Impact of Climate Change and Variability on Surface Water Availability and Crop Water Requirement in Eastern Tigray, Northern Ethiopia: Implications for Dryland Water Management and Adaptation

A PhD dissertation submitted to the Institute of Climate and Society in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Climate and Food Systems

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Declaration

I hereby declare that this PhD dissertation, entitled Impact of Climate Change and Variability on Water Availability and Crop Water Requirement in Eastern Tigray, Northern Ethiopia: Implications for Dryland Water Management and Adaptation, is my own work. All sources that have been used or quoted are fully acknowledged through proper references. I also confirm that this work has not been previously submitted for any other degree at any other institution.

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Abstract

Climate change and variability pose significant threats to agricultural productivity and water resources, particularly in vulnerable areas like Eastern Tigray. This situation underscores the urgent need for adaptive, integrated water management strategies to address the challenges climate change exerts on agriculture and water resources. Consequently, this study aims to analyze the impacts of climate change and variability on water availability and crop water requirement, as well as to identify adaptation strategies.

This study employed various models and analytical tools to evaluate the impacts of climate change and variability on water availability, crop growing season characteristics, and crop water requirements. The research involved analyzing historical climate data and examining temperature and precipitation patterns to establish a baseline scenario. Future projections were developed using selected General Circulation Models (GCMs) from the Coupled Model Intercomparison Project, which were downscaled to accurately represent local conditions. Building on this data, the study assessed spatio-temporal patterns in crop water requirement and surface water availability across the research area. The hydrological simulations generated by the HEC-HMS model, along with irrigation demand estimates and additional inputs from various sectors, were integrated into the WEAP model. This comprehensive framework facilitated scenario-based analyses of water supply and demand within the watershed, providing a robust foundation for effective water resource management strategies. By synthesizing insights from climate models, hydrological simulations, and water management tools, this study presents a thorough examination of historical trends and projected climate shifts, focusing on their implications for agriculture and water resources management.

The analysis of historical data revealed non-significant upward trends in rainfall, while temperature trends showed significant increases. There was high variability in *Kiremt* season rainfall (21–31%) and in the duration of dry spells (25–43%) during the observed period. The length of the growing period (LGP) ranged from 68 to 90 days, indicating a limited time frame for crops to mature. Furthermore, projected climate change scenarios suggest a shift towards wetter conditions. Despite such conditions, the combined impact of rainfall variability and warming is

projected to reduce the LGP by 5.5% to 19%, restricting crop growth and maturation and posing challenges for agricultural productivity in the future.

As temperatures rise, reference evapotranspiration rates are projected to increase across mid- and end-century periods under all scenarios and stations. Mean monthly crop water requirement is also expected to rise, with shifts ranging from modest changes to as much as 19.4% by the end of the century. Seasonal crop water requirements are projected to increase as well, varying between 6% and 13% depending on the period. Simulations from the HEC-HMS model further indicate that, under the SSP2-4.5 scenario, surface runoff may decrease substantially during most months in both the mid-term (2040–2069) and end-term (2070–2099) periods, with reductions ranging from 0.56% to nearly 25.8%. Under the extreme SSP5-8.5 scenario, surface runoff is anticipated to decline during the mid-term but could increase during several months in the end-term.

Forecasts of future water demand produced by the WEAP model cover a range of "what if" scenarios and go through 2055. The findings show that population growth alone could increase water demand by 81%, even without the influence of climate change. If irrigation expansion is included, increasing from 10% to 30%, water demand could rise further, ranging from 86.6% to 98.3%. Moreover, water availability may drop by 12% under the mid-term SSP245 scenario, and unmet demand may double by 2055 due to both rising demand and falling supply.

The findings highlight the growing complexities of water demand, influenced by population growth, economic development, and intensified irrigation practices, all of which exacerbate the risks of water scarcity in the context of climate change. As temperatures rise and precipitation patterns become more erratic, the region encounters additional challenges, including increased heat stress, variable crop water requirements, and potential flooding under extreme scenarios such as SSP585. Mitigating these risks will necessitate sustainable water storage solutions, enhanced irrigation efficiency, and integrated cross-sectoral water management. These strategies, underpinned by flexible policies, are essential for achieving long-term resilience in water security and agricultural productivity throughout Eastern Tigray.

List of Abbreviations

AU	African Union
CMhyd	Climate Model Data for Hydrological Modelling
CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
CRGE	Climate Resilient Green Economy
CSA	Central Statistical Agency
CV	Coefficient of Variation
CWR	Crop Water Requirement
DEM	Digital Elevation Model
DOY	Day of Year
DS	Dry Spell
DWD	Domestic Water Demand
EFR	Environmental Flow Requirement
ENACTS	Enhancing National Climate Services Initiative
ET	End Term Period
ETp	Crop Evapotranspiration
ETo	Reference Evapotranspiration
EMWR	Ethiopian Ministry of Water Resources
GCMs	General Circulation Models
HEC-HMS	Hydrologic Engineering Center's Hydrologic Modeling System
IPCC	Intergovernmental Panel for Climate Change
ISRIC	International Soil Reference and Information Centre
IWRM	Integrated Water Resource Management
Kc	Crop Coefficient
LGP	Length of Growing Period
LULC	Land Use Land Cover
LWD	Livestock Water Demand
MK	Mann-Kendall

MT	Mid Term Period
NAPs	National Adaptation Plans
NDCs	Nationally Determined Contributions
NDVI	Estimation of Normalized Difference Vegetation Index
NIR	Near Infrared
NMSA	National Meteorological Service Agency
NSE	Nash-Sutcliffe Efficiency
PBIAS	Percent Bias
RCPs	Representative Concentration Pathways
SCS-CN	Soil Conservation Service-Curve Number
SSPs	Shared Socioeconomic Pathways
SRES	Special Reports for Emission Scenarios
SRTM	Shuttle Radar Topography Mission
UNFCCC	United Nations Framework Convention on Climate Change
WEAP	Water Evaluation and Planning system

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CHAPTER ONE

1. INTRODUCTION

1.1 Background

Climate change and variability are pressing global challenges, particularly for developing countries like Ethiopia, where agricultural practices and water resources are highly susceptible to fluctuations in temperature and precipitation (IPCC, 2014; IPCC, 2021). The impact of climate change is primarily evident in these critical parameters, which have undergone significant alterations over the past several decades, resulting in considerable risks to agricultural productivity, water supply, and the overall ecosystem. Since the 1950s, Ethiopia has experienced an increase in its annual average temperature of approximately 0.37°C per decade, leading to a variety of climate-related issues (Aragie, 2013; Mcsweeney et al., 2010; NMA, 2007). The nation is characterized by substantial inter-annual variability in rainfall, particularly disruptive in the northern and eastern lowlands, including the Tigray region (Gebrehiwot et al., 2011). These climatic changes have adversely impacted agricultural yields, exacerbating food insecurity and heightening water scarcity (Conway & Schipper, 2011). Additionally, the unpredictable nature of seasonal rainfall, combined with rising temperatures, has resulted in more frequent and severe droughts, placing further strain on the vulnerable farming communities and natural resources of the country (Deressa et al., 2009).

The Tigray region is especially prone to climate-induced droughts, with recurrent meteorological droughts significantly affecting its eastern and southern zones (Gebrehiwot & van der Veen, 2013). These droughts have caused extensive crop failures and considerable livestock losses, jeopardizing the livelihoods of the rural population, which relies heavily on agriculture (Araya & Stroosnijder, 2010). Moisture stress is a persistent challenge for crop production in the region, with erratic rainfall patterns leading to localized droughts that not only diminish agricultural productivity but also obstruct development initiatives and worsen food insecurity (Awulachew et al., 2011; Gebrehiwot & van der Veen, 2013). Furthermore, the increasing frequency and severity of drought events have heightened the vulnerability of smallholder farmers, who often lack adequate irrigation infrastructure and the capacity to adapt to these adverse conditions. Without sufficient support and adaptation measures, the long-term development and sustainability of the region are at significant risk.

Despite the availability of considerable irrigation potential in the eastern zone of Tigray, where the study area is located, challenges are imposed on agricultural production. This area is blessed with ephemeral rivers and streams with water resources potential for harnessing and supporting irrigation initiatives. However, the future of crop production is filled with challenges. Water scarcity, exacerbated by climate change, poses serious obstacles to sustainable agriculture (Teka et al., 2012). Moreover, competition for freshwater from non-agricultural sectors complicates the situation further. As urbanization, industrialization, and other sectors compete for limited water resources, the allocation for agricultural irrigation is likely to decline in the future.

Therefore, the research presented in this study examines the multifaceted impacts of climate change and variability on water resources, crop growth characteristics, spatiotemporal crop water requirements, and overall water supply and demand in the eastern Tigray region of northern Ethiopia. By integrating climate models, hydrological simulations, and water management tools, this study provides a comprehensive understanding of how climate change and variability affect the water demand and supply of various sectors. The findings will be crucial for developing effective adaptation strategies to mitigate the adverse effects of climate change, thereby contributing to the assurance of water and food security for the region's vulnerable populations.

1.2 Rationale for the study

The rationale for this study stems from the urgent need to understand and mitigate the impacts of climate change and variability on water availability and crop water requirements, particularly in climate-sensitive regions like the Eastern Tigray, Northern Ethiopia. Climate change poses significant risks to agricultural productivity and water resources through alterations in key climate parameters such as temperature and precipitation (IPCC, 2014). These changes have already manifested as observable trends over recent decades in Ethiopia, where increased temperatures and high inter-annual rainfall variability are notably affecting crop production and water resources (Gebremicael et al., 2017; Mekasha et al., 2014). Furthermore, the changing climate is not only reducing water availability but also intensifying competition among various sectors for the limited resources available (Hussen et al., 2018; Orkodjo et al., 2022; Taye et al., 2018).

Despite the critical role of rainfall and temperature trends in determining fate of agriculture, prior studies have largely focused on analyzing rainfall patterns alone, often overlook the influence of temperature variations on crop productivity (Abrha, 2015; Gebrehiwot & van der Veen, 2013; Gebrehiwot et al., 2011; Gebremicael et al., 2017; Hayelom et al., 2017; Mekasha et al., 2014; Meze-Hausken, 2004; Seleshi & Zanke, 2004). Additionally, the lack of detailed temperature trend analysis, alongside limited rainfall studies based on long term data, highlights the need for a comprehensive analysis that considers both rainfall and temperature patterns and their relationship to agricultural practices.

The study also addresses the inadequacies in climate impact assessments on spatio-temporal crop water requirements under both current and future scenarios. Given the increasing water demands for both agricultural and non-agricultural uses, it is critical to accurately assess crop water requirements and non-agricultural demands to implement sustainable irrigation practices and water allocation strategies for all sectors. Such assessments help in preparing proactive adaptation measures to ensure that the agricultural sector can remain productive in the face of climate variability and change (Reda & Mamo, 2013).

Furthermore, understanding the implications of these climatic variations on water resources is essential. Changes in surface runoff, driven by climate variability, threaten water security and balance in the region's watersheds. As previous studies primarily focus on the supply aspect, more integrated evaluations of both water demand and supply are needed for a holistic understanding of water resource management in response to climate change. The use of models such as Hydrologic Engineering Center's Hydrologic Modelling System (HEC-HMS) and Water Evaluation Planning system (WEAP) enables simulation-based analyses that can predict future scenarios, supporting more adaptive and resilient water management strategies (Dile et al., 2013; Gebre & Ludwig, 2015). While considerable research has been conducted on water supply in Ethiopia, there is limited comprehensive analysis that addresses both water demand and supply, including climate change scenarios. The application of the WEAP in this study is thus intended to provide a more integrated analysis of future water demand and supply dynamics under varying climate conditions. By combining projections from the latest Coupled Model Intercomparison Project Phase 6 (CMIP6) models with hydrological and agricultural data, the study will generate insights for developing robust, long-term water resource management strategies in the eastern zone of Tigray region.

In conclusion, this study is crucial for enhancing understanding of the complex interactions between climate change, water availability, crop production, and water resource management in the eastern Tigray region. The findings will support policymakers, agricultural planners, and local communities in devising more informed adaptation strategies to mitigate climate risks, optimize water resource use, and sustain agricultural productivity in the face of increasing climate variability.

1.3 Objectives

1.3.1 General Objective

The primary objective of this research was to assess the impacts of climate change and variability on water resource availability, crop growing period, and crop water requirements in Eastern Tigray region, Northern Ethiopia. Furthermore, the study aims to develop adaptation measures to promote sustainable crop production and water management, with the goal of enhancing resilience to climate-related challenges.

1.3.2 Specific Objectives

The specific objectives of this research were to:

- Investigate historical trends and variability in temperature and precipitation patterns, along with the characteristics of crop growing seasons and projected future changes.
- Analyze the spatial and temporal effects of climate change on crop water requirements, considering variations across different months and seasons.
- Evaluate the implications of climate change on surface runoff.
- Evaluate current and future scenarios of water supply and demand using comprehensive water management frameworks.

1.4 Research questions

This research has addressed the following key research questions:

- What are the historical trends and variability in temperature, rainfall, and crop growing season characteristics, and what future changes are anticipated in the eastern Tigray region?
- In what ways does climate change influence the spatial and temporal distribution of crop water requirements?
- How is surface runoff expected to be impacted by different climate change scenarios in the selected watersheds?

- To what extent does existing water resource meet both current and projected water demands under various climate and socio-economic scenarios?
- Which adaptation strategies can be implemented to effectively minimize the impacts?

1.5 Methodological approaches

1.5.1 Description of the study area

This study was conducted in the eastern zone of the Tigray region in northern Ethiopia, geographically located between 13°33′2″–14°40′54″ N latitude and 39°11′39″–39°59′11″ E longitude (Fig. 1-1). Covering an area of 561,000 hectares, the zone includes seven districts: Erob, Hawzen, Wukro, Atsbi-Womberta, Ganta-Afeshum, Gulo-Mekeda, and Saesie-TsaedaEmba. Elevation ranges from 1,500 to 3,280 meters above sea level, with three traditional agro-ecological zones: highland (above 2,300 meters), midland (1,500 to 2,300 meters), and lowland (below 1,500 meters) (Hurni, 1998). The climate of the study area is semi-arid, featuring a main rainy season from June to September, known locally as *"Kiremt"*, and a shorter rainy season from February to May, called *"Belg"*. Rainfall is highly variable due to the region's complex topography. The average annual rainfall of the study area ranges between 554 and 617 mm, with mean annual temperatures of 17–19.2°C (Berhe et al., 2023).

For this study, the Agulae, Suluh, and Genfel watersheds of the eastern Tigray zone were selected considering factors like high population growth, urbanization, and small-scale irrigation practices (Fig. 1-1). Farming in this area primarily relies on rain-fed agriculture, with common crops of teff, wheat, barley, maize, sorghum, and pulses. However, household-level irrigation practice has grown significantly in recent years (Nyssen et al., 2010). Dominant soil types include sandy clay loam (42%), loam (33%), and clay loam (22%).

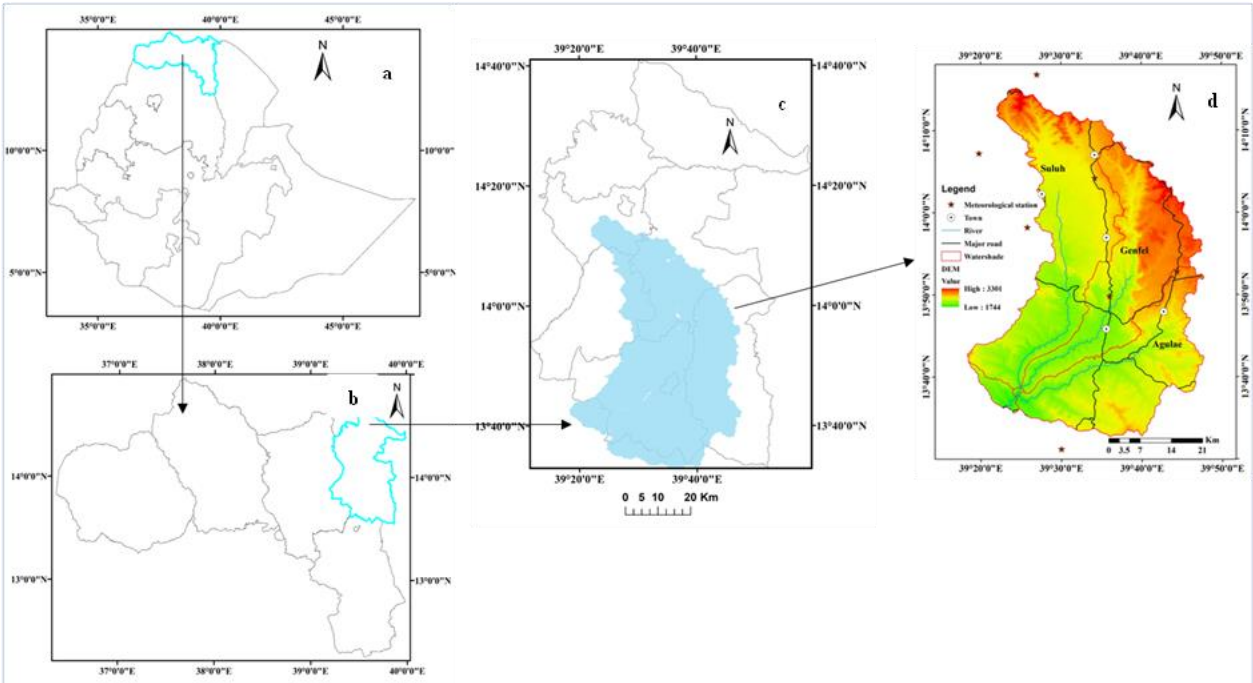

Figure 1-1: Location of the study area, watersheds and stations a. Ethiopia and Tigray region, b.Tigray and Eastern Zone, c. Eastern Zone and selected watersheds, d. Selected Watersheds

1.5.2 Methodological framework

This study utilized various models and tools to evaluate the impacts of climate change on water availability, crop growing season characteristics, and crop and irrigation water requirements in the Eastern Zone of the Tigray region, Northern Ethiopia. The assessment began with climate characterization using historical data, where temperature and precipitation patterns were analyzed. Projections were derived from the latest Coupled Model Intercomparison Project Phase 6 (CMIP6) General Circulation Models (GCMs), utilizing a 35-year (1980 to 2014) baseline daily weather dataset.

Given that GCMs are typically operated at a coarse spatial resolution, the delta statistical downscaling method was employed to refine these projections, allowing for a more accurate representation of local climatic conditions. The downscaled outputs served as critical input for the Hydrologic Engineering Center's Hydrologic Modeling System (HEC-HMS), which simulated surface water availability within the study area.

In addition, the spatial distribution of crop water requirement was assessed to understand how water requirements varied across different locations within the study area. To integrate both supply and demand aspects of water resources, the Water Evaluation and Planning (WEAP) tool developed by the Stockholm Environment Institute was utilized. This tool modeled water availability while considering the competing sectors of supply and demand in the study area.

The hydrological dynamics obtained from the HEC-HMS modeling, along with irrigation water demand data and inputs from other relevant sectors, fed into the WEAP model. This comprehensive approach enabled a scenario-based analysis of water supply and demand within the watershed, providing insights into effective water resource management strategies. The overall methodological framework that served as a guide for this research is presented in Figure 1-2.

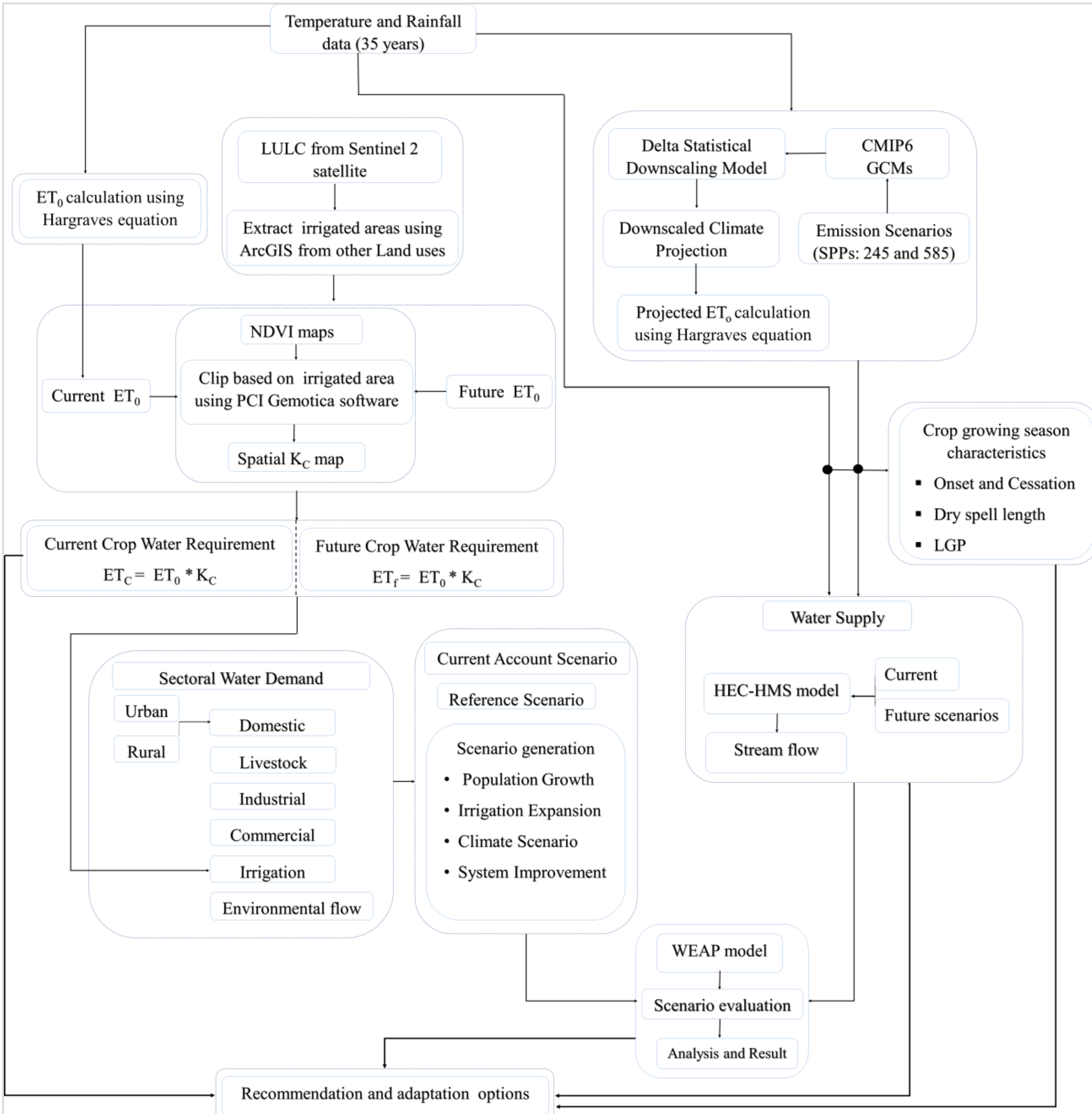

Figure 1-2: Methodological framework of the study

1.6 Organization of the dissertation

This dissertation is organized into eight chapters, each addressing a distinct aspect of the research:

Chapter one introduces the study, offering background information, the rationale, and outlining the research questions and objectives,

Chapter two presents a comprehensive literature review covering critical and relevant topics such as climate and hydrological modeling, crop water requirements, the effects of climate change on Ethiopia—specifically on crop yields and water resources in Tigray—and adaptation strategies,

Chapter three provides an analysis of long-term trends and variability in temperature, rainfall, and crop growth season characteristics, focusing on historical data,

Chapter four builds on Chapter three by examining how climate change scenarios affect temperature, rainfall, and crop growth season characteristics,

Chapter five evaluates how climate change influences crop water requirements,

Chapter six assesses the impact of climate change on water resources, with a primary focus on surface water availability,

Chapter seven analyzes water demand and supply using a water allocation model, and

Chapter eight summarizes the synthesis of all chapters. It presents the key findings, discusses their implications, and offers recommendations to strengthen resilience in the face of climate change.

References

Abrha, M. G. (2015). Local climate trends and farmers' perceptions in Southern Tigray, Northern Ethiopia. *International Journal of Environment and Sustainability*, *4*(3).

Aragie, E. A. (2013). Climate change, growth, and poverty in Ethiopia. *Texas Univ at Austin*.

Araya, A., & Stroosnijder, L. (2010). Effects of tied ridges and mulch on barley (Hordeum vulgare) rainwater use efficiency and production in Northern Ethiopia. *Agricultural water management*, *97*(6), 841-847.

Awulachew, S. B., Erkossa, T., & Balcha, Y. (2011). *Irrigation and Water for Sustainable Development: Proceedings of the Second Forum December 15-16, 2008, Addis Ababa, Ethiopia*. IWMI.

Conway & Schipper. (2011). Adaptation to climate change in Africa: Challenges and opportunities identified from Ethiopia. *Global environmental change*, *21*(1), 227-237.

Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., & Yesuf, M. (2009). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global environmental change*, *19*(2), 248-255.

Dile, Y. T., Berndtsson, R., & Setegn, S. G. (2013). Hydrological response to climate change for gilgel abay river, in the lake tana basin-upper blue Nile basin of Ethiopia. *PloS one*, *8*(10), e79296.

Gebre, S. L., & Ludwig, F. (2015). Hydrological response to climate change of the upper blue Nile River Basin: based on IPCC fifth assessment report (AR5). *Journal of Climatology & Weather Forecasting*, *3*(01), 1-15.

Gebrehiwot, T., & van der Veen, A. (2013). Assessing the evidence of climate variability in the northern part of Ethiopia. *Journal of development and agricultural economics*, *5*(3), 104-119.

Gebrehiwot, T., Van der Veen, A., & Maathuis, B. (2011). Spatial and temporal assessment of drought in the Northern highlands of Ethiopia. *International Journal of Applied Earth Observation and Geoinformation*, *13*(3), 309-321.

Gebremicael, T. G., Mohamed, Y. A., & Hagos, E. Y. (2017). Temporal and spatial changes of rainfall and streamflow in the Upper Tekezē–Atbara river basin, Ethiopia. *Hydrology and Earth System Sciences*, *21*(4), 2127-2142.

Hayelom, B., Chen, Y., Marsie, Z., & Negash, M. (2017). Temperature and precipitation trend analysis over the last 30 years in Southern Tigray Regional State, Ethiopia.

Hurni, H. (1998). Agroecological belts of Ethiopia. *Explanatory notes on three maps at a scale of*, *1*(1,000,000).

Hussen, B., Mekonnen, A., & Pingale, S. M. (2018). Integrated water resources management under climate change scenarios in the sub-basin of Abaya-Chamo, Ethiopia. *Modeling Earth Systems and Environment*, *4*, 221-240.

IPCC. (2014). *Climate change 2014-impacts, adaptation and vulnerability, part A: global and sectoral aspects*. Cambridge University Press.

IPCC, C. C. (2021). Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the IPCC. Cambridge University Press. *(No Title)*.

Mcsweeney, C., New, M., Lizcano, G., & Lu, X. (2010). The UNDP Climate Change Country Profiles: Improving the accessibility of observed and projected climate information for studies of climate change in developing countries. *Bulletin of the American Meteorological Society*, *91*(2), 157-166.

Mekasha, A., Tesfaye, K., & Duncan, A. J. (2014). Trends in daily observed temperature and precipitation extremes over three Ethiopian eco-environments. *International Journal of Climatology*, *34*(6).

Meles, K., Maria, A., Tesfamichael, N., Sunil, S., Francis, K., & Lynne, M. (1997). Coping with low and erratic rainfall in the Eastern zone of Tigray.

Meze-Hausken, E. (2004). Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. *Climate research*, *27*(1), 19-31.

NMA. (2007). Climate change national adaptation programme of action (Napa) of Ethiopia. *National Meteorological Services Agency, Ministry of Water Resources, Federal Democratic Republic of Ethiopia, Addis Ababa*.

Nyssen, J., Clymans, W., Descheemaeker, K., Poesen, J., Vandecasteele, I., Vanmaercke, M., Zenebe, A., Van Camp, M., Haile, M., & Haregeweyn, N. (2010). Impact of soil and water conservation measures on catchment hydrological response—a case in north Ethiopia. *Hydrological processes*, *24*(13), 1880-1895.

Orkodjo, T. P., Kranjac-Berisavijevic, G., & Abagale, F. K. (2022). Impact of climate change on future availability of water for irrigation and hydropower generation in the Omo-Gibe Basin of Ethiopia. *Journal of Hydrology: Regional Studies*, *44*, 101254.

Reda, A. G., & Mamo, G. (2013). Detection of Climate Trends Over Ethiopia Using Geospatial Techniques. *Journal of Meteorology and Climate Science*, *11*(1), 10-17.

Seleshi, Y., & Zanke, U. (2004). Recent changes in rainfall and rainy days in Ethiopia. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *24*(8), 973-983.

Taye, M. T., Dyer, E., Hirpa, F. A., & Charles, K. (2018). Climate change impact on water resources in the Awash basin, Ethiopia. *Water*, *10*(11), 1560.

Teka, K., Van Rompaey, A., Poesen, J., Welday, Y., & Deckers, J. (2012). Impact of climate change on small-holder farming: A case of Eastern Tigray, Northern Ethiopia. *African Crop Science Journal*, *20*, 337-347.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Climate models and Climate Change Scenarios

Climate models, often referred to as General Circulation Models (GCMs), employ mathematical equations to simulate the Earth's climate system, encompassing both global and regional scales (Schneider et al., 2017). The development and execution of these models involve a complex process of identifying and quantifying the interactions within the Earth's systems such as oceans, the atmosphere, and land and resolving these processes through advanced equations using high-performance supercomputers (Palmer, 2020).

Climate models depend on specific assumptions when predicting future climate developments. These assumptions are integrated into climate change scenarios, which generate climate projections and serve as the foundation for evaluating the risks and opportunities associated with future climate change, as well as for formulating adaptation strategies (Masson-Delmotte et al., 2023).

Climate change scenarios describe potential future climate conditions and are used to evaluate impacts and guide planning efforts (Rosentrater, 2010; Von Storch, 2008). Rather than serving as predictions, they represent plausible, coherent visions of alternative futures (Von Storch, 2008). These scenarios assist stakeholders in exploring options to address uncertain futures and in implementing strategies to prevent undesirable outcomes. They can be derived from general circulation models, climate spatial analogs, or historical climate patterns (Mortsch & Quinn, 1996). While scenarios are valuable for assessing climate change impacts, they face challenges, such as managing uncertainties, particularly at local and national levels, and encouraging behavioral changes (Rosentrater, 2010). Continued refinement and improvements in model accuracy are essential for enhancing conservation efforts (Liu et al., 2023).

2.1.1 Climate Modelling Intercomparison Project Models (CMIPs)

The Coupled Model Intercomparison Project (CMIP) is an international initiative aimed at enhancing the understanding of climate change. By employing a multi-model approach, CMIP facilitates the assessment and improvement of climate model simulations, providing insights into past, present, and future climate patterns. Additionally, it assists researchers in exploring potential climate changes at both global and regional scales while ensuring open access to data for a growing global research community (Eyring et al., 2016; Taylor et al., 2012).

Coordinated by the World Climate Research Programme, CMIP systematically evaluates the capabilities of global coupled climate models, which are essential for projecting future climate changes and informing policy decisions (Meehl et al., 1997). These models typically incorporate components of the atmosphere, ocean, sea ice, and land surface (Eyring et al., 2016). Since its inception, CMIP has evolved with advancements such as reduced reliance on flux adjustments and improved simulations of El Niño phenomena (Meehl et al., 2005). Specialized intercomparison projects, including AMIP (Atmospheric), OMIP (Ocean), PMIP (Paleo), and C4MIP (Climate-Carbon Cycle), focus on distinct aspects of climate modelling, contributing to model development and refinement while recognizing that no single model excels across all domains (Stocker, 2011).

CMIP has progressed through multiple phases, each yielding new insights into climate model development and addressing specific scientific objectives. CMIP2, which commenced in 2001, was an early effort to standardize climate model comparisons, setting the groundwork for subsequent model intercomparisons. This phase concentrated on understanding climate variability and change by comparing the responses of different models to various forcing scenarios. While CMIP2 included contributions from several global coupled climate models, its scope was somewhat limited compared to later phases such as CMIP5 and CMIP6. Nonetheless, CMIP2 significantly advanced the knowledge of climate dynamics and served as a precursor to more complex intercomparisons that followed, despite being constrained by the model capabilities available at the time (Stocker, 2011).

