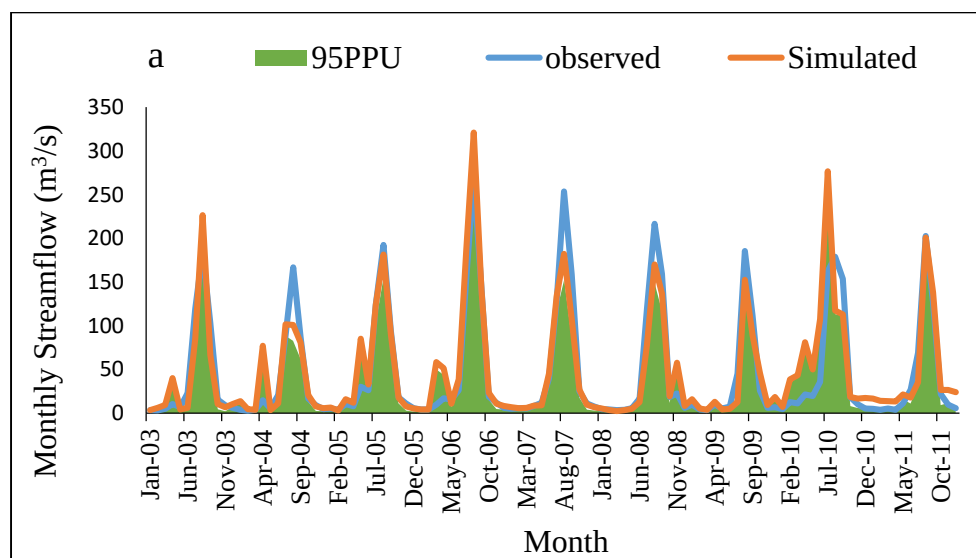


Figure 4.15 Observed and simulated streamflow hydrograph as well as a Scatter plot at Mojo gauging station: a hydrograph during validation, b scatter plot during validation

When examining the suitability of the SWAT model for simulating streamflow, there are differences in the variations such as R^2 , NSE, and PBIAS, as reported by various studies including Serur (2023), Guder et al., (2023), Shawul et al. (2019), Getahun et al. (2020), and Musie et al. (2020). These variations could be attributed to the utilization of different hydro-meteorological data in their respective analyses. In the study conducted by Serur (2023), the SWAT hydrologic model was developed to evaluate the performance of a hydrological model in simulating streamflow and water balance analysis. The model was specifically applied to the upper Awash sub-basin in Ethiopia. The findings indicated the model's proficiency, with R^2 values falling within the range of 0.80 to 0.74 during the calibration period and 0.74 to 0.66 during the validation period. Similarly, NSE values ranged from 0.74 to 0.66 in the calibration phase and 0.71 to 0.62 in the validation phase. As for PBIAS values, they varied from 14.20 to -3.20 in the calibration period and from 18.60 to 8.0 in the validation period. Similarly, Shawul et al. (2019) found that in their study, the SWAT hydrologic model displayed varying performance indicators during the monthly calibration period from 1982 to 1987 and the validation period from 1991 to 1994 in the prior study. Specifically, the previous study reported R^2 , NSE, and PBIAS values of 0.77, 0.76, and -11.8 during calibration and 0.78, 0.76, and 10.6 during validation. These values reflected the level of agreement between the observed and simulated streamflow at the Mojo gauged station in the upper Awash sub-basin. The variation in these values could potentially be attributed to the longer duration of hydro-meteorological data utilized in their study, which was used from 1988 to 2018.

4.2.3. Streamflow uncertainty analysis

The evaluation of the calibrated model's accuracy and its degree to incorporate uncertainties can be conducted using the two measures (P-factor and R-factor) through the Sequential Uncertainty Fitting, version 2 (SUFI-2) program. The P-factor evaluates the comprehensiveness of uncertainty consideration and signifies the proportion of observed data falling within the 95% prediction uncertainty (95PPU) range. Conversely, the R-factor acts as an indicator of calibration quality, gauging the breadth of the 95PPU range and contrasting it with the standard deviation of the observed data. These measures were originally described by Abbaspour, et al. 2007. Figure 4.13 and Figure 4.14 in the SWAT CUP program present the results of uncertainty analysis using the SUFI-2 technique. These figures display the uncertainty outputs for calibration and validation, respectively. The SUFI-2 uncertainty measure indicates a P-factor of 0.56 and R-Factor of 0.35 for calibration at the Hombole gauge station. For validation at the same station, the P-factor is 0.73 and the R-Factor is 0.58. Similarly, during the calibration period, the uncertainty measure shows a P-factor of 0.48 and R-Factor of 0.64, while during the validation period, the P-factor is 0.44 and the R-Factor is 0.68 at the mojo gauge station. These results are similar to the results of Kassa (2009) studied hare watersheds. He reported that the P-factor of 0.65 and R-factor of 0.58 for calibration and P-factor of 0.62 and R-factor of 0.40 for validation. Similarly, a study by Shawul & Chakma, (2020) on the Suitability of global precipitation estimates for hydrologic prediction in the main watersheds of the Upper Awash basin reported that the P-factor of 0.57 and R-factor of 0.6 for calibration at Hombole gauge station and P-factor of 0.26 and R-factor of 0.37 for calibration at Mojo gauge station.



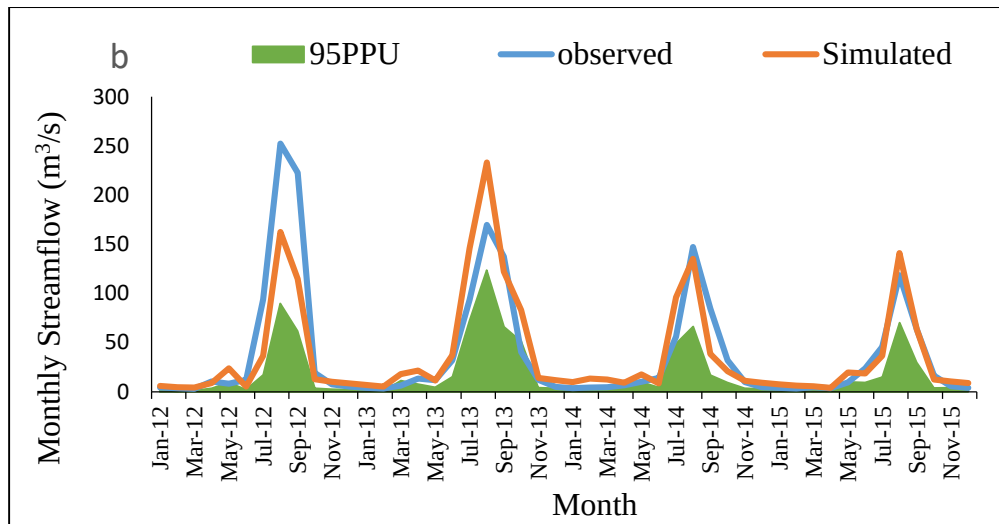


Figure 4.16 Monthly streamflow of Hombole gauge station showing the 95 PPU uncertainty intervals: **(a)** during calibration period and **(b)** during validation period

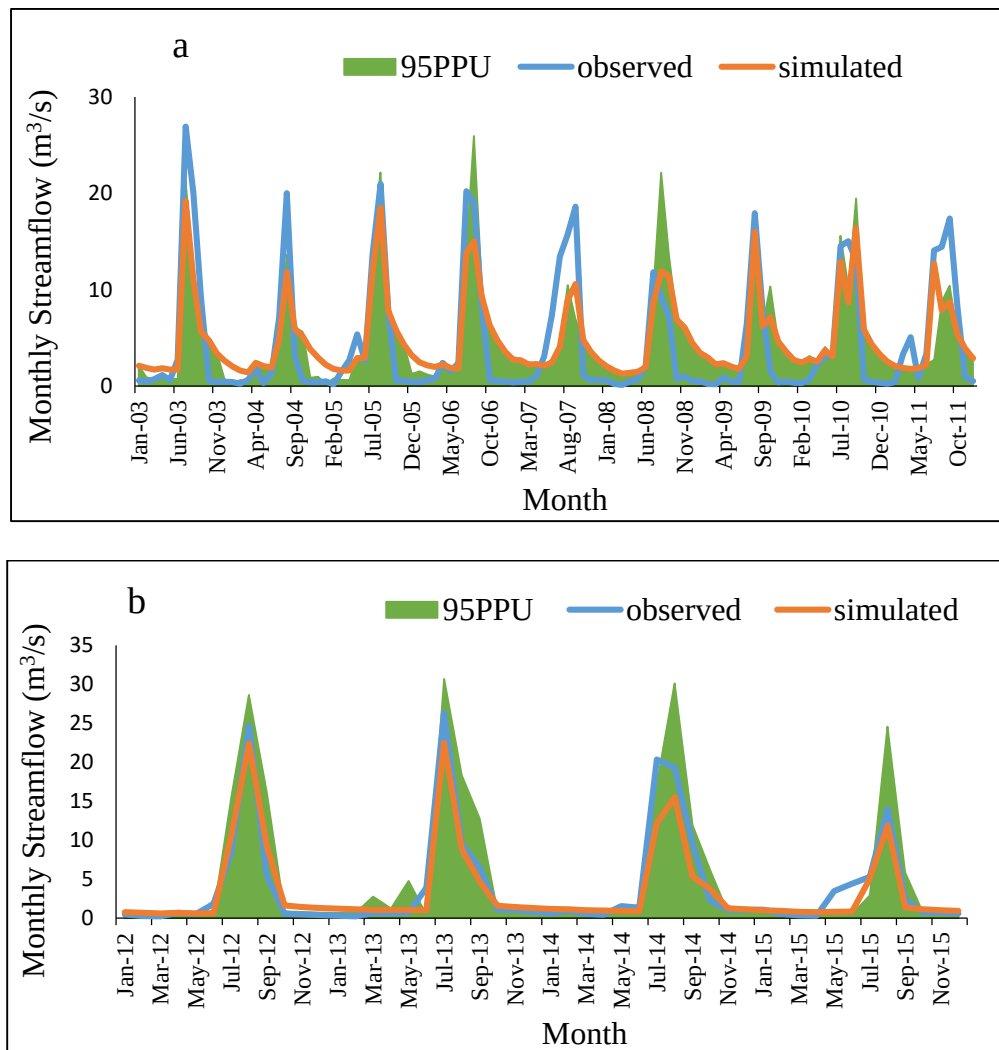


Figure 4.17 Monthly streamflow of Mojo gauge station showing the 95 PPU uncertainty intervals: (a) during calibration period and (b) during validation period

4.3. Climate Change Impact on Monthly Streamflow

After calibrating and validating the SWAT model, the bias-adjusted weather inputs corresponding to each regional climate model (RCM) were integrated into the model. Subsequently, the calibrated and validated SWAT model was utilized to generate future stream-flow projections using a chosen RCM (CanESM2, CNRM, and MPI) at a specific gauge station. These projections covered three time periods of twenty-five years each: near-future (2024-2048), mid-future (2049-2074), and end-future (2075-2100). The modifications in future surface runoff, determined through simulations carried out by the SWAT model using bias-adjusted projections from three different regional climate models (RCM), serve as an indicator of the anticipated modifications in precipitation. The analysis of RCM-based runoff estimates indicates a significant increase in monthly mean surface runoff for certain months in the future. However, there are also projections indicating a decrease in runoff for certain months during the projected periods.

For CanESM2, the expected change of increment of Streamflow was observed in June (38.46% and 32.96%) in the mid and near future periods at Mojo and Hombole catchments, respectively under RCP4.5. On the other hand, the most significant decrease was observed in April (-116.99%) and May (-117.53%) for the mid future periods at Mojo and Hombole catchments, respectively. Similarly, under RCP8.5, the maximum increase in streamflow was observed in June (37.54%) and Jul (23.55%) for the mid and end future periods at Mojo and Hombole catchments, respectively. The most expected reduction in streamflow was observed in May (-123.68% and -106.12%) for the near future periods at Mojo and Hombole catchments as indicated in figure 4.18 to figure 4.23 below, respectively.

Concerning MPI impacts, significant changes in streamflow increments were identified across various months and future periods. Under the RCP4.5 climate scenario, the most expected increases were observed in May (51.58%) and Feb (43.38%) for the near-future periods within the Mojo and Hombole catchment, respectively. Conversely, the most expected declines occurred in February (-119.45%) for the end future and Jun (-91.20%) for the mid future period within the Mojo and Hombole catchment, respectively. Similarly, when considering the RCP8.5 climate scenario, the expected rise in streamflow was observed in May (40.23%) for the end-future and Jan (51.70%) for the mid-future periods within the Mojo and Hombole catchment, respectively. On the other hand, the most expected reductions were registered in April (-108.24% and -138.72%) for the mid future periods

within the Mojo and Hombole catchment, which are shown in figure 4.18 to figure 4.23 below, respectively.

For CNRM, the most expected alteration in streamflow increment occurred in May (51.79% and 34.16%) during the end-future periods under the RCP4.5 scenario within the Mojo and Hombole catchment, respectively. On the other hand, the most notable reduction occurred in Feb (-89.74%) for the near future and May (-87.81%) for the mid future periods in the Mojo and Hombole catchment, respectively. Similarly, within the context of the RCP8.5 scenario, the most significant increases in streamflow occurred in May (67.21% and 50.06%) for the near future periods in the Mojo and Hombole catchment, respectively. Whereas, the most expected decreases in streamflow were recorded in March (-64.33% and -78.37%) for the corresponding periods within the Mojo and Hombole catchment, respectively.

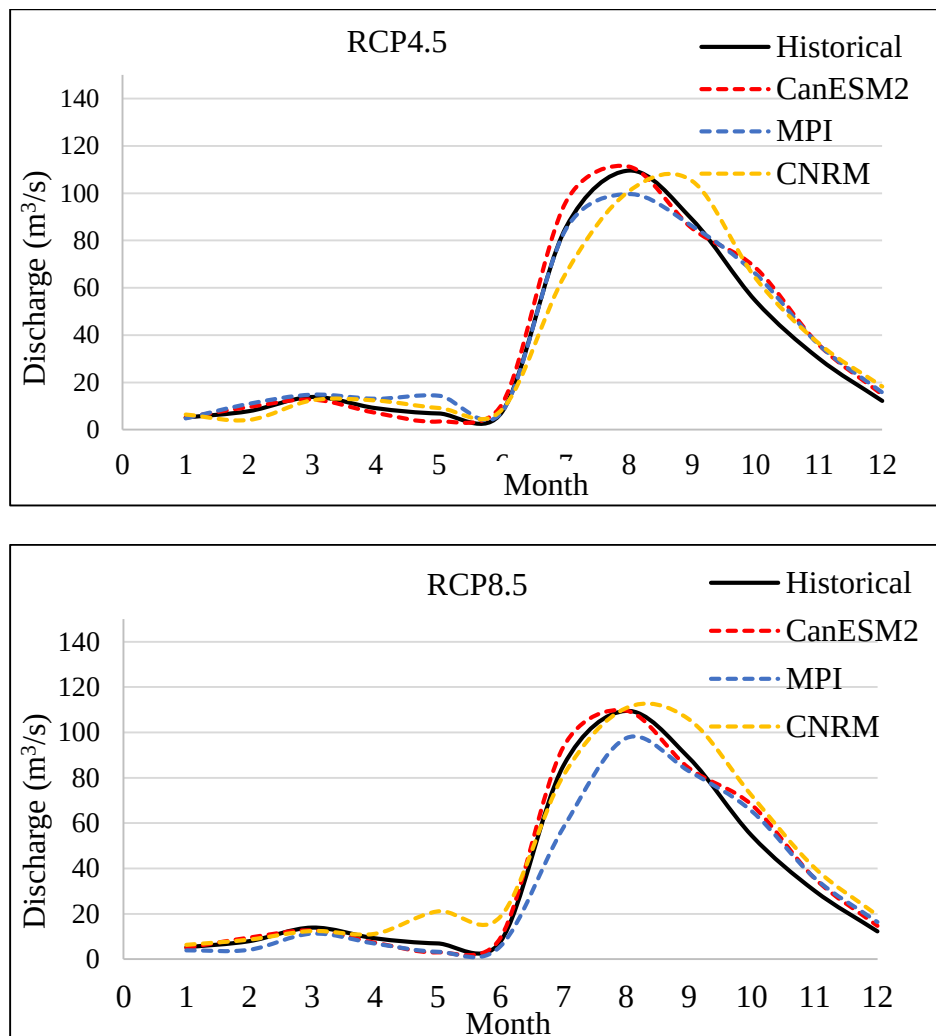


Figure 4.18 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected near-future period (2024-2048) in Mojo watershed

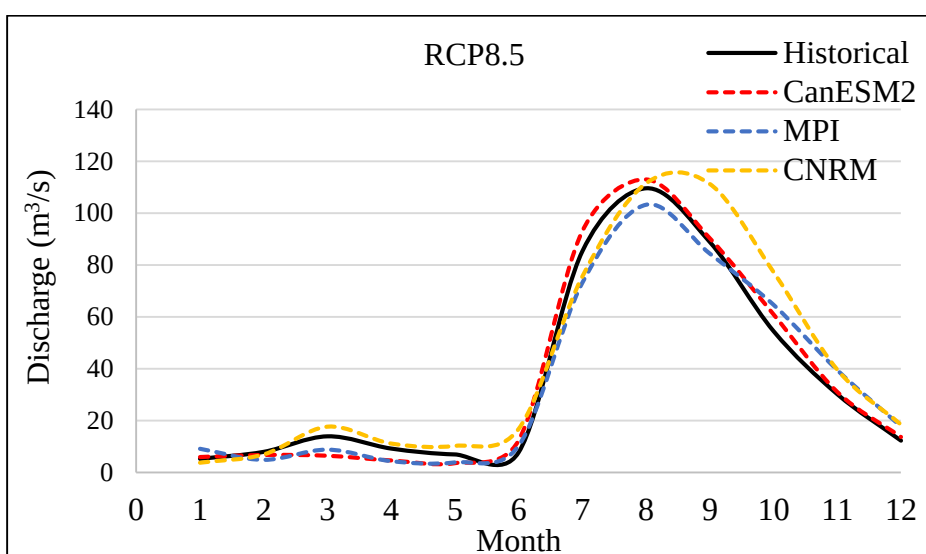
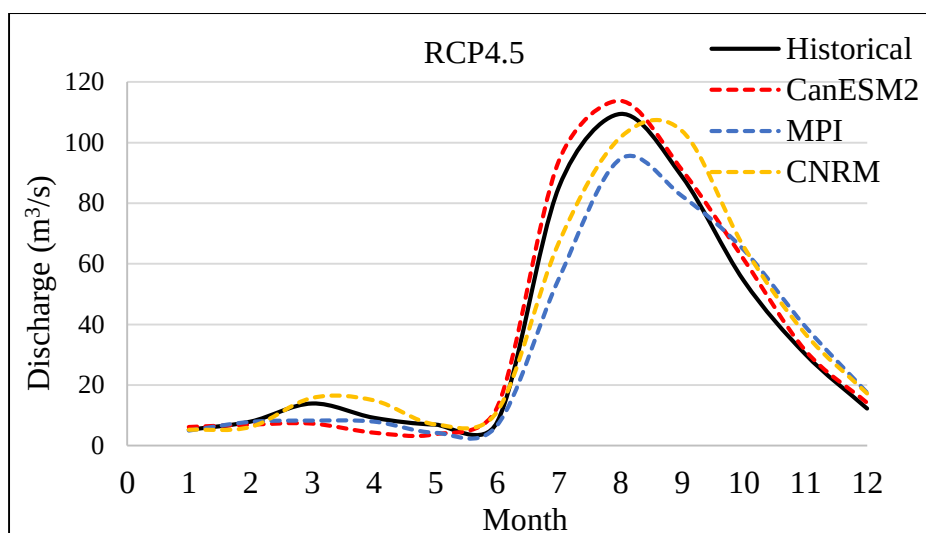
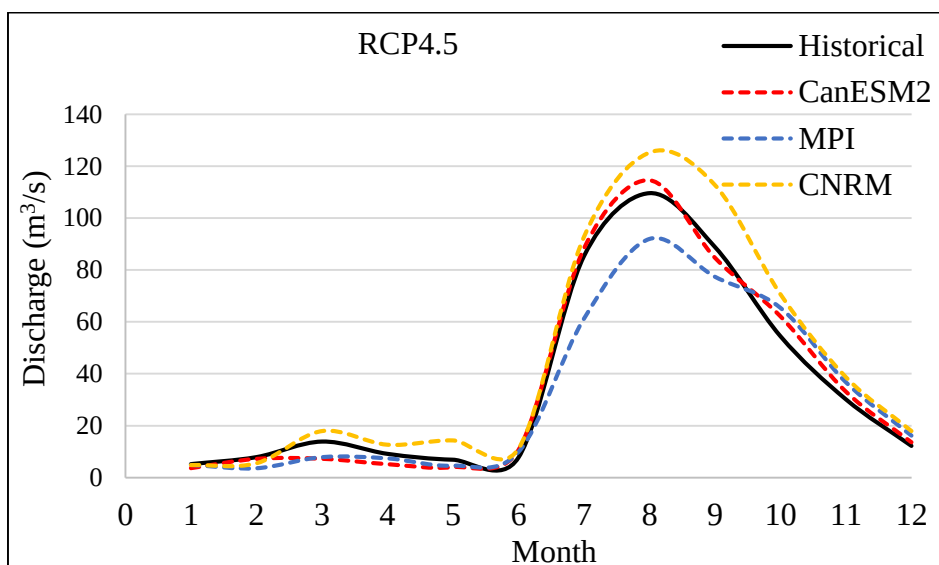


Figure 4.19 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected mid-future period (2049-2074) in Mojo watershed



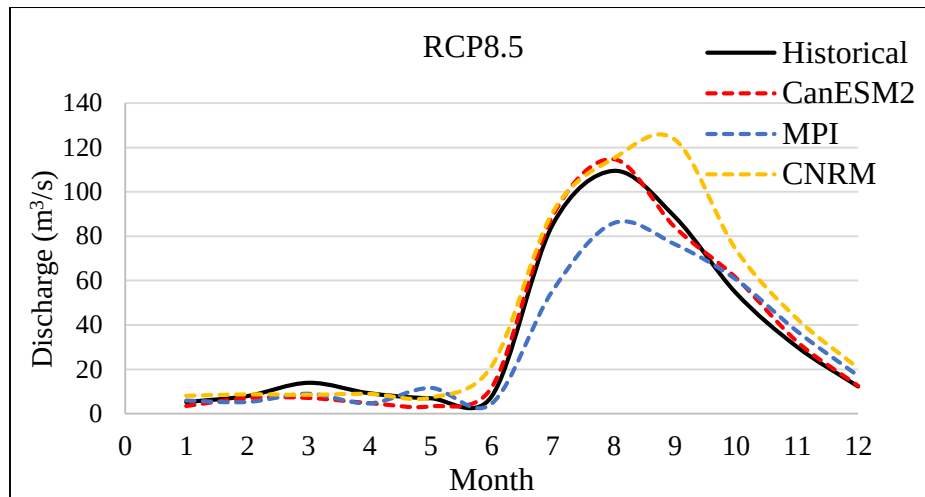


Figure 4.20 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected end-future period (2075-2100) in Mojo watershed

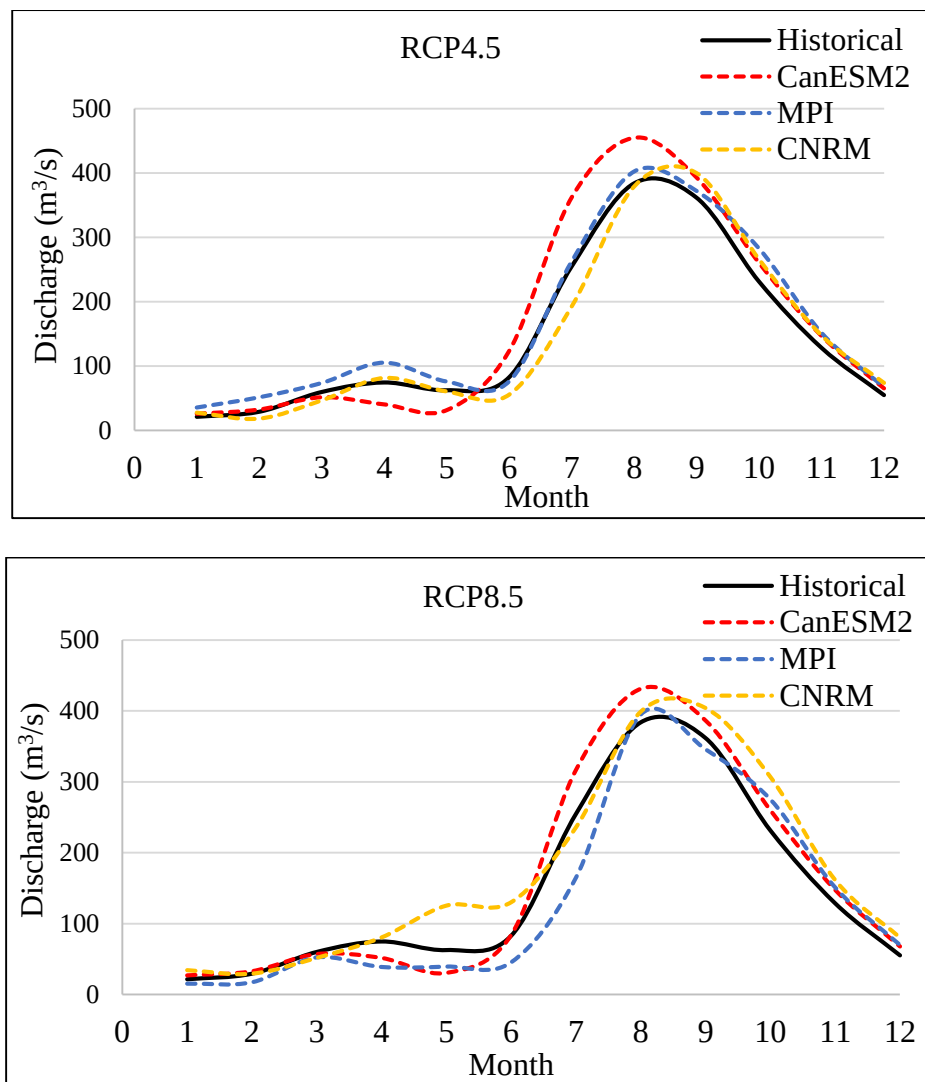


Figure 4.21 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected near-future period (2024-2048) in Hombole watershed