CMIP3, the third phase of the Coupled Model Intercomparison Project, significantly contributed to climate science by supporting the IPCC's Fourth Assessment Report (AR4). This phase evaluated climate models based on various greenhouse gas emission scenarios, known as SRES. CMIP3 focused on future climate projections, including temperature and sea level rise, under different levels of greenhouse gas concentrations. It established a vital framework for understanding potential climate futures and enhanced the IPCC's assessment of climate change. The simulations conducted during this phase also facilitated more robust comparisons of model performance, significantly contributing to the conclusions of AR4 regarding global warming and its impacts. The findings from CMIP3 are frequently cited for their essential role in improving our understanding of climate dynamics and informing policy formulation (IPCC, 2008; Meehl et al., 2005).

CMIP5, which provided critical contributions to the IPCC's Fifth Assessment Report (AR5), represented a notable advancement in climate modelling. This phase was distinguished by the introduction of Representative Concentration Pathways (RCPs), a new set of greenhouse gas concentration pathways that offered more refined climate projections than earlier models (Van Vuuren et al., 2011). The RCPs encompassed a broad spectrum of emission scenarios, from low to high greenhouse gas concentrations, providing a comprehensive foundation for evaluating future climate impacts.

In addition to incorporating the RCPs, CMIP5 featured significant improvements over previous phases, particularly regarding aerosol treatment, land-use dynamics, and climate feedback mechanisms (Seneviratne et al., 2013). These advancements enabled more detailed and accurate simulations of climate processes, including temperature changes, precipitation patterns, and the effects of human activities on the climate system. CMIP5 also increased the overall complexity of climate models, facilitating better projections and more precise assessments of potential future climate scenarios (Seneviratne et al., 2013).

The latest phase of the Coupled Model Intercomparison Project (CMIP), known as CMIP6, builds upon its predecessor, CMIP5. CMIP6 introduces more detailed climate scenarios focusing on both global and regional projections. A noteworthy advancement in CMIP6 is the incorporation of new specialized sub-projects (MIPs), such as the Ocean Model Intercomparison Project (OMIP), the Carbon Cycle Model Intercomparison Project (C4MIP), and the Paleoclimate Model

Intercomparison Project (PMIP), which address specific components of the climate system, including the carbon cycle, ocean processes, and past climate dynamics (Eyring et al., 2016).

Moreover, CMIP6 incorporates the Shared Socioeconomic Pathways (SSPs), allowing for a more comprehensive exploration of future climate scenarios under diverse socioeconomic conditions. These models also feature improved representations of critical physical processes, such as cloud dynamics and ocean circulation, which enhance the accuracy of future climate projections (Kikstra et al., 2022).

2.2.2 Climate change scenarios

Climate change scenarios like the Representative Concentration Pathways (RCPs) in CMIP5 and Shared Socioeconomic Pathways (SSPs) in CMIP6 model future climate conditions based on varying levels of greenhouse gas emissions. These scenarios are crucial for evaluating the potential impacts of climate change on resources like water and crop yields under different projections of temperature and precipitation (O'Neill et al., 2017). The RCPs and SSPs provide valuable frameworks for exploring future scenarios and understanding the relationships between socio-economic factors and climate change impacts (Van Vuuren et al., 2011).

In 2000, the IPCC released its Special Report on Emissions Scenarios (SRES), which outlined four distinct scenario families (A1, A2, B1, B2) to represent a range of potential future conditions. The A1 scenario envisions rapid economic growth, a mid-century peak in global population, and significant technological advancement, with subgroups focusing on fossil fuels (A1FI), non-fossil energy (A1T), and balanced energy sources (A1B). In contrast, the A2 scenario depicts a more diverse world characterized by continuous population growth, slower development, and elevated emissions due to regional self-reliance and gradual technology adoption. The B1 scenario anticipates a transition to a global, sustainable economy with low emissions, whereas B2 emphasizes moderate growth, regional sustainability, and environmental protection, resulting in emission levels that fall between those of A2 and B1 (Nakicenovic et al., 2000). Each scenario family represents distinct pathways influenced by population growth, economic development, and technological change, providing a range of possible future emissions and climate outcomes.

Later, the scientific community established a new set of climate scenarios known as the Representative Concentration Pathways (RCPs) to better model future climate conditions. These pathways represent different levels of radiative forcing, measured in watts per square meter (W/m^2), that are expected to result from varying greenhouse gas emissions by the year 2100 (Van Vuuren et al., 2011). The RCPs help in projecting the effects of these emissions on global temperatures and other climate variables. The four main RCPs range from RCP 2.6, which assumes significant mitigation of emissions, to RCP 8.5, often referred to as the worst-case scenario due to its higher emission projections (Kharin et al., 2013). These pathways provide essential inputs for climate models used in the Intergovernmental Panel on Climate Change's (IPCC) assessments, including those from the Fifth Assessment Report (AR5) and beyond (Stocker et al., 2014).

In Coupled Model Intercomparison Project Phase 6 (CMIP6), the Shared Socioeconomic Pathways (SSPs) play a key role in projecting future climate change scenarios. These pathways were designed to complement the Representative Concentration Pathways (RCPs), which primarily focus on greenhouse gas emissions levels. SSPs provide a framework for analyzing diverse future socioeconomic conditions that could be influenced by emissions, land use, and climate policies to better assess vulnerability and adaptation (Ebi et al., 2014). There are five SSPs: SSP1 (Sustainability), SSP2 (Middle of the Road), SSP3 (Regional Rivalry), SSP4 (Inequality), and SSP5 (Fossil-fuelled Development). Each of these represent different global development pathways based on factors like economic growth, population dynamics, and technological progress (O'Neill et al., 2014).

2.2 Hydrological models

Hydrological models are vital tools used to simulate components of the water cycle, aiding in water resource management, flood prediction, and assessing climate change impacts (Ibrahim & Dan'azumi, 2020; Ogden, 2021). These models are broadly classified into different categories, including physically-based, conceptual, empirical, and hybrid models (Kuppusamy et al., 2021), or as analytical, conceptual, data-driven, and process-based models (Ogden, 2021). Another common classification is based on spatial representation, where models are divided into lumped or distributed, and on the type of uncertainty, where they are deterministic or stochastic (Ibrahim & Dan'azumi, 2020; Jajarmizadeh et al., 2012).

The choice of model depends on factors such as the specific hydrological problem being addressed, the availability and quality of data, computational resources, and economic or social constraints (Ibrahim & Dan'azumi, 2020). Popular hydrological models include Water Evaluation and Planning System (WEAP), Storm Water Management Model (SWMM), Hydrologic Engineering Center-Hydrologic Modelling System (HEC-HMS), Hydrologic Engineering Center-River Analysis System (HEC-RAS), and Hydrologic Engineering Center-Reservoir System Simulation (HEC-ResSim), each of which serves different purposes, such as simulating surface runoff, river flow, or reservoir operations. Despite the clear distinctions in categorization, many models possess overlapping features, which can complicate their classification (Jajarmizadeh et al., 2012). Additionally, all hydrological models, regardless of type, require some form of spatial or temporal discretization, and they are lumped at a certain scale (Ogden, 2021). In recent years, the integration of advanced techniques such as machine learning and remote sensing has further enhanced the accuracy and applicability of hydrological models in addressing complex water-related challenges (Hasan et al., 2024; Shen et al., 2018).

2.3 Crop Water Requirements

Crop Water Requirement (CWR) represents the total volume of water necessary for a crop to complete its life cycle from planting to maturity under optimal agronomic and climatic conditions. Accurate estimation of CWR is fundamental for addressing global food security challenges, enhancing water use efficiency, and mitigating environmental impacts associated with excessive water use or mismanagement. Research on CWR is vital for improving irrigation management strategies, optimizing agricultural productivity, and fostering sustainable water resource utilization (LingLing et al., 2005).

Several approaches for estimating CWR vary in complexity and applicability: (i) Empirical Approaches: these methods rely on statistical relationships between CWR and climatic variables, such as temperature, solar radiation, and precipitation. Examples include the Blaney-Criddle and Hargreaves-Samani equations, which are relatively simple but less precise under diverse environmental conditions (Dixit et al., 2024); (ii) Analytical Approaches: these involve applying physical principles of water balance, energy balance, and plant physiology to estimate CWR (Mehta & Pandey, 2016; Nithya & Shivapur, 2016; Yadav et al., 2018). The Penman-Monteith equation, widely considered the standard method for evapotranspiration calculation, falls under this category due to its ability to integrate climatic and plant-related variables; (iii) Remote Sensing-Based Approaches: advancements in satellite technology enable the use of remote sensing data to estimate CWR at broader spatial and temporal scales. By analyzing vegetation indices, soil moisture, and evapotranspiration, remote sensing techniques offer valuable insights for large-scale agricultural water management (Calera, 2015; Calera et al., 2017; Peschechera et al., 2018; Spiliotopoulos et al., 2015); (iv) Simulation Modelling: dynamic crop growth simulation models, such as CROPWAT and Aqua Crop, integrate biophysical and environmental processes to provide detailed estimates of CWR. These models account for soil properties, crop types, and weather data, making them effective tools for scenario analysis and irrigation planning.

Despite the progress in developing these methods, significant challenges persist. Jiang (2005) underscores the difficulties in accurately modeling CWR for heterogeneous landscapes, which are influenced by varying soil types, topographies, and climatic conditions. Moreover, improving the precision of evapotranspiration estimation, particularly under changing climate scenarios, remains an active area of research (Lakhiar et al., 2024).

Future studies should focus on integrating machine learning and artificial intelligence into general crop management and CWR estimation methods to enhance predictive accuracy and scalability (Gul & Banday, 2024). Additionally, combining remote sensing with ground-based measurements and simulation models can provide a more comprehensive understanding of CWR dynamics, particularly in water-scarce regions (Wanniarachchi & Sarukkalige, 2022; Zhang et al., 2016).

2.4 Remote sensing-based crop water requirements

Remote sensing-based approaches have significantly advanced agricultural water management by offering accurate, timely, and spatially detailed estimates of crop water requirements (CWR). These methods utilize satellite technology, multispectral imagery, and geospatial analytics to monitor crop growth and evapotranspiration (ET) across diverse landscapes. High-resolution multispectral imagery is particularly valuable for precise monitoring of crop development and water use throughout the growing season, thereby supporting efficient irrigation planning (Calera, 2015; Calera et al., 2017).

Various studies have demonstrated the applicability of remote sensing in estimating CWR. For instance, Spiliotopoulos et al. (2015) used satellite-based energy balance models and NDVI data as inputs to the CropWat model to estimate daily CWR, linking vegetation indices with irrigation management tools. Similarly, Parmar et al. (2023) employed remote sensing and GIS techniques to estimate CWR for maize in Gujarat, India, highlighting the role of geospatial data in optimizing irrigation planning and water conservation. Barbagallo et al. (2004) emphasized the importance of high-resolution satellite data, such as Quick Bird, for assessing CWR in an orange orchard, demonstrating the value of fine-scale spatial monitoring in capturing heterogeneity.

Other studies have explored the use of Landsat imagery for broader agricultural applications. For example, El-Shirbeny et al. (2014) used Landsat 8 and NDVI to estimate ETc and water requirements for major crops in Egypt, showcasing the cost-effectiveness of remote sensing in large-scale agricultural assessments. Furthermore, remote sensing-derived vegetation indices have been utilized to estimate crop coefficients (Kc). Bashir et al. (2007) found that remote sensing-based Kc values provided superior accuracy for estimating ET and CWR for irrigated sorghum in Sudan's Gezira scheme, improving irrigation planning and reducing water wastage. The integration of remote sensing with models such as SEBAL and METRIC further enhances the precision of CWR estimates by combining geospatial data with biophysical and climatic parameters (Morari et al., 2020).

Remote sensing also offers significant advantages, including scalability for regional or global applications, frequent temporal monitoring of crop growth stages, and compatibility with advanced modelling frameworks. Emerging technologies, such as unmanned aerial vehicles (UAVs) equipped with multispectral sensors, cloud-based platforms like Google Earth Engine, and machine learning algorithms, are further advancing the potential of remote sensing for real-time CWR estimation (El Imanni et al., 2023; Ndlovu et al., 2021). However, challenges such as data availability in cloudy regions, resolution limitations, and the need for ground-based calibration persist (Ozdogan et al., 2010). Integrating remote sensing with Internet of Things (IoT) sensors, which gather and transmit environmental data, along with improved modelling techniques and region-specific studies in water-scarce areas like Ethiopia, can significantly improve sustainable irrigation management and boost agricultural productivity (Tegegne et al., 2019).

2.5 Impacts of climate change and variability

Climate change and variability in Ethiopia have caused severe consequences on agriculture, food security, and the environment. The country has experienced rising temperatures, changing rainfall patterns, and more frequent extreme weather events such as droughts and floods (Gezie, 2019; Zegeye, 2018). These climate shifts have led to desertification, biodiversity loss, and reduced agricultural productivity, with rainfall variability being a key factor affecting crop yields (Abeje & Alemayehu, 2019). Ethiopia's most vulnerable sectors to climate change include agriculture, roads, water, energy, and health (Ware, 2022).

The rainfall amount and duration in the main rainy season, *Kiremt* (June-September) has been decreasing, while significant variability is observed in the *Belg* (February-May/ FMAM), which is the short season (Teshome & Zhang, 2019). Regional differences in rainfall trends are also evident, with some areas experiencing increased rainfall and others facing a decline. By the late 21st century, precipitation in Ethiopia is projected to decrease by 25.5 mm annually on average (Zeray & Demie, 2015). Despite no significant national trend in annual rainfall, regional variations in seasonal rainfall are apparent (Gummadi et al., 2018).

Since the 2000s, over 38 million Ethiopians have experienced severe disruptions in their livelihoods due to climate-related crises (Demem, 2023). Moreover, by 2050, climate change is projected to reduce Ethiopia's GDP by 8-10% and result in food insecurity for 2.4 million people (Bezu, 2020). Hence, given the far-reaching impacts of climate change on Ethiopia's economy, agriculture, and food security, effective adaptation measures are essential. These may include strengthening climate-resilient agricultural practices, improving water resource management, and investing in infrastructure that can withstand extreme weather events. Moreover, policy frameworks that incorporate climate change mitigation and adaptation strategies at national and local levels are crucial for safeguarding livelihoods and ensuring sustainable development in the face of ongoing climate challenges.

2.5.1 Impacts of climate change on agriculture and crop yield

Agriculture in Ethiopia is particularly affected by increased temperatures, reduced and more variable rainfall, and frequent droughts and floods, which threaten food security, especially for vulnerable small-scale farmers (Mohammed, 2020). Climate change has led to reduced productivity and cultivable land for key crops such as maize and barley, while also negatively affecting the water sector by reducing soil moisture, groundwater, and streamflow due to higher evapotranspiration (Abebaw, 2020). Rainfall variability significantly impacts crop production in Ethiopia (Wubie, 2015).

Climate change and variability significantly impact agriculture and food security in Ethiopia's Tigray region. Numerous studies analyzing historical data show a clear upward trend in temperature, along with considerable variability and a declining trend in annual rainfall across different parts of the region (Araya et al., 2015; Hayelom et al., 2017). Further research presents a more complex picture that annual rainfall has remained relatively stable overall, *Kiremt* (summer) rainfall has significantly increased in the lowlands, while *Belg* (spring) rainfall has notably decreased in the highlands (example in Abrha & Simhadri, 2015).

Projections based on different global climate models (GCMs) and scenarios predict further increases in temperature and rainfall in the future. For example, projections for the southern zone of Tigray suggest that by the 2080s, maximum and minimum temperatures could rise by 5.9°C and 6.4°C, respectively, with precipitation increasing by 27% (Gebrekiros et al., 2015). Despite the increased rainfall, sorghum yields in this region are projected to decline by 5-24% under current sowing and management practices. Similarly, Abrha and Hagos (2022) also found that both temperature and precipitation are expected to rise under climate change scenarios.

In the Western lowlands of Tigray, climate change impacts on sesame production have been modeled under different sowing dates using historical and projected climate data. Niguse and Aleme (2015) found that sowing sesame on normal dates led to the highest yields, while late sowing resulted in yield decreases of up to 23.31% by the end of the century under the RCP8.5 scenario. Conversely, sowing on normal dates could increase yields by up to 33.1% under the RCP4.5 scenarios in the midterm.

In addition, climate projections by Gebresamuel et al. (2022) also suggest that the areas suitable for growing wheat and barley will shift to higher altitudes due to temperature increases, with their suitable areas potentially declining by 16-100%. However, sorghum and teff are projected to remain more stable under future climate conditions.

2.5.2 Impact of climate change on water resources

Climate change is expected to have a substantial impact on streamflow and water resources across Ethiopia, including the Tigray region. While some studies project overall increases in precipitation and temperature (Gebremeskel & Kebede, 2018b; Kidanemariam et al., 2020), others highlight the absence of consistent rainfall trends (Mesfin et al., 2018; Tesfaye et al., 2014b).

Tesfaye et al. (2014b) used statistical downscaling and water balance models to assess climate scenarios in the Geba catchment. Results indicated rising temperatures and decreased surface runoff by as much as 12.9% during the rainy season under high-emission scenarios by the 2080s. This analysis suggests that the warming projected by all GCMs across various scenarios could significantly lower annual runoff in the Geba catchment. Furthermore, Goitom et al. (2012) projected significant reductions in river flow, exacerbating water stress in the Tigray region.

Similarly, Mesfin et al. (2018) evaluated climate impacts on the Ilala watershed, showing temperature increases without significant rainfall shifts, and due to increase trend in temperature and evaporation loss for the future, projected a decline in surface runoff between 0.36% and 1.74% under different climate scenarios and time period.

In the Werii watershed of the Tekeze basin, Gebremeskel and Kebede (2018b) projected temperature rises, increased rainfall (24-25%), and greater groundwater recharge, yet with notable decreases in surface runoff (13-14%) by mid-century. This decrease in runoff is likely due to the implementation of exclosures and soil and water conservation measures within the Werii watershed. In contrast, Kidanemariam et al. (2020) anticipated a marked increase in streamflow of up to 35.6% by the end of century, reflecting varied temporal impacts.

Despite inconsistent rainfall trends, the majority of studies emphasize that increases in temperature and declines in surface runoff will significantly affect hydrological dynamics, such as groundwater recharge, base flow, and evapotranspiration. Consequently, the findings underscore the importance of adaptive water management strategies to mitigate the adverse impacts of climate variability on water security in Tigray and other Ethiopian regions.

2.6. Adaptation to climate change impact and variability

2.6.1 Definitions of adaptation to climate change impacts

Adaptation to climate change impacts has been defined in various ways across the literature, reflecting the diversity of contexts and approaches. According to the IPCC (2014), adaptation is described as "the process of adjustment to actual or expected climate and its effects, in order to moderate harm or exploit beneficial opportunities." This process involves changes in social, economic, and environmental practices to reduce vulnerability to climate impacts. Adaptation is further defined as "actions taken to help communities and ecosystems cope with changing climate conditions" (UNFCCC, 2007). The concepts emphasize actions undertaken at local, regional, and global levels. Moreover, some literature define adaptation as a "process of deliberate change in anticipation of or in reaction to external stimuli and stress," involving both reactive and proactive measures to adjust to climate variability (Smit & Wandel, 2006).

Although these definitions focus on reducing vulnerability and enhancing resilience, they differ in their emphasis on reactive versus proactive measures, the scales of action, and whether adaptation is perceived as a process or a set of actions.

2.6.1 Adaptation strategies on agriculture and food security

Adaptation strategies for agriculture and food security are vital for bolstering resilience against the impacts of climate change. Important approaches include enhanced water management, agroforestry practices, and crop diversification (Lipper et al., 2014).

Efficient water management is crucial for promoting sustainable agricultural practices amid climate variability. Techniques aimed at improving irrigation efficiency focus on minimizing water loss while maximizing crop yields. Methods like drip irrigation and precision agriculture optimize water usage, significantly increasing agricultural productivity and conserving water resources (Bhaduri et al., 2016). Additionally, rainwater harvesting systems enable to collect and store rainwater for agricultural purposes, which are particularly beneficial in drought-prone areas. The techniques effectively increase water availability for irrigation and reduces reliance on groundwater sources (Welderufael et al., 2013). Furthermore, developing drought-resistant crop varieties can alleviate the negative impacts of climate change on food production. Research by Nguyen et al. (1997) highlights the importance of breeding programs that enhance drought resistance in staple crops to secure food availability in arid regions.

Additionally, agroforestry and crop diversification serve as effective strategies for increasing resilience to climate variability and improving food security. Agroforestry involves the deliberate integration of agricultural and forestry practices, resulting in productive and sustainable land use that offers multiple benefits, such as better soil health, enhanced biodiversity, and increased resilience to climate extremes. Agroforestry systems not only boost food production but also contribute to essential ecosystem services (Garrity, 2012). Similarly, diversifying crop production mitigates risks by distributing the potential effects of climate variability across different crops. A study by Cohn et al. (2017) demonstrates that crop diversification enhances resilience to pests, diseases, and extreme weather events, ultimately leading to improved food security and livelihoods for farmers.

2.6.2 Adaptation strategies on water resources

There are two key adaptation strategies for water resources, which are integrated water resource management (IWRM) and infrastructure adjustments**.** IWRM is a holistic framework that promotes coordinated management of water, land, and related ecosystems to ensure sustainable use of water resources, especially under changing climate conditions (Agarwal et al., 2000). Key principles include integrating different water uses (agriculture, domestic, industrial), promoting stakeholder participation, and balancing environmental sustainability with human needs (Biswas, 2004; UNESCO, 2009).

Moreover, adaptation through infrastructure adjustments involves making changes to water-related infrastructure to mitigate the impacts of climate variability and change. This includes, building flood defenses using dikes, levees, and flood barriers to protect urban and rural areas from extreme rainfall and floods (Milly et al., 2008). Constructing dams using dams and reservoirs for water storage, flood control, and irrigation, although they must be designed considering environmental impacts (IPCC, 2014; Milly et al., 2008), and Sustainable Urban Drainage Systems (SUDS) using green infrastructure solutions such as wetlands, permeable pavements, and bio-retention systems that manage urban water runoff sustainably (Fletcher et al., 2015).

2.6.3 Multi-scale adaptation strategies

Adaptation strategies for climate change and variability are implemented at different levels, from local to global, with each level employing distinct approaches and methods to enhance climate resilience and sustainability. At the local level, Community-Based Adaptation (CBA) is a bottom-up approach that draws on local knowledge, skills, and practices to improve community resilience against climate risks. Its key focus is on involving local communities in identifying, planning, and executing strategies that address their specific vulnerabilities. Ayers and Forsyth (2009) highlight that CBA connects climate adaptation with development goals, with a strong emphasis on local knowledge and community involvement. Similarly, Reid and Schipper (2014) highlight that building a knowledge base on CBA tools and scaling up of practices presents challenges, but also provides opportunities to enhance climate resilience by connecting local actions to broader policy frameworks.

At the national level, adaptation strategies are driven by policies, regulations, and national plans that address climate risks across key sectors such as agriculture, water, energy, and infrastructure. National Adaptation Plans (NAPs), introduced under the UNFCCC, are vital tools for countries to assess and address medium- and long-term adaptation needs. The UNFCCC (2012) guidelines provide comprehensive instructions on how to integrate adaptation strategies into national development planning. Ethiopia's Climate Resilient Green Economy, CRGE (2011) exemplifies a national approach that aligns adaptation with economic development goals, emphasizing resilience and low-carbon growth in sectors like agriculture, water, and energy.

At the international level, there are frameworks include the United Nations Framework Convention on Climate Change (UNFCCC) and the Paris Agreement guide global adaptation efforts. The Paris Agreement, UN (2015) stresses the importance of enhancing adaptive capacities through Nationally Determined Contributions (NDCs) and international collaboration (Article 7). Regional initiatives, like the AU (2014) Strategy on Climate Change, encourage regional cooperation in adaptation, with a focus on building resilience in vulnerable sectors such as agriculture, water, and energy.

References

Abebaw, W. A. (2020). Review on climate change adaptation and mitigation practices in Ethiopian agriculture sector. *Black Sea Journal of Agriculture*, *3*(4), 340-343.

Abeje, A., & Alemayehu, M. (2019). Impacts of Climate Change on Crop Production and Its Adaptation and Mitigation Strategies in Ethiopia.

Abrha, H., & Hagos, H. (2022). Characterization of changing trends of baseline and future predicted precipitation and temperature of Tigray, Ethiopia. *Journal of Agrometeorology*.

Agarwal, A., de los Angeles, M. S., Bhatia, R., Chéret, I., Davila-Poblete, S., Falkenmark, M., Gonzalez-Villarreal, F., Jønch-Clausen, T., Aït Kadi, M., & Kindler, J. (2000). *Integrated water resources management*. Global water partnership Stockholm.

Araya, A., Hoogenboom, G., Luedeling, E., Hadgu, K. M., Kisekka, I., & Martorano, L. G. (2015). Assessment of maize growth and yield using crop models under present and future climate in southwestern Ethiopia. *Agricultural and forest Meteorology*, *214*, 252-265.

AU. (2014). Draft African Union strategy on climate change. *African Union, May*.

Ayers, J., & Forsyth, T. (2009). Community-based adaptation to climate change. *Environment: science and policy for sustainable development*, *51*(4), 22-31.

Barbagallo, S., Consoli, S., D'Urso, G., Gaggia, R. G., & Toscano, A. (2004). Remote sensing of crop water requirements in orange orchards using high-spatial-resolution sensors. Remote Sensing for Agriculture, Ecosystems, and Hydrology V,

Bashir, M., Hata, T., Tanakamaru, H., Abdelhadi, A., & Tada, A. (2007). Remote sensing derived crop coefficient for estimating crop water requirements for irrigated sorghum in the Gezira scheme, Sudan. *Journal of Environmental Informatics*, *10*(1), 47-54.

Bezu, A. (2020). Analyzing impacts of climate variability and changes in Ethiopia: A review. *American Journal of Modern Energy*, *6*(3), 65-76.

Bhaduri, A., Bogardi, J., Siddiqi, A., Voigt, H., Vörösmarty, C., Pahl-Wostl, C., Bunn, S. E., Shrivastava, P., Lawford, R., & Foster, S. (2016). Achieving sustainable development goals from a water perspective. *Frontiers in Environmental Science*, *4*, 64.

Biswas, A. K. (2004). Integrated water resources management: a reassessment: a water forum contribution. *Water international*, *29*(2), 248-256.

Calera, A. (2015). Remote Sensing for Crop Water Management. *Agrociencia Uruguay*, *19*(3), 77-77.

Calera, A., Campos, I., Osann, A., D'Urso, G., & Menenti, M. (2017). Remote sensing for crop water management: From ET modelling to services for the end users. *Sensors*, *17*(5), 1104.

Cohn, A. S., Newton, P., Gil, J. D., Kuhl, L., Samberg, L., Ricciardi, V., Manly, J. R., & Northrop, S. (2017). Smallholder agriculture and climate change. *Annual Review of Environment and Resources*, *42*(1), 347-375.

CRGE. (2011). Ethiopia's climate-resilient green Economy (CRGE). *Federal Democratic Republic of Ethiopia, Addis Ababa, Ethiopia*, *188*.

Demem, M. S. (2023). Impact and adaptation of climate variability and change on small-holders and agriculture in Ethiopia: A review. *Heliyon*, *9*.

Ebi, K. L., Hallegatte, S., Kram, T., Arnell, N. W., Carter, T. R., Edmonds, J., Kriegler, E., Mathur, R., O'Neill, B. C., & Riahi, K. (2014). A new scenario framework for climate

change research: background, process, and future directions. *Climatic change*, *122*, 363-372.
El-Shirbeny, M. A., Ali, A.-E. M., & Saleh, N. H. (2014). Crop water requirements in Egypt using remote sensing techniques. *Journal of Agricultural Chemistry and Environment*, *3*(2), 57-65.
El Imanni, H. S., El Harti, A., Bachaoui, E. M., Mouncif, H., Eddassouqui, F., Hasnai, M. A., & Zinelabidine, M. I. (2023). Multispectral UAV data for detection of weeds in a citrus farm using machine learning and Google Earth Engine: Case study of Morocco. *Remote Sensing Applications: Society and Environment*, *30*, 100941.
example in Abrha, M. G., & Simhadri, S. (2015). Effects of rainfall variability on production of five major cereal crops in Southern Tigray, Northern Ethiopia.
Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E. (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization. *Geoscientific Model Development*, *9*(5), 1937-1958.
Fletcher, T. D., Shuster, W., Hunt, W. F., Ashley, R., Butler, D., Arthur, S., Trowsdale, S., Barraud, S., Semadeni-Davies, A., & Bertrand-Krajewski, J.-L. (2015). SUDS, LID, BMPs, WSUD and more–The evolution and application of terminology surrounding urban drainage. *Urban water journal*, *12*(7), 525-542.
Garrity, D. (2012). *Agroforestry and the future of global land use*. Springer.
Gebrekiros, G., Araya, A., & Yemane, T. (2015). Modeling Impact of Climate Change and Variability on SorghumProduction in Southern Zone of Tigray, Ethiopia. *Journal of Earth Science & Climatic Change*, *7*, 1-10.
Gebremeskel, G., & Kebede, A. (2018). Estimating the effect of climate change on water resources: Integrated use of climate and hydrological models in the Werii watershed of the Tekeze river basin, Northern Ethiopia. *Agriculture and Natural Resources*, *52*, 195-207.
Gebresamuel, G., Abrha, H., Hagos, H., Elias, E., & Haile, M. (2022). Empirical modeling of the impact of climate change on altitudinal shift of major cereal crops in South Tigray, Northern Ethiopia. *Journal of Crop Improvement*, *36*(2), 169-192.
Gezie, M. (2019). Farmer's response to climate change and variability in Ethiopia: A review. *Cogent Food & Agriculture*, *5*.
Goitom, H., Smedt, F. D., Yohannes, T. G., Walraevens, K., Gebrehiwot, K., Bauer, H., & Deckers, J. (2012). Modeling Climate Change Impact in the Geba Basin, Ethiopia.
Gul, D., & Banday, R. U. Z. (2024). Transforming crop management through advanced AI and machine learning: Insights into innovative strategies for sustainable agriculture. *AI, Computer Science and Robotics Technology*.
Gummadi, S., Rao, K., Seid, J., Legesse, G., Kadiyala, M. D. M., Takele, R., Amede, T., & Whitbread, A. M. (2018). Spatio-temporal variability and trends of precipitation and extreme rainfall events in Ethiopia in 1980–2010. *Theoretical and Applied Climatology*, *134*, 1315-1328.
Hasan, F., Medley, P., Drake, J., & Chen, G. (2024). Advancing Hydrology through Machine Learning: Insights, Challenges, and Future Directions Using the CAMELS, Caravan, GRDC, CHIRPS, PERSIANN, NLDAS, GLDAS, and GRACE Datasets. *Water*.

Hayelom, B., Chen, Y., Marsie, Z., & Negash, M. (2017). Temperature and precipitation trend analysis over the last 30 years in Southern Tigray Regional State, Ethiopia.

Ibrahim, U. A., & Dan'azumi, S. (2020). An Overview of Some Hydrological Models in Water Resources Engineering Systems. *Arid Zone Journal of Engineering, Technology and Environment*, *16*, 285-292.

IPCC. (2008). Synthesis report. *Climate Change 2007. Working Groups I, II and III to the Fourth Assessment*.

IPCC. (2014). *Climate change 2014-impacts, adaptation and vulnerability, part A: global and sectoral aspects*. Cambridge University Press.

Jajarmizadeh, M., Harun, S., & Salarpour, M. (2012). A review on theoretical consideration and types of models in hydrology. *Journal of Environmental Science and Technology*, *5*(5), 249-261.

Kharin, V. V., Zwiers, F. W., Zhang, X., & Wehner, M. (2013). Changes in temperature and precipitation extremes in the CMIP5 ensemble. *Climatic change*, *119*, 345-357.

Kidanemariam, S., Goitom, H., & Desta, Y. (2020). Coupled application of R and WetSpa models for assessment of climate change impact on streamflow of Werie Catchment, Tigray, Ethiopia. *Journal of Water and Climate Change*.