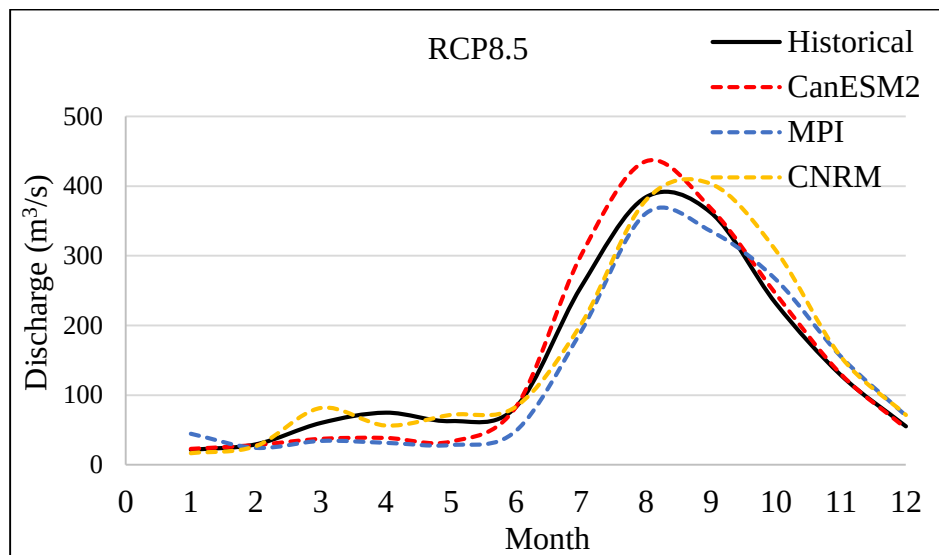
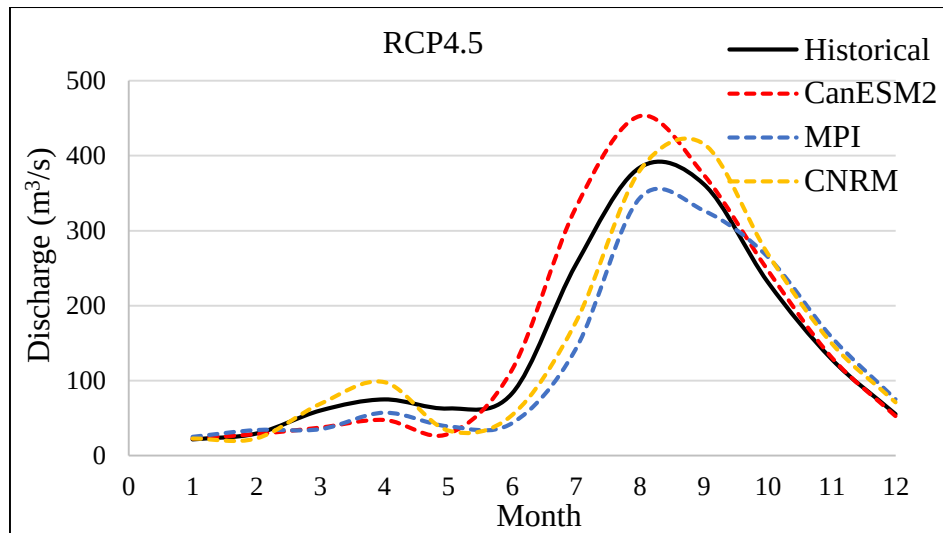
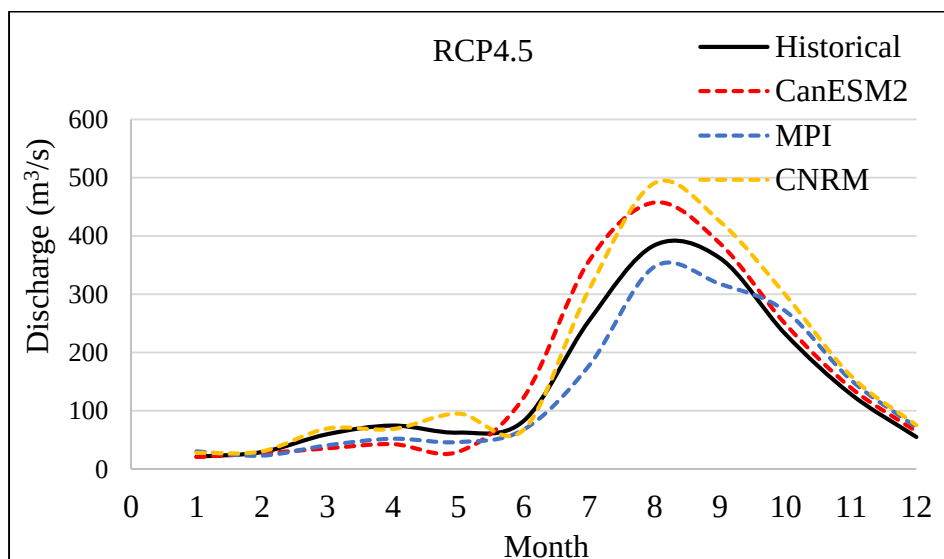


Figure 4.22 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected mid-future period (2049-2074) in Hombole watershed



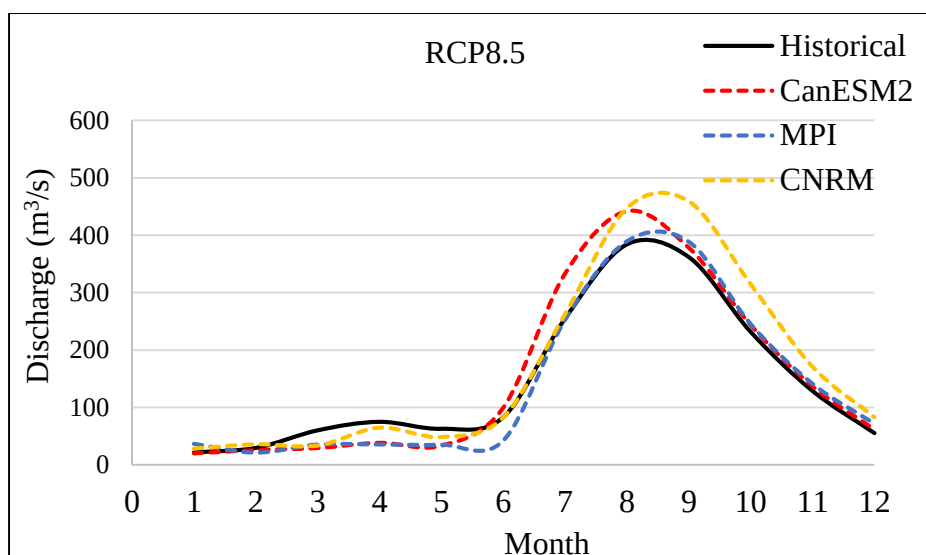


Figure 4.23 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected end-future period (2075-2100) in Hombole watershed

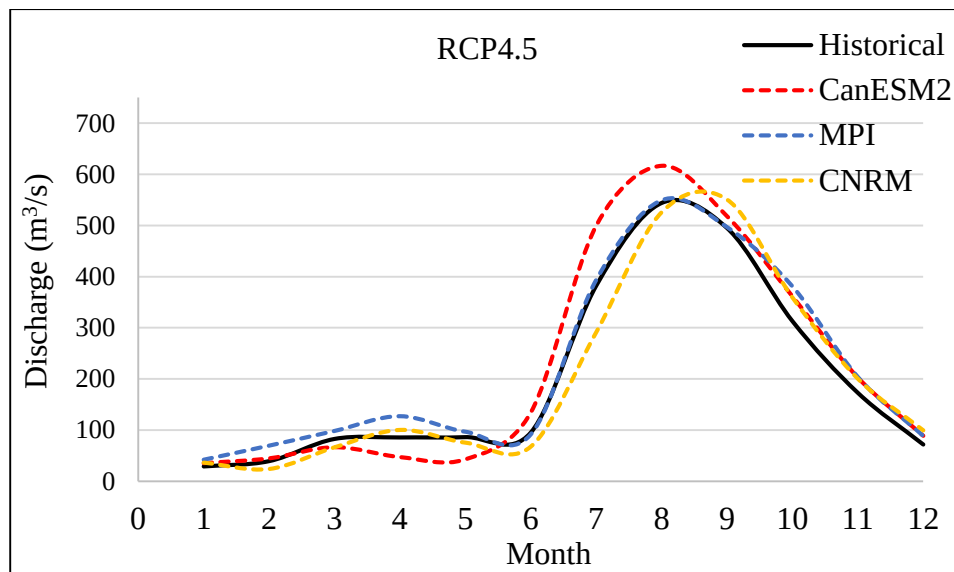
In the upper Awash watersheds, the most significant increase in monthly average streamflow was observed in June (31.32%) and December (20.64%) during the mid and near-future periods within the scenarios of RCP 4.5 and RCP 8.5, respectively, when considering the CanESM2 model. On the other hand, the most expected reduction occurred in Apr (-117.69% and -119.01%) for the mid future periods under the RCP 4.5 and RCP 8.5 scenarios, respectively. The average annual streamflow is projected to increase by 9.77% and 6.05% under RCP 4.5 and RCP 8.5 scenarios, respectively, by the end of the century for the upper Awash watersheds as shown in Figure 4.24 to Figure 4.26 below.

For MPI, the expected change of increment of monthly average streamflow was observed in Feb (43.62%) and Jan (50.02%) in the near and mid future and the most expected reduction occurred in May (-119.82%) and -115.89%) in the mid future within the scenarios of RCP 4.5 and RCP 8.5, respectively within the upper Awash watersheds as indicated in the figure 4.24 to figure 4.26 below. The upper Awash watersheds are anticipated to experience a 9.15% rise in average annual streamflow in the coming years by the RCP 4.5 scenarios, while a substantial decline of -28.87% is predicted by the end of the century under the RCP 8.5 scenarios.

For CNRM, the most significant increase in monthly average streamflow was observed in Apr (30.88%) and May (45.14%) during the mid and near-future periods under the RCP 4.5 and RCP 8.5 scenarios, respectively, and the most expected reduction was occurred in May (-98.50%) and (Mar-84.31%) for the mid and end future periods under the RCP 4.5 and RCP

8.5 scenarios, respectively for the upper Awash watersheds as shown in the figure 4.24 to figure 4.26 below. The average annual streamflow is projected to increase by 17.85% and 14.73% under RCP 4.5 and RCP 8.5 scenarios, respectively, by the end of the century for the upper Awash watersheds.

The previous study conducted by (Tessema et al., 2021), which examined the impact of climate change on streamflow in the Kesem sub-basin of the Awash River basin, Ethiopia, our study's findings regarding mean annual flow volume reaffirm that the Kesem sub-basin is expected to experience an increase in mean annual streamflow when compared to historical data. On the other hand, the result obtained from streamflow analysis in this study was in a similar trend to results reported by Abdulahi et al., (2022) conducted on upper Awash subbasins. The findings indicated that both RCPs expect an overall increase in streamflow following the precipitation enhancement. Under the RCP4.5 and RCP8.5 scenarios, during the periods 2021-2040 and 2041-2060, it is projected that the average monthly streamflow changes will increase by 40.1% and 29.4%, and 16.9% and 18.5%, respectively.