Kikstra, J. S., Nicholls, Z. R., Smith, C. J., Lewis, J., Lamboll, R. D., Byers, E., Sandstad, M., Meinshausen, M., Gidden, M. J., & Rogelj, J. (2022). The IPCC Sixth Assessment Report WGIII climate assessment of mitigation pathways: from emissions to global temperatures. *Geoscientific Model Development*, *15*(24), 9075-9109.

Kuppusamy, M., Kothandaraman, S., & Pandi, D. (2021). Hydrological models: a review. *International Journal of Hydrology Science and Technology*.

Lakhiar, I. A., Yan, H., Zhang, C., Zhang, J., Wang, G., Deng, S., Syed, T. N., Wang, B., & Zhou, R. (2024). A review of evapotranspiration estimation methods for climate-smart agriculture tools under a changing climate: vulnerabilities, consequences, and implications. *Journal of Water and Climate Change*, jwc2024048.

LingLing, M., CheSheng, Z., LingLi, T., & XiaoGuang, J. (2005). Review and prospect on the study progress in crop water requirements.

Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., Caron, P., Cattaneo, A., Garrity, D., & Henry, K. (2014). Climate-smart agriculture for food security. *Nature climate change*, *4*(12), 1068-1072.

Liu, H., Li, P., Peng, C., Liu, C., Zhou, X., Deng, Z., Zhang, C., & Liu, Z. (2023). Application of climate change scenarios in the simulation of forest ecosystems: an overview. *Environmental Reviews*, *31*(3), 565-588.

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., & Gomis, M. (2023). IPC 2021. Summary for Policymakers. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change.

Meehl, G. A., Boer, G. J., Covey, C., Latif, M., & Stouffer, R. J. (1997). Intercomparison makes for a better climate model. *Eos, Transactions American Geophysical Union*, *78*(41), 445-451.

Meehl, G. A., Covey, C., McAvaney, B., Latif, M., & Stouffer, R. J. (2005). Overview of the coupled model intercomparison project. *Bulletin of the American Meteorological Society*, *86*(1), 89-93.

Mehta, R., & Pandey, V. (2016). Crop water requirement (ETc) of different crops of middle Gujarat. *Journal of Agrometeorology*, *18*(1), 83-87.

Mesfin, H. S., Berhe, A. G., Gebretsadkan, T., & Zenebe, A. (2018). Modelling hydrological response under climate change scenarios using SWAT model: the case of Ilala watershed, Northern Ethiopia. *Modeling Earth Systems and Environment*, *4*(1), 437-449. https://doi.org/10.1007/s40808-018-0439-8

Milly, P. C., Betancourt, J., Falkenmark, M., Hirsch, R. M., Kundzewicz, Z. W., Lettenmaier, D. P., & Stouffer, R. J. (2008). Stationarity is dead: Whither water management? *Science*, *319*(5863), 573-574.

Mohammed, J. I. (2020). Surface Water Potential Assessment by Using HEC-HMS (Case Study Dabus Sub Basin, Abay/Nile Basin, Ethiopia). *International Journal of Energ y and Environmental Science*, *5*(6), 101.

Morari, F., Harb Rabia, A., Lo Presti, S., Gobbo, S., & Vellidis, G. (2020). Remote Sensing of Evapotranspiration Using SEBAL and Metric Energy Balance Models for Enhanced Precision Agriculture Cotton Irrigation Scheduling. EGU General Assembly Conference Abstracts,

Mortsch, L. D., & Quinn, F. H. (1996). Climate change scenarios for Great Lakes Basin ecosystem studies. *Limnology and oceanography*, *41*(5), 903-911.

Nakicenovic, N., Alcamo, J., Davis, G., Vries, B. d., Fenhann, J., Gaffin, S., Gregory, K., Grubler, A., Jung, T. Y., & Kram, T. (2000). Special report on emissions scenarios.

Ndlovu, H. S., Odindi, J., Sibanda, M., Mutanga, O., Clulow, A., Chimonyo, V. G., & Mabhaudhi, T. (2021). A comparative estimation of maize leaf water content using machine learning techniques and unmanned aerial vehicle (UAV)-based proximal and remotely sensed data. *Remote Sensing*, *13*(20), 4091.

Nguyen, H. T., Babu, R. C., & Blum, A. (1997). Breeding for drought resistance in rice: physiology and molecular genetics considerations. *Crop Science*, *37*(5), 1426-1434.

Niguse, A., & Aleme, A. (2015). Modeling the impact of climate change on production of Sesame in Western zone of Tigray, Northern Ethiopia. *Journal of Climatology & Weather Forecasting*, *3*(3), 03.

Nithya, K., & Shivapur, A. (2016). Study on water requirement of selected crops under tarikere command area using CROPWAT. *Irrigation and Drainage Systems Engineering*, *5*(153), 1-4.

O'Neill, B. C., Kriegler, E., Ebi, K. L., Kemp-Benedict, E., Riahi, K., Rothman, D. S., Van Ruijven, B. J., Van Vuuren, D. P., Birkmann, J., & Kok, K. (2017). The roads ahead: Narratives for shared socioeconomic pathways describing world futures in the 21st century. *Global environmental change*, *42*, 169-180.

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., Mathur, R., & Van Vuuren, D. P. (2014). A new scenario framework for climate change research: the concept of shared socioeconomic pathways. *Climatic change*, *122*, 387-400.

Ogden, F. L. (2021). Geohydrology: Hydrological Modeling. *Encyclopedia of Geology*.

Ozdogan, M., Yang, Y., Allez, G., & Cervantes, C. (2010). Remote sensing of irrigated agriculture: Opportunities and challenges. *Remote Sensing*, *2*(9), 2274-2304.

Palmer, T. (2020). A vision for numerical weather prediction in 2030. *arXiv preprint arXiv:2007.04830*.

Parmar, S. H., Patel, G., & Tiwari, M. (2023). Assessment of crop water requirement of maize using remote sensing and GIS. *Smart Agricultural Technology*, *4*, 100186.
Peschechera, G., Tarantino, E., & Fratino, U. (2018). Crop water requirements estimation at irrigation district scale from remote sensing: a comparison between MODIS ET product and the analytical approach. Sixth International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2018),
Reid, H., & Schipper, E. L. F. (2014). Upscaling community-based adaptation: An introduction to the edited volume. In *Community-Based Adaptation to Climate Change* (pp. 3-21). Routledge.
Rosentrater, L. D. (2010). Representing and using scenarios for responding to climate change. *Wiley Interdisciplinary Reviews: Climate Change*, *1*(2), 253-259.
Schneider, T., Lan, S., Stuart, A., & Teixeira, J. (2017). Earth system modeling 2.0: A blueprint for models that learn from observations and targeted high-resolution simulations. *Geophysical Research Letters*, *44*(24), 12,396-312,417.
Seneviratne, S. I., Wilhelm, M., Stanelle, T., van den Hurk, B., Hagemann, S., Berg, A., Cheruy, F., Higgins, M. E., Meier, A., & Brovkin, V. (2013). Impact of soil moisture-climate feedbacks on CMIP5 projections: First results from the GLACE-CMIP5 experiment. *Geophysical Research Letters*, *40*(19), 5212-5217.
Shen, C., Laloy, E., Elshorbagy, A., Albert, A., Bales, J., Chang, F.-J., Ganguly, S., Hsu, K.-l., Kifer, D., Fang, Z. N., Fang, K., Li, D., Li, X., & Tsai, W.-P. (2018). HESS Opinions: Incubating deep-learning-powered hydrologic science advances as a community. *Hydrology and Earth System Sciences*.
Smit, B., & Wandel, J. (2006). Adaptation, adaptive capacity and vulnerability. *Global environmental change*, *16*(3), 282-292.
Spiliotopoulos, M., Loukas, A., & Mylopoulos, N. (2015). A new remote sensing procedure for the estimation of crop water requirements. Third International Conference on Remote Sensing and Geoinformation of the Environment (RSCy2015),
Stocker, T. (2011). Model hierarchy and simplified climate models. *Introduction to Climate Modelling*, 25-51.
Stocker, T. F., Qin, D., Plattner, G.-K., Tignor, M. M., Allen, S. K., Boschung, J., Nauels, A., Xia, Y., Bex, V., & Midgley, P. M. (2014). Climate Change 2013: The physical science basis. contribution of working group I to the fifth assessment report of IPCC the intergovernmental panel on climate change.
Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*(4), 485-498.
Tegegne, T., Balcha, H. B., & Beyene, M. (2019). Internet of Things technology for agriculture in Ethiopia: a review. Information and Communication Technology for Development for Africa: Second International Conference, ICT4DA 2019, Bahir Dar, Ethiopia, May 28-30, 2019, Revised Selected Papers 2,
Tesfaye, S., Raj, A. J., & Geberesamuel, G. (2014). Assessment of Climate Change Impact on the Hydrology of Geba Catchment, Northern Ethiopia. *American Journal of Environmental Engineering*, *4*, 25-31.
Teshome, A., & Zhang, J. (2019). Increase of Extreme Drought over Ethiopia under Climate Warming. *Advances in Meteorology*.

UN. (2015). Paris Agreement. United Nations Framework Convention on Climate Change. Available at: https://unfccc.int/sites/default/files/english_paris_agreement.pdf [Accessed 22 Oct. 2024]. In.

UNESCO, U.-W. W. W. A. P. (2009). Water in a changing world.

UNFCCC. (2007). *Climate Change: Impacts, Vulnerabilities and Adaptation in Developing Countries. United Nations Framework Convention on Climate Change.*

UNFCCC. (2012). Expert Group. 2012. National Adaptation Plans. Technical guidelines for the national adaptation plan process. Bonn: UNFCCC secretariat. Bonn, Germany. December 2012. In.

Van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., & Lamarque, J.-F. (2011). The representative concentration pathways: an overview. *Climatic change*, *109*, 5-31.

Von Storch, H. (2008). Climate change scenarios—purpose and construction. In *Environmental Crises* (pp. 5-15). Springer.

Wanniarachchi, S., & Sarukkalige, R. (2022). A review on evapotranspiration estimation in agricultural water management: Past, present, and future. *Hydrology*, *9*(7), 123.

Ware, G. B. (2022). Climate change adaptation and mitigation measures in Ethiopia: Review. *International Journal of Agriculture and Food Science*.

Welderufael, W., Woyessa, Y., & Edossa, D. (2013). Impact of rainwater harvesting on water resources of the modder river basin, central region of South Africa. *Agricultural water management*, *116*, 218-227.

Wubie, A. A. (2015). Review on the Impact of Climate Change on Crop Production in Ethiopia. *Journal of Biology, Agriculture and Healthcare*, *5*, 103-111.

Yadav, D., Awasthi, M., & Nema, R. (2018). Study on crop water requirement of field crops under different climatic conditions of Madhya Pradesh. *Agricultural Science Digest-A Research Journal*, *38*(2), 81-87.

Zegeye, H. (2018). Climate change in Ethiopia : impacts , mitigation and adaptation.

Zeray, N., & Demie, A. (2015). Climate Change Impact, Vulnerability and Adaptation Strategy in Ethiopia: A Review. *Journal of environment and earth science*, *5*, 45-56.

Zhang, K., Kimball, J. S., & Running, S. W. (2016). A review of remote sensing based actual evapotranspiration estimation. *Wiley interdisciplinary reviews: Water*, *3*(6), 834-853.

CHAPTER THREE

3. VARIABILITY AND TREND ANALYSIS OF TEMPERATURES, RAINFALL AND CHARACTERISTICS OF CROP GROWING SEASON IN THE EASTERN ZONE OF TIGRAY REGION, NORTHERN ETHIOPIA[1]

Abstract

In this study, auto-correlated Mann-Kendall (MK) and Sen's slope estimator tests were utilized to determine trends of rainfall, temperatures and characteristics of crop growing season during 1980–2009. Moreover, the Van Belle and Hughes' for homogeneity of general trend and Pettitt's test for the occurrence of abrupt changes were applied. On monthly basis, *Kiremt* (June–September) and annual time scale, the MK-trend test for rainfall exhibited non-significant increasing trend, while in *Belg* (February–May) rainfall season exhibited non-significant decreasing trend in the most of the stations. On the contrary, temperatures showed significant increasing trends in annual and *Belg* at the 5% significant level. In *Kiremt* season, however, the maximum temperature showed non-significant increasing, while the minimum temperature showed non-significant decreasing trend. Results of homogeneity for general trend obtained by the Van Belle and Hughes' test seem fairly consistent with those of the MK-trend test. Moreover, results of Pettitt's test indicated a homogeneous trend in monthly, annual and seasonal rainfall series and no break point was distinguished, except few stations. On the contrary, the abrupt changes were found to be quite variable in temperatures. The study also found that trends of growing season characteristics (June–September) have not changed significantly at the 5% significant level. Nevertheless, the high coefficient of variation in *Kiremt* rainfall (21–31%) as well as dry spell length (25–43%) in conjunction with the short nature of the length of growing period (68–90 days) had negative implications to crop production in the eastern zone of Tigray region.

Key words: Climate Variability, Crop Growing Season, Coefficient of Variation, Trend Analysis, Mann-Kendall (MK) Test, Van Belle and Hughes' Test, Pettitt Test

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3.1 Background and justification

Developing countries face heightened vulnerability to climate variability and change due to limited adaptive capacity, dependence on rain-fed agriculture, and restricted resources for building resilience (IPCC, 2014; Smit et al., 2010). Regions such as Ethiopia's Tigray region are particularly susceptible to these impacts, experiencing frequent droughts, irregular rainfall, and fluctuating temperatures, all of which severely undermine agricultural productivity and food security (Asheber, 2010; Gebrehiwot & van der Veen, 2013). These climate-related pressures often create a cycle of poverty and food insecurity, compounding the challenges for rural communities that rely heavily on crops and livestock for their livelihoods.

The Tigray region exemplifies these climate challenges, being highly prone to drought and famine due to recurrent shifts in weather patterns (Asheber, 2010; Weldearegay & Tedla, 2018). Climate-driven droughts have predominantly affected the eastern and southern areas of the region (Gebrehiwot & van der Veen, 2013). In particular, the eastern zone, where this study area is located, frequently experiences drought, which disrupts crop growth and reduces yields (Araya & Stroosnijder, 2010). Moisture stress is thus a significant constraint on both crop and livestock production in this part of Tigray (Meles et al., 1997). Almost annually, localized droughts linked to erratic and inconsistent rainfall lead to crop failures, threatening both livelihoods and development efforts in the region (Awulachew et al., 2011; Gebrehiwot & van der Veen, 2013; Oxfam, 2010).

Although rainfall variability and associated localized droughts have been the greatest concern in the study area, few attempts have made so far to quantify the variability and trend analysis of rainfall and temperatures. Yet, the emphasis by the most of the studies on trends analysis so far carried out in Tigray region has been limited to rainfall analysis (Abrha, 2015; Cheung et al., 2008; Gebrehiwot & van der Veen, 2013; Gebrehiwot et al., 2011; Gebremicael et al., 2017; Hayelom et al., 2017; Mekasha et al., 2014; Meze-Hausken, 2004; Seleshi & Zanke, 2004), whereas temperature analysis has been ignored in many of these studies, although it is also vital for crop production and water-related issues. Furthermore, the rainfall trend analyses made by many of the studies listed above are based on few station data and/or with few number of years especially regarding the study area (eastern zone of Tigray region) and many of the studies were restricted to even trends of annual or monthly or seasonal total values. Rainfall variability based on agricultural practices, such as onset and cessation at an interval of days, length of growing period (LGP), and dry spells weren't included in those studies with the only exception of Araya and Stroosnijder (2010) who determined LGP of two crops, Teff (Eragrostis tef) and barley (Hordeum vulgare) in Geba catchment of the Tigray region. Yet, the rainfall and rainy season characteristics are important to make proper crop-based decisions in seeding, fertilizing, selecting crop variety, selecting suitable cropping pattern, and selecting the best agro-techniques. Assessing long-term trends of rainfall and rainy season characteristics (including onset, cessation and LGP) can help to formulate farming strategies to efficiently use the available water (Fiwa et al., 2014). In addition, rainfall statistics for dry spells are also very important for planning and management of water resources (Almazroui et al., 2017).

Therefore, the aim of this study was to assess long term variability and trends of temperatures, rainfall, and crop growth season characteristics, which is essential to better understand the uncertainties associated with rainfall and temperature patterns and favor knowledge-based management of agriculture, irrigation and other water related sectors in the region.

3.2 Materials and methods

3.2.1 Data used

Thirty years (1980–2009) of climate data (rainfall and temperatures) from the currently existing seven meteorological stations within and nearby the eastern zone of Tigray region were collected from Enhancing National Climate Services Initiative (ENACTS), which is recently implemented at Ethiopian National Meteorological Agency (Table 3.1). The climate data provided by ENACTS is available with high spatial resolution and the quality of the data is improved by combining careful quality control of data from the weather stations with that of satellite estimates. This is the best available dataset for the country which is homogeneous and recommended for climate analysis (Dinku et al., 2014). The detailed information about ENACTS is elucidated in Dinku et al. (2014) and Dinku et al. (2018).

Table 3-1: Geographical location of the meteorological stations

Station	Latitude (N)	Longitude (E)	Elevation (meter)
Illala	13º31′12″	39º30′0″	2012
Adigrat	14º16′48″	39º27′0″	2470
Edagahamus	14º7′12″	39º19′48″	2700
Atsbi	13º52′48″	39º44′24″	2600
Sinkata	14º4′12″	39º34′12″	2480
Wukro	13º49′48″	39º36′0″	1995
Hawzen	13º58′12″	39º25′48″	2255

3.2.2 Data analysis

Long term variability and trends of rainfall and temperatures data series were analyzed using the non-parametric methods: Mann-Kendall and Sen’s estimator of slope. Linear regression was utilized to visualize the trend directions. Moreover, the Van Belle and Hughes’ homogeneity for general trend test and Pettitt’s test for the occurrence of abrupt changes were utilized. More specifically:

3.2.3 Linear regression

A straight line was fitted to the data series to determine whether the slope was different from zero or not. A simple linear regression method was utilized to determine the tendency.

3.2.4 Mann-Kendall (MK) and Theil-Sen's slope estimator

The presence of non-linear trends were assessed using the MK-trend test (Kendall, 1975) and Sen´s slope estimator (Sen, 1968). The MK and Sen’s estimator of slope tests are two non-parametric tests and widely applied in various trend detection studies (Asfaw et al., 2018; Chattopadhyay & Edwards, 2016; Hamzah et al., 2017; Palaniswami & Muthiah, 2018; Samo et al., 2017).

3.2.5 Influence of serial correlation

Prior to applying the MK and Theil-Sen's slope estimator tests, it is essential that the time series data sets require consideration of auto-correlation or serial correlation. If the data exhibits positive serial correlation, it can interfere with the accuracy of trend detection using the Mann-Kendall

(MK) trend test. Positive auto-correlation inflates the likelihood of type I errors, or false positives, by artificially increasing the probability of detecting a trend even when none exists (Kulkarni & von Storch, 1995; Von Storch & Navarra, 1999; Yue & Wang, 2004; Yue Sheng et al., 2002). Therefore in view of the above fact, it is imperative to pre-whiten the time series data before applying the MK-trend test and Theil-Sen's slope estimator (Von Storch & Navarra, 1999). Yue Sheng et al. (2002) suggested that removal of serial correlations by pre-whitening can effectively eliminate the influence of serial correlation on the MK test. Thus, this study incorporates pre-whitening approach modified by Yue and Wang (2004) for the variables having significant serial correlation in the time series data. The presence of auto-correlation in each of the time series was tested at the 5% significant level using lag-1 auto-correlation function. Pre-whitening method has been applied in many of the previous studies in precipitation and temperature trend analysis (Gocic & Trajkovic, 2013; Oguntunde et al., 2011; Yue & Hashino, 2003; Zhang et al., 2000).

3.2.6 Van Belle and Hughes' homogeneity of trend tests

To make catchment-based statement about all possible trend features using a single method, application of a homogeneity test Van Belle and Hughes (1984) is useful to combine data from several stations to obtain a single global trend test. This test provides a single statistic value to indicate whether the months/seasons/annual values are behaving in similar (homogeneous) or different (heterogeneous) fashion from each other. This test uses Z-values (standardized test statistics) from MK-test statistics for each station. To get the trend homogeneity of temperatures and rainfall at multiple stations, Van Belle and Hughes proposed a procedure based on the partitioning of the sum of squares. The procedure applies a series of chi-square (X^2) test statistics to determine the level of homogeneity, helping to assess the significance and variability of climatic trends across the selected station. A similar approach was applied in line with Jhajharia et al. (2014); Kahya and Kalaycı (2004), and Panda et al. (2007).

3.2.7 Change point detection analysis

The recognition of change points is a statistical technique that plays a vital role in spotting climate jumps in the long term climate data series. The Pettitt's test is commonly applied non-parametric approach to detect a single change-point in climate and hydrological time series with continuous data sets (Pettitt, 1979). This test method detects a significant change in the average of a time series when the exact time of the change is unknown (Gao et al., 2011). To carry out change point detection analysis mean monthly rainfall, seasonal rainfall, and seasonal maximum and minimum temperatures were analyzed with the help of Pettitt's test at the 5% significant level. This approach has been applied in different studies to detect abrupt changes in climate and hydrological time series (Chakraborty et al., 2017; Gao et al., 2011; Gebremicael et al., 2017; Gulakhmadov et al., 2020; Salarijazi et al., 2012).

3.2.8 Crop risk assessments

Crop risks associated with extreme events including dry spells and other growing season characteristics were assessed using R-Instat (V.0.6.2) software developed under the African Math's Initiative (AMI) (https://africandata.org/) (AMI, 2018). Growing season characteristics, such as onset and cessation date, length of growing period (LGP), and dry spell length, were determined based on 30 years of rainfall data provided by the National Meteorological Service Agency of Ethiopia.

Onset and cessation date: The onset of rainfall can be described as the start of the growing season during which sufficient rain is received for the seedling (Ati et al., 2002), while the cessation is a period that is characterized by the end of rainfall of the growing season, including the scanty few days of rainfall which may occasionally occur (Ojo & Ilunga, 2018). Similar to previous studies (Sivakumar, 1992; Tesfaye & Walker, 2004), the onset of the main rainy season (June–September) in the study area was assumed to start as of June 19 after the wet spells occurred for at least three consecutive days and when the total rainfall is 20 mm or more if there was no dry spell longer than 7 or more days within 30 days. Moreover, cessation date was assumed as the date when the stored soil moisture reaches 100 mm that is after the rainfall falls below half of the reference evapotranspiration (ETo) values (Stern et al., 1982). The reason for selecting 100 mm is based on the fact that annual crops utilize 75–100 mm stored soil moisture during crop harvest season (Higgins & Kassam, 1981).

Length of Growing Period (LGP): It was computed using the difference between the onset date and cessation date of total seasonal rainfall (Mugalavai et al., 2008).

Dry spell length: It was computed considering a time period with no rain or less than 1 mm rain for more than 7 days within 30 days. The average value of the dry spells was computed at a seasonal time scale during the main rainy season (Sivakumar, 1992).

3.3 Results and Discussion

3.3.1 Annual and seasonal rainfall variability

The mean annual rainfall amount throughout the study area was found to be 572 mm (Fig. 3-1). A minimum and a maximum total rainfall amount of 554 mm and 617 mm were observed in Edagahamus and Hawzen stations, respectively. The contribution of the *Kiremt* season to that of the annual total rainfall amount was very large at all stations which varied between 54% and 84%. In addition, the contribution of the *Belg* season was not to be underestimated. At the most of the stations, it contributed 15–35% of the total annual rainfall. In the study area, the *Belg* season is very useful for long maturing crop varieties. These crop varieties are planted in this season before the main rainy season, *Kiremt*. Moreover, farmers are utilizing this season for land management practices, such as repeated ploughing and in-situ soil moisture conservation activities.

The coefficient of variation (*CV*) in Fig. 3-1 (in blue line) indicated that the rainfall had high inter-annual variability at the most of the stations. Likewise, the variability was much higher for *Belg* season that ranged from 37–45% than *Kiremt* season rainfall (21–31%), indicating a very high temporal variability of the seasons. Several studies also showed that the *CV* of *Belg* season is higher than *Kiremt* season in the northern Ethiopia (Hadgu et al., 2013b; Kiros et al., 2017; Weldesenbet, 2019). Of all stations, Hawzen station showed the highest in both *Kiremt* and *Belg* inter-annual variability with 31% and 45%, respectively. Overall, the variability of the seasonal total rainfall in the study area can be categorized from moderate to high variability (25 to 41%). Our finding is in agreement with the previous studies that have reported the annual and seasonal rainfall variability with moderate and high inter-annual variability (Ademe et al., 2020; Ayalew et al., 2012; Bewket & Conway, 2007; Hadgu et al., 2013a).

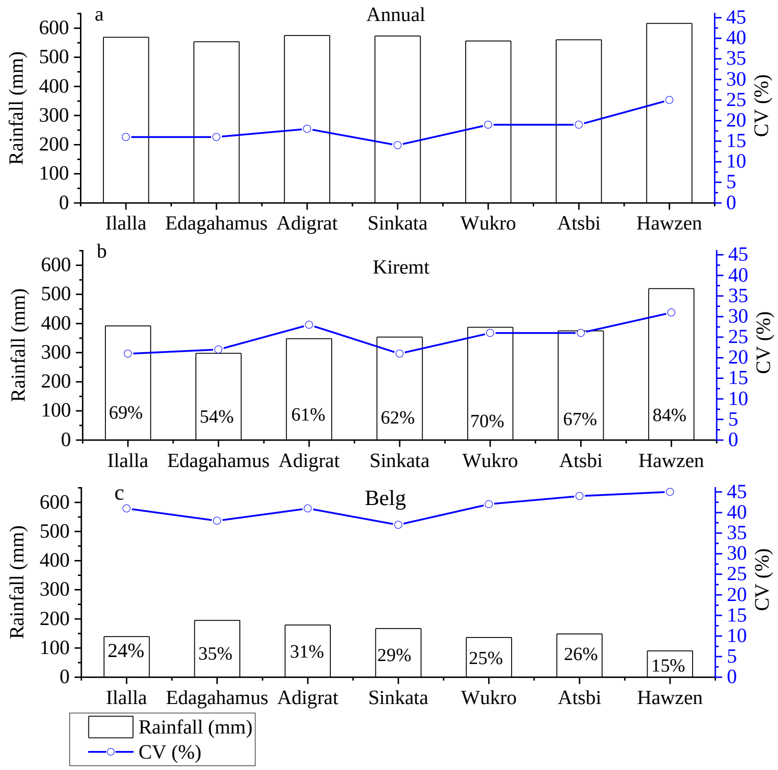


Figure 3-1: Annual and seasonal (Kiremt and Belg) variables

3.3.2 Trend analysis of rainfall and temperatures

3.3.2.1 Monthly, seasonal and annual rainfall trend

Results of statistical tests for monthly, seasonal and annual rainfall are presented in Table 3-2. As shown, the two-tailed MK-trend statistical test for monthly rainfall showed an increasing trend at the most of the stations and in all months. The magnitude of change is indicated by Sen's slope estimator that ranges from 0.29 to 0.99 mm/month for June, 0.27–2.51 mm/month for July, 0.82–2.96 mm/month for August and 0.22–0.55 mm/month for September. The fitted linear regression in Fig. 3.2 also revealed the presence of positive linear trend at all stations as well as in all of the months. Nevertheless, only significant trends were observed at few stations. For example, June and July months exhibited statistically significant increasing trend at only Hawzen station. And, September month exhibited statistically significant increasing trend at Sinkata and Wukro stations. August month, however, showed statistically non-significant increasing trends at all of the stations at 5% significant level.

Likewise, annual rainfall showed an increasing trend at the most of the stations and varied from 0.8 to 5.51 mm/year (maximum at Hawzen station). In addition, *Kiremt* season rainfall values also showed an increasing trend that varied from 2.34 to 6.78 mm/season (also maximum at Hawzen station), whilst *Belg* rainfall season showed a decreasing trend that varied from 0.74 to 2.29 mm/season (maximum at Edagahamus station). Trend analysis using the fitted linear regression is also presented in Fig. 3-3 from which it is clear that the results are in consistent with the Sen's test results found in Table 3-1. Although there were increasing and decreasing trends in annual and seasonal rainfall values, the trends are found to be non-significant at 5% significant level. Our results corroborate with the findings of previous studies that indicated non-significant rainfall trend, neither annually nor in any of the seasons in northern Ethiopia at 5% significant level (Cheung et al., 2008; Gebremicael et al., 2017; Seleshi & Camberlin, 2006; Seleshi & Zanke, 2004; Viste et al., 2013).

In general, the findings of the auto-correlated MK-trend test revealed that there was non-significant trend in the annual and seasonal rainfall series at all stations. Moreover, most of stations showed non-significant trends in monthly rainfall series; June at 6 out of 7 stations, July at 6 out of 7 stations, August at 7 out of 7 stations and September at 5 out of 7 stations. Contrary to this, monthly rainfall of June and July at only 1out of 7 stations and September at 2 out of 7 stations showed statistically significant increasing trend over the study area at 5% significant level.

Table 3-2: Monthly, seasonal and annual rainfall statistical trend values

		Stations						
Rainfall	**Statistics**	**Illala**	**Edagahamus**	**Adigrat**	**Sinkata**	**Wukro**	**Atsbi**	**Hawzen**
June	MK (z-test)	1.75	1.71	1.25	1.32	1.61	1.78	2.00*
	ϴ	0.52	0.38	0.30	0.29	0.34	0.31	0.99
	ϴ (95% CI)	0.4-0.7	0.3-0.5	0.2-0.4	0.2-0.4	0.2-0.4	0.3-0.4	0.8-1.1
July	MK (z-test)	1.82	0.39	1.82	1.68	1.64	1.03	2.07*
	ϴ	1.16	0.27	1.30	1.29	1.55	1.07	2.51
	ϴ (95% CI)	1.0-1.6	0.03-0.6	1.1-1.5	1.0-1.7	1.3-1.8	0.8-1.6	2.1-2.8
August	MK (z-test)	0.54	1.03	1.36	0.89	1.43	1.57	1.53
	ϴ	0.82	1.17	2.04	1.00	2.26	2.27	2.96
	ϴ (95% CI)	0.5-1.3	0.8-1.7	1.4-2.5	0.5-1.7	1.7-2.8	1.8-2.8	2.2-3.5
September	MK (z-test)	0.89	1.82	1.14	1.96*	2.07*	1.53	0.71
	ϴ	0.22	0.22	0.26	0.31	0.55	0.52	0.27
	ϴ (95% CI)	0.1-0.3	0.2-0.3	0.2-0.4	0.3-0.34	0.4-0.6	0.4-0.6	0.2-0.5
Belg	MK (z-test)	-1.07	-1.89	-1.57	-1.32	-1.03	-1.18	-1.07
	ϴ	-1.27	-2.29	-1.94	-1.67	-0.84	-1.05	-0.74
	ϴ (95% CI)	-1.7-(-1)	-2.8-(-2.1)	-2.4-(-1.5)	-1.9-(-1.2)	-1.2-(-0.4)	-1.4-(-0.7)	-1.1-(-0.4)
Kiremt	MK (z-test)	1.14	1.61	1.53	1.78	1.64	1.78	1.61
	ϴ	2.34	2.38	3.19	2.93	3.97	3.61	6.78
	ϴ (95% CI)	1.6-2.9	1.8-2.7	2.8-4.2	2.5-3.2	2.9-5.1	3.2-4.3	6.0-7.6
Annual	MK (z-test)	0.32	-0.25	0.86	0.64	1.43	1.50	1.43
	ϴ	0.8	-0.82	2.12	1.3	3.12	3.24	5.51
	ϴ (95% CI)	-0.1-1.7	-1.4-0.4	1.3-3.2	0.6-1.8	2.2-3.9	2.4-3.6	3.9-6.7

* Statistically significant at 5% significance level, ϴ: Sen's slope

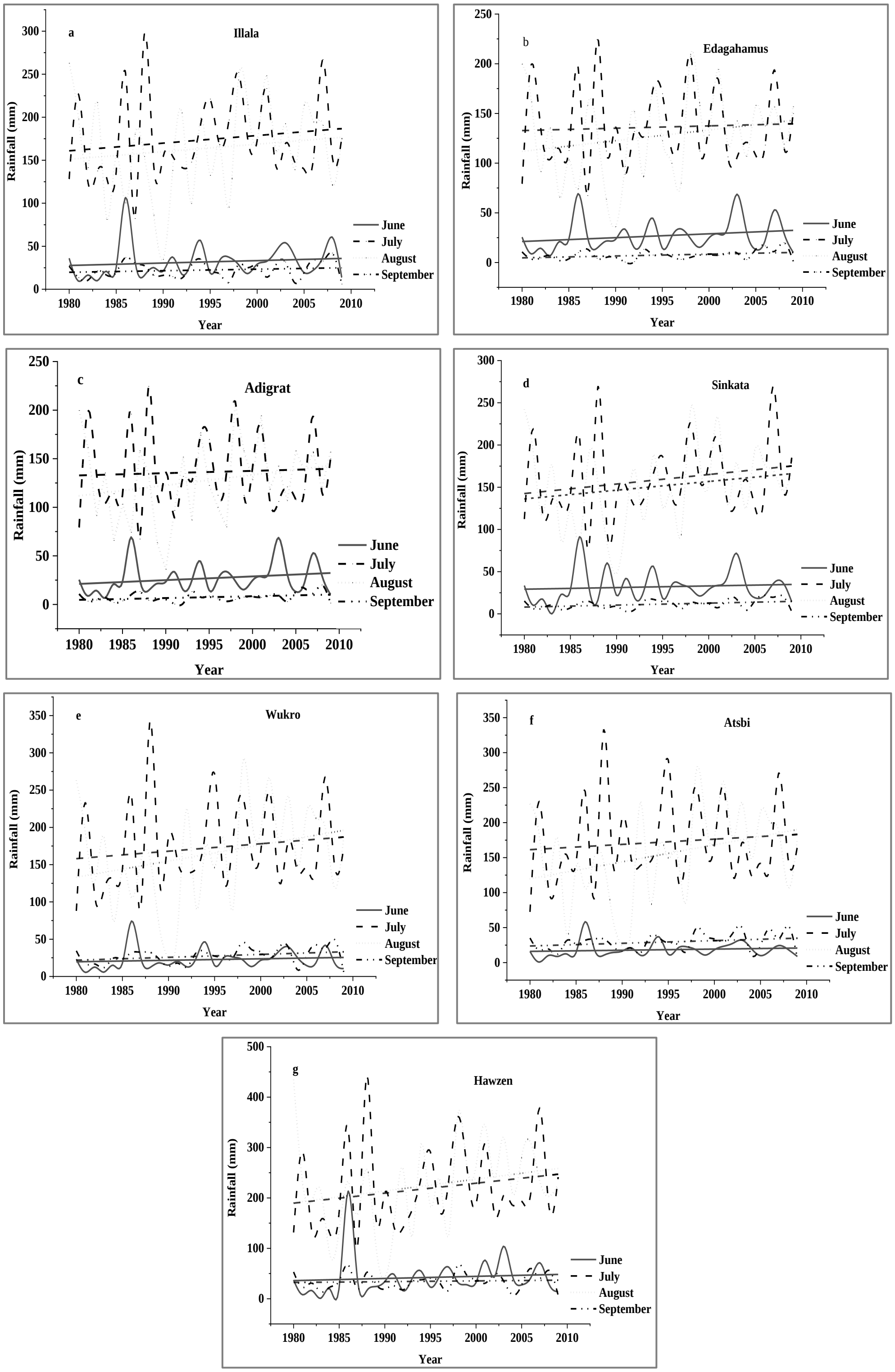


Figure 3-2: Monthly rainfall trends of a. Illala, b. Edagahamus, c. Adigrat, d. Sinkata, e. Wukro, f. Atsbi, g. Hawzen

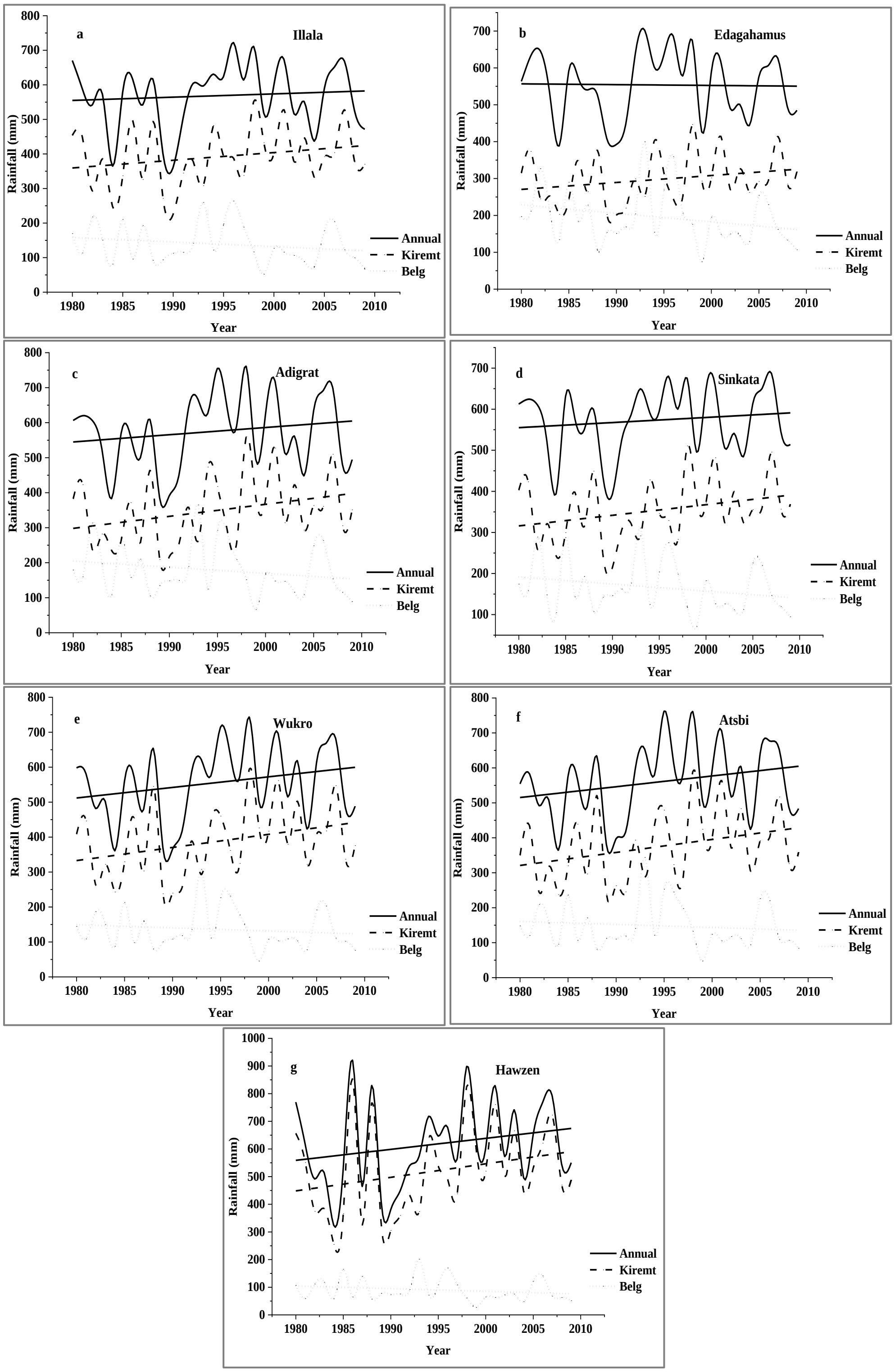


Figure 3-3: Annual, Kiremt and Belg total rainfall of a. Illala, b. Edagahamus, c. Adigrat, d. Sinkata, e. Wukro, f. Atsbi, g. Hawzen

3.3.2.2 Seasonal maximum and minimum temperature trends

Results of MK and Sen's slope estimator statistical tests for maximum and minimum temperatures are presented in Table 3-3. In addition, Fig. 3-4 and 3-5 also showed the fitted linear regression for the mentioned parameters. On the annual and *Belg* time scale, statistically significant increasing trend was detected at 5% significant level. The observed trends showed a magnitude of 0.04 to 0.07°C per year for maximum temperature, 0.024 to 0.06°C per year for minimum temperature, 0.07 to 0.10°C per *Belg* season for maximum temperature, and 0.06 to 0.12°C per *Belg* season for minimum temperature across all stations (Table 3-3).

Unlike the annual and *Belg* season, the maximum and minimum temperature for *Kiremt* season showed an increasing and decreasing trend patterns, respectively. Increasing trends were detected at 71.43% of the stations for maximum temperature, while a decreasing trends were detected at 85.7% of the stations for minimum temperature. Yet, the *Kiremt* season maximum and minimum temperatures trends were not statistically significant at the most of the stations. Few stations, however, such as Edagahamus showed a significant increasing trend for maximum temperature with a magnitude of 0.08°C per season. Moreover, Adigrat and Hawzen station showed a significant decreasing trend in minimum temperature by 0.04°C per season and 0.03°C per season, respectively. Fig. 3.4 and 3.5 also revealed consistent linear trend direction as of the Sen's slope magnitude. It is generally expected that an increase in maximum temperature increases the rate of evapotranspiration and increase the rate of water consumption by the crops and causing more water stress. In addition, temperature increment beyond the threshold level can affect the growth and reproduction which reduces crop yield and the risk of crop failure.

Table 3-3: Seasonal maximum and minimum temperature statistical trend values

		Stations						
T_{max} (^{O}C)	**Statistics**	**Illala**	**Edagahamus**	**Adigrat**	**Sinkata**	**Wukro**	**Atsbi**	**Hawzen**
Annual	MK (z-test)	4.85*	4.53*	4.32*	4.85*	4.32*	4.57*	5.07*
	ϴ	0.05	0.07	0.05	0.05	0.044	0.048	0.052
	ϴ (95% CI)	0.05-0.06	0.07-0.08	0.047-0.05	0.051-0.06	0.04-0.05	0.046-0.05	0.05-0.06
Kiremt	MK (z-test)	1.25	3.32*	0.43	1.25	0.00	-0.32	1.86
	ϴ	0.02	0.08	0.004	0.015	-0.0007	-0.002	0.022
	ϴ (95% CI)	0.01-0.02	0.07-0.09	0.0-0.012	0.01-0.02	-0.01-0.01	-0.01-0.00	0.02-0.03
Belg	MK (z-test)	4.42*	2.89*	3.57*	4.42*	3.60*	4.39*	3.35*
	ϴ	0.09	0.08	0.07	0.09	0.083	0.108	0.068
	ϴ (95% CI)	0.09-0.1	0.07-0.09	0.07-0.08	0.09-0.10	0.08-0.09	0.1-0.11	0.06-0.08
T_{min} (^{O}C)	**Statistics**	**Illala**	**Edagahamus**	**Adigrat**	**Sinkata**	**Wukro**	**Atsbi**	**Hawzen**
Annual	MK (z-test)	4.75*	2.82*	1.89	5.35*	4.60*	4.10*	3.93*
	ϴ	0.063	0.05	0.024	0.053	0.055	0.046	0.047
	ϴ (95% CI)	0.06-0.07	0.04-0.06	0.02-0.03	0.05-0.06	0.05-0.06	0.042-0.05	0.04-0.05
Kiremt	MK (z-test)	0.00	0.79	-2.89*	-0.46	-1.39	-1.18	-1.93*
	ϴ	-0.0005	0.01	-0.04	-0.01	-0.02	-0.02	-0.033
	ϴ (95% CI)	-0.004-0.01	0.01-0.02	-0.05-(-0.04)	-0.01-(-0.001)	-0.03-(-0.02)	-0.03-(-0.013)	-0.04-(-0.03)
Belg	MK (z-test)	5.00*	1.93*	4.42*	5.67*	6.17*	5.17*	5.14*
	ϴ	0.1	0.057	0.088	0.1	0.117	0.089	0.098
	ϴ (95% CI)	0.09-0.11	0.05-0.07	0.08-0.09	0.098-0.1	0.1-0.12	0.084-0.09	0.09-0.1

* Statistically significant at 5% significance level, ϴ: Sen's slope

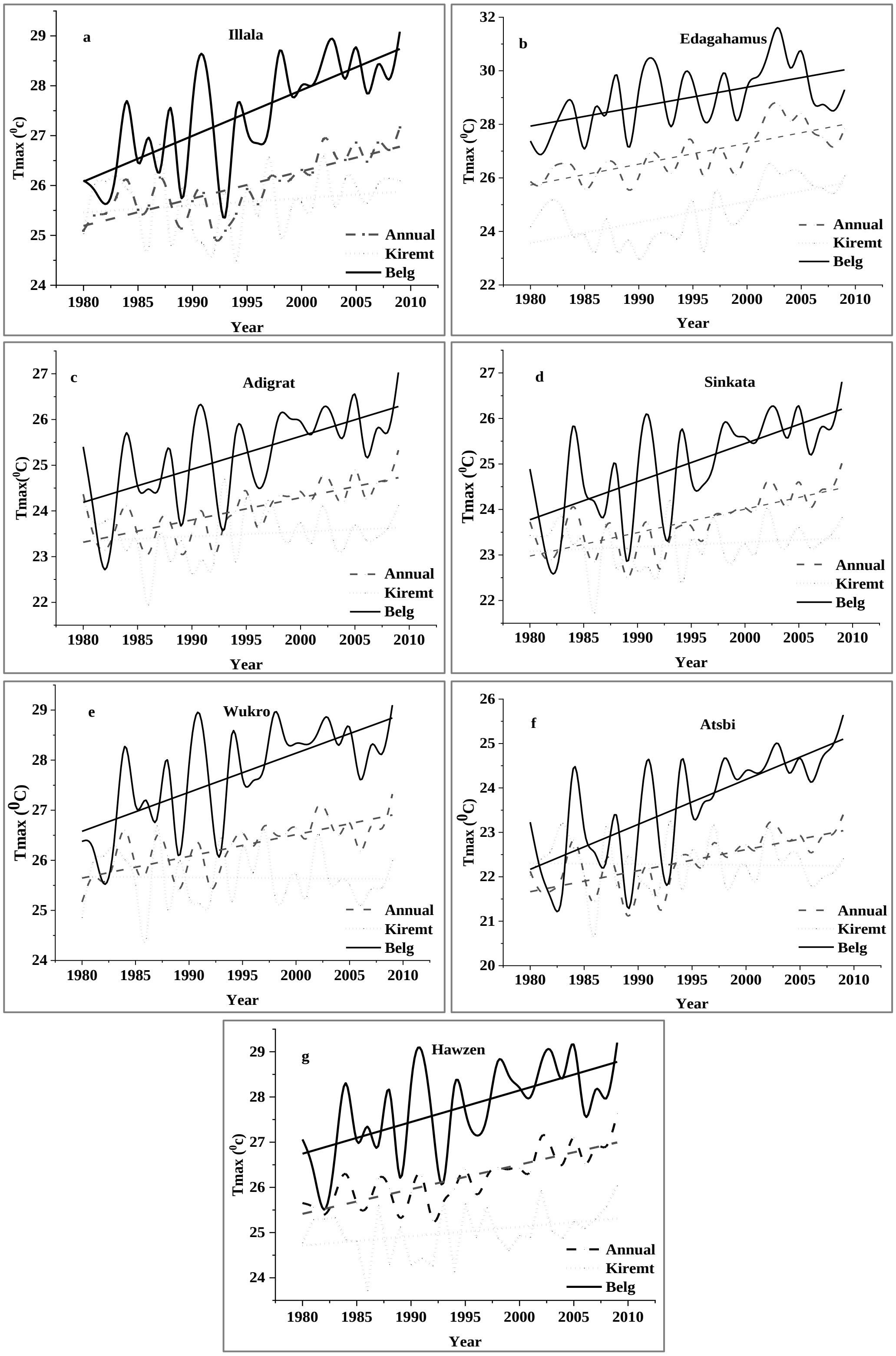


Figure 3-4: Annual, Kiremt and Belg Maximum Temperature of a. Illala, b. Edagahamus, c. Adigrat, d. Sinkata, e. Wukro, f. Atsbi, g. Hawzen

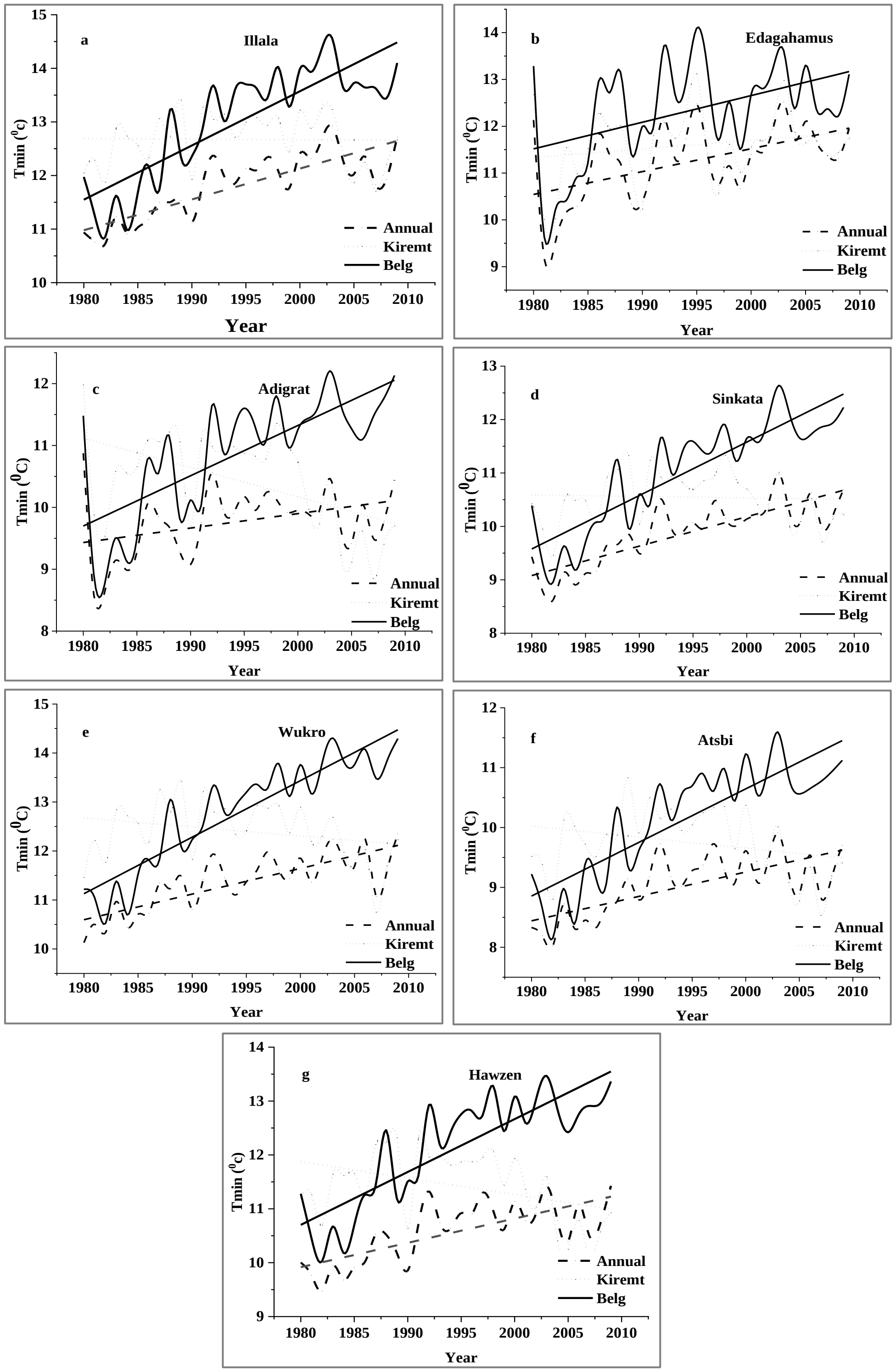


Figure 3-5: Annual, Kiremt and Belg Minimum Temperature of a. Illala, b. Edagahamus, c. Adigrat, d. Sinkata, e. Wukro, f. Atsbi, g. Hawzen

3.3.3 Van Belle and Hughes' trend test for the general case

To determine a single global trend for the entire basin, van Belle and Hughes' homogeneity trend test was applied to the rainfall and temperatures series. Accordingly, in the monthly rainfall series (June–September), all months showed an evidence of trend, as X^2 trend value for each month exceed the critical X^2 value (with d.f.=1, i.e., 3.84) at the 5% significant level (Table 3-4). Table 3-4 also indicated that trends in all months were in the same direction. However, trends of June, July and September months were stronger than that for August, as indicated by larger magnitude of the X^2 trend.

Table 3-4: Significance test of trend homogeneity for monthly rainfall (June–September)

	June		**July**		**August**		**September**	
Source	X^2	d.f.	X^2	d.f.	X^2	d.f.	X^2	d.f.
Total	19.05	7	17.64	7	10.85	7	16.13	7
Homogeneity	0.42	6	2.02	6	0.89	6	1.67	6
Trend	18.63*	1	15.61*	1	9.96*	1	14.46*	1

* significant at the 5% significant level; d.f.: degrees of freedom

In the annual and seasonal rainfall series, X^2 for annual and seasons exhibited trend heterogeneity since X^2 for annual and seasons is greater than X^2 critical values, while the stations were found to have homogeneous trends (Table 3-5). Hence, trend direction analysis for annual and each season was conducted. Annual and each season was tested using the average MK-trend test statistics (Z_k). Here, the $M\bar{Z}_k^2$ was obtained to test the overall trend homogeneity and referred to the value of X^2 critical (with d.f.=1, i.e., 3.84) at the 5% significant level. Accordingly, the annual and seasonal statistics of $M\bar{Z}_k^2$ is greater than the X^2 critical values for annual, *Kiremt* and *Belg* seasons (Table 3-6). Table 3-6 collectively showed that annual and *kiremt* rainfall indicated significant upward trend, while *Belg* season indicated significant downward trend. Although the individual MK-trend test for rainfall were not significant at the most of the stations in Table 3-2, *Kiremt* and *Belg* seasons have $M\bar{Z}_k^2$ values that are much larger than the annual rainfall. This means *Kiremt* and *Belg* rainfall seasons have trends that are stronger than that of the annual rainfall. The visible weaker trend in the annual rainfall series could be due to the results of the net cancellations of the trend effects from the seasonal series.

Table 3-5: Significance test of trend homogeneity for annual and seasonal (Kiremt and Belg) rainfall

Source	X^2 value	d.f.	X^2 critical, at 5%	Sign.
Total	38.04	21	32.67	-
Homogeneous	35.08	20	31.41	-
Annual and Season	31.56	2	5.99	
Station	1.96	6	12.59	
Annual and Season-Station	1.56	12	21.03	
Annual and Season homogeneity		X^2 annual and seasons > X^2 critical		S
Station homogeneity		X^2 station<X^2 critical		NS
Interaction		X^2 annual and seasons-station< X^2 critical		NS
X^2 trend	2.96	1	3.84	Not used

Sign.: Significance; NS: not significant; S: significant; d.f.: degrees of freedom

Table 3-6: Annual and seasonal rainfall trend homogeneity statistical test

Rainfall	$\bar{Z}_K$	$\bar{Z}_k^2$	$M\bar{Z}_k^2$	Sign.
Annual	0.85	0.72	5.01	S
Kiremt	1.59	2.51	17.59	S
Belg	-1.30	1.70	11.92	S

$\bar{Z}_K$: average MK-trend test statistics; M: number of stations;
Sign.: Significance; NS: not significant; S: significant

Results of trend homogeneity for maximum and minimum temperatures are also presented in Table 3-7. Table 3-7 revealed that the value of X^2 for annual and seasons for both maximum and minimum temperature was significant which suggests trend heterogeneity since X^2 for annual and seasons is greater than X^2 critical at the 5% (5.99). In other words, we cannot assume a monotonic trend between annual and seasons, or trends of annual are different from those of *Belg* or *Kiremt* seasons, etc. In contrast, the value of X^2 station for maximum temperature was non-significant indicating trend homogeneity in the time series data, i.e., X^2 station is less than the X^2 critical at the 5% (12.59), but heterogeneous for minimum temperature. This means that maximum temperature across stations are consistent.

Since maximum temperature trends across stations are homogeneous, we can further test the significance of the overall maximum temperature trend of the annual and each season (Table 3-8). Accordingly, Table 3-8 indicated that the computed $M\bar{Z}_k^2$ values for annual and each season were found to be greater than the X^2 critical (equal to 3.84) with d.f. = 1 at the 5% significance level. Table 3-8 collectively showed that annual and seasons for maximum temperature indicated a significant warming trends. From the values of $M\bar{Z}_k^2$, it is clear that annual and *Belg* season have $M\bar{Z}_k^2$ values that are much larger than *Kiremt* season. This means annual and *Belg* have trends that are stronger than that of the *Kiremt* season.

Table 3-7: Maximum and Minimum temperature trend homogeneity test statistics

Sources	**Maximum Temperature**				**Minimum Temperature**			
	X^2 - value	d.f.	X^2 critical, at 5%	Sign.	X^2 - value	d.f.	X^2 critical, at 5%	Sign.
Total	273.05	21	32.67	-	304.05	21	32.67	-
Homogeneous	59.67	20	31.41	-	165.81	20	31.41	-
Annual and Seasons	47.71	2	5.99	S	136.83	2	5.99	S
Station	2.96	6	12.59	NS	12.88	6	12.59	S
Interaction	9.00	12	21.03	NS	16.10	12	21.03	NS
Trend	213.38	1	3.84	Not used	138.24	1	3.84	Not used

Sign.: Significance; NS: not significant; S: significant; d.f.: degrees of freedom

Table 3-8: Annual and seasonal maximum temperature trend homogeneity test statistics

T_{max}	$\bar{Z}_K$	$\bar{Z}_k^2$	$M\bar{Z}_k^2$	**Sign.**
Annual	4.64	21.56	150.95	S
Kiremt	1.11	1.23	8.64	S
Belg	3.81	14.50	101.49	S

3.3.4 Change point detection analysis using Pettitt's test

Pettitt test was used in a two-tailed test at which a change point can be detected and the mean of the dataset shifts at this break point. Accordingly, the homogeneity analysis for rainfall showed that only one station in annual rainfall series and two stations in monthly rainfall series (August month) indicated a significant change point, while other rainfall series at the rest of the stations can be consider as a homogeneous in nature. In the annual rainfall series, a significant upward shift was statistically observed only at the Atsbi station. The average precipitation before the break point (shown by the solid line in Fig. 3-6) was 496.7 mm, whereas it increased to 602.2 mm after the break point (shown by the broken line in Fig. 3-6). The break point occurred in 1991. Likewise, a significant upward shift can be detected in August month at Atsbi and Wukro stations. The mean monthly amount of precipitation was 127.1 mm and 137.2 mm in the period before the date of the break point (shown by the solid line in Fig. 3-6) and 196.7 mm and 205.7 mm, in the period following the shift (shown by the broken line in Fig. 3-6), respectively. The break point occurs in 1997 at the two stations. After extensive research in the archive information about historical registered values of concern, no physical reason which would explain for these change points could be found.

Separating the time series at the significant change point, no significant trend could be recognized in the annual and in the August month rainfall series. This implies that the shift in the mean in the annual and August rainfall amounts at few of the stations might be due to abrupt and drastic shifts not as a result of slow and gradual changes. In contrary, although significant increasing trend tendencies were observed in Table 3-2 using the auto-correlated MK-trend test at few of the stations, i.e., at Hawzen station in June and July months, and at Sinkata and Wukro stations in September month, no break points could be detected. The significant increasing tendency should be accepted as valid. Hence, the result of the significant trends was not as a consequence of the shift of the mean, but as a result of long term changes of the rainfall.

However, the change points were found to be quite variable in temperatures as compared to rainfall series (Table 3-9). The change point analysis for maximum temperature in annual, *Kiremt* and *Belg* season indicated different change points. Annual rainfall series in the year of 1994 to 1999, and *Belg* in the years of 1989,1993 and 1997 indicated a significant upward change at all stations, while *Kiremt* season indicated a significant change only in 2 out of 7 stations: Edagahamus in the year of 1996 (upward shift) and Wukro in the year of 1984 (downward shift). Likewise, minimum temperature analysis also indicated a significant upward change point in the series of annual at all stations in the years of 1990 and 1991, *Belg* season indicated a significant upward change in 5 out of 7 stations in the years of 1991 and 1994. *Kiremt* season, however, indicated a downward change in 3 out of 7 stations in the year of 2000.

Overall, the change point analysis results of the temperature variables indicated different change points from the years of 1984 to 2000, with maximum change points in the year of 1997 for maximum temperature and in the year of 1991 for minimum temperature. Moreover, most of the stations showed upward shift, while few stations, such as Wukro, Adigrat, Atsbi and Hawzen indicated a downward shift in *Kiremt* season (Table 3-9). The significant upward change points in these series observed during 1984 to 2000 might be due to the influence of high population growth and expansion of urbanization in the region. Besides these factors, the probable cause of the abrupt change in the temperatures might have also associations with frequent drought occurrence in the region. The study area is known by one of the drought-prone areas in the Tigray region. And, the region has suffered frequent meteorological droughts (e.g., in 1982, 1983, 1984, 1985, 1987, 1991, 1999, 2000, 2002, 2004 and 2009) (Gebrehiwot et al., 2011). However, after extensive research in the archive information about historical registered values of concern, the physical reasons for the downward trend for minimum temperature in *Kiremt* season was missing.

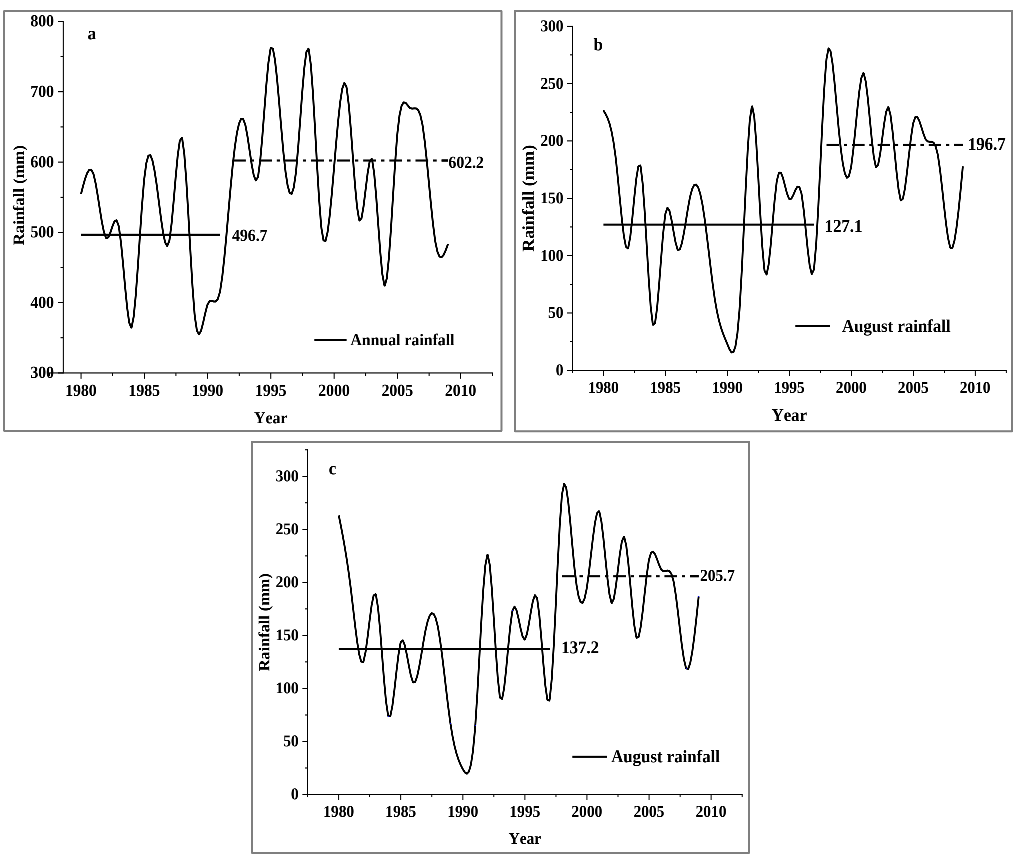


Figure 3-6: Significant change points in historical series of rainfall at Atsbi station (a-Annual rainfall, b-August rainfall) and Wukro station (c-August rainfall)

Table 3-9: Change points in historical series of maximum and minimum temperature

Station	Period	T_{max}			T_{min}		
		K-value	Shift	Year of shift	K-value	Shift	Year of shift
Illala	Annual	213	Yes ▲	1996	212	Yes	1991▲
	Kiremt	96	No	—	108	No	—
	Belg	200	Yes▲	1997	214	Yes	1991▲
Edagahamus	Annual	194	Yes▲	1999	134	Yes	1991▲
	Kiremt	195	Yes▲	1996	68	No	—
	Belg	142	Yes▲	1989	116	No	—
Adigrat	Annual	195	Yes▲	1994	136	Yes	1991▲
	Kiremt	89	No	—	167	Yes	2000 ▼
	Belg	178	Yes▲	1997	188	Yes	1991▲
Sinkata	Annual	213	Yes▲	1996	214	Yes	1991▲
	Kiremt	96	No	—	94	No	—
	Belg	200	Yes▲	1997	212	Yes	1991▲
Wukro	Annual	197	Yes▲	1994	188	Yes	1991▲
	Kiremt	35	Yes▼	1984	127	No	—
	Belg	170	Yes▲	1993	217	Yes	1994▲
Atsbi	Annual	205	Yes▲	1996	199	Yes	1990▲
	Kiremt	63	No	—	151	Yes	2000▼
	Belg	188	Yes▲	1993	214	Yes	1991▲
Hawzen	Annual	214	Yes▲	1997	201	Yes	1990▲
	Kiremt	97	No	—	155	Yes	2000 ▼
	Belg	158	Yes▲	1997	208	Yes	1991▲

▲ symbolized an upward trend change; ▼ symbolized a downward trend change; K-value is Pettitt's test statistics; T_{max} is maximum temperature (ºC); T_{min} is minimum temperature (ºC)

3.3.5 Trend characteristics of crop growing season

The determination of the trend characteristics of crop growing season is very useful information for planning land preparation and planting activities. In this study, the trends of crop growing season characteristics was analyzed using 30 years of data in *Kiremt* season and computed at the 5% significant level (Table 3-10). As shown, the 30-years median early onset date of the *Kiremt* season was found to be within the range of 30-June/182.5 DOY (Day of Year) at Hawzen to 8-July/190 DOY at Wukro stations. Likewise, the onset dates of Ilalla, Adigrat, Edagahamus, Wukro and Atsbi stations were found to be very close to the Hawzen station. The median cessation date, however, indicated a wide range of dates among the stations. The earliest cessation was on 11-Sep./255 DOY at Edagahamus and late cessation was on 25-Sep/269 DOY at Hawzen. Onset and cessation variability was found to be very low (CV<10%) at all of the stations, indicating a relatively stable onset and cessation dates. Having stable onset and cessation dates is an advantageous for the farmers to schedule their farm activities while searching of the off farm activities.