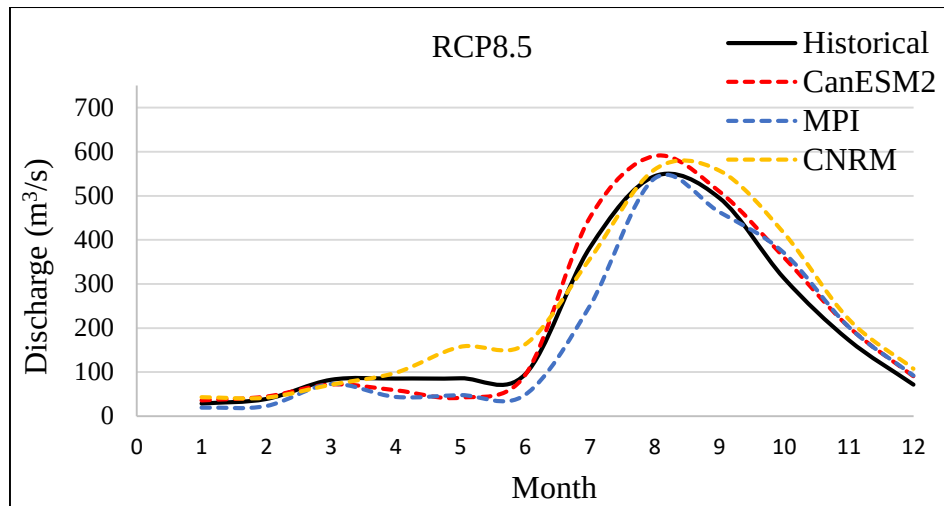


Figure 4.24 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected near-future period in the upper Awash watershed

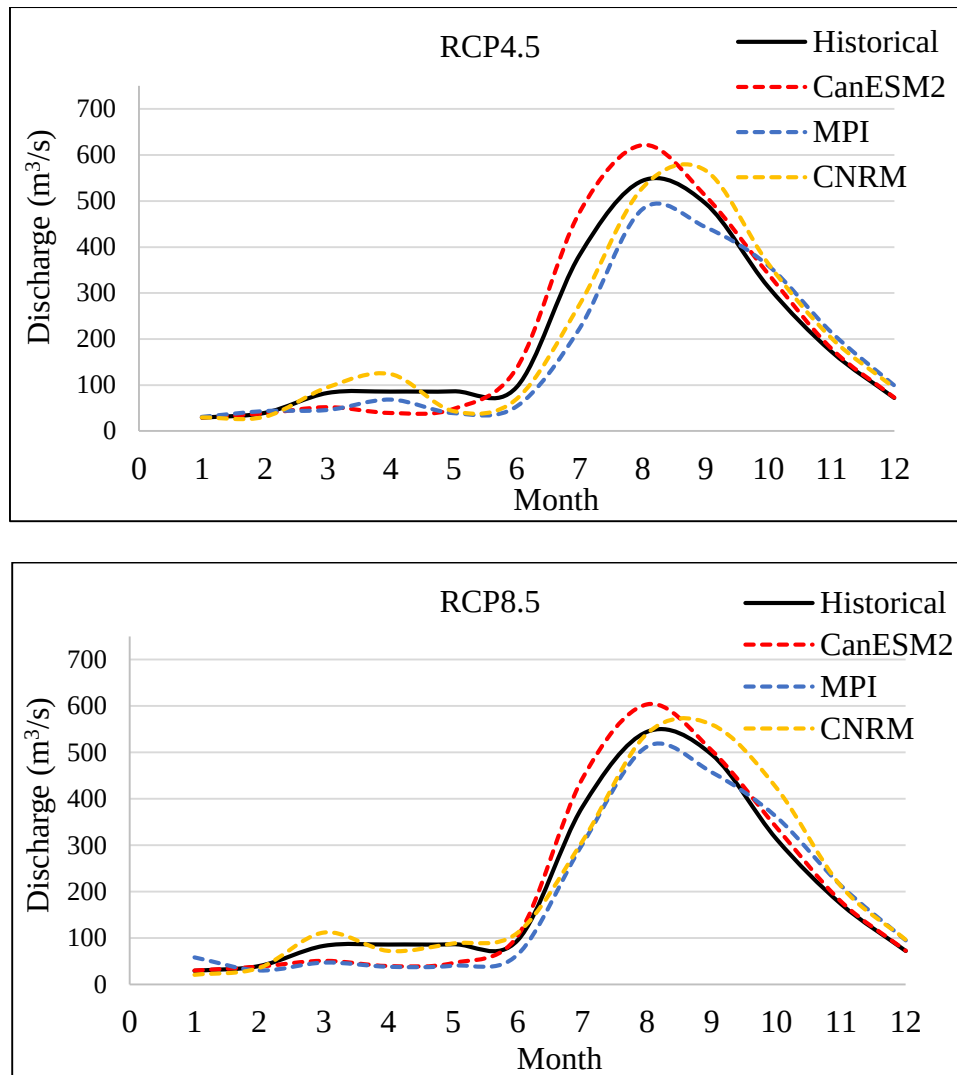


Figure 4.25 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected mid-future period in upper Awash watershed

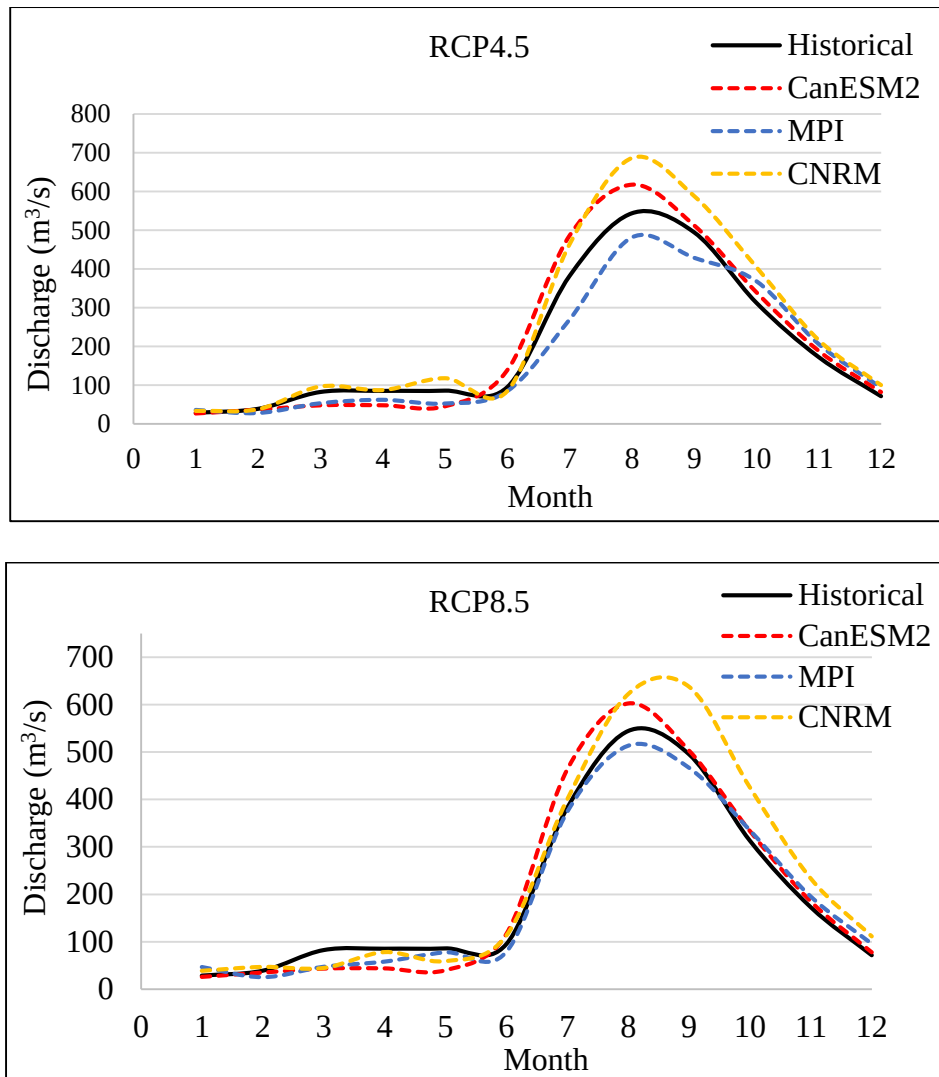


Figure 4.26 Average monthly streamflow projected by the selected climate models, under RCP 4.5 and RCP 8.5 projected end-future period (2075-2100) in upper Awash watershed

4.4. Reservoir Routing

Reservoir routing results for the Koka dam, as assessed by HEC-HMS, reveal two scenarios - RCP4.5 and RCP8.5, focusing on peak inflow and outflow values. In the context of the RCP4.5 scenarios, the peak inflow values for the near, mid, and end future periods amount to 7752.03 m³/s, 7240.78 m³/s, and 6510.68 m³/s, respectively. Concurrently, the corresponding outflow values for these durations are 1354.3 m³/s, 1316.2 m³/s, and 1252.5 m³/s as shown in the Figures 4.27, 4.28, and 4.29 below. Similarly, for the RCP8.5 scenarios, the peak inflow values for the near, mid, and end future periods stand at 10456.6 m³/s, 7224.78 m³/s, and 8000.48 m³/s, respectively. Simultaneously, the corresponding outflow values for these periods are 1505.9 m³/s, 1315 m³/s, and 1372.3 m³/s as indicated in Figure 4.30 to Figure 4.32 below.

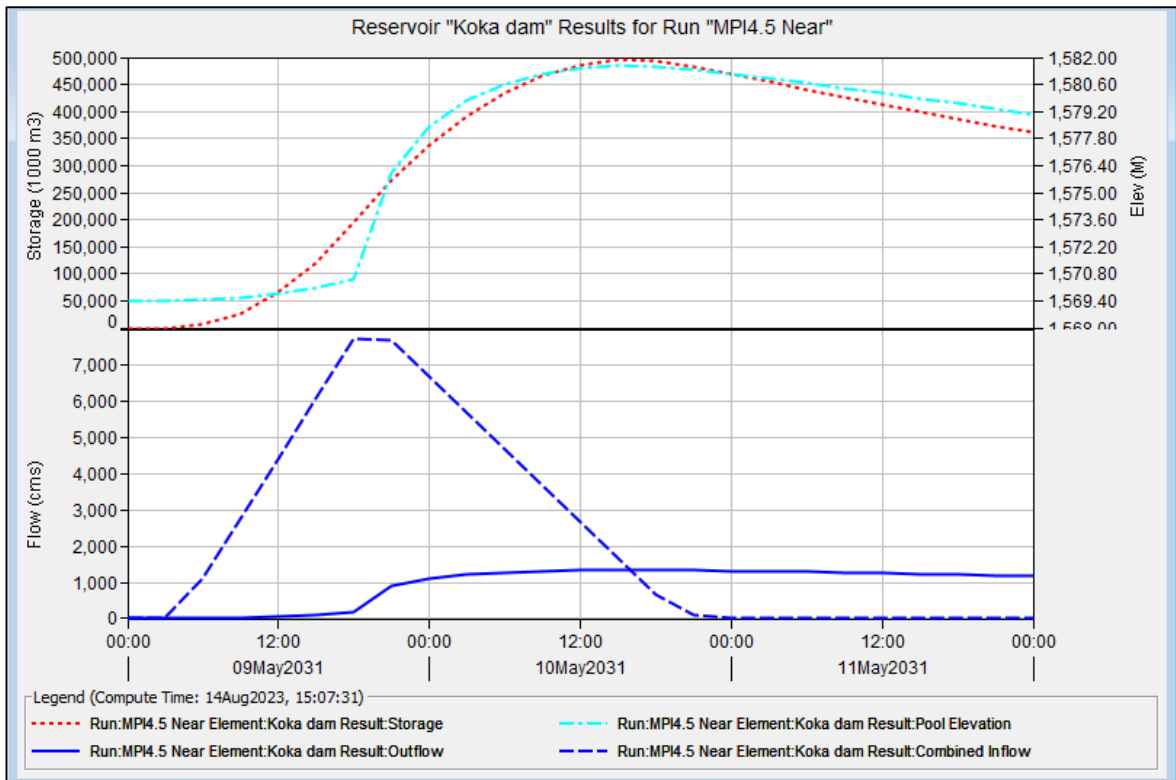


Figure 4.27 Near future of RCP4.5 routed inflow and outflow hydrograph of Koka dam