There was a general increasing trend of LGP which could be attributed to the observed early in onset and delay in the cessation date, although not significant at the 5% significant level. Mean LGP values in the study area varied from 68 days at Edagahamus to 85 days at Hawzen. Previous studies using different criterions for the onset and the cessation analysis reported that the LGP in the northeastern stations found to be in a range of 60–100 days (Berhe, 2011; Hadgu et al., 2013a). The CV of the LGP was low (< 20%) at all of the stations, which is very helpful to plant crops based on their maturity period. And, providing such kind of information is essential for deciding on crop types and cultivars and dates for land preparation. But, the short nature of LGP in the study area is very challenging to produce long maturing crop varieties that need greater than 90 days. Hence, farmers in the study area need to adopt husbandry practices which can fit to the shortened growing period.

Similarly, the mean seasonal dry spell length was analysed and found to be in a range of 23 days at Wukro to 30 days at Edagahamus. The dry spell length was highly variable with CV from 25–43%. These findings agree with Gebreselassie and Moges (2016) who reported larger than 30% of variability in the dry spell length of daily rainfall in Northern Ethiopia. High CV of dry spells indicate the possibility of soil water deficit during the peak rain fall period in the study area. Hence, water conservation activity becomes very important to supplement with irrigation during the season as well as after cessation of the rain to cover the crop water requirement. In addition, the use of early maturing and drought tolerant cultivars can be highly beneficial.

Table 3-10: Statistical values and trends of onset, cessation, LGP and dry spell length at 7 stations over the period of 1980-2009

Characteristics of crop growth	Statistics	Stations						
		Illala	Adigrat	Edagahamus	Wukro	Hawzen	Sinkata	Atsbi
Onset	Median	7-Jul	7-Jul	6-Jul	8-Jul	30-Jun	4-Jul	7-Jul
	Kendall's tau	-0.07	-0.10	-0.16	-0.06	-0.01	-0.18	0.07
	Slope	-0.10	-0.13	-0.29	-0.07	-0.05	-0.27	0.06
	$^*P_{Value}$	0.60	0.45	0.23	0.68	0.94	0.17	0.60
	SD (Days)	9	9	11	8	13	12	7
	CV%	5	5	6	4	7	6	4
Cessation	Median	22-Sep	20-Sep	11-Sep	21-Sep	25-Sep	20-Sep	23-Sep
	Kendall's tau	0.16	0.24	0.03	0.18	0.15	0.19	0.20
	Slope	0.14	0.13	0.00	0.20	0.15	0.13	0.30
	$^*P_{Value}$	0.23	0.09	0.85	0.17	0.25	0.15	0.13
	SD (Days)	6	7	3	7	7	6	9
	CV%	2	3	1	3	3	2	3
LGP	Mean	74	72	68	74	85	77	78
	Kendall's tau	0.10	0.16	0.14	0.16	0.06	0.19	0.11
	Slope	0.25	0.35	0.29	0.33	0.20	0.50	0.25
	$^*P_{Value}$	0.44	0.24	0.30	0.22	0.68	0.15	0.40
	SD (Days)	11	11	12	11	14	13	11
	CV%	15	16	17	15	16	17	15
Dry Spell	Mean	26	24	30	23	26	27	29
	Kendall's tau	-0.10	-0.12	-0.25	-0.12	-0.06	-0.07	0.06
	Slope	-0.18	-0.11	-0.23	-0.16	-0.10	-0.08	0.08
	$^*P_{Value}$	0.47	0.35	0.06	0.38	0.65	0.59	0.67
	SD (Days)	11	8	7	9	10	10	10
	CV (%)	43	34	25	39	37	36	34

Kendall's tau is MK-trend test; Slope (Sen's slope) is the change (days)/annual; $^*P_{value}$ is significant level at $\alpha = 0.05$, SD is standard deviation; CV is coefficient of variation.

3.4 Conclusions and implications

Variability and trends of rainfall, temperatures and characteristics of crop growing seasons were analyzed using MK-trend test in the eastern zone of Tigray region over the period of 1980–2009. In addition, the study analyzed the homogeneity test for general trend analysis using the Van Belle and Hughes method as well as for change point detection using Pettitt's test. According to the results, the individual MK-trend analysis for monthly, annual and *Kiremt* rainfall showed an increasing trend, while *Belg* rainfall season showed a decreasing trend at almost all of the stations. Nevertheless, only statistically significant trends were observed at few of the stations in monthly time series. Annual, *Kiremt* and *Belg* rainfall series were found to be statistically non-significant. On the contrary, temperatures (T_{max} and T_{min}) showed statistically significant increasing trends in annual and *Belg* at all of the stations. However, *Kiremt* season temperatures showed non-significant trend at the most of the stations at 5% significant level.

Results of tests of trend homogeneity by the Van Belle and Hughes method for general trend showed that the trends for monthly, annual and *Kiremt* rainfall showed upward trend direction, while *Belg* rainfall showed downward trend direction. Likewise; on the annual and *Belg* time scale, temperatures (T_{max} and T_{min}) showed upward trend direction. *Kiremt* season, however, showed upward trend direction for T_{max} and downward trend directions for T_{min}. The results obtained from Van Belle and Hughes test seem fairly consistent with those of the individual MK-trend tests.

Moreover, the results of the Pettitt test showed that most of the stations indicated a homogeneous trend in the annual and seasonal rainfall series and no break point was distinguished except few stations. However, the change points were found to be quite variable in temperatures as compared to rainfall series. The change point analysis results of the temperature variables indicated different change points from year 1984 to 2000. The significant upward change points in these series might be due to the influence of high population growth and expansion of urbanization in the region. Besides these factors, the probable cause of the abrupt change in the temperatures might have also associations with frequent drought occurrence in the region. Nevertheless, after extensive research in the archive information about historical registered values of concern, the physical reasons for the upward trend changes in rainfall as well as a downward trend changes for minimum temperature could not be found. Thus, further research study may be conducted to find out the possible causes of these changes over the study area.

It is important to note that in line with the non-significant trends of rainfall and temperatures in *Kiremt* season, the trends of growing season characteristics have not changed significantly at the 5% significant level at all of the stations over the study period. In addition, the coefficient of variation of the onset (CV, <10%) and the cessation (CV, <5%) was found to be very small, indicating relatively stable onset and cessation. Furthermore, the CV of LGP was less than 20%, which is vital to plant crops based on their maturity period. Contrary to this, the CV of the dry spell length was larger than 25% at all of the stations. This showed the high possibility of soil water deficit during the peak rain fall period in the study area. Moreover, despite non-significant trends of rainfall and temperatures in *Kiremt* season at the most of the stations, there was highly significant increasing of temperatures and significant decreasing of rainfall trends in *Belg* season. Although future research is needed on the influence of the short rainy season (*Belg)* to that of the long rain season (*Kiremt*), it is certain that it will cause more complications to land preparation and cropping long maturing varieties. Because, the local farmers ration this season for planting long maturing crop varieties as well as for land management practices, such as repeated ploughing and in-situ soil moisture conservation activities. Hence, crop production in the study area demands adaptation strategies that considers the erratic nature of the rainfall associated with long dry spells length in *Kiremt* season as well as the high temperatures and declining rainfall trends during the *Belg* season. It is worthwhile to note that the results may be of practical implications for formulating long term adaptation strategies for sustainable crop production as well as sustainable management of water resources in the region.

References

Abrha, M. G. (2015). Local climate trends and farmers' perceptions in Southern Tigray, Northern Ethiopia. *International Journal of Environment and Sustainability*, *4*(3).

Ademe, D., Zaitchik, B. F., Tesfaye, K., Simane, B., Alemayehu, G., & Adgo, E. (2020). Climate trends and variability at adaptation scale: Patterns and perceptions in an agricultural region of the Ethiopian Highlands. *Weather and climate extremes*, *29*, 100263.

Almazroui, M., Balkhair, K. S., Islam, M. N., & Şen, Z. (2017). Climate Change Impact on Monthly Precipitation Wet and Dry Spells in Arid Regions: Case Study over Wadi Al-Lith Basin. *Advances in Meteorology*, *2017*(1), 5132895.

AMI. (2018). *African Math's Initiative (AMI), Analyzing climatic data with R-Instat, https://github.com/africanmathsinitiative/R-Instat.wiki.git/)*.

Araya, A., & Stroosnijder, L. (2010). Effects of tied ridges and mulch on barley (Hordeum vulgare) rainwater use efficiency and production in Northern Ethiopia. *Agricultural water management*, *97*(6), 841-847.

Asfaw, A., Simane, B., Hassen, A., & Bantider, A. (2018). Variability and time series trend analysis of rainfall and temperature in northcentral Ethiopia: A case study in Woleka sub-basin. *Weather and climate extremes*, *19*, 29-41.

Asheber, S. A. (2010). *Mitigating drought: policy impact evaluation: a case of Tigray region, Ethiopia* University of Twente].

Ati, O. F., Stigter, C. J., & Oladipo, E. O. (2002). A comparison of methods to determine the onset of the growing season in northern Nigeria. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *22*(6), 731-742.

Awulachew, S. B., Erkossa, T., & Balcha, Y. (2011). *Irrigation and Water for Sustainable Development: Proceedings of the Second Forum December 15-16, 2008, Addis Ababa, Ethiopia*. IWMI.

Ayalew, D., Tesfaye, K., Mamo, G., Yitaferu, B., & Bayu, W. (2012). Variability of rainfall and its current trend in Amhara region, Ethiopia. *African Journal of Agricultural Research*, *7*(10), 1475-1486.

Berhe, A. A. (2011). *Coping with drought for food security in Tigray, Ethiopia*. Wageningen University and Research.

Bewket, W., & Conway, D. (2007). A note on the temporal and spatial variability of rainfall in the drought-prone Amhara region of Ethiopia.

Chakraborty, D., Saha, S., Singh, R., Sethy, B., Kumar, A., Saikia, U., Das, S., Makdoh, B., Borah, T. R., & Nomita Chanu, A. (2017). Trend analysis and change point detection of mean air temperature: a spatio-temporal perspective of North-Eastern India. *Environmental Processes*, *4*, 937-957.

Chattopadhyay, S., & Edwards, D. R. (2016). Long-term trend analysis of precipitation and air temperature for Kentucky, United States. *Climate*, *4*(1), 10.

Cheung, W. H., Senay, G. B., & Singh, A. (2008). Trends and spatial distribution of annual and seasonal rainfall in Ethiopia. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *28*(13), 1723-1734.

Dinku, T., Funk, C., Peterson, P., Maidment, R., Tadesse, T., Gadain, H., & Ceccato, P. (2018). Validation of the CHIRPS satellite rainfall estimates over eastern Africa. *Quarterly Journal of the Royal Meteorological Society*, *144*, 292-312.

Dinku, T., Hailemariam, K., Maidment, R., Tarnavsky, E., & Connor, S. (2014). Combined use of satellite estimates and rain gauge observations to generate high-quality historical rainfall time series over Ethiopia. *International Journal of Climatology*, *34*(7), 2489-2504.

Fiwa, L., Vanuytrecht, E., Wiyo, K. A., & Raes, D. (2014). Effect of rainfall variability on the length of the crop growing period over the past three decades in central Malawi. *Climate research*, *62*(1), 45-58.

Gao, P., Mu, X.-M., Wang, F., & Li, R. (2011). Changes in streamflow and sediment discharge and the response to human activities in the middle reaches of the Yellow River. *Hydrology and Earth System Sciences*, *15*(1), 1-10.

Gebrehiwot, T., & van der Veen, A. (2013). Assessing the evidence of climate variability in the northern part of Ethiopia. *Journal of development and agricultural economics*, *5*(3), 104-119.

Gebrehiwot, T., Van der Veen, A., & Maathuis, B. (2011). Spatial and temporal assessment of drought in the Northern highlands of Ethiopia. *International Journal of Applied Earth Observation and Geoinformation*, *13*(3), 309-321.

Gebremicael, T. G., Mohamed, Y. A., & Hagos, E. Y. (2017). Temporal and spatial changes of rainfall and streamflow in the Upper Tekezē–Atbara river basin, Ethiopia. *Hydrology and Earth System Sciences*, *21*(4), 2127-2142.

Gebreselassie, M. G., & Moges, S. A. (2016). Spatial and temporal variability of dry spell lengths and indication of climate change in rainfall extremes at Tekeze River Basin, Ethiopia. *International Journal of Water Resources and Environmental Engineering*, *8*(3), 39-51.

Gocic, M., & Trajkovic, S. (2013). Analysis of changes in meteorological variables using Mann-Kendall and Sen's slope estimator statistical tests in Serbia. *Global and planetary change*, *100*, 172-182.

Gulakhmadov, A., Chen, X., Gulahmadov, N., Liu, T., Davlyatov, R., Sharofiddinov, S., & Gulakhmadov, M. (2020). Long-Term hydro–climatic trends in the mountainous kofarnihon river basin in central asia. *Water*, *12*(8), 2140.

Hadgu, G., Tesfaye, K., Mamo, G., & Kassa, B. (2013a). Trend and variability of rainfall in Tigray, northern Ethiopia: analysis of meteorological data and farmers' perception.

Hadgu, G., Tesfaye, K., Mamo, G., & Kassa, B. (2013b). Trend and variability of rainfall in Tigray, Northern Ethiopia: Analysis of meteorological data and farmers' perception. . *Academia Journal of Environmental Sciences 1:159-171*.

Hamzah, F. M., Saimi, F. M., & Jaafar, O. (2017). Identifying the monotonic trend in climate change parameter in Kluang and Senai, Johor, Malaysia. *Sains Malaysiana*, *46*(10), 1735-1741.

Hayelom, B., Chen, Y., Marsie, Z., & Negash, M. (2017). Temperature and precipitation trend analysis over the last 30 years in Southern Tigray Regional State, Ethiopia.

Higgins, G., & Kassam, A. (1981). The FAO agro-ecological zone approach to determination of land potential. *Pedologie*, *31*(2), 147-168.

IPCC. (2014). *Climate change 2014-impacts, adaptation and vulnerability, part A: global and sectoral aspects*. Cambridge University Press.

Jhajharia, D., Dinpashoh, Y., Kahya, E., Choudhary, R. R., & Singh, V. P. (2014). Trends in temperature over Godavari River basin in Southern Peninsular India. *International Journal of Climatology*, *34*(5).

Kahya, E., & Kalaycı, S. (2004). Trend analysis of streamflow in Turkey. *Journal of Hydrology*, *289*(1-4), 128-144.
Kendall, M. G. (1975). Rank Correlation Methods; Charles Griffin & Co. *Ltd.: London, UK*, 15.
Kiros, G., Shetty, A., & Nandagiri, L. (2017). Extreme rainfall signatures under changing climate in semi-arid northern highlands of Ethiopia. Cogent Geoscience, 3(1): 1353719.
Kulkarni, A., & von Storch, H. (1995). Monte Carlo experiments on the effect of serial correlation on the Mann-Kendall test of trend. *Meteorologische Zeitschrift*, *4*(2), 82-85.
Mekasha, A., Tesfaye, K., & Duncan, A. J. (2014). Trends in daily observed temperature and precipitation extremes over three Ethiopian eco-environments. *International Journal of Climatology*, *34*(6).
Meles, K., Maria, A., Tesfamichael, N., Sunil, S., Francis, K., & Lynne, M. (1997). Coping with low and erratic rainfall in the Eastern zone of Tigray.
Meze-Hausken, E. (2004). Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. *Climate research*, *27*(1), 19-31.
Mugalavai, E. M., Kipkorir, E. C., Raes, D., & Rao, M. S. (2008). Analysis of rainfall onset, cessation and length of growing season for western Kenya. *Agricultural and forest Meteorology*, *148*(6-7), 1123-1135.
Oguntunde, P. G., Abiodun, B. J., & Lischeid, G. (2011). Rainfall trends in Nigeria, 1901–2000. *Journal of Hydrology*, *411*(3-4), 207-218.
Ojo, O. I., & Ilunga, M. F. (2018). Application of nonparametric trend technique for estimation of onset and cessation of rainfall. *Air, Soil and Water Research*, *11*, 1178622118790264.
Oxfam. (2010). *The rain doesn't come on time any more: poverty, vulnerability and climate variability in Ethiopia. Oxfam: Addis Ababa*.
Palaniswami, S., & Muthiah, K. (2018). Change Point Detection and Trend Analysis of Rainfall and Temperature Series over the Vellar River Basin. *Polish Journal of Environmental Studies*, *27*(4).
Panda, D. K., Mishra, A., Jena, S., James, B., & Kumar, A. (2007). The influence of drought and anthropogenic effects on groundwater levels in Orissa, India. *Journal of Hydrology*, *343*(3-4), 140-153.
Pettitt, A. N. (1979). A non-parametric approach to the change-point problem. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, *28*(2), 126-135.
Salarijazi, M., Akhond-Ali, A.-M., Adib, A., & Daneshkhah, A. (2012). Trend and change-point detection for the annual stream-flow series of the Karun River at the Ahvaz hydrometric station. *African Journal of Agricultural Research*, *7*(32), 4540-4552.
Samo, S. R., Bhatti, N.-u.-K., Saand, A., Keerio, M. A., & Bangwar, D. K. (2017). Temporal Analysis of Temperature and Precipitation Trends in Shaheed Benazir Abad Sindh, Pakistan. *Engineering, Technology & Applied Science Research*, *7*(6).
Seleshi, Y., & Camberlin, P. (2006). Recent changes in dry spell and extreme rainfall events in Ethiopia. *Theoretical and Applied Climatology*, *83*, 181-191.
Seleshi, Y., & Zanke, U. (2004). Recent changes in rainfall and rainy days in Ethiopia. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, *24*(8), 973-983.
Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American statistical association*, *63*(324), 1379-1389.

Sivakumar, M. (1992). Empirical analysis of dry spells for agricultural applications in West Africa. *Journal of Climate*, 532-539.

Smit, B., Pilifosova, O., Burton, I., Challenger, B., Solomon, S., Plattner, G.-K., Knutti, R., Stern, N., Peters, S., & Bakhshi, V. (2010). World Development Report 2010: Development and Climate Change. By World Bank. Washington, DC: World Bank, 2010. Pp. xxi, 417. $26.00, paper. ISBN 978–0–8213–7987–5. JEL 2010–0282. *Journal of Economic Literature*, *48*, 786.

Stern, R., Dennett, M., & Dale, I. (1982). Analysing daily rainfall measurements to give agronomically useful results. I. Direct methods. *Experimental Agriculture*, *18*(3), 223-236.

Tesfaye, K., & Walker, S. (2004). Matching of crop and environment for optimal water use: the case of Ethiopia. *Physics and Chemistry of the Earth, Parts a/b/c*, *29*(15-18), 1061-1067.

Van Belle, G., & Hughes, J. P. (1984). Nonparametric tests for trend in water quality. *Water resources research*, *20*(1), 127-136.

Viste, E., Korecha, D., & Sorteberg, A. (2013). Recent drought and precipitation tendencies in Ethiopia. *Theoretical and Applied Climatology*, *112*, 535-551.

Von Storch, H., & Navarra, A. (1999). *Analysis of climate variability: applications of statistical techniques*. Springer Science & Business Media.

Weldearegay, S. K., & Tedla, D. G. (2018). Impact of climate variability on household food availability in Tigray, Ethiopia. *Agriculture & Food Security*, *7*, 1-9.

Weldesenbet, G. (2019). *Analysis of Rainfall Variability for Mekelle Meteorological Station, Northern Ethiopia (1960-2009)*.

Yue, S., & Hashino, M. (2003). Long term trends of annual and monthly precipitation in Japan 1. *JAWRA Journal of the American Water Resources Association*, *39*(3), 587-596.

Yue, S., & Wang, C. (2004). The Mann-Kendall test modified by effective sample size to detect trend in serially correlated hydrological series. *Water resources management*, *18*(3), 201-218.

Yue Sheng, Y. S., Pilon, P., Phinney, B., & Cavadias, G. (2002). The influence of autocorrelation on the ability to detect trend in hydrological series.

Zhang, X., Vincent, L. A., Hogg, W., & Niitsoo, A. (2000). Temperature and precipitation trends in Canada during the 20th century. *Atmosphere-ocean*, *38*(3), 395-429.

CHAPTER FOUR

4. IMPACTS OF CLIMATE CHANGE ON CROP GROWING SEASON CHARACTERISTICS IN NORTHERN ETHIOPIA[2]

Abstract

Understanding the potential effects of climate change on crop growth is crucial for pinpointing areas where interventions can enhance resilience and address climate-related risks to agriculture. By analyzing projected climate impacts, this research aims to provide insights into changes in rainfall patterns, temperature fluctuations, and their effects on crop growing season characteristics. Five global climate models under two representative concentration paths were projected for future periods using a delta downscaling approach. Results indicate that projections of rainfall showed an increase in annual and summer (*Kiremt*) rainfall at most stations. However, the Belg rainfall season had a declining trend except under RCP4.5 in a mid-term period that showed positive changes at most stations. On the contrary, projections of maximum and minimum temperatures indicated a continuous increase. In line with the increase in temperatures, the reference evapotranspiration consistently increased at all stations. Cumulatively, late onset and early cessation of rainfall are observed, accompanied by a range of 5.5% to 19% reduction in the length of the growing period (LGP), exacerbating the current short LGP in the study area and affecting the proper growth and maturity of major crops. The findings of this study have global implications in that similar areas may be alarmed to get prepared ahead and develop adaptive and sustainable crop production strategies.

Key words: climate change, crop growing season, evapotranspiration, northern Ethiopia, Tigray

[2] A. Gebremedhin, H. Solomon, G. Girmay, and A. Zenebe (2023). Impacts of future climate change on local climate and crop growing season characteristics in the eastern zone of Tigray region, northern Ethiopia, Journal of Water and Climate Change. https://doi.org/10.2166/wcc.2023.069.

4.1 Background and Justification

Developing countries are the most vulnerable countries to the impacts of present and future climate change and variability. Climate change and variability are the most determinant constraints to agricultural production and food security in areas that rely on rainfed production systems (Gitz et al., 2016).

The impacts of climate change and variability are predominantly noticed through changes in the two most important climate parameters, which are temperature and rainfall. The trends of these parameters are crucial for crop production, as they have changed in Ethiopia for the last several decades. For instance, Ethiopia's annual average temperature has increased by 1 °C since 1960 at an average rate of 0.25 °C per decade (World Bank Group, 2021). Moreover, Ethiopia has experienced a very high degree of rainfall variability annually and seasonally (Gebremicael et al., 2017; Mekasha et al., 2014; Zeray & Demie, 2016). The impacts of increased temperatures and high variability of rainfall patterns are expected to reduce crop production and water availability for irrigation and other water-consuming sectors, especially in the north, northeast, and eastern low lands of the country (Aragie, 2013). Moreover, projections of climate change indicated a decrease in the length of the growing period through the shifting of onset and cessation dates over different regions in Ethiopia (Gebrekiros et al., 2015; Jima et al., 2019; Kassie, 2014). This is very critical to the majority of the population of the country who are dependent on rainfed agriculture for their livelihood, such as in the case of the Tigray region.

Climate change and variability today are serious threats to crop production in Ethiopia in general and in the Tigray region in particular. For example, the climate of the study area (the eastern part of the Tigray region in northern Ethiopia) indicates that it is characterized by frequent droughts. The region has encountered frequent meteorological droughts (e.g., in 1982, 1983, 1984, 1985, 1987, 1991, 1999, 2000, 2002, 2004, and 2009) (Gebrehiwot et al., 2011). Especially in the Tigray region, the majority of the droughts had a drastic impact on agricultural outputs, with total crop failure and massive livestock deaths (Asheber, 2010).

Even though rainfall and temperature variability and associated localized droughts in the study area have been of the greatest concern, many studies have emphasized only a single parameter, i.e., rainfall variability and its distribution. Despite the fact that temperature is a crucial variable in crop production, its impact analysis has been ignored by many studies (example in Abrha & Simhadri, 2015; Gebrehiwot & van der Veen, 2013; Gebrehiwot et al., 2011; Hayelom et al., 2017; Meze-Hausken, 2004). Yet, some studies have pointed out that temperature increases have a much stronger impact on crop production than rainfall (Ochieng et al., 2016; Schlenker & Lobell, 2010). Similarly, some other studies indicated that even with sufficient rainfall, increasing temperatures contribute to reduced yields (Cooper et al., 2009; Luhunga et al., 2017). In addition, the shortening of the growing period with increasing temperatures has been identified as the main yield reducing factor (Gardi et al., 2022). In an arid and semi-arid climate with a dry environment, such as the study area, a slight increase in temperature will have a significant impact. Hence, in a drier environment, temperature changes, particularly the minimum temperature, have a drastic impact on crop production (Mupangwa et al., 2023).

Moreover, previous studies regarding rainfall analyses were restricted to trends in annual, monthly, or seasonal total values. Rainfall variability based on crop growing season characteristics such as onset and cessation at an interval of days, length of the growing period (LGP), and dry spells (DSs) has not been included in many of the studies. In addition, the analysis of rain- fall and rainy season characteristics have not been covered within the context of climate change impacts, with the only exception of Gebrekiros et al. (2015) who determined the LGP of sorghum (Sorghum bicolor) crop under climate change in southern Tigray. This implies that there are no previous studies that consider the impact of climate model projections on growing season characteristics (onset and cessation, LGP, and DSs) over the eastern zone of the Tigray region. Yet, the characterization of these systematic variations is very important for practitioners to improve water resources and agricultural planning. This study was therefore conducted to investigate the impact of climate change on growing season characteristics in the eastern zone of the Tigray region in northern Ethiopia.

4.2 Materials and Methods

4.2.1 Data used

The data set comprised daily rainfall and maximum and minimum temperature data collected from seven stations in and around the eastern zone of the Tigray region for the period 1980–2009. These datasets were obtained through the Enhancing National Climate Services Initiative (ENACTS), recently established at the Ethiopian National Meteorological Agency (NMA).

4.2.2 Data analysis

4.2.2.1 Delta statistical climate downscaling

Daily temperatures and rainfall data were projected from the Fifth Phase Coupled Model Inter-Comparison Project (CMIP5) global climate modes (GCMs) using a 30-year baseline daily weather dataset (1980–2009). As presented in Table 4.1, five GCMs were used for climate change projections. These GCMs were selected based on their consistency and resolution performance for East and sub-Saharan Africa (Msongaleli et al., 2015; Rosenzweig et al., 2015; Sillmann & Roeckner, 2008). The five selected GCMs were used in many climate change impact studies in East Africa in general and in northern Ethiopia in particular. Moreover, two RCPs (RCP4.5 and RCP8.5) were used for future climate change scenario analysis. RCP4.5 is an intermediate forcing level, and RCP8.5 is a very high emission forcing level. Each RCP defines a specific trajectory and radiative forcing level. The radiative forcing values are 4.5 and 8.5 W/m^2, respectively (Wayne, 2014).

GCMs have course resolution. Hence, the delta statistical downscaling method of GCMs was applied to represent local conditions. The delta statistical method is one of the simplest methods of downscaling. In this method, historical data and future projections are expressed and interpolated from a common reference period. R script in R statistical software was used to prepare delta-based future climate change scenarios in the mid-term (2050:2040–2069) and end-term (2080:2070–2099) periods. The process of the delta downscaling method comprises the following steps: (i) Gathering of baseline data (current climates corresponding to WorldClim). WorldClim contains files including latitude, altitude, elevation, precipitation, and temperatures for each sub-region. (ii) Gathering of the full GCM time series. WorldClim and the full GCM time series are freely available on the internet at www.worldclim.org. (iii) Calculation of 30-year running averages for the present-day simulations (1980–2009) and two future periods in this study. (iv) Calculation of anomalies as the absolute difference between future values in temperatures and proportional differences in total precipitation. (v) Interpolation of these anomalies using centroids of GCM cells as points for interpolation. (vi) Addition of the interpolated gridded data to the current climates from WorldClim, using absolute sum for temperatures, and addition of relative changes for precipitation (Ruiter, 2012).

Table 4-1: Coupled Model Inter-Comparison Project Phase 5 (CMIP5) General Circulation Models (GCMs)

Modeling center	Country	Model	Latitude	Longitude	Resolution
Hadley Global Environment Model 2 – Earth System	UK	HadGEM2-ES	1.75°	1.25°	Medium
Max Plank Institute for Earth System Model – Medium Resolution	Germany	MPI-ESM-MR	1.87°	1.87°	Medium
Community Climate System Model	USA	CCSM4	1.25°	0.95°	High
Geophysical Fluid Dynamics Laboratory –Earth System Model	US-New Jersey	GFDL-ESM2M	2.5°	2.0°	Low
Model for Interdisciplinary Research on Climate	Japan	MIROC5	1.4°	1.4°	High

4.2.2.2 Rainfall onset, cessation, LGP, and DS length

In the present study, crop risks associated with extreme events and crop growing season characteristics, such as DS length, onset, cessation, and LGP, were analyzed using R-Instat Statistical Program (Version 0.6.2), http://r-instat.org/Download (AMI, 2018). In Chapter three the long-term trends and variabilities in temperature, rainfall, and crop growth season characteristics based on years from 1980 to 2009 are examined. These years are the historical period that served as a reference for several studies on climate change. Hence, these 30-year daily data were used as input to the current study as a baseline period in order to predict the future periods under two RCPs and five selected GCMs.