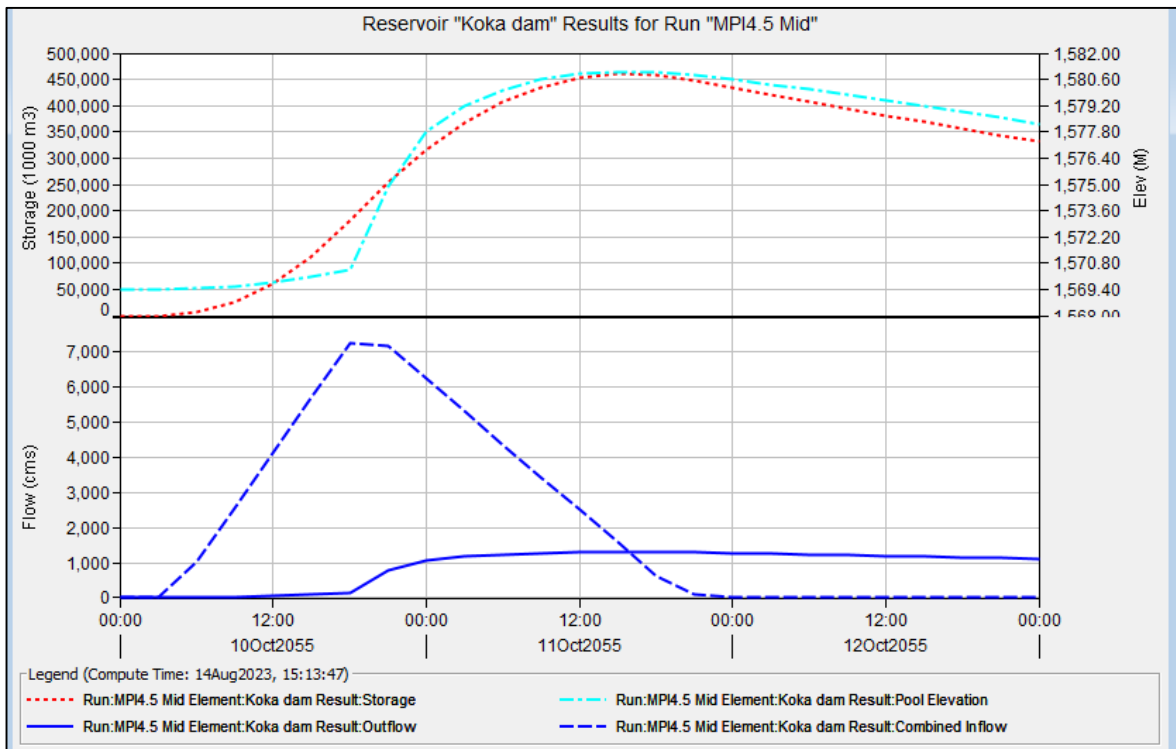


Figure 4.28 Mid future RCP4.5 routed inflow and outflow hydrograph of Koka dam

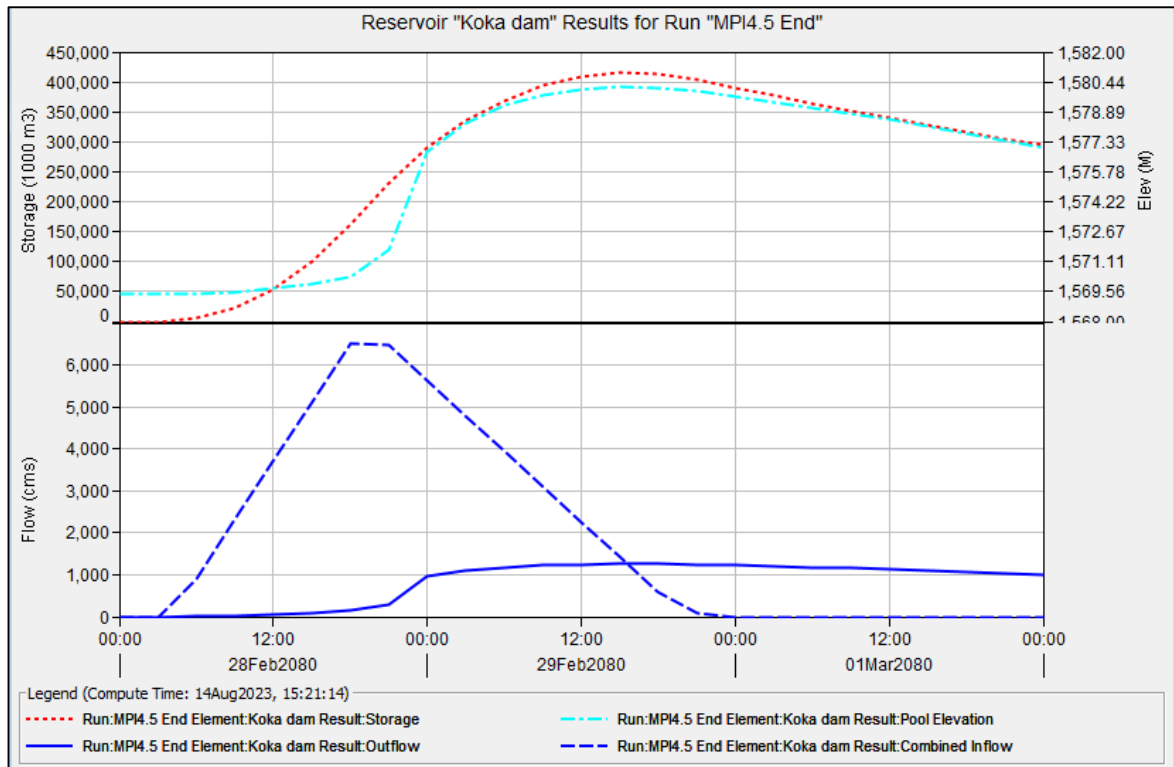


Figure 4.29 End future RCP4.5 routed inflow and outflow hydrograph of Koka dam

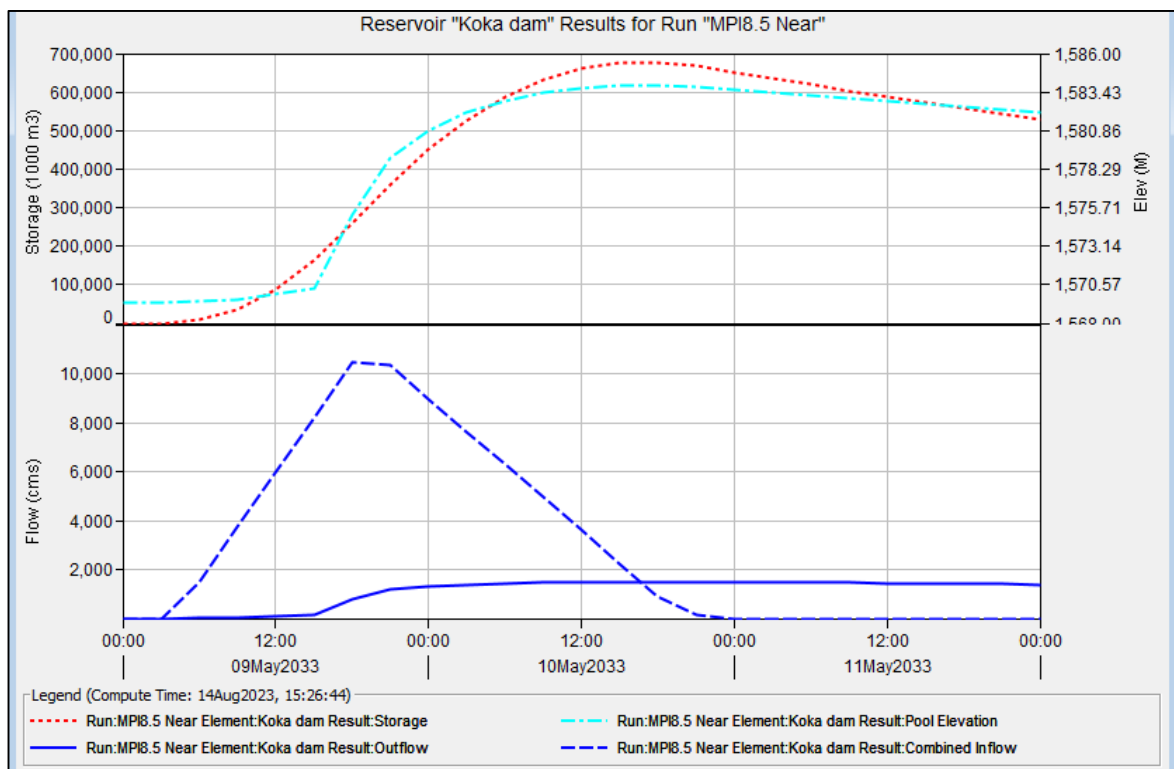


Figure 4.30 Near future of RCP8.5 routed inflow and outflow hydrograph of Koka dam

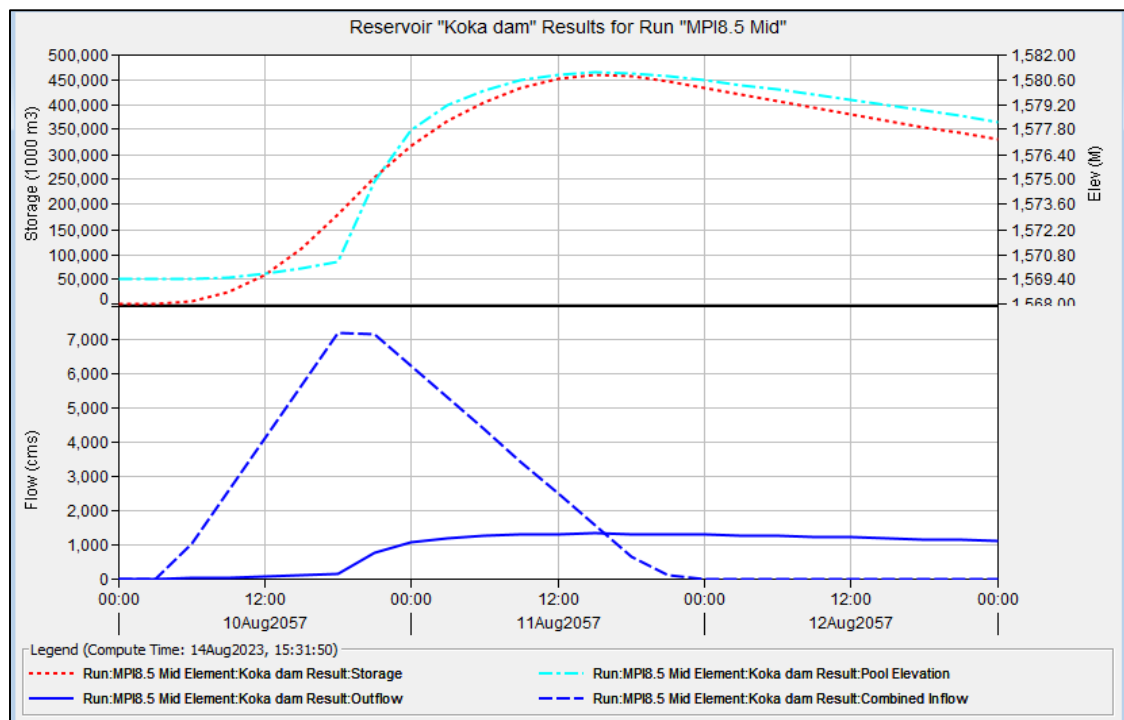


Figure 4.31 Mid future of RCP8.5 routed inflow and outflow hydrograph of Koka dam

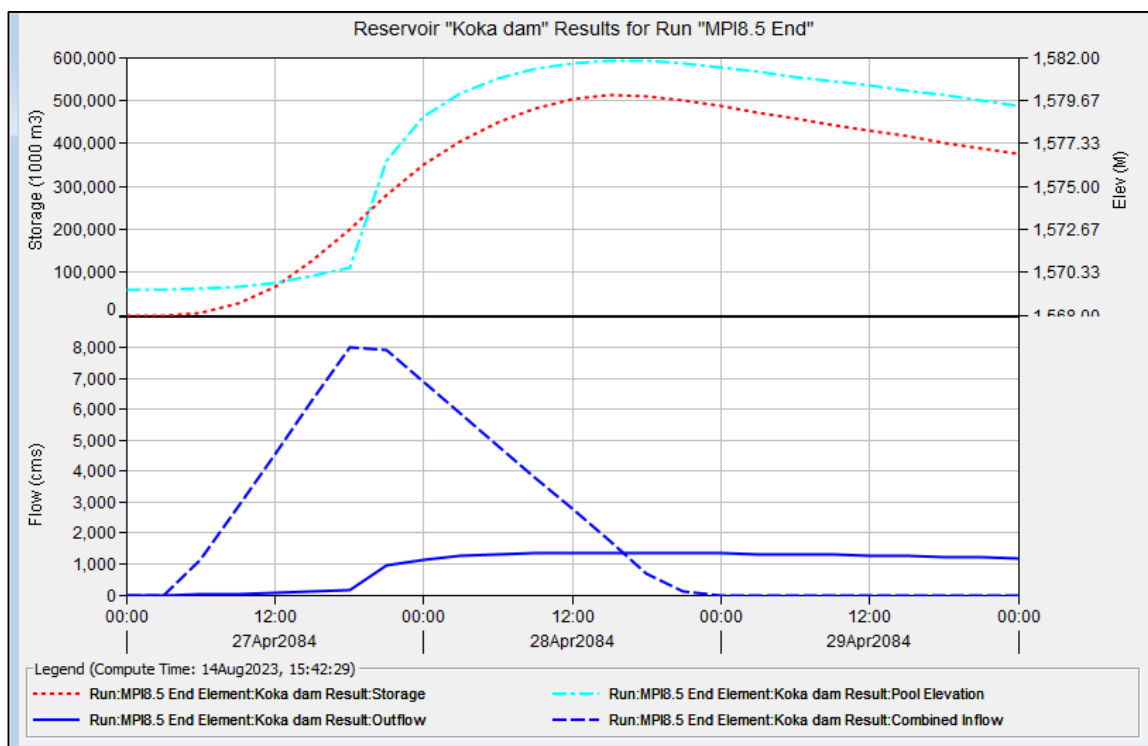


Figure 4.32 End future of RCP8.5 routed inflow and outflow hydrograph of Koka dam

Table 4.4 Summary of routing outflow result of Koka Dam

Scenario	Predicted outflow	Dam Capacity at FSL (1590.7 asl)	Remark	Dam Capacity at max flood retention level (1292.2 asl)	Remark
RCP4.5	1354.3 m ³ /s	1040 m ³ /s	unsafe	1322 m ³ /s	Unsafe
	1316.2 m ³ /s	1040 m ³ /s	unsafe	1322 m ³ /s	Safe
	1252.5 m ³ /s	1040 m ³ /s	unsafe	1322 m ³ /s	Unsafe
RCP8.5	1505.9 m ³ /s	1040 m ³ /s	unsafe	1322 m ³ /s	Unsafe
	1315 m ³ /s	1040 m ³ /s	unsafe	1322 m ³ /s	Safe
	1372.3 m ³ /s	1040 m ³ /s	unsafe	1322 m ³ /s	Unsafe

The Koka Dam is equipped with gated spillways to regulate water flow. However, its operation has not been without challenges, as it occasionally contends with high flood conditions. According to the dam's design documentation, the Probable Maximum Flood is anticipated to result in an outflow of 1040 m³/s at full capacity level (1590.7). However, according to the routing analysis findings, in the near, mid, and distant future periods, the peak outflow surpasses the capacity of the designed spillway for Koka in both the RCP4.5 and RCP8.5 scenarios, surpassing the probable maximum flood capacity.

Depending on the routing results obtained from HEC-HMS, it is evident that the routing outflow exhibits increases of 23.21%, 20.98%, and 16.97% for the near, mid, and end future periods, respectively, within the RCP4.5 scenarios. Similarly, in the context of the RCP8.5 scenarios, the routing outflow increases by 30.94%, 20.91%, and 24.21% for the corresponding periods when compared to the maximum probable flood capacity of the designed spillway.

These findings suggest that the dam's current spillway capacity may not be sufficient to safely manage extreme flood events under the projected climate scenarios of RCP4.5 and RCP8.5. Further evaluation and potential upgrades to the spillway capacity and overall dam safety measures may be necessary to mitigate the risks associated with increased peak outflow and ensure the safety of the Koka Dam. In the event of extreme flood events, especially under the projected climate scenarios of RCP4.5 and RCP8.5, the dam might struggle to manage the heightened peak outflows effectively. This situation could lead to potential downstream flooding, posing risks to communities, infrastructure, and the environment.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

The study examined how climate change impacts the Koka Dam's safety. To do this, the study utilized regional climate models from CORDEX-Africa, focusing on the RCP4.5 and RCP8.5 scenarios for three future periods: 2024-2048, 2049-2074, and 2075-2100, comparing them to the historical period. Concluding the particular data used, the analysis methodology applied, and the resulting findings, we arrive at the following findings: The influence of land use and land cover change is presumed to remain consistent in the subsequent scenarios, and it is established that it has no impact on surface runoff within the watershed.

The historical data and bias correction of climate change data through downscaled RCP scenarios are conducted using the distribution-mapping approach, relying on observed meteorological data. Under the RCP 4.5 scenario, In the CanESM2 model, there is a slight projected increase in average annual precipitation for end periods and a decrease for the near and mid periods. For the CNRM model, average annual precipitation is expected to increase during the near and end periods under RCP 4.5 scenarios, while the mid period is anticipated to decrease. Within the MPI model, average annual precipitation is expected to increase during the near period, but projections indicate decreases for the mid and end periods. Under the RCP 8.5 scenario, Both the CanESM2 and CNRM models predict an increase in precipitation for the near, mid, and end periods. However, under RCP 8.5, the MPI model suggests decreases in precipitation for the near, mid, and end periods. These findings provide insights into the expected shifts in precipitation patterns across various climate change scenarios and models.

Regarding the simulated average temperature for the future, all models indicate an increase in values for the near, mid, and end-future periods under both the RCP4.5 and RCP8.5 scenarios. This temperature increase is observed across all months and years.

The results suggest that future climate changes will impact streamflow, the anticipated temperature and precipitation increases are projected to result in a greater flow of water in streams. Finally, the findings indicate that streamflow within the watershed will fluctuate in response to alterations in precipitation and temperature during the near, mid, and distant future periods for both RCP4.5 and RCP8.5 scenarios.

The result of calibrating and validating the hydrological model suggests that the Arc SWAT model effectively replicates the climate change data from the RCM for the study area, facilitating the assessment of the spillway in the upcoming period. In the case of the Koka dam, the routed results from the HEC-HMS models indicate that the dam's spillway capacity will not be sufficient to accommodate the outflow.

5.2. Recommendation

Based on the findings obtained from this study, the following recommendations are proposed: -

- This study was concentrated on RCP4.5 and RCP8.5 scenarios, it is suggested that other RCP scenarios should be applied to make a comparison of their results.
- The findings presented in this study are valid only for the current land-use conditions in the study area. It is crucial to incorporate projected land cover changes in the upcoming decades and evaluate their associated effects. Therefore, it is important to assess and plan for various mitigation measures and management practices.
- The availability of hydrological data holds significant importance when employing any model analysis for present and future predictions. However, the upper Awash watershed streamflow and weather data gauging station have data missing and quality problems. The SWAT hydrological model requires intensive input data; it is recommended that the relevant organization collaborates in an integrated manner to enhance the quality of the required data.
- It is suggested that the investigation be expanded to include Modifications in reservoir seepage, dam seepage, a reevaluation of dam efficiency, sedimentation processes, and any other water resource developments within the basin should be considered.
- To minimize the impact of climate change on pre-existing projects, it is important to conserve the conservation and implementation of watershed conservation or mitigation methods. Therefore, the ongoing study needs to incorporate a mitigation approach that focuses on reducing the effects on reservoirs and dam structures, given the uncertainty of the hydrological system.
- The study did consider only in Koka reservoir, thus better to incorporate other Ethiopian reservoirs in the SWAT model simulation and routing using HEC-HMS.

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APPENDICES

Appendix A

Appendix A1. Average annual rainfall of station in the study area

year	AA Bole	Akaki	Alem Tena	Ginchi	Hombole	Mojo	Tulu Bolo
1990	1121.7	1069.9	841.6	1132.3	1081.1	927.8	845.7
1991	991	994	523.7	905.1	987.5	878.6	775.2
1992	975.4	854.3	906.2	1023.6	996.5	798	1705
1993	1207.8	958.5	952.1	1463	1077.8	831.5	1756
1994	816.8	792.1	719	1173.5	842.5	934.3	1399.5
1995	1009.7	912.4	638.5	991.8	694.2	1055.1	626.5
1996	1552.5	1112.2	817.3	1249.8	1053.3	1087.4	1217.4
1997	877.1	856.7	884.2	1029.2	707.7	1061	1050.8
1998	1379.8	1071.8	803.2	1226.5	872.1	1133.9	1448.2
1999	946.7	955.2	713.7	1135.5	659.3	1199.5	1372.4
2000	902.1	854.5	882.3	993.2	752.5	952.2	1215.5
2001	1102.7	895.7	866.5	1102.6	796.3	888.2	819.4
2002	891	771.3	589	1047.4	490.5	1064.6	1021.5
2003	939.1	1095.8	936.1	1082.8	894.6	1060.1	979.4
2004	1015	787.1	822.4	1133.3	654.4	1215.9	1158.6
2005	1084.1	1103.9	895.6	1148.3	841.4	1256.2	1127.3
2006	1205.9	1017.4	768.1	2152.6	792.3	1199.1	1039
2007	1135.6	1018.7	851.3	1090.7	824.3	1001.6	1093.7
2008	1004.6	1006.6	957.6	1024.1	794.3	1441.4	1139.1
2009	947	982.7	812.3	940.4	829.2	1108.3	978.7
2010	1146.1	1306.1	838.3	1211.4	958.6	1110.4	1394.8
2011	944.2	964.6	815.1	801.2	687.4	833.8	853.7
2012	931.2	791.5	846.8	821.4	778.2	1303.9	919.6
2013	960.8	936.3	945	1152.1	867.9	1096.4	1683.9
2014	772.2	806.1	933.9	1003.6	668.1	875.1	1019.2
2015	853.2	790.3	661.8	963.7	835.8	859.4	827.1
2016	963.8	1052.4	1098.8	1112.1	835.7	1275.6	972.8
2017	968.3	756.6	829.9	1020.7	901.7	1039.2	1047.2
2018	1205.4	1066	774.8	1118.9	773.4	1058.6	1171.7
2019	1409.8	966.2	1035.9	1179.9	832.2	1293.9	995.2
2020	1639.2	1112.8	1088.5	1276.8	1134.9	1014	1167.2
2021	1267.1	899.4	778.3	954.3	692.8	1091.5	1131.7

Appendix A2. Average annual rainfall of station in the study area

1.Maximum Temperature of the stations

year	AABole	Akaki	Alem Tena	Ginchi	Hombole	Mojo	Tulu Bolo
1990	23.2	26.3	27.8	22.3	27.8	27.3	23
1991	23.7	26.8	28.5	22.8	27.8	28.2	26
1992	23.1	26.4	29.7	22.6	27.5	28.2	27
1993	23	25.9	28.6	21.9	27.6	28.3	27.4
1994	23.8	27	27.4	23.2	27.5	27.9	26.9
1995	23.7	27.2	28.6	23.5	28.3	27.8	24.2
1996	23.3	25.9	27.5	22.2	26.9	27.7	21.9
1997	23.9	26	28.2	22.9	28	28.3	22.2
1998	23.8	25.8	28.4	22.6	28	28.7	21.8
1999	23.8	25.8	28.2	23.3	28.7	29.2	21.3
2000	23.6	26	28.3	23.9	28.7	28.2	21.3
2001	23.6	26.2	28.9	24.4	29.4	28.8	25.2
2002	24.5	26.7	29.5	25.5	30	29	25.6
2003	24	26.4	29.8	25	29	29.1	24.9
2004	23.8	26.5	29.2	25	29	29.8	25.2
2005	23.8	26.4	29.5	24	28.9	29.7	26.0
2006	23.2	26.3	28.5	24.3	28.9	30.2	25.2
2007	23	26.1	28.1	24.2	28.5	31.2	25.0
2008	23.4	26.4	28	24.5	28.4	27.9	25.3
2009	23.8	27.1	29	24.6	29.1	28.8	25.5
2010	23	26.1	28.9	22.8	28.6	28.3	25.6
2011	23.6	26.4	29.4	23.2	25.4	28.9	25.7
2012	24	26.5	29.2	23.5	25.3	29.1	25.3
2013	23.9	26.7	29	22.0	24.2	29.2	25.6
2014	24	25.8	28.8	22.3	24.5	29.6	26.1
2015	24.5	27.1	30.2	23.7	25.7	30	26.4
2016	24.0	26.5	29.4	22.5	24.6	29.7	26.1
2017	22.4	26.7	29.3	22.7	24.7	30.1	26.2
2018	23.4	25.6	29	22.5	24.5	29.9	25.6
2019	24	26.5	29.1	22.8	24.6	30.6	26.0
2020	23.8	26.3	28.8	22.3	23.9	30.3	25.8
2021	24	24.1	28.8	22.7	24.6	29.6	25.8