4.3 Results and Discussion

4.3.1 Projections of rainfall and temperatures

Rainfall projections from five GCMs indicated higher variability across stations as well as RCPs in all time periods (Figure 4-1). Especially in the end-term period, RCP8.5 showed higher variability compared to RCP4.5 in all time periods. The change in mean rainfall indicated an increasing trend and varied from relatively no change to a +10% in annual rainfall and from no change to +17% in

Kiremt rainfall at most of the stations, as well as under all scenarios and in all time periods. Rainfall projections under RCP8.5 in the end-term period generally predicted a higher increase compared to other scenarios. On the contrary, *Belg* rainfall showed a decreasing trend at most of the stations in all time periods, ranging from -9 to -52.6%, except under RCP4.5 in the mid-term period, which showed positive changes in four out of seven stations. Comparing across stations, *Belg* rainfall decreased by -45.3 to -52.6% at the Wukro station under all scenarios and in all time periods. And the values are higher in magnitude compared to the projected results obtained in other stations. This implies that during the *Belg* season, agriculture will no longer be available at the Wukro station and the surrounding areas. Thus, farmers should be cautious of this phenomenon in aligning with land preparation and in situ soil and water conservation activities that are carried out in this season.

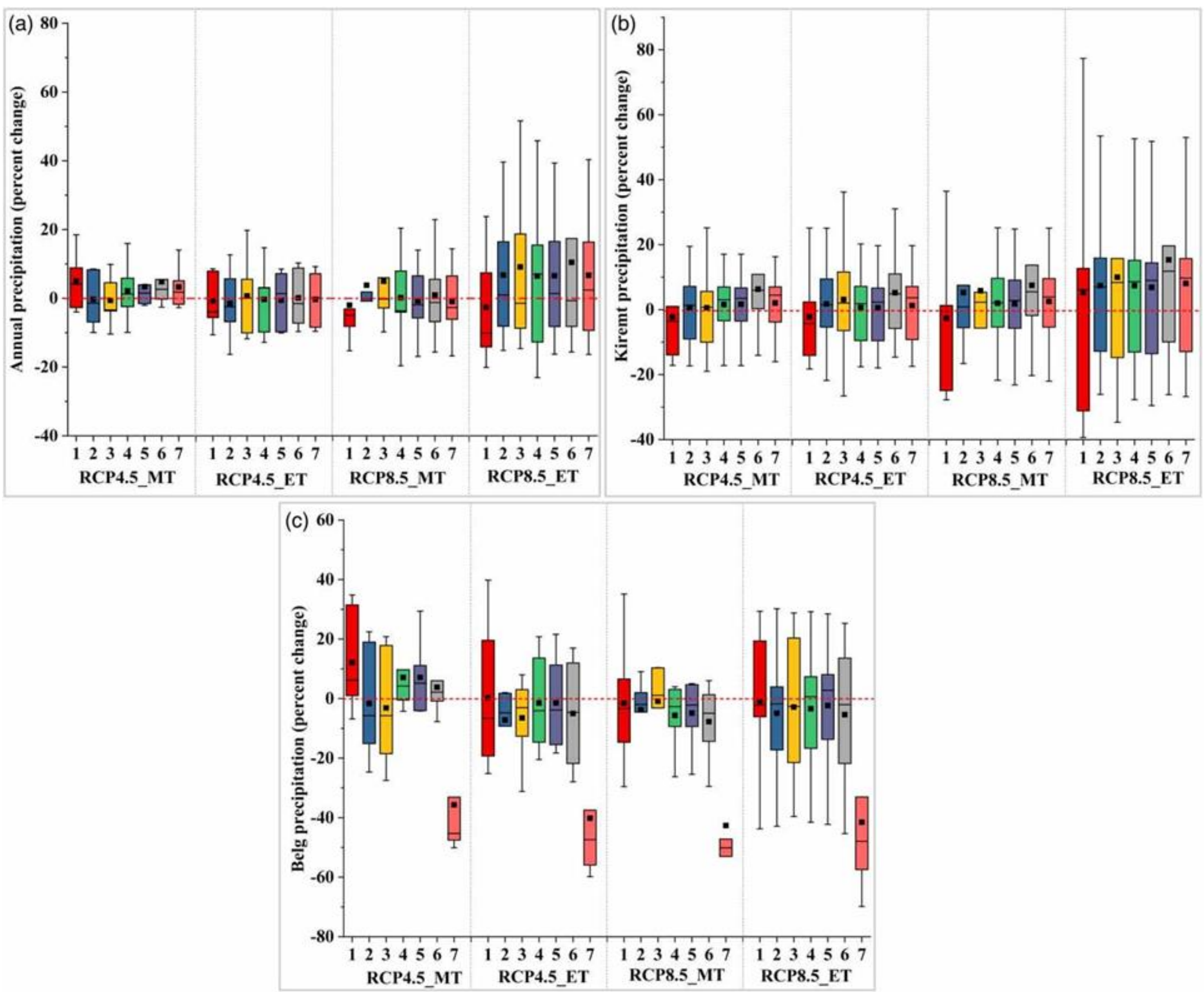


Figure 4-1: Rainfall change by the period and scenarios: (a) annual; (b) Kiremt; and (c) Belg rainfall. 1=Adigrat, 2 =Atsbi, 3=Edagahamus, 4=Hawzen, 5=Illala, 6=Sinkata, 7=Wukro.

Moreover, the study area exhibited a continuously increasing trend of maximum and minimum temperatures over different time periods and RCPs (Figure 4.2). The mean maximum temperature at most of the stations varied from +1.1 to +2.2 °C under RCP4.5 and +1.7 to +4.1 °C under RCP8.5. Likewise, the mean minimum temperature showed an increasing trend and varied from +1.5 to +2.4 °C under RCP4.5 and from +2.3 to +4.8 °C under RCP8.5. Most of the stations predicted a higher increase in the minimum temperature than the maximum temperature. In field crops, increasing the minimum temperature has the potential to promote early senescence, which in turn shortens the grain-filling period, resulting in low yields (Hatfield & Prueger, 2015).

The mean projections of all GCMs under RCP8.5 are higher and more variable compared to RCP4.5 scenarios. Mid-term projections under RCP8.5 are higher than those predicted under RCP4.5 and varied from +30 to +50%. Similarly, end-term projections under RCP8.5 are about +84 to +120% higher than projected results under RCP4.5 at all stations. On average, end-term period projections are higher by about 75% than those predicted for the mid-term under RCP8.5, while in the case of RCP4.5, the end-century projections are higher by about 30%. Across all scenarios, temperatures will continue to increase in the study area throughout the end of the century. Temperature increases are expected to result in more intense heat waves and higher rates of evapotranspiration. This will have significant implications for human and animal health, agriculture, water resources, and ecosystems. Results on projected temperature increases will help to develop effective adaptation measures to reduce the impacts of climate change and draw up long-term crop and water resource management plans in the study area. Because of differences in the time periods, GCMs, RCPs, and downscaling methods, it is difficult to make a direct comparison between the results of previous studies and the current ones. Yet, most previous studies on the impact of climate change on future temperatures in northern Ethiopia indicated an overall rise. The same studies, however, reported the absence of a significant and clear trend in the annual rainfall pattern. In line with the findings in this study, some previous studies indicated an increase in annual rainfall (Berhe et al., 2023; Gebrekiros et al., 2015; Kidanemariam et al., 2021; Niguse & Aleme, 2015; Shiferaw et al., 2018; Thomas et al., 2020), while other studies indicated a slight decrease in rainfall (Gebrehiwot & van der Veen, 2013; Kahsay et al., 2018; Takele et al., 2022). Some other studies, however, indicated that the rainfall did not show any systematic increase or decrease in their study locations (Gardi et al., 2022; Tesfaye et al., 2014b). But it is worthwhile to note that most of the studies found that the increasing or decreasing trend of rainfall is not significant. In spite of the fact that the high variability of the rainfall associated with climate change damages crop and livestock interventions, the impact of temperatures is found to be a main limiting factor for crop production as compared to rainfall (Gardi et al., 2022; Gebrekiros et al., 2015; Niguse & Aleme, 2015).

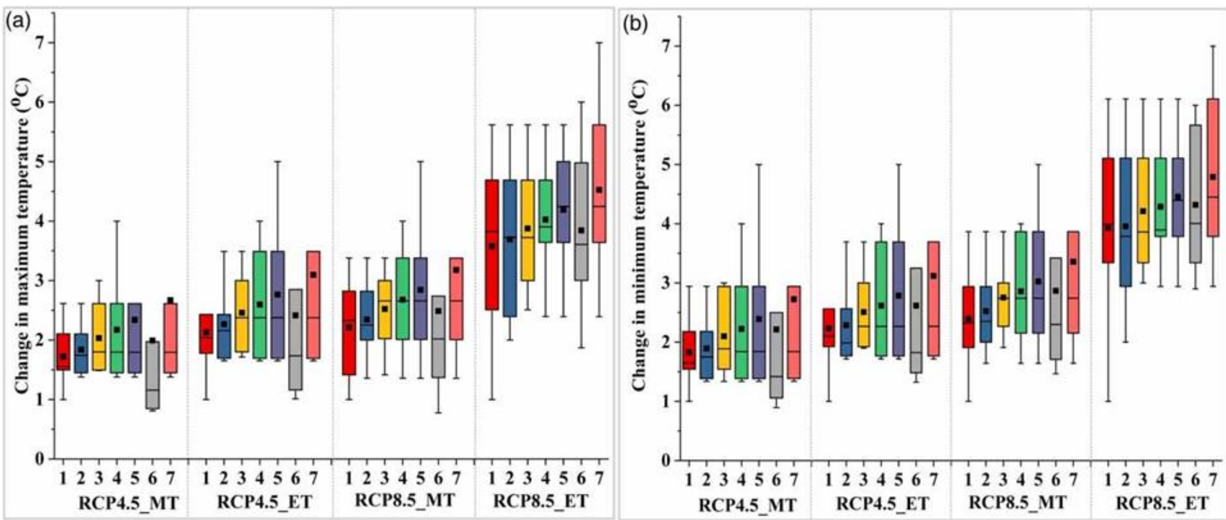


Figure 4-2: Temperature change by the period and scenarios: (a) maximum temperature; and (b) minimum temperature. 1=Adigrat, 2 =Atsbi, 3=Edagahamus, 4=Hawzen, 5=Illala, 6=Sinkata, 7=Wukro.

Different crop varieties all over the world have a given set of temperature thresholds for growth and reproduction. The increase in temperatures in the next years in the study area will thus lead to an alteration in growing days and yield. Furthermore, high temperatures cause crops to mature quickly, thereby reducing grain and forage production. One critical period of exposure to temperatures is the pollination stage. High temperature exposure during the pollination stage can greatly reduce crop yield and increase the risk of crop failure (Walthall et al., 2012). Similarly, rising temperatures create warm environments. This would favor rapid insect development, with more insect generations and a higher population of pests. In addition, it could also create favorable environmental conditions for some secondary insects to become key pests (El Bouhssini et al., 2011). Moreover, rising temperatures and changes in moisture are expected to cause changes in the distribution of crop diseases, the development of epidemic diseases, and the appearance of new pathogens, as well as new or minor pathogens that are likely to become key diseases under climate change (Ahmed et al., 2010). On the other hand, some areas will likely experience increased rainfall over a short period, leading to increased soil erosion and land degradation due to increased rainfall intensities and an increased incidence of floods in flood prone areas. All of them undermine the production capability of the area. In general, by reducing production capabilities and increasing production risks, the area becomes unsuitable for crop production. Hence, as a coping mechanism, specific crop production will gradually shift to another suitable area (Gebresamuel et al., 2022).

Moreover, several literatures indicate that there are major challenges to be faced concerning climate change and variability in crop production in the Tigray region (Araya et al., 2021; Berhe et al., 2018; Gebrekiros et al., 2015; Niguse & Aleme, 2015). Model predictions have shown that climate change will affect grain yield significantly in different locations of the region. For example, Araya et al. (2021) predicted the impact of climate change from three global climate models using the Decision Support System for Agrotechnology Transfer (DSSAT) crop model in the Adigudom area. They found that an increase in the temperature of 2–8 °C is expected to significantly decrease the grain yield of barley (Hordeum vulgare L.) by 6–11% in mid-century (2040–2069) under a higher emission scenario (RCP8.5). Similarly, projections done by Gebrekiros et al. (2016), also using the DSSAT model, have found that a reduction in sorghum (S. bicolor L.) yields by 5–24%. Likewise, Niguse and Aleme (2015) projected the yield of sesame (Sesamum indicum) using the Aqua crop model in the western part of the Tigray region and found that the yield of sesame is expected to increase by about 33.1% using the GFDL-ESM2M model in the mid-century (2050) under RCP4.5, while it will decline by about —5.88% and by —23.31% at the end of the century (2100) under RCP8.5 using the GFDL-ESM2M and HadGEM2-EM climate models, respectively.

Overall, most of the studies in the Tigray region projected that crop production under future climate change will be very challenging as the yield of different crops is expected to decline significantly. In the past, farmers in the region have been practicing locally adopted coping mechanisms in response to changes; however, climate variability and change are eroding the coping mechanisms by causing climatic extremes with an increasing rate of recurrence and intensity that local people have never experienced before. Therefore, future climate change adaptation mechanisms should correspond with the magnitude of the problem. This requires an in-depth, multidimensional understanding of the problems and research based solutions all over the world.

4.3.2 Annual and seasonal reference evapotranspiration (ETo) changes

It is very relevant to focus on the change in ETo in combination with the change in precipitation because this indicates possible changes in water stress. In this study, results of annual and seasonal ETo projections showed that the ETo is likely to increase in the mid- and end-term under all RCPs in all stations (Figure 4-3). This increase can be directly translated into increased demand for water in the future. Changes in annual and seasonal ETo were, however, higher in the end-term period projections compared to the mid-term period in all scenarios at most of the stations. Similarly, Kiremt's (June to September) ETo is expected to increase at a higher rate than the annual and Belg rainfall. The Kiremt ETo will increase by nearly 5–10% in the end-term under RCP4.5 and 9–15% in the end-term under RCP8.5 across stations compared to the baseline period. Even though projections of precipitation in the Kiremt season are expected to increase at most of the stations, this could be largely offset by the negative contribution of the ETo. Comparing across stations, the Atsbi station showed the highest ETo projection increase under all scenarios, seasons, and periods, while the Hawzen station showed the lowest one. The highest increase of ETo at the Atsbi station could be attributed to the vicinity of the station with the hottest Afar lowlands in the northeastern part of the country.

Future changes in ETo are of increasing importance in assessing the potential impacts on hydrology and water resources. Similar to the findings of this study, several previous studies indicated an increase in evapotranspiration in their corresponding study locations (Gebremeskel & Kebede, 2018a; Kahsay et al., 2018; Shiferaw et al., 2018; Takele et al., 2022). The studies pointed out that the change in evapotranspiration is associated with changes in temperatures and rainfall variability, which will influence the hydrological responses of river basins over northern Ethiopia in the future. For example, Shiferaw et al. (2018) reported that increasing trends in temperature and evaporation are predicted in the future in the Illala watershed. They found that the surface runoff will also decline from 1.74% under RCP4.5 in the near term (2010–2039) to 0.36% under RCP8.5 in the end-term periods (2070–2099). Likewise, Takele et al. (2022) pointed out a significant increasing trend of temperatures and a decreasing trend of precipitation in the upper Blue Nile basin in the mid-century

(2040– 2069). This leads to an increase in the annual evapotranspiration of about 10.4%, while it causes a reduction in the streamflow of up to 54%, surface runoff of up to 31%, and water yield of up to 31%. Similarly, Kahsay et al. (2018) found an increase in the evapotranspiration of 0.4% under RCP2.6 and 8.1% under RCP4.5 in the sub catchment of the Tekeze River basin throughout 2020–2079. As a result, they found a decrease in the groundwater recharge of 3.4 and 1.3% and a decrease in the base flow of 1.5 and 0.55% under RCP2.6 and RCP4.5, respectively. Gebremeskel and Kebede (2018b) also investigated the hydrological responses in the Werii watershed based on A1B and B1 special reports for emission scenarios (SRES) and found an increase in rainfall as well as temperatures in mid-century (2015–2050). This causes an increase in the evapotranspiration of 15% under A1B and 18% under B1, and a decrease in the runoff of 13 and 14% under the respective scenarios. Many of the studies mentioned above projected that the changes in evapotranspiration, in association with changes in temperatures and rainfall, are expected to bring changes in river flows and runoff in the future at different river basins in northern Ethiopia. And the changes in these hydrological variables are expected to affect the availability of water for irrigation and other water-consuming sectors in the region. Hence, to meet the food and potable water demands of the ever-growing population, water resources need to be managed efficiently.

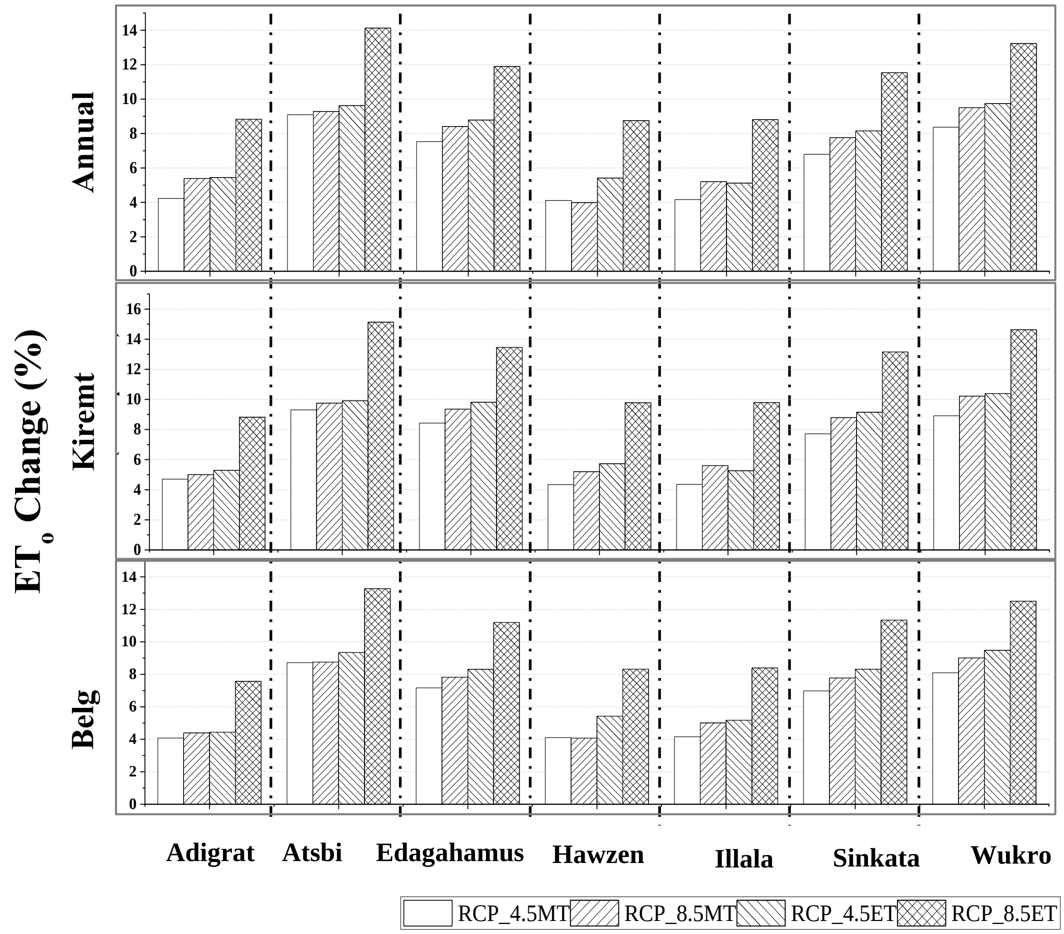


Figure 4-3: Annual and seasonal changes in reference evapotranspiration (ETo) by the period and scenarios.

4.3.3 Changes in Kiremt rainfall onset, cessation, LGP, and DSs

The analysis of rainfall onset in the Kiremt season (June to September) across stations indicated that planting can start as early as the end of June at the Hawzen station (183 Day of Year, DOY) and as late as the first week of July in the rest of the stations in the baseline period, i.e., from 186 to 190 DOY. There is a tendency for the late onset at all of the stations under future climate change scenarios (Figures 4-4 and 4-5). The median onset date ranged from 192 DOY to 201 DOY under RCP4.5 and from 192 DOY to 203 DOY under RCP8.5. This extended the onset date by 2–11 days in Wukro, Atsbi, Illala, and Adigrat stations and by 12–17 days in Hawzen, Edagahamus, and Sinkata stations in all periods. Although there is no significant difference in onset between mid- and end-term periods under RCP4.5, late onset was more pronounced under RCP8.5 in mid- and end-term periods at most of the stations.

The cessation of the season ranged from 255 to 269 (DOY) in the baseline period. Contrary to the onset, there is a tendency toward early cessation at most of the stations under future climate scenarios, ranging from no change at the Edagahamus station to 8 days at the Adigrat station. The tendency of late onset and early cessation will make the LGP decline over the study area in the future. The LGP of the season shortens by 4 days at the Wukro station to a maximum of 19 days at the Hawzen station in all periods compared to the baseline period. The results indicated that the LGP will decline at all stations under all RCPs and all time periods. Consequently, the short nature of the LGP of the study area will be further shortened, which is expected to affect crop production in the study area. Our results corroborate the findings of the previous study that indicated a decrease in the LGP in the future in southern Tigray (Gebrekiros et al., 2015).

The average DS length determined based on a 1 mm threshold rainfall in the Kiremt season varied from 11 to 15 days in the baseline period (Figures 4-4 and 4-5). Comparing the future scenarios with the baseline, the future DS length showed decreasing with a maximum of 5 days in the Edagahamus and Sinkata stations, but there is no significant difference under the two RCPs as well as across the stations. The small decreasing tendency of the DS length during the *Kiremt* season in the future time period could be a result of the contribution of the increasing rainfall projections obtained by the multiple GCMs at most of the stations over the study area.

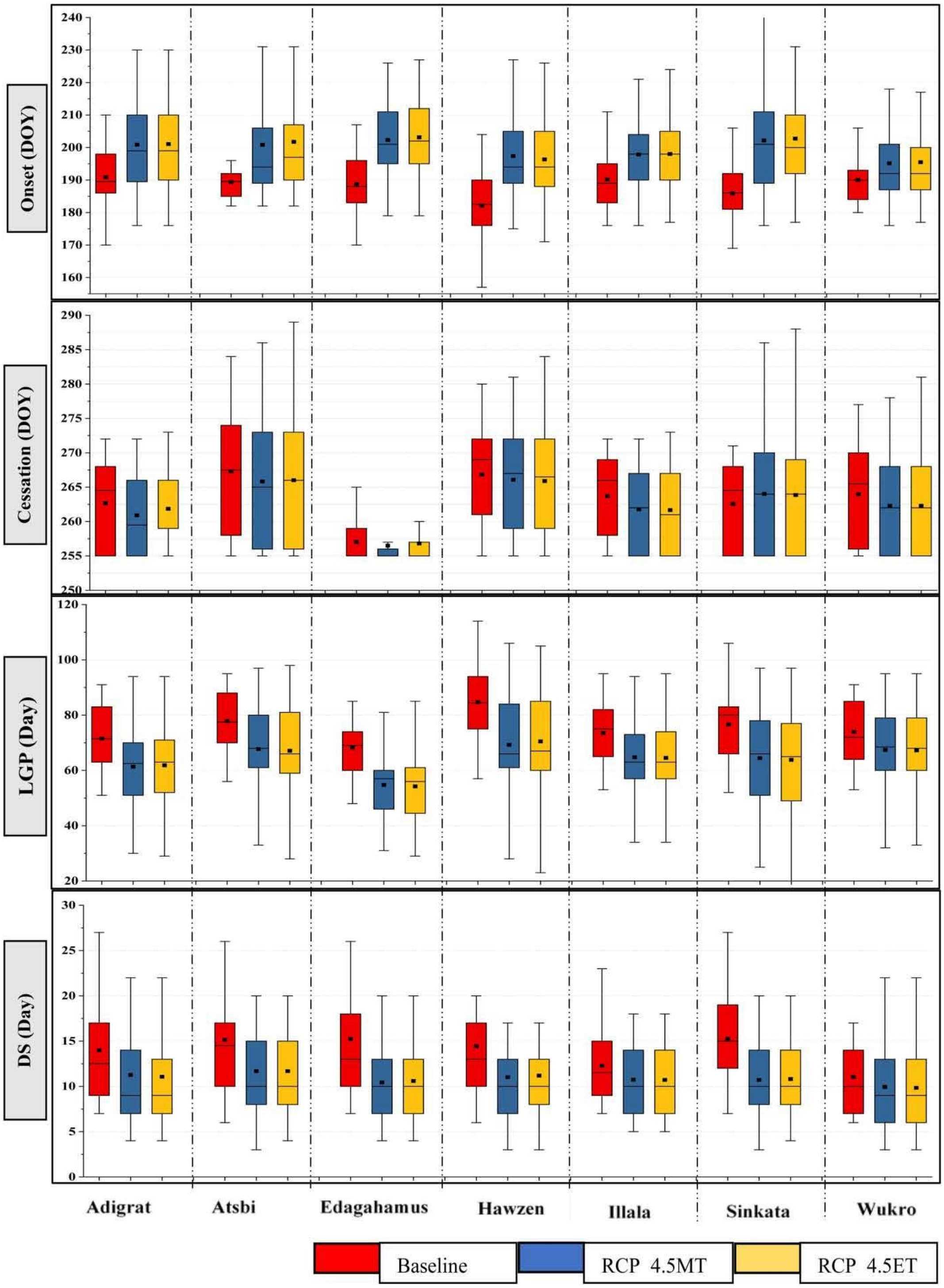


Figure 4-4: Baseline and projected crop growing season characteristics in the Kiremt season under RCP4.5

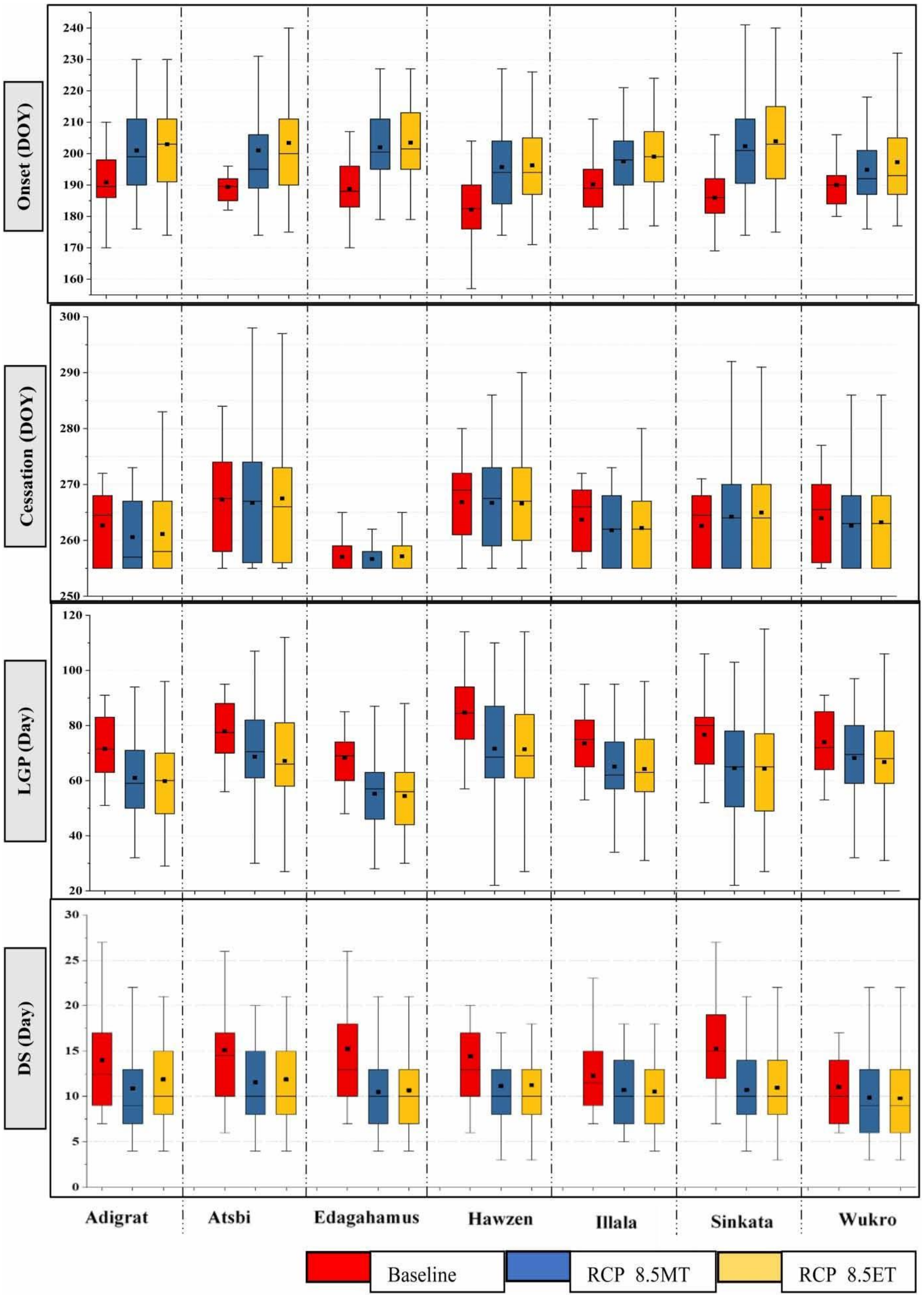


Figure 4-5: Baseline and projected crop growing season characteristics in the Kiremt season under RCP8.5.

4.4 Conclusion and recommendation

The effects of climate change are being felt in many sectors all over the world. Hence, quantifying its effect on crop growing season characteristics will allow better preparation for small scale farmers who are dependent on rainfed agriculture to make decisions on selecting crop varieties, where and when to plant, and when to harvest. In this study, daily temperatures and rainfall variables were projected for a future time period using selected GCMs under two RCPs (RCP4.5 and RCP8.5) to investigate the impact of climate change on crop growing season characteristics.

Results from this analysis indicate that the length of the growing period (LGP) shortened from 5.5 to 19% from mid-to-end of the century compared to the baseline period (1980–2009). In addition, the shortening of the growing season over the study area is expected toward the end of the century under RCP8.5. This shortening is associated with both a later onset and an early cessation. These changes are attributed to modifications in both precipitation and potential evapotranspiration.

Overall, the results revealed that the study area may experience more warming in the future with the high and increasing trend of temperatures, which will exacerbate moisture stress and affect yield. Furthermore, higher variability and an increasing trend in rainfall may increase the risk of flooding and waterlogging conditions, eventually damaging crops and infrastructure. The implications of high temperatures as well as changes in moisture conditions in the future time period will possibly create favorable conditions and increase the risk of disease and pest outbreaks. The negative outcomes as a result of climate change in association with the decreasing trend of the LGP in the future pose a clear message that the continuation of crop production in the study area depending solely on rainfed conditions will be unthinkable. Hence, crop production in the area demands adaptation strategies that encourage supplemental irrigation and water harvesting technologies, as well as introducing tolerant varieties for high temperatures and new diseases while formulating appropriate pesticides for the adapted ones. It is very important to note that the results may have practical implications for formulating long term adaptation strategies for sustainable crop production as well as the sustainable management of water resources in the region in particular and in other parts of the world in general. Finally, this research recommends that further research is needed that compares the latest CMIP6 with CMIP5 for the study region and examines the similarities and differences to be used for future climate change projections considering CMIPs.

References

Ahmed, S., Muhammad, I., Kumar, S., Malhotra, R., & Maalouf, F. (2010). Impact of climate change and variability on diseases of food legumes in the dry areas. *FOOD SECURITY AND CLIMATE CHANGE IN DRY AREAS*, 157-165.

AMI. (2018). *African Math's Initiative (AMI), Analyzing climatic data with R-Instat, https://github.com/africanmathsinitiative/R-Instat.wiki.git/)*.

Aragie, E. A. (2013). Climate change, growth, and poverty in Ethiopia. *Texas Univ at Austin*.

Araya, A., Prasad, P., Gowda, P., Djanaguiramana, M., & Gebretsadkan, Y. (2021). Modeling the effects of crop management on food barley production under a midcentury changing climate in northern Ethiopia. *Climate Risk Management*, *32*, 100308.

Asheber, S. A. (2010). *Mitigating drought: policy impact evaluation: a case of Tigray region, Ethiopia* University of Twente].

Berhe, A. G., Mesfin, H. S., Abraha, A., Abraha, G. G., Misgna, S. H., & Gebremicael, T. G. (2018). The impact of climate change on irrigation water requirement of Maize and Onion: the case of Gum-Selasa small-scale irrigation scheme, Tigray, Ethiopia.

Berhe, A. G., Misgna, S. H., Abraha, G. G.-S., & Abraha, A. Z. (2023). Variability and trend analysis of temperatures, rainfall, and characteristics of crop-growing season in the eastern zone of Tigray region, northern Ethiopia. *Theoretical and Applied Climatology*, *152*(1), 25-43.

Cooper, P., Rao, K., Singh, P., Dimes, J., Traore, P., Rao, K., Dixit, P., & Twomlow, S. (2009). Farming with current and future climate risk: Advancing a'Hypothesis of Hope'for rainfed agriculture in the semi-arid tropics. *Journal of SAT Agricultural Research*, *7*, 1-19.

El Bouhssini, M., Lhaloui, S., Amri, A., & Trissi, A. (2011). Implications of climate change on insects: the case of cereal and legume crops in North Africa, West and Central Asia. *FOOD SECURITY AND CLIMATE CHANGE IN DRY AREAS*, 166.

example in Abrha, M. G., & Simhadri, S. (2015). Effects of rainfall variability on production of five major cereal crops in Southern Tigray, Northern Ethiopia.

Gardi, M. W., Memic, E., Zewdu, E., & Graeff-Hönninger, S. (2022). Simulating the effect of climate change on barley yield in Ethiopia with the DSSAT-CERES-Barley model. *Agronomy Journal*, *114*(2), 1128-1145.

Gebrehiwot, T., & van der Veen, A. (2013). Assessing the evidence of climate variability in the northern part of Ethiopia. *Journal of development and agricultural economics*, *5*(3), 104-119.

Gebrehiwot, T., Van der Veen, A., & Maathuis, B. (2011). Spatial and temporal assessment of drought in the Northern highlands of Ethiopia. *International Journal of Applied Earth Observation and Geoinformation*, *13*(3), 309-321.

Gebrekiros, G., Araya, A., & Yemane, T. (2015). Modeling Impact of Climate Change and Variability on SorghumProduction in Southern Zone of Tigray, Ethiopia. *Journal of Earth Science & Climatic Change*, *7*, 1-10.

Gebremeskel, G., & Kebede, A. (2018a). Estimating the effect of climate change on water resources: Integrated use of climate and hydrological models in the Werii watershed of the Tekeze river basin, Northern Ethiopia. *Agriculture and Natural Resources*, *52*, 195-207.

Gebremeskel, G., & Kebede, A. (2018b). Estimating the effect of climate change on water resources: Integrated use of climate and hydrological models in the Werii watershed of the Tekeze river basin, Northern Ethiopia. *Agriculture and Natural Resources*, *52*(2), 195-207.
Gebremicael, T. G., Mohamed, Y. A., & Hagos, E. Y. (2017). Temporal and spatial changes of rainfall and streamflow in the Upper Tekezē–Atbara river basin, Ethiopia. *Hydrology and Earth System Sciences*, *21*(4), 2127-2142.
Gebresamuel, G., Abrha, H., Hagos, H., Elias, E., & Haile, M. (2022). Empirical modeling of the impact of climate change on altitudinal shift of major cereal crops in South Tigray, Northern Ethiopia. *Journal of Crop Improvement*, *36*(2), 169-192.
Gitz, V., Meybeck, A., Lipper, L., Young, C. D., & Braatz, S. (2016). Climate change and food security: risks and responses. *Food and Agriculture Organization of the United Nations (FAO) Report*, *110*(2), 3-36.
Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. *Weather and climate extremes*, *10*, 4-10.
Hayelom, B., Chen, Y., Marsie, Z., & Negash, M. (2017). Temperature and precipitation trend analysis over the last 30 years in Southern Tigray Regional State, Ethiopia.
Jima, W. L., Korecha, D., & Ture, K. (2019). Impact of climate change on seasonal rainfall patterns over Bale Highlands, Southeastern Ethiopia. *International Journal of Environmental Chemistry*, *3*(2), 84.
Kahsay, K. D., Pingale, S. M., & Hatiye, S. D. (2018). Impact of climate change on groundwater recharge and base flow in the sub-catchment of Tekeze basin, Ethiopia. *Groundwater for Sustainable Development*, *6*, 121-133.
Kassie, B. T. (2014). *Climate variability and change in Ethiopia: Exploring impacts and adaptation options for cereal production*. Wageningen University and Research.
Kidanemariam, S., Goitom, H., & Desta, Y. (2021). Coupled application of R and WetSpa models for assessment of climate change impact on streamflow of Werie Catchment, Tigray, Ethiopia. *Journal of Water and Climate Change*, *12*(3), 916-936.
Luhunga, P., Chang'a, L., & Djolov, G. (2017). Assessment of the impacts of climate change on maize production in the Wami Ruvu basin of Tanzania. *Journal of Water and Climate Change*, *8*(1), 142-164.
Mekasha, A., Tesfaye, K., & Duncan, A. J. (2014). Trends in daily observed temperature and precipitation extremes over three Ethiopian eco-environments. *International Journal of Climatology*, *34*(6).
Meze-Hausken, E. (2004). Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. *Climate research*, *27*(1), 19-31.
Msongaleli, B. M., Rwehumbiza, F., Tumbo, S. D., & Kihupi, N. (2015). Impacts of climate variability and change on rainfed sorghum and maize: implications for food security policy in Tanzania.
Mupangwa, W., Chipindu, L., Ncube, B., Mkuhlani, S., Nhantumbo, N., Masvaya, E., Ngwira, A., Moeletsi, M., Nyagumbo, I., & Liben, F. (2023). Temporal changes in minimum and maximum temperatures at selected locations of southern Africa. *Climate*, *11*(4), 84.

Niguse, A., & Aleme, A. (2015). Modeling the impact of climate change on production of Sesame in Western zone of Tigray, Northern Ethiopia. *Journal of Climatology & Weather Forecasting*, *3*(3), 03.

Ochieng, J., Kirimi, L., & Mathenge, M. (2016). Effects of climate variability and change on agricultural production: The case of small scale farmers in Kenya. *NJAS-Wageningen journal of life sciences*, *77*, 71-78.

Rosenzweig, C. E., Jones, J. W., Hatfield, J., Antle, J., Ruane, A., Boote, K., Thorburn, P., Valdivia, R., Porter, C., & Janssen, S. (2015). *Guide for regional integrated assessments: handbook of methods and procedures, Version 5.1*.

Ruiter, A. (2012). Delta-change approach for CMIP5 GCMs. *Trainee report, Royal Netherlands Meteorological Institute*.

Schlenker, W., & Lobell, D. B. (2010). Robust negative impacts of climate change on African agriculture. *Environmental Research Letters*, *5*(1), 014010.

Shiferaw, H. M., Gebremedhin, A., Gebretsadkan, T., & Zenebe, A. (2018). Modelling hydrological response under climate change scenarios using SWAT model: the case of Ilala watershed, Northern Ethiopia. *Modeling Earth Systems and Environment*, *4*, 437-449.

Sillmann, J., & Roeckner, E. (2008). Indices for extreme events in projections of anthropogenic climate change. *Climatic change*, *86*, 83-104.

Takele, G. S., Gebrie, G. S., Gebremariam, A. G., & Engida, A. N. (2022). Future climate change and impacts on water resources in the Upper Blue Nile basin. *Journal of Water and Climate Change*, *13*(2), 908-925.

Tesfaye, S., Raj, A. J., & Geberesamuel, G. (2014). Assessment of Climate Change Impact on the Hydrology of Geba Catchment, Northern Ethiopia. *American Journal of Environmental Engineering*, *4*, 25-31.

Thomas, T. S., Dorosh, P., & Robertson, R. (2020). Climate Change Impacts on Crop Yields. IFPRI Book Chapters, pp. 97–113. In: Ethiopia's agrifood system: Past trends, present challenges, and future scenarios. (Paul A. Dorosh & Bart Minten, eds). Part One: Natural Resources and Production, Chapter 4, pp. 97–113. Washington, DC: International Food Policy Research Institute (IFPRI). Washington, DC: International Food Policy Research Institute (IFPRI). . *ETHIOPIA's*, 97. https://doi.org/https://doi.org/10.2499/9780896296916_04.

Walthall, C., Hatfield, J., Backlund, P., Lengnick, L., Marshall, E., Walsh, M., Adkins, S., Aillery, M., Ainsworth, E., & Ammann, C. (2012). USDA Technical Bulletin.

Wayne, G. (2014). Representative concentration pathways. *Skeptical science*, *24*.

World Bank Group. (2021). *Climate Risk Profile: Ethiopia. The World Bank Group, Washington, DC, USA (accessed October 2022).*

Zeray, N., & Demie, A. (2016). Climate change impact, vulnerability and adaptation strategy in Ethiopia: A review. *Journal of Earth and Environmental Sciences*, *5*, 45-56.

CHAPTER FIVE

5. IMPACT OF CLIMATE CHANGE AND VARIABILITY ON SPATIO-TEMPORAL CROP WATER REQUIREMENT, IN EASTERN TIGRAY, NORTHERN ETHIOPIA[3]

Abstract

This research study investigates how climate change and variability affect crop water requirement in the eastern zone of the Tigray region, northern Ethiopia, and explores potential adaptation strategies. We used daily temperature and precipitation data from the latest Coupled Model Intercomparison Project-Phase 6 (CMIP6) under two Shared Socioeconomic Pathways (SSPs) (SSP2-4.5 and SSP5-8.5). The analysis covers the period from 1980 to 2014 as the baseline, and extends to 2040–2069 and 2070–2099 as the future period. Our findings indicate that future precipitation is projected to increase in most stations and scenarios, suggesting a shift towards wetter conditions with higher variability. However, rising temperatures will exacerbate the challenges related to climate-induced changes in evapotranspiration and crop water requirement. With increasing temperatures, reference evapotranspiration is expected to rise in both the mid- and end-term periods under all SSPs at all stations. The mean monthly crop water requirement is projected to increase, ranging from minor changes to 19%, from mid- to end-of-century. Seasonal crop water requirements also show increases ranging from 6% to 13%. These findings have significant implications. It is crucial to take proactive adaptation measures and continue research to effectively manage the risks associated with high variability nature of the rainfall. Understanding local temperature fluctuations is essential to address issues like heat stress and climate change impacts on ecosystems. Moreover, our study highlights the dynamic nature of crop water requirements and the challenges posed by increasing water requirements. By recognizing these complexities, stakeholders can develop tailored adaptation plans to ensure sustainable water management and agricultural productivity in the face of climate uncertainty.

[3] Amdom G., Klaus R. Solomon H., Girmay G., Amanuel Z. 2024. Impact of Climate Change and Variability on Spatio-Temporal Crop Water Requirement in Eastern Tigray, Northern Ethiopia. Report submitted to Bayer Foundation

Key words: Climate Change and Variability, Temperature, Precipitation, Evapotranspiration, Crop Water Requirement, Adaptation Strategies, CMIP6, SSPs

5.1 Introduction

Communities who are dependent on rain-fed agricultural systems are especially vulnerable to climate change and variability, which pose significant challenges to agricultural productivity and food security. Therefore, there is an urgent need to explore and implement adaptive strategies to mitigate climate-related impacts, protect vulnerable livelihoods, and ensure food security for impoverished populations.

Climate change and variability pose significant challenges to crop production in Ethiopia, particularly in the Tigray region. The climate in the study area is marked by frequent droughts, with localized occurrences almost annually due to erratic and unpredictable rainfall patterns. These conditions often lead to crop failures and hinder development efforts (Awulachew et al., 2011; Gebrehiwot & van der Veen, 2013; Gebrehiwot et al., 2011). As a result, ensuring water security through full or supplementary irrigation is crucial for sustaining the livelihoods of agriculture-dependent communities in the region.

Over the last five decades, the frequency of the occurrence of extreme weather events such as droughts and floods has shown an increasing trend (Gebrehiwot & van der Veen, 2013; Nigusse & Adhanom, 2019; Tefera et al., 2019). Seasonal and inter-annual rainfall variability and warming as a result of temperature fluctuation also showed an increasing trend. Spatio-temporal analysis of such changes at the watershed level would help better understand the impacts of climate change, formulate better strategies for climate change adaptation and mitigation in Ethiopia, and encourage local proactive community participation and national efforts as a contribution to global climate change mitigation (Reda & Mamo, 2013).

To alleviate the problem of moisture stress, many water harvesting and irrigation structures have been constructed throughout the region. As a result, the interventions have brought promising crop and livestock production results in the past decades. However, the future of crop production with the already scarce water resources and the continuous changing of the climate is not certain and very challenging. In addition, water resources available for agriculture will decrease shortly due to competing uses of freshwater resources by other non-agriculture sectors.

Despite the significant agricultural potential of the study area, research on the impacts of climate change on the spatio-temporal variability of crop water requirements, both in the present and future, at the watershed level remains limited. Existing studies indicate that irrigation practices in the Tigray region are often inefficient, characterized by instances of both over-irrigation and under-irrigation across various irrigation sites. To address these issues, researchers have utilized a range of modeling tools, such as CROPWAT, to estimate crop water requirements and develop irrigation schedules for diverse crops (Mebrahtu, 2021; Mebrahtu et al., 2021). Additionally, some studies have explored crop water use efficiencies and productivities (Behailu & Nata, 2005; Gebremedhin & Berhe, 2015; Kahsay & Reda; Kifle & Gebretsadikan, 2016; Tsegay et al., 2012) and evaluated crop water requirements under different climate change scenarios (Berhe et al., 2018).

However, these studies are often confined to fragmented areas, such as specific dam sites or research field plots, and do not extend to larger scales such as entire basins or watersheds. To fill this gap, the present study focuses on estimating crop water requirements at the watershed level using advanced tools, including Landsat satellite imagery to derive spatial data and the latest General Circulation Models (GCMs) to incorporate future climate scenarios. By integrating these methodologies, the study aims to provide a comprehensive understanding of crop water demands across spatial and temporal scales, offering critical insights for sustainable water resource management in the context of climate change.

5.2 Materials and Methods

5.2.1 Delta statistical climate downscaling

Daily temperatures (tasmax and tasmin) and precipitation (pr) data were projected from the latest sixth phase Coupled Model Intercomparison Project Phase 6 (CMIP6, https://esgf-node.llnl.gov/search/cmip6/) General Circulation Models (GCMs). Four GCM outputs, as mentioned in Table 5-1, were selected from the available CMIP6 GCMs. The GCMs were selected based on their consistency and resolution performance for East and sub-Saharan Africa (Msongaleli et al., 2015; Rosenzweig et al., 2015; Sillmann & Roeckner, 2008).

The daily atmospheric predictors, spanning from 1985 to 2100, were applied in the statistical analysis to generate and project future climatic variables under two Shared Socioeconomic Pathways-Representative Concentration Pathways (SSP-RCPs) scenarios (SSP2-4.5 and SSP5-8.5) for mid-term (2050:2040-2069) and end-term (2080:2070-2099) periods from the reference period (1980-2014). The latest CMIP6 combines elements from the new narratives of socioeconomic assumptions, namely the Shared Socioeconomic Pathways (SSPs) scenarios, with the previous scenarios, namely the Representative Concentration Pathways (RCPs), to force climate models, which makes future scenarios more reasonable (Peng et al., 2023).

The results obtained from GCMs, with coarse resolution, have been reported to have large uncertainties (Diro et al., 2012; Woldemeskel et al., 2012). Hence, the delta statistical downscaling method of GCMs was applied to represent local conditions with a much finer spatial resolution. The delta downscaling method was employed using Climate Model Data for Hydrological Modeling (CMhyd) software (https://swat.tamu.edu/software/cmhyd/). This software has extensive usage in correcting biases in temperatures as well as precipitation data for various applications (Assfaw et al., 2023; Daniel, 2023; Hordofa et al., 2021; Musie et al., 2020; Yeboah et al., 2022).

Table 5-1: Coupled Model Intercomparison Project Phase 6 (CMIP6) GCMs

Modelling center	**Country**	**Model**	**Atmosphere lat/lon grid (°)**
UK Met Office Hadley Center	UK-Exeter	HadGEM3-GC31-LL (https://doi.org/ 10.22033/ESGF/CMIP6.6109)	1.25 × 1.88
Max Plank Institute for Meteorology (MPI)	Germany	MPI-ESM1.2-HR (https://doi.org/ 10.22033/ESGF/CMIP6.6594)	0.94 × 0.94
NOAA Geophysical Fluid Dynamics Laboratory (GFDL)	US-New Jersey	GFDL-ESM4 (https://doi.org/10.22033/ ESGF/CMIP6.8597)	1.0 × 1.25
National Institute for Environmental Studies, Japan	Japan	MIROC6 (https://doi.org/10.22033/ ESGF/CMIP6.5603)	1.4 × 1.4

5.2.2 Estimation of crop water requirement (CWR)

To estimate CWR, values of crop coefficient (K_C) and reference evapotranspiration (ETo) are needed. To obtain the Kc values of the crops, land use and land cover (LULC) maps of the watersheds were prepared. At this stage, only irrigated crops were extracted from other land use classes as polygons for further analysis using Esri ArcGIS. After that, the spatial distribution of the Kc values of different images was estimated from Normalized Difference Vegetation Index (NDVI) images and extracted using PCI Geomatica software. The software enables users to select and extract the NDVI values of only irrigated crops from other land use classes. Furthermore, the ETo values were calculated using the Hargraves method at the reference period as well as for future periods with the help of the ETo calculator (Version 3.2, September 2012). Finally, CWR was computed using the product of Kc and ETo values. The overall schematic work flow is indicated in Figure 5-1.

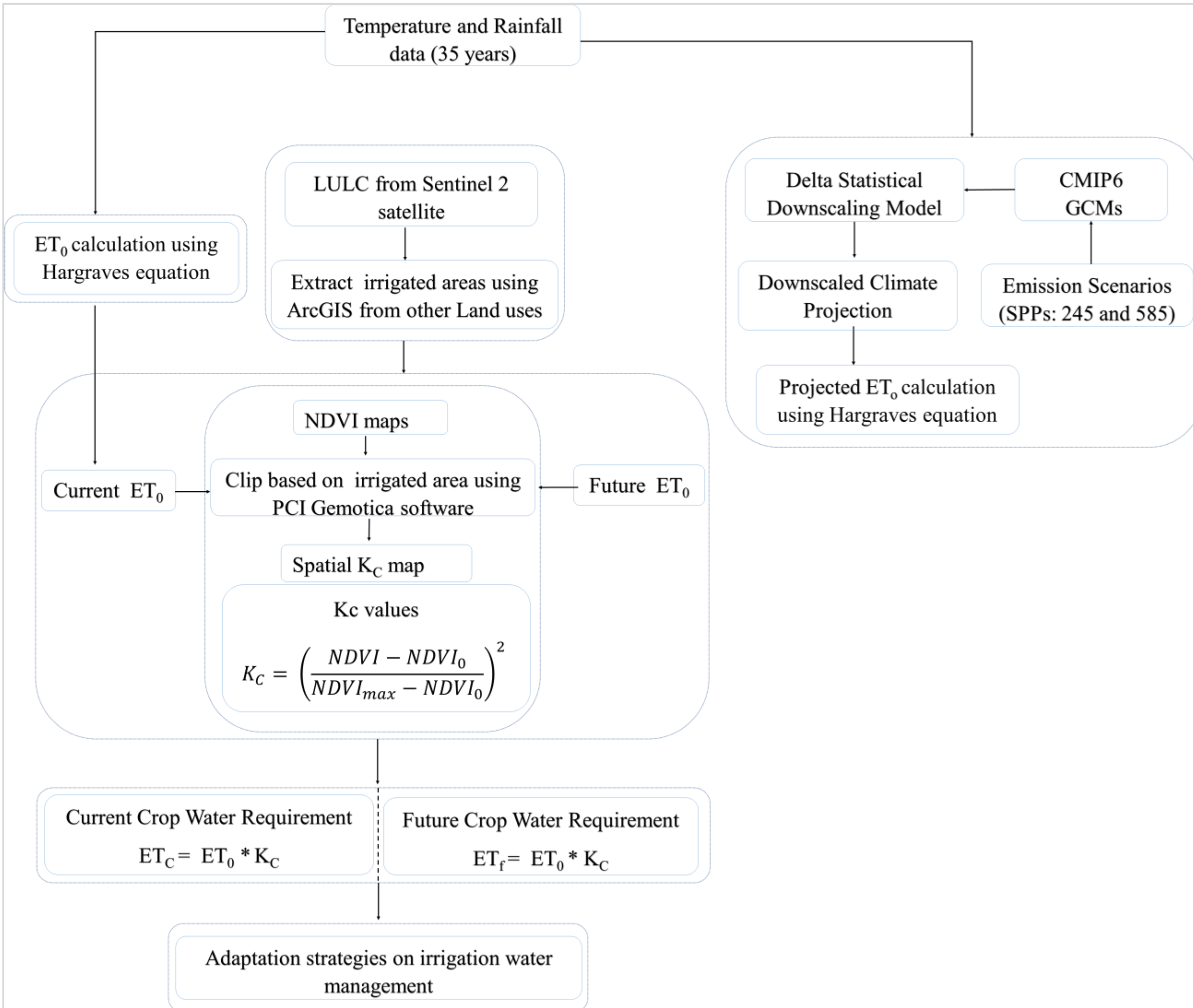


Figure 5-1: Schematic workflow: Spatio-temporal crop water requirement and adaptation strategies

5.2.3 Mapping Crop coefficients (Kc) from NDVI based method

5.2.3.1 Preparation of land use/ land cover (LULC) maps

In order to analyze LULC, high-resolution satellite remote sensing data from Sentinel-2 sensors acquired on March 29, 2020, was used so as to capture all the heterogeneous and small parcels of irrigated lands. The decision to opt for data acquisition on March 29, 2020, is that this month acquired the maximum vegetation density as compared to other images during the irrigated season (December, 2019–June, 2020) and mostly it falls within the mid-season crop growth stage in the study area. A land-use map of the basin was derived using the maximum livelihood-supervised image classification procedure. The image classification process involved selecting and outlining multiple training sites for each land-use category, supported by the analysis of Google Earth images. Additionally, the accuracy was enhanced by utilizing 396 ground truth data points collected with a Global Positioning System (GPS) during prior field visits to the study area.

5.2.3.2 Estimation of Normalized Difference Vegetation Index (NDVI)

To compute the spatial distribution of crop coefficients (Kc) values, time series satellite dataset of high-resolution (10 m) Sentinel-2 images were acquired from the European Space Agency, data available at https://dataspace.copernicus.eu/. The multispectral aerial images provided by Sentinel 2 can be used to calculate many vegetation indices, including the Normalized Difference Vegetation Index (NDVI), which is commonly used in agriculture. For this study, 12 cloud-free images acquired from December 15, 2019 to June 7, 2020 were used (Table 5-2). The irrigation season was established based on information obtained from the regional Bureau of Agriculture, which encompasses the entire research study area where various crops are irrigated. This period was selected to account for the diverse cropping schedules of different crops across the watersheds. For example, in regions such as Hawzen, irrigation typically commences in December, whereas in other areas, such as Atsbi, it begins in late December. This extended timeframe incorporates early planting, late harvesting, and staggered irrigation schedules, which are common practices in the study area due to variations in climatic conditions, water availability, and cropping patterns.

The NDVI is computed using equation 5.1, where its value ranges from -1 to 1. Extremely negative values indicate water, values near zero indicate bare soil, and values above 0.6 indicate dense green vegetation.

$$NDVI = \frac{(NIR_{band} - Red_{band})}{(NIR_{band} + Red_{band})} \qquad (equation\ 5.1)$$

Where NDVI is the normalized difference vegetation index, NIR_{band} *and* Red_{band} *are the corrected spectral radiance in the near-infrared and red bands, respectively.*

Table 5-2: Sentinel-2 satellite images used for computing NDVI during the 2019 and 2020 growing seasons

Image accusation date	Mission ID	Level	Entity ID
20191215	S2A	2A	S2A_MSIL2A_20191215T074321_N0213_R092_T37PER_20191215T101835
20191220	S2B	2A	S2B_MSIL2A_20191220T074229_N0213_R092_T37PER_20191220T101537
20200119	S2B	2A	S2B_MSIL2A_20200119T074139_N0213_R092_T37PER_20200119T101410
20200129	S2B	2A	S2B_MSIL2A_20200129T074049_N0213_R092_T37PER_20200129T105644
20200208	S2B	2A	S2B_MSIL2A_20200228T073839_N0214_R092_T37PER_20200228T120136
20200218	S2B	2A	S2B_MSIL2A_20200218T073949_N0214_R092_T37PER_20200218T105932
20200228	S2B	2A	S2B_MSIL2A_20200228T073839_N0214_R092_T37PER_20200228T120136
20200324	S2A	2A	S2A_MSIL2A_20200324T073611_N0214_R092_T37PER_20200324T105851
20200329	S2B	2A	S2B_MSIL2A_20200329T073609_N0214_R092_T37PER_20200329T115211
20200408	S2B	2A	S2B_MSIL2A_20200408T073609_N0214_R092_T37PER_20200408T123001.SAFE
20200513	S2A	2A	S2A_MSIL2A_20200513T073621_N0214_R092_T37PER_20200513T111258
20200607	S2B	2A	S2B_MSIL2A_20200607T073619_N0214_R092_T37PER_20200607T110519.

5.2.3.3 Estimation of Kc values from NDVI

Crop coefficient (Kc) refers to the ratio of well-watered crop evapotranspiration (ETc) to the reference (ETo). The Kc values reflect the relative water consumption capacity of a crop during different growing stages. In this study, the Kc was generated following the procedure outlined by (Brunsell & Gillies, 2002). The method computes the fraction of vegetation cover and the fraction between the emissivity of a fully covered canopy and bare soil (equation 5.2).

$$K_C = \left(\frac{NDVI - NDVI_0}{NDVI_{max} - NDVI_0}\right)^2 \qquad (equation\ 5.2)$$

Where Kc is crop coefficient, $NDVI_0$ *is bare soil NDVI value,* $NDVI_{max}$ *is full cover dense vegetation and NDVI is the normalized difference vegetation index*

5.2.3.4 Estimating reference evapotranspiration (ET_O)

The Hargreaves equation was utilized in this study due to the unavailability of long-term meteorological data such as wind speed, sunshine hours, and relative humidity, as well as the poor quality of the limited data available for the study area. The Hargreaves method requires only minimum and maximum temperature, along with solar radiation, as input parameters (Hargreaves & Samani, 1985). Several studies have shown that the Hargreaves equation provides potential evapotranspiration estimates that closely align with those obtained using the FAO Penman-Monteith method (Rajabi & Babakhani, 2018; Shahidian et al., 2012).

ET_O was calculated using the Hargraves method, equation 5.3. Daily temperature data from the selected stations under the reference period and from the downscaled method of the selected stations were used to develop daily ET_O values under current and future climate change scenarios and later change to monthly ET_O values.

$$ET_O = 0.0023\, R_a\, (T_{max} - T_{min})^{0.5} \left(\frac{T_{max} + T_{min}}{2} + 17.8\right) \qquad (equation\ 5.3)$$

Where, ET_O = Reference evapotranspiration (mm/day), R_a = extraterrestrial radiation ($MJ/m^2/day$), T_{max} = maximum air temperature (^0C), T_{min} = minimum air temperature (^0C)

5.2.3.5 Estimating crop water requirement

Using ESRI-ArcGIS, monthly and seasonal crop water requirement (ETc) values were estimated based on the product of pixel-wise monthly Kc multiplied by monthly ETo values (equation 5.4).

$$ET_c = K_c * ET_O \qquad (equation\ 5.4)$$

Where ET_C is crop evapotranspiration/crop water requirement, K_C is crop coefficient and ET_O is reference evapotranspiration

Future crop water requirements under different climate change scenarios and timeframes were estimated by assuming that Kc-NDVI values would remain constant, while only changes in reference evapotranspiration (ETo) were considered. Monthly ETo values for each station were calculated for the current growing season and projected for the future under two scenarios (SSP2-

4.5 and SSP5-8.5). These projected ETo values were then multiplied by the Kc values derived from NDVI imagery to estimate crop water requirements for the mid-term and end-term periods. Finally, the percentage change in crop water requirements under the two scenarios was calculated relative to the current growing period.

5.3 Results and Discussion

5.3.1 Projections of rainfall and temperatures

Rainfall projections from four GCMs indicated higher variability across stations as well as SSPs in all time periods (Fig. 5-2). Especially in the end-term period, SSP5-8.5 showed higher variability and magnitude of change compared to SSP2-4.5 in all time periods. This is in line with our expectations because at a higher emission scenarios changes in climate variable are tend to more pronounced.

The change in mean rainfall indicated an increasing trend and varied from relatively no change to +56% in annual rainfall and from +7% to +118% in *Kiremt* rainfall in most of the stations, as well as under all scenarios and in all time periods. The magnitude of change varies widely, with some stations experiencing minimal change while others showing substantial increases in *Kiremt* rainfall. Moreover, *Belg* rainfall also showed an increasing trend in most of the stations in all time periods, ranging from +2 to +46% except for two stations, which showed a decreasing trend under SSP5-8.5 in the mid-term and in the end-term periods

The heightened variability and magnitude of rainfall changes, particularly under SSP5-8.5, are driven by a combination of factors. These include global-scale climate changes induced by greenhouse gas (GHG) emissions, regional influences such as topography, local-scale factors like microclimatic variability and land use changes, seasonal climate drivers such as the Intertropical Convergence Zone (ITCZ), and the temporal and spatial resolution of climate models. Together, these factors contribute to a complex and dynamic response in rainfall patterns, with variations depending on geographic location, seasonal timing, and emission scenarios (Mahmood et al., 2014; Maraun et al., 2010; Masson-Delmotte et al., 2021; Nicholson, 2017, 2018).

The projections indicate a general increase in mean rainfall across most stations and scenarios, although the magnitude of change and variability remain significant. This suggests a shift toward wetter conditions, which could have far-reaching implications for water resource management, agricultural productivity, and ecosystem dynamics. Increased rainfall may enhance water availability, potentially benefiting both surface and groundwater resources. However, high variability could present challenges in managing extreme events, such as floods and prolonged dry spells (Trenberth, 2011). While higher rainfall may support crop growth and reduce irrigation demands, excessive rainfall could lead to waterlogging, soil erosion, and crop damage (Rosenzweiga et al., 2014). Additionally, shifts in rainfall patterns may result in changes to species distributions and biodiversity, disrupting ecosystems (Bellard et al., 2012).

Moreover, the study area shows a consistent upward trend in both maximum and minimum temperatures across various time periods and shared socioeconomic pathways (SSPs) (Figs. 5-3 and 5-4). This aligns with the broader trend of global warming observed in various climate models and historical data (Masson-Delmotte et al., 2021). Maximum temperatures show varying increases depending on the SSPs, ranging from nearly +1.0 to +3.6 °C under SSP2-4.5 and +1.9 to +5.4 °C under SSP5-8.5. Similarly, minimum temperatures also exhibit a range of increases, from +0.3 to +3.6 °C under SSP2-4.5 and from +1.2 to +4.8 °C under SSP5-8.5. This indicates that higher emissions scenarios lead to more significant temperature rises.

In addition, the result highlights varying degrees of temperature rise across distinct seasons. The *Belg* season exhibits the most substantial increase in both maximum and minimum temperatures, followed by the *Bega* season, whereas the *Kiremt* season demonstrates the lowest increase, particularly under SSP2-4.5 and SSP5-8.5 during the end-term periods.

Temperature changes vary across different stations. For example, Illala station shows the smallest mean increase in both maximum and minimum temperatures projected for the future. This may be due to its location in valley bottom with a dense vegetation area of Mekelle research center, which could help moderate temperatures around the station. This finding underscores the importance of accounting for local factors and microclimates in climate impact assessments.

Overall, across all scenarios, temperatures will continue to increase in the study area throughout the end of the century. Rising maximum temperatures significantly impact crop water requirements by increasing evapotranspiration, leading to higher water demand for crops and reduced surface water availability. Furthermore, rising maximum temperatures are closely linked to more frequent and intense heat waves, exacerbating heat stress on humans, livestock, and plants. This often results in crop failures and health crises (Alotaibi, 2023; Deryng et al., 2014; Masson-Delmotte et al., 2021).