2. Minimum Temperature of the stations

year	AA Bole	Akaki	Alem Tena	Ginchi	Hombole	Mojo	Tulu Bolo
1990	9	13.6	11.4	9.3	10.2	11.9	6.1
1991	9.5	13.7	11.5	9.3	9.9	12.8	6.3
1992	9.5	13.8	13.5	9.3	9.8	12.6	9.6
1993	9.1	13.5	13.1	9.1	9.7	12.2	9.6
1994	8.9	13.4	12.5	9	9.4	12.2	10.0
1995	9.5	13.9	13.3	9.5	9.7	13.1	12.1
1996	9.3	13.7	13.3	9.5	9.9	12.2	11.3
1997	10	15	14	9.5	10.3	12.8	11.4
1998	10.1	14.2	14.2	10.1	10.8	12.3	10.4
1999	8.9	12.8	14	8.9	9.7	11.9	9.5
2000	9.6	12.9	13.7	9.1	9.6	12.2	8.7
2001	9.3	13.7	13.5	9.8	10.2	11.6	10.3
2002	9.9	14.5	13.9	10	10.5	11.5	10.4
2003	9.9	14.2	13.1	10	10.2	10.1	10.1
2004	10	14.9	13.3	9.9	10.4	9.5	9.5
2005	10	15.3	13.2	9.7	10.2	8.8	9.6
2006	10.8	15.4	14	9.8	10.6	9.3	9.1
2007	10.5	16.3	13	9.7	10.2	10.4	10.6
2008	10.0	15.5	10.7	9.1	9.6	11.9	9.6
2009	10.8	16.0	12.7	9.9	10.4	12.4	9.7
2010	11	12.8	13	10.3	11.2	12.6	10.5
2011	10.7	12.3	12.9	10.7	11.9	12.2	9.8
2012	10.5	11.1	12.1	10.4	11.5	11.4	9.5
2013	11.2	7.5	13.7	10.7	12.0	11.5	9.6
2014	11.4	11.3	13.9	10.7	12.1	11.6	9.5
2015	11.0	10.9	13.6	10.9	12.1	11.6	9.6
2016	11.3	10.9	15.3	10.9	12.2	12.3	10.1
2017	9.4	10.6	13.6	10.2	11.5	11.7	9.3
2018	11.2	11.8	13.9	10.7	11.9	11.6	10.5
2019	12	11.9	14.4	11.2	12.4	12	10.4
2020	11.6	12.3	14.6	10.9	12.1	11	10.2
2021	10.9	11.0	14.9	10.4	11.6	10.9	10.8

Appendix B

Appendix B 1. Soil parameters of the study area

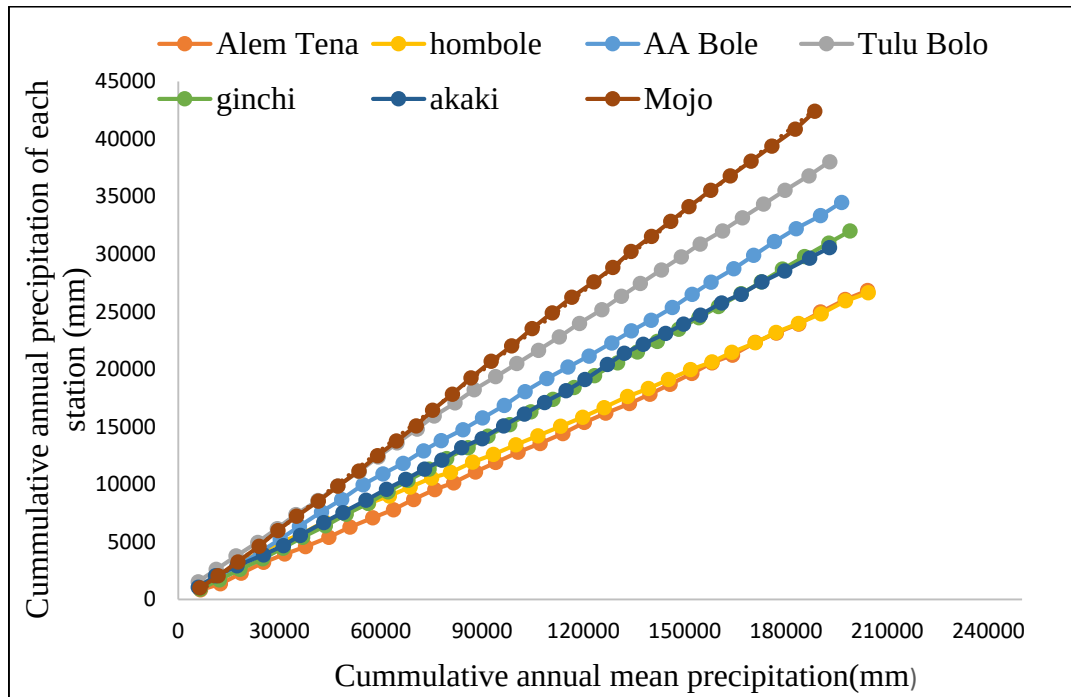
SNAM	NL AY ER S	HY DG RP	SOL_ ZMX	SO L_ CR K	TE XT UR E	SOL _Z1	SOL _BD 1	SO L_ A WC 1	SOL _K1	SO L_ CB N1	C L A Y 1	SI L T1	S A N D 1	R O C K	SOL _AL B1	USL E_K 1
Be9-3c-26	2	C	930	0.5	C	300	1.1	0.2	23.6	0.7	43	28	29	0	0.13	0.26
I-Re-3a-83	2	C	1000	0.5	SC L	300	1.2	0.1	18.8	1.6	26	22	52	0	0.02	0.28
Ne10-3b-154	2	C	910	0.5	C	300	1.3	0.2	8.5	1.1	43	28	29	0	0.06	0.24
Ne13-3b-158	2	C	910	0.5	C	300	1.3	0.1	8.6	1.1	47	26	27	0	0.06	0.23
Vp14-3a-286	2	C	1000	0.5	C	300	1.1	0.1	20.1	0.7	54	23	24	0	0.13	0.20
Xh16-a-309	2	C	980	0.5	SL	300	1.3	0.2	10.1	1.4	20	53	27	0	0.03	0.29
WATER-1972	1	D	25.4	0.5	W	25	0	0	99	0	0	0	0	0	0.23	0

Appendix B 2. Streamflow parameters and parameter ranges used for a sensitivity analysis

Name	Min	Max	description	process
CN ₂ .mgt	-0.25	0.25	SCS runoff CN for moisture condition II	Runoff
			Base flow Alpha factor(days)	
ALPHA_BF.gw	0	1	Threshold depth of water in the shallow	Groundwater
GWQMN.gw	0	5000	aquifer required for return flow to	Groundwater
			occur(mm)	
			Average slope length	
SLSUBBSN.hru	10	150	Threshold depth of water in the shallow	Evaporation
REVAPMN.gw	0	500	aquifer for "revap" to occur(mm)	Groundwater
			Manning's "n" value for overland flow	
			Available water capacity of soil layer	
OV_N.hru	-0.22	-0.07	(mm/mm soil)	Evaporation
			soil evaporation compensation factor	
SOL_AWC	-0.25	0.25	groundwater delay(days)	Soil
			soil hydraulic conductivity	
ESCO.hru	0	1	channel effective hydraulic conductivity	Evaporation
GW_DELAY.gw	0	500	(mm/hrs)	Groundwater
SOL_K.sol	-0.25	0.25		Soil
CH_K2.rte	56	160		Channel

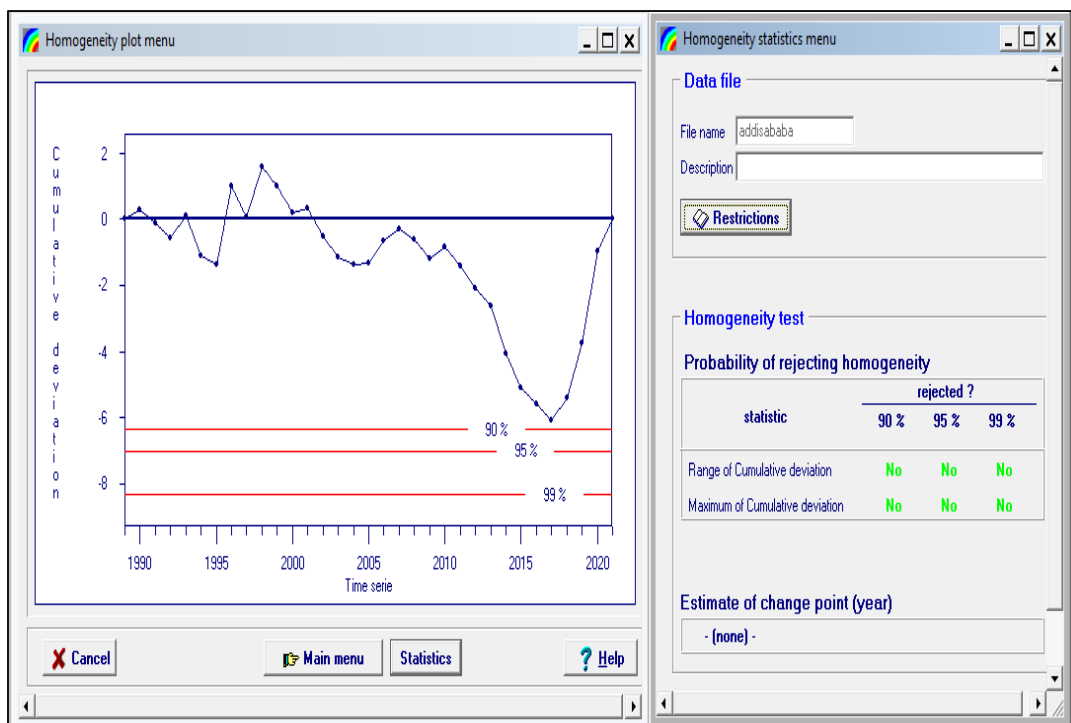
Appendix C

Appendix C1. Double mass curve for seven stations of upper awash watershed

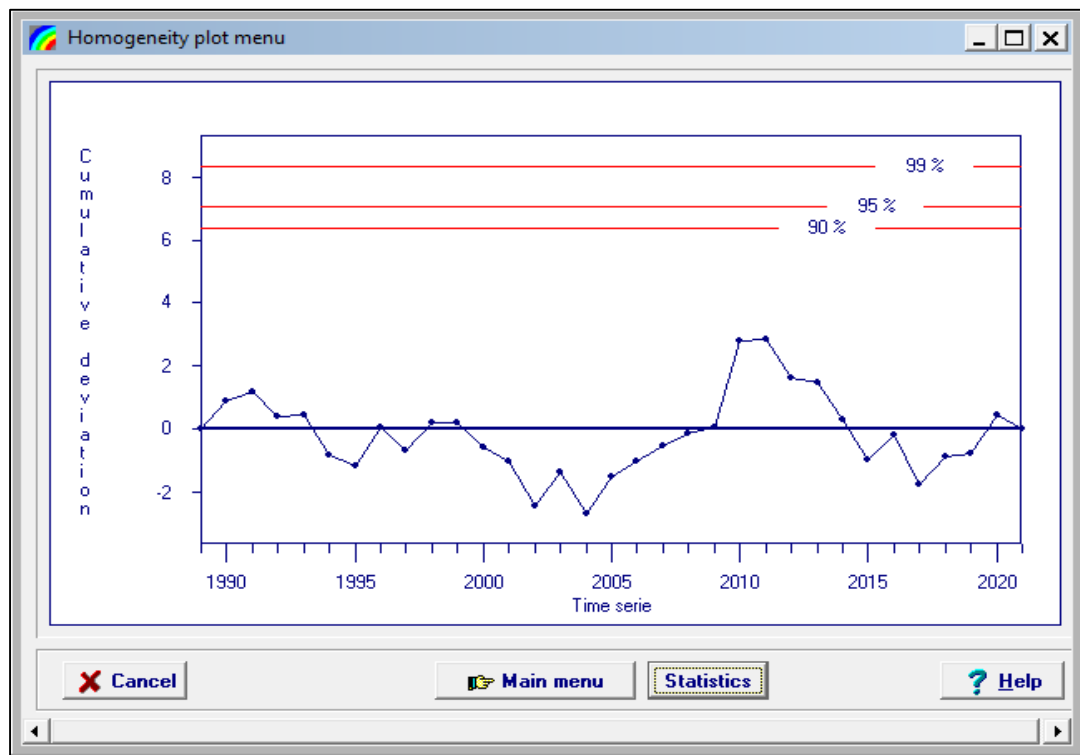


Appendix C2. Homogeneity test plot for rainfall station

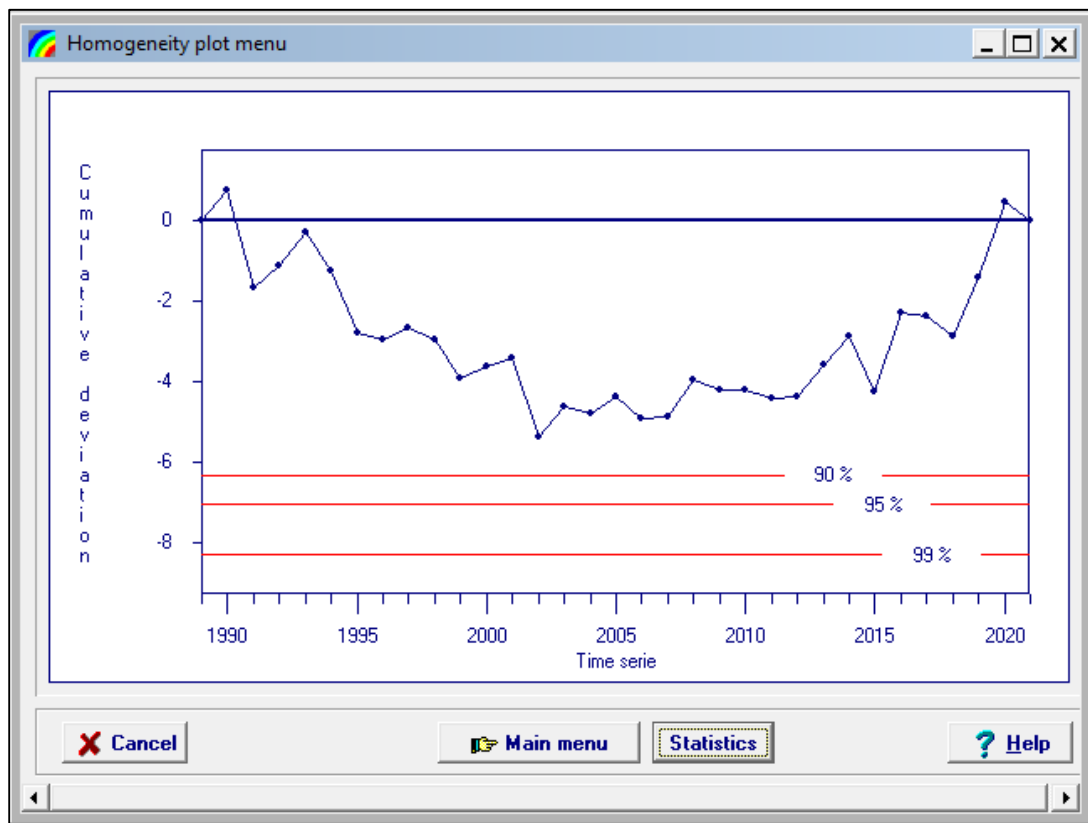
i. AA Bole rainfall station



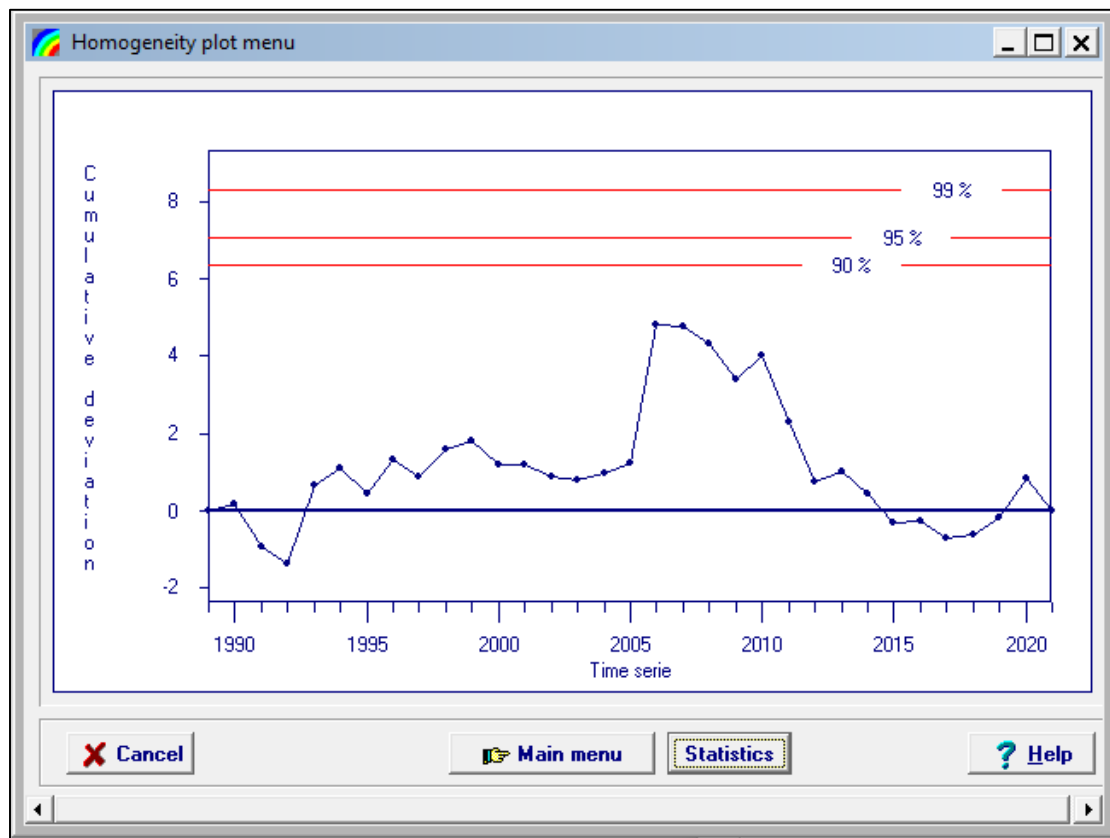
ii. Akaki rainfall station



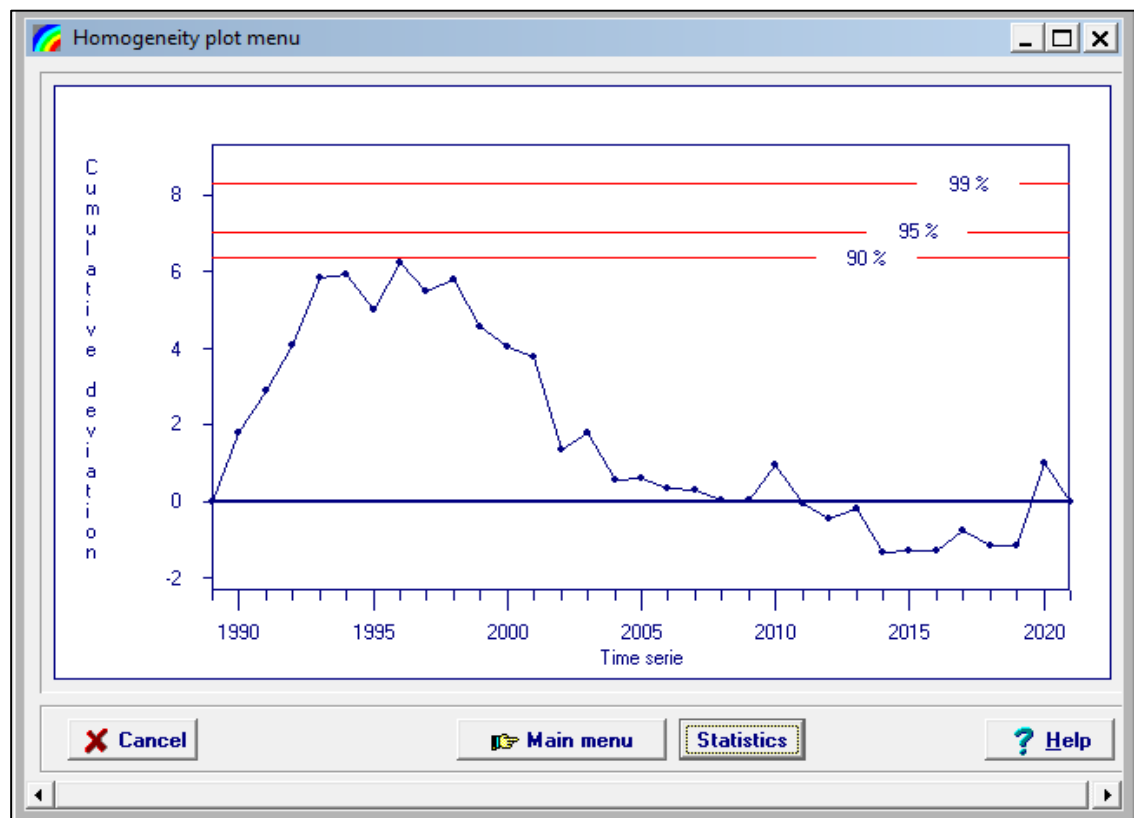
iii. Alem Tena rainfall station



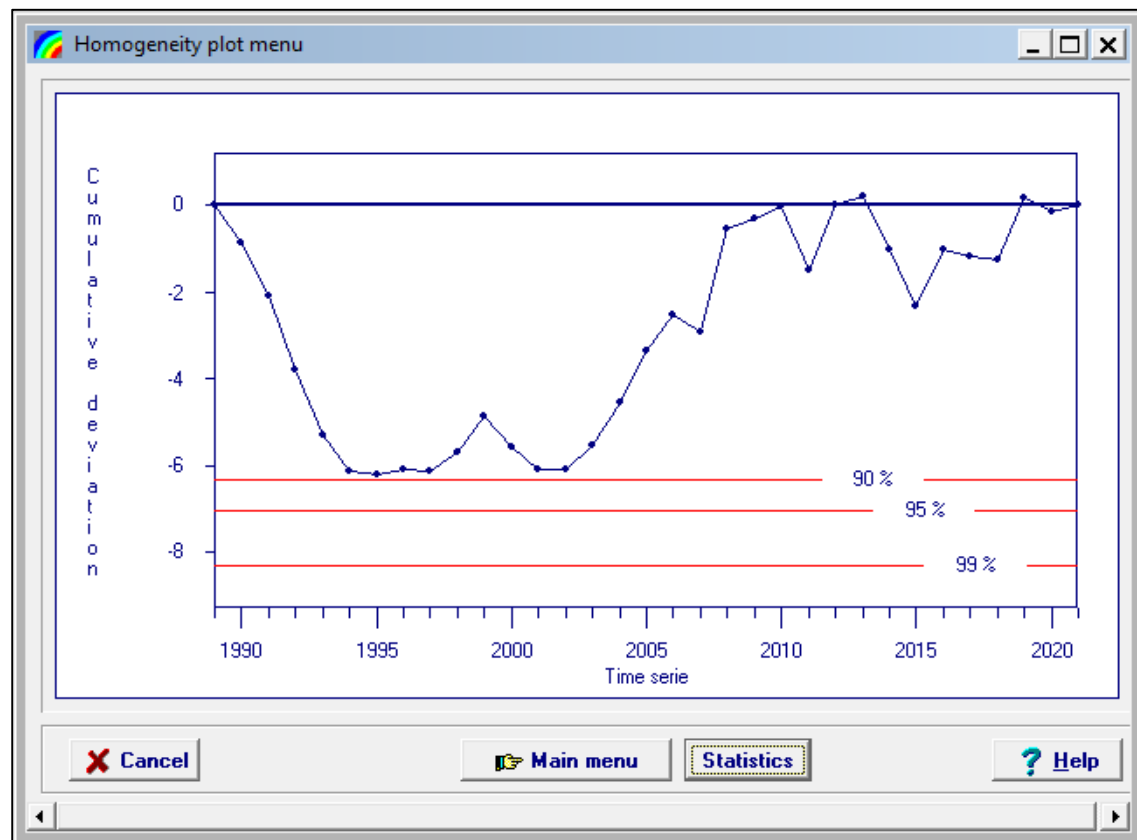
iv. Ginchi rainfall station



v. Hombole rainfall station



vi. Mojo rainfall station



vii. Tulu Bolo rainfall station