On the other hand, while higher minimum temperatures may reduce frost risks, offering localized benefits in certain highland areas, their overall impact is predominantly negative. They contribute to intensified drought conditions by increasing evapotranspiration, reduce agricultural yields by accelerating crop growth and potentially shortening growing seasons, and lower productivity for long-duration crops. Additionally, warmer nights heighten vulnerability to pests and diseases, further threatening agricultural sustainability in vulnerable regions (Field & Barros, 2014; Hatfield & Prueger, 2015; Lobell et al., 2008; Porter et al., 2014).

The projected temperature increases will provide crucial information to develop effective adaptation strategies aimed at mitigating the impacts of climate change. This information will also assist in crafting long-term plans for crop and water resource management, as well as enhancing food security, protecting ecosystems, and promoting sustainable land use practices in the study area. These comprehensive measures will support climate resilience and ensure the sustainability of agricultural and water resources in the face of changing climatic conditions.

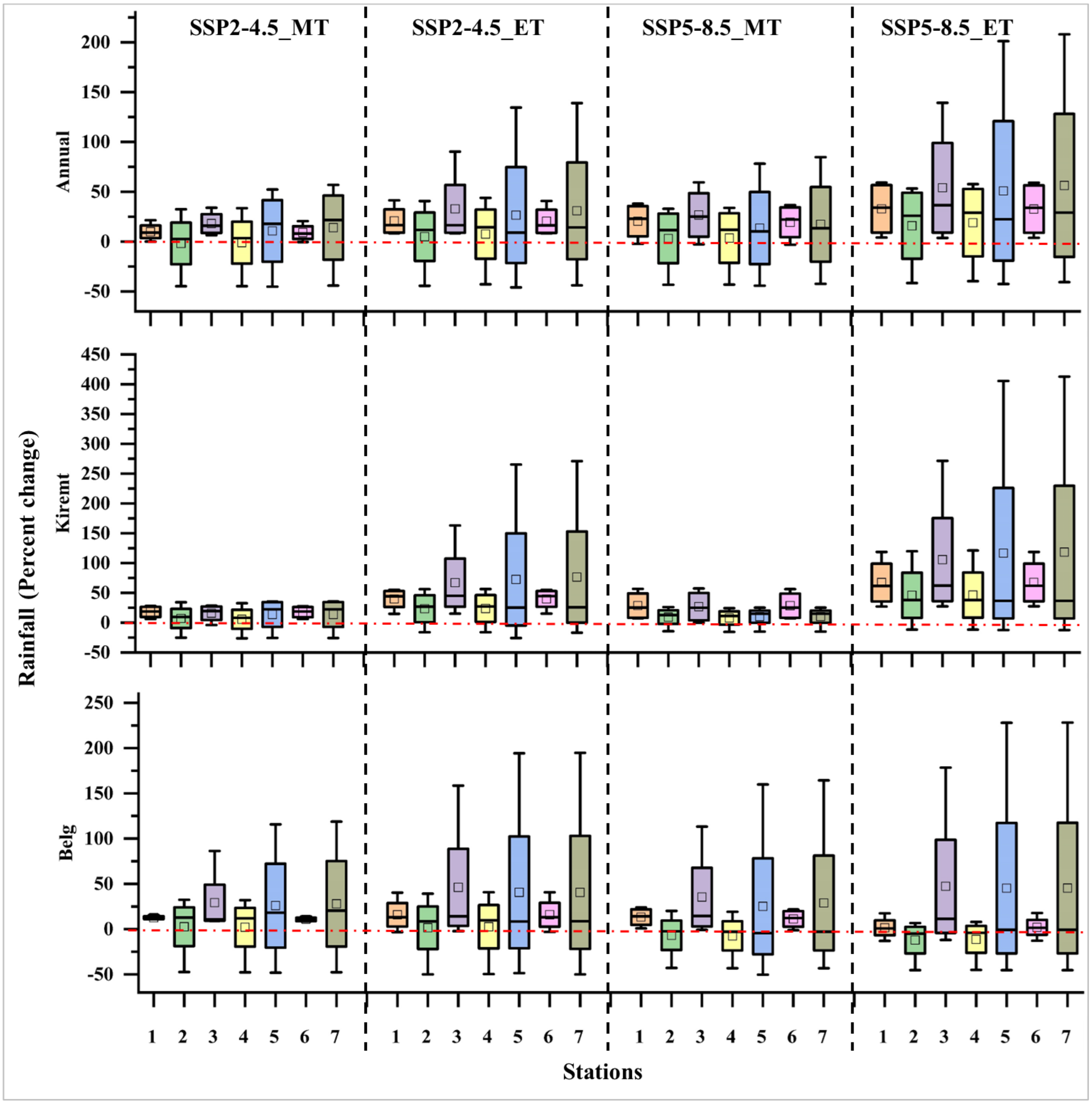


Figure 5-2: Projected rainfall change in seven stations (1 = Adigrat, 2 = Atsbi, 3 = Edagahamus, 4 = Hawzen, 5 = Illala, 6 = Sinkata, 7 = Wukro).

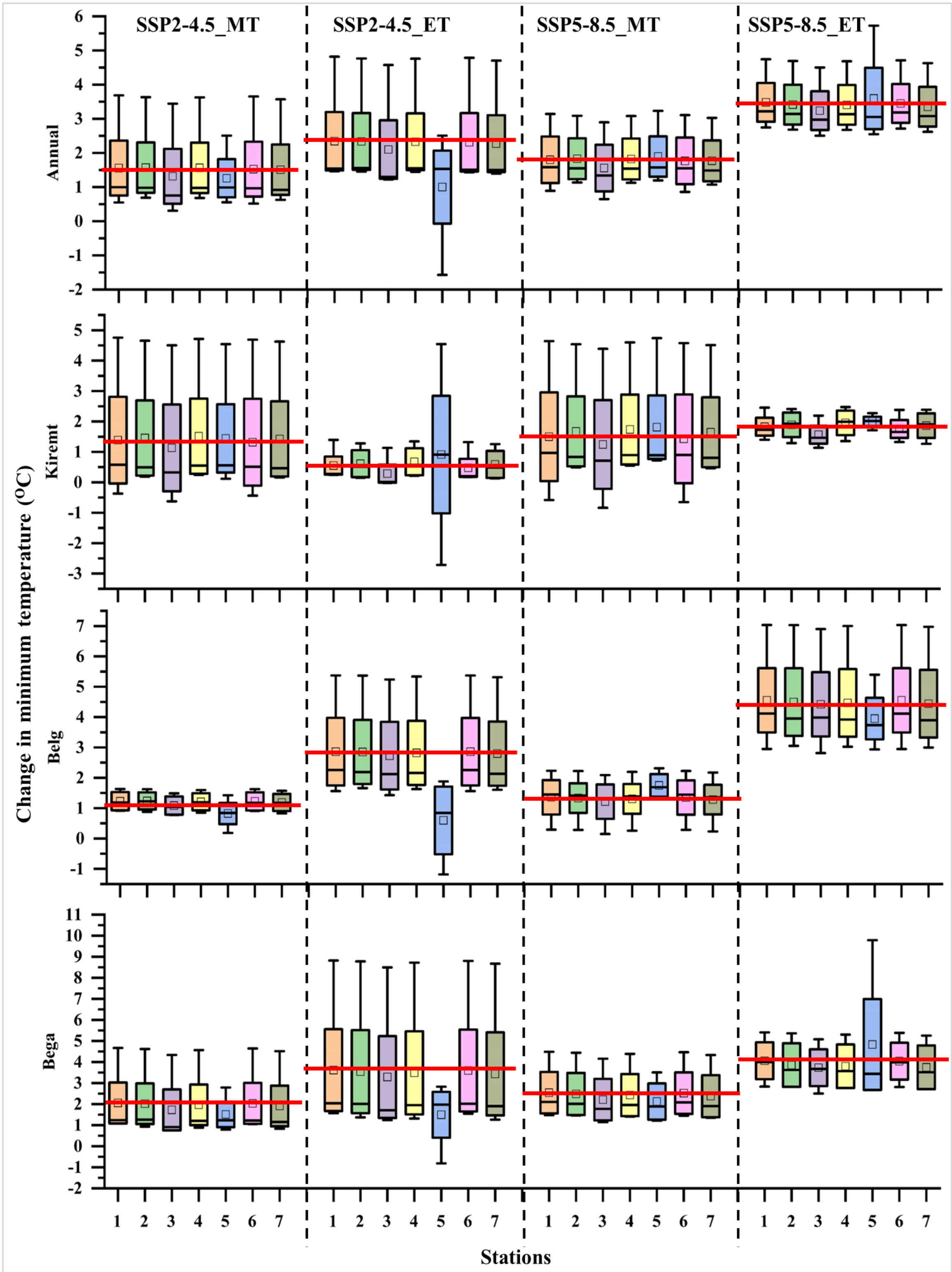


Figure 5-3: Projected maximum temperature change in seven stations (1 = Adigrat, 2 = Atsbi, 3 = Edagahamus, 4 = Hawzen, 5 = Illala, 6 = Sinkata, 7 = Wukro).

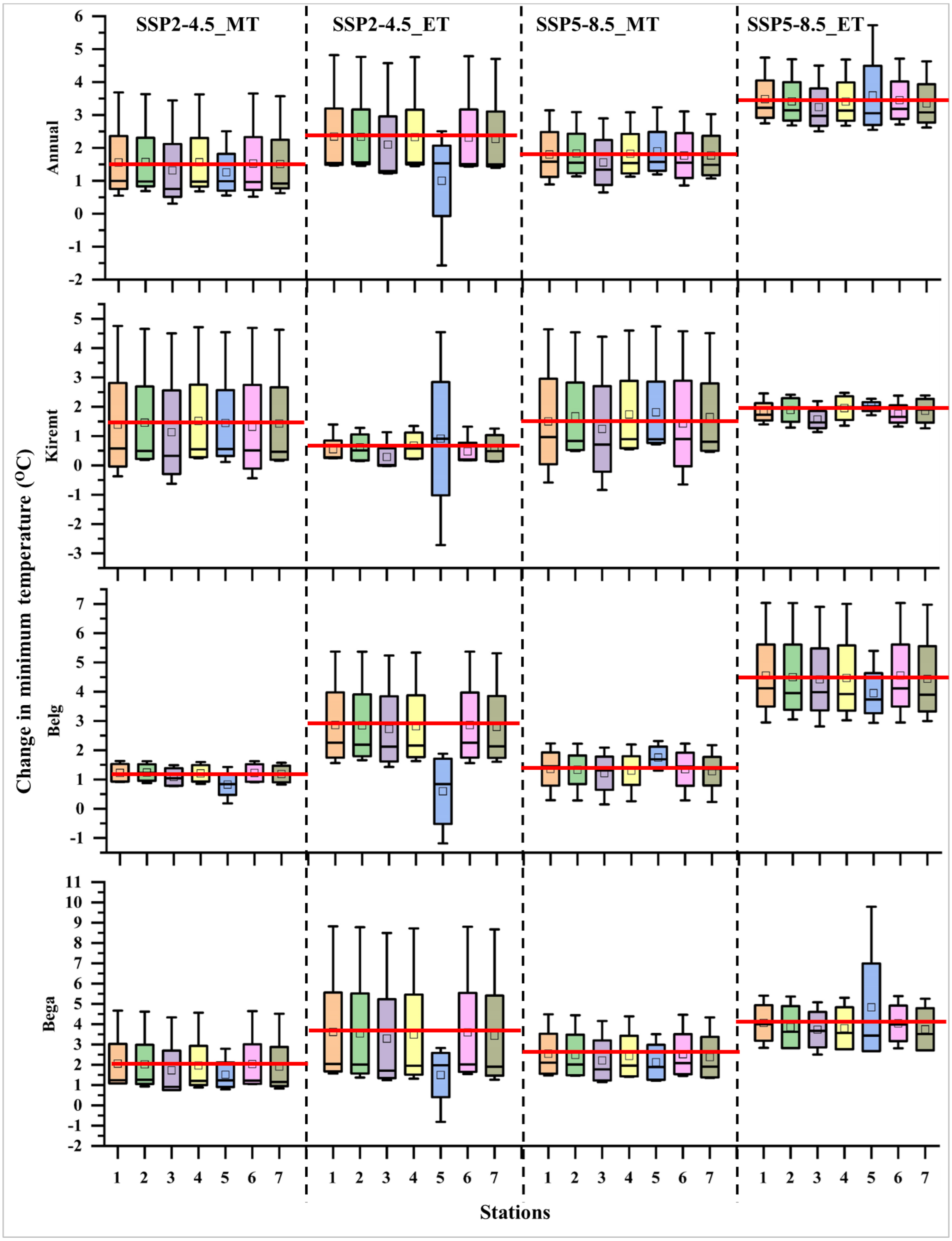


Figure 5-4: Projected minimum temperature change in seven stations (1 = Adigrat, 2 = Atsbi, 3 = Edagahamus, 4 = Hawzen, 5 = Illala, 6 = Sinkata, 7 = Wukro).

5.3.2 Annual, seasonal and monthly reference evapotranspiration (ETo) changes

Future changes in ETo are of increasing importance in assessing the potential impacts of climate change on hydrology and water resources. Hence, it is very relevant to focus on the change in ETo in combination with the change in precipitation because this indicates possible changes in water stress.

This study reveals that annual, seasonal, and monthly projections of reference evapotranspiration (ETo) suggest an expected increase during the mid- and end-term periods across all Shared Socioeconomic Pathways (SSPs) in all stations (Figs. 5-5 and 5-6). This increase can be directly translated into increased requirement for water in the future. Changes in annual, seasonal, and monthly ETo were, however, higher in the end-term period projections compared to the mid-term period in all scenarios in all of the stations. The results indicate that ETo is expected to increase from 3 to 17% in Annual, *Kiremt*, and *Belg*, while *Bega* season is expected to increase from 4.2 to 12%. Moreover, the monthly ETo values also followed the same trend, which show an increase from mid- to end-of-century (Fig. 5-6). The highest ETo was projected in June (6–18%) in three of the scenarios and in most of the stations. In addition, in May also showed the highest increase, from 9 to 14% under SSP2-4.5_ET in most of the stations. This seasonal variation is crucial for understanding the potential shifts in water availability and requirement throughout the year. Additionally, the monthly analysis reveals specific months, such as June and May, showing the highest projected increases in ETo. This information can guide water resource management strategies, allowing for targeted interventions during periods of heightened water stress.

Comparing across stations, Edagahamus station showed the highest ETo projection increase under all scenarios, seasons, and periods, while Hawzen station showed the lowest in Annual and *Kiremt*, and Illala station showed the lowest in Belg rainfall season. Moreover, comparing among months, June and May shows the highest ETo projection as compared to the other months with the highest being projected in Edagahamus station (Fig. 5-6). Edagahamus station consistently shows the highest projected increase in ETo, while other stations exhibit varying levels of change. Understanding these spatial variations is essential for implementing region-specific adaptation measures and prioritizing areas that are particularly vulnerable to changes in water availability.

Many studies in northern Ethiopia about potential evapotranspiration (ETo) have mentioned that changes in ETo, in association with changes in temperatures and rainfall, are expected to bring changes in river flows and runoff in the future at different river basins (Gebremeskel & Kebede, 2018b; Kahsay et al., 2018; Shiferaw et al., 2018; Takele et al., 2022). In regions with short but intense rainy seasons, particularly in dry areas with high ETo, the initial soil conditions play a crucial role in determining surface runoff generation. When the soil is dry before a rainfall event, its infiltration capacity is high, meaning much of the initial rainfall is absorbed rather than contributing to surface runoff. However, if the rainfall intensity exceeds the infiltration rate or if the soil reaches saturation, excess water will contribute to surface runoff. Thus, while increasing ETo generally leads to reduced soil moisture and lower runoff potential over time, the immediate effect of rainfall on surface runoff generation can vary depending on antecedent soil moisture conditions, rainfall intensity, and duration (Ziadat & Taimeh, 2013).

Furthermore, fluctuations in ETo often interact with variations in rainfall. For example, if rainfall decreases while ETo rises, the combined impact exacerbates water deficits, further diminishing runoff and river flow (Lobell et al., 2008). Conversely, even in regions experiencing stable or slightly increasing rainfall, higher ETo can offset the benefits of additional precipitation (Gebrechorkos et al., 2023). And the changes in these hydrological variables are expected to affect the availability of water for irrigation and other water-consuming sectors in the area. Hence, to meet the food and potable water demands of the ever-growing population, water resources need to be managed efficiently.

Overall, the results of the study emphasize the importance of incorporating ETo projections into water resource management strategies to address the challenges posed by climate change. By understanding how ETo is expected to change across different temporal and spatial scales, policymakers and stakeholders can develop informed strategies to enhance water security and resilience in the face of evolving climatic conditions.

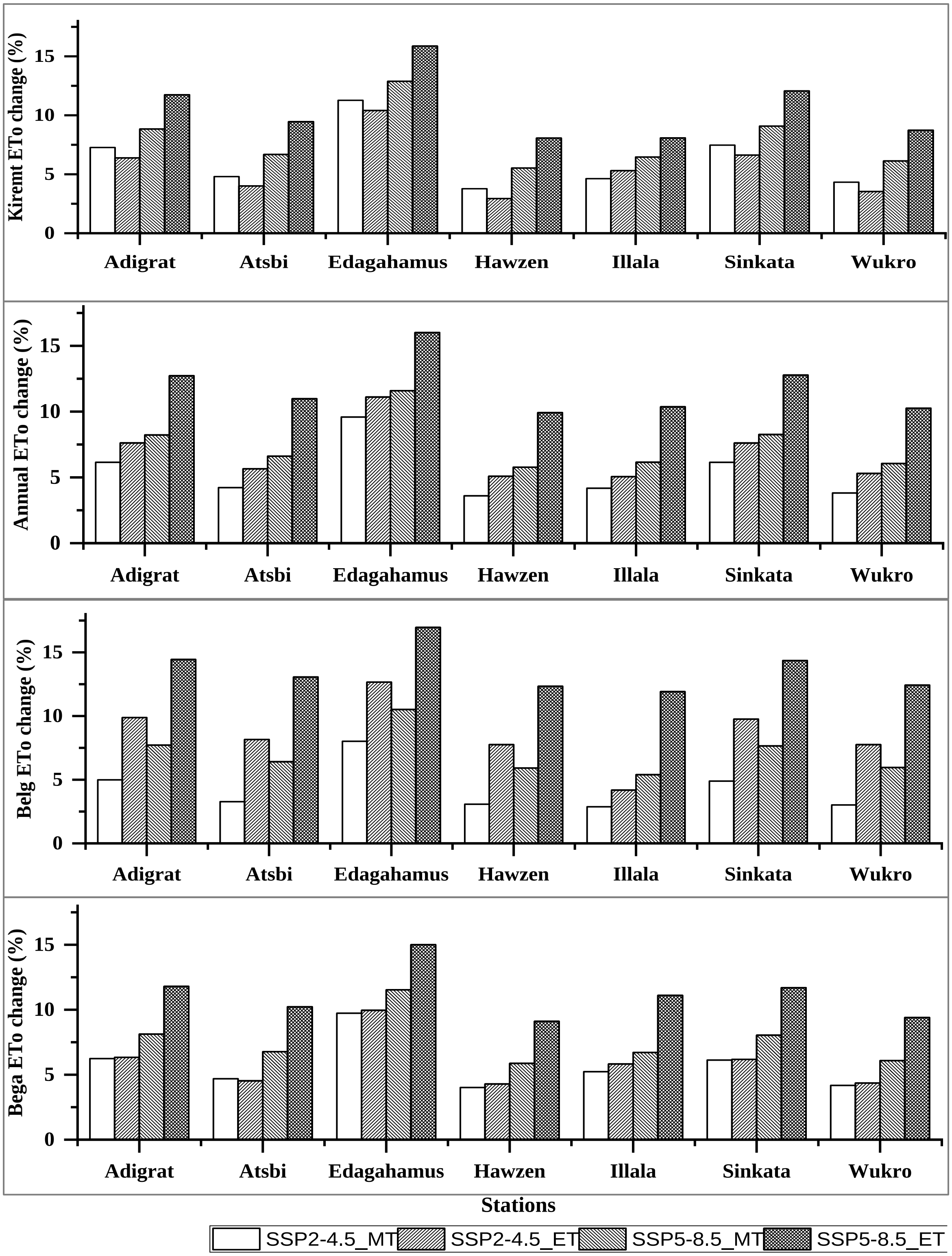


Figure 5-5: Annual and seasonal changes in reference evapotranspiration (ETo) change (%) by period and SSPs scenarios

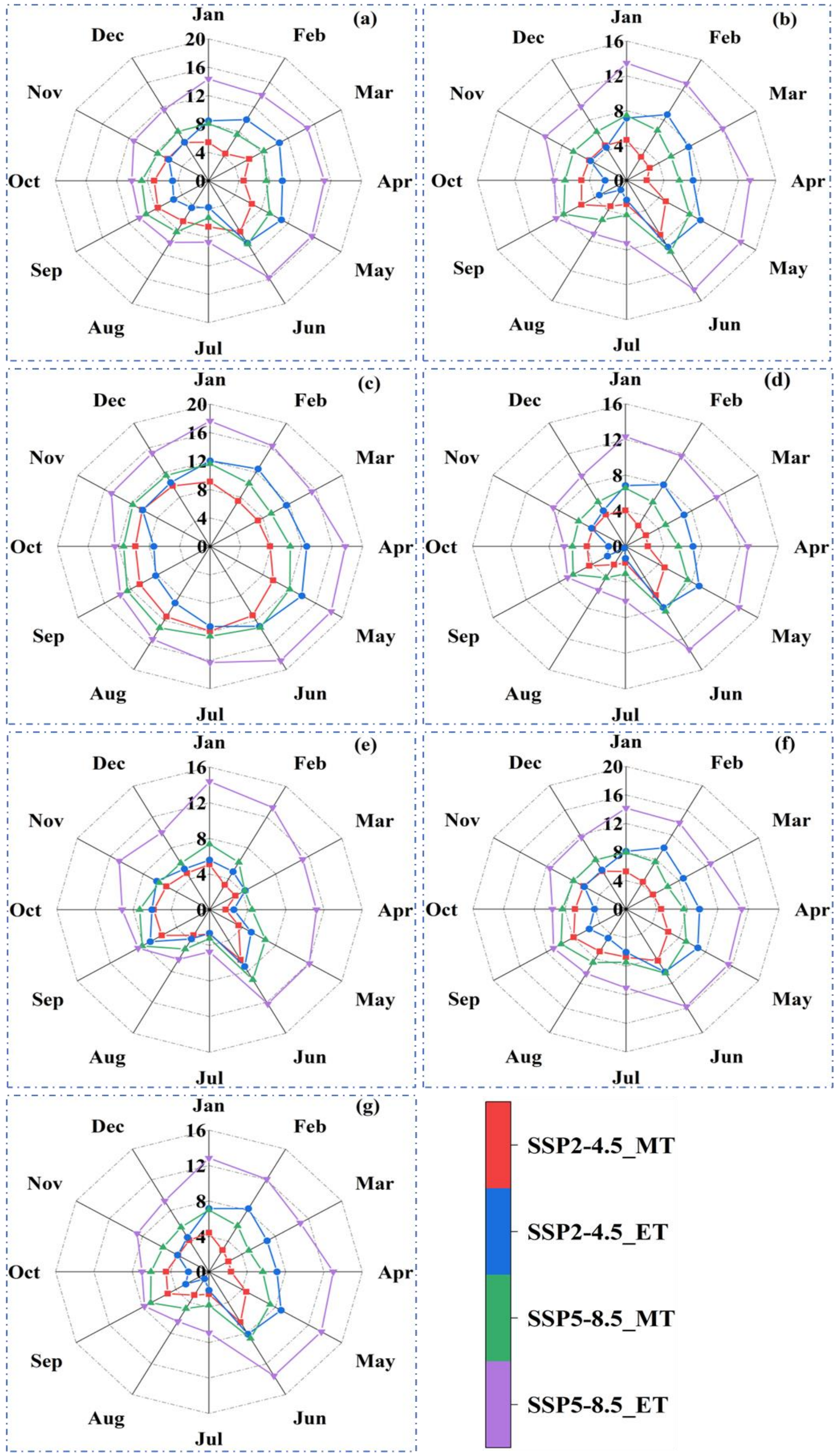

(a)
(b)
(c)
(d)
(e)
(f)
(g)
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
SSP2-4.5_MT
SSP2-4.5_ET
SSP5-8.5_MT
SSP5-8.5_ET

Figure 5-6: Monthly changes in reference evapotranspiration (ETo) by the period and scenarios: a. Adigrat, b. Atsbi, c. Edagahamus, d. Hawzen, e. Illala, f. Sinkata, g. Wukro

5.3.3 Land use land cover changes in the study area

The result of the LULC classification is shown in Fig. 5-7. The outputs consisted of seven major land cover types: bare land, forest, irrigated, rainfed, shrub, built-up area, and water body. The land-use map of the study area shows that more than 35% is covered by rainfed agriculture, while bare land and shrubs cover about 27% each, and irrigated, forest, built-up areas, and water bodies constitute the remainder. The coverage of the irrigated area shows the least, i.e., less than 2% of the watershed. The LULC classification showed that the nature of the land use class across the basin is very mixed.

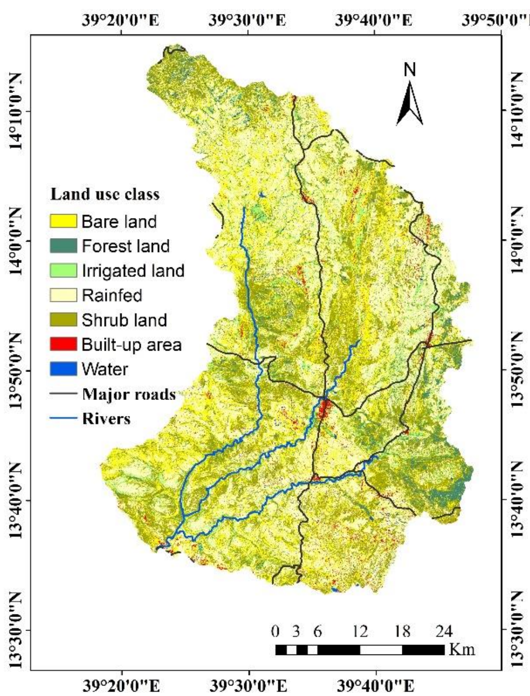


Figure 5-7: Land use land cover map of the study area for the year 2020

5.3.4 Generation of Normalized Difference Vegetation Index (NDVI) and Crop Coefficient (Kc) Maps

The NDVI maps of 12 images from Sentinel-2 images for the whole growing season were generated for the study area (Annex 1). The Kc values generated from NDVI represent the aggregate water use characteristics of the entire watershed, accounting for vegetation cover and bare soil fractions (Fig. 5-8). This means that the derived Kc values inherently reflect the mixed cropping systems in the watershed. Moreover, by using Kc values corresponding to different months, the temporal variability in water needs during different crop growth stages is captured. This aligns with the cropping patterns and their growth phases in the watershed. During the initial stage, characterized by bare soil or early crop emergence, Kc values remain low in December. As the canopy develops, Kc values gradually increase between January and February. During the mid-season, when the crop achieves full canopy cover, Kc values peak in March and April. In the late season, as the crop begins to senesce or is harvested, Kc values decline toward May and June. Satellite-based vegetation indices (VIs) have emerged as valuable tools for estimating crop evapotranspiration (ET) and crop coefficients (Kc). These methods utilize the relationship between VIs, such as NDVI, and crop water consumption (Reyes-González et al., 2018; Tasumi et al., 2006). VI-based Kc estimation has been applied to various crops and natural ecosystems, offering a more accurate representation of actual crop water needs compared to traditional methods (Glenn et al., 2011).

It was found that the scheme based Kc values of different crops varied from the minimum of 0.03 to the maximum of 0.71, 0.79, 0.85, 1.01, 0.99, 0.71, and 0.63 for Dec, Jan, Feb, Mar, Apr, May, and Jun, respectively. The maximum higher value of Kc was found in March (1.01). The presented Kc values from each month offer a snapshot of the temporal variations in crop water requirement throughout the growing season. The monthly observed range of Kc values (0.03 to 1.01) reflects the diversity of crops grown in the study area and their respective water needs. The maximum Kc value occurring in March (1.01) suggests a peak period of water requirement coinciding with the critical growth stage of many crops.

It was found that the Kc value of different crops increased gradually from December to March and decreased towards the end of the season. The gradual increase in Kc values from December to

March corresponds to the early stages of crop development when vegetation density and canopy size are increasing, leading to higher water requirements. Conversely, the decrease in Kc values towards the end of the season reflects the senescence of vegetation as crops mature, resulting in reduced water needs. Overall, the generation of NDVI and Kc maps provides essential information for understanding the spatiotemporal dynamics of vegetation cover and crop water requirements. These findings can serve as inputs for agricultural development, designing water resource management strategies, and land use planning efforts aimed at promoting sustainable and efficient use of natural resources in the study area. The Kc values indicated in Fig. 5-8 are only for irrigated areas. The irrigation areas from the LULC were analyzed for the three watersheds in the study area. However, due to the small size of the irrigated lands, a portion of the area near Wukro town was magnified to enhance visualization.

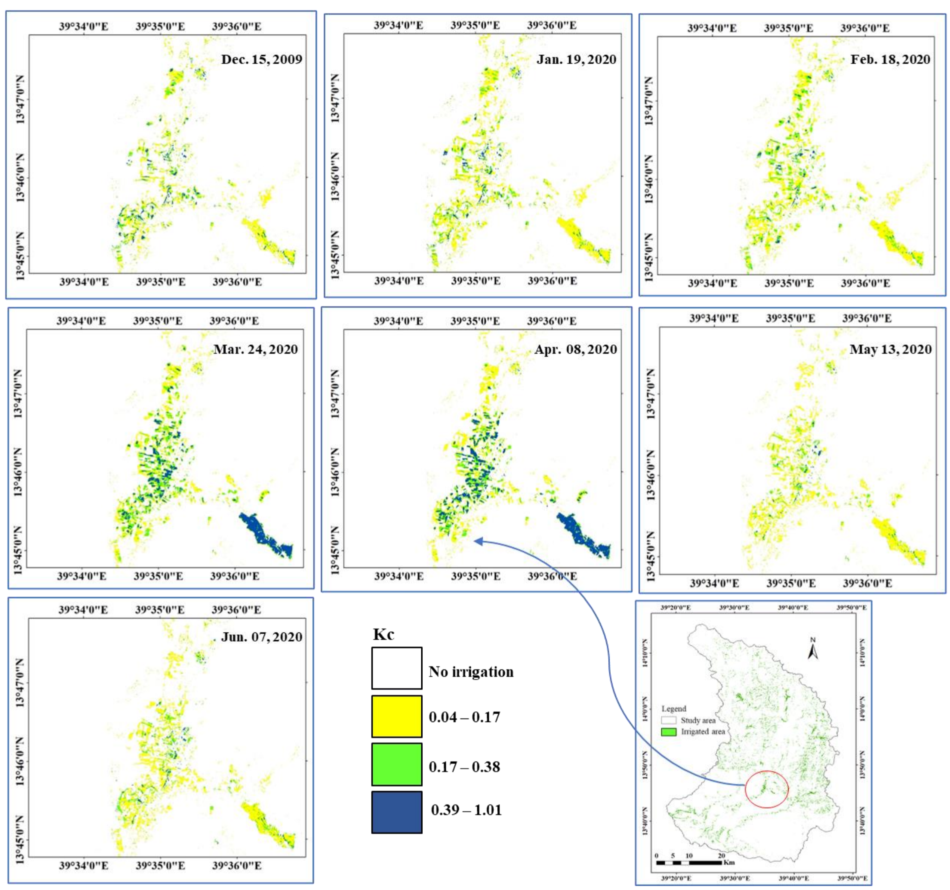


Figure 5-8: Spatial and temporal crop coefficient map for the irrigated area in the study area from December 2019 to June 2020

5.3.5 Crop water requirement (CWR) and changes under climate change scenarios

The CWR values, computed by multiplying Kc maps by the corresponding reference evapotranspiration values, obtained from the meteorological stations, are shown in (Fig. 5-9). It was observed that the CWR value varied across months, following the Kc values. The CWR also gradually increased from December, reaching its maximum value in the month of March, and decreasing towards June. Overall, the seasonal CWR of the irrigated crops ranged from 25-766 mm/season. The wide range of seasonal crop water requirements (CWR) for irrigated crops (25–766 mm/season) likely reflects the variability in water requirements among different crops, growth stages, soil properties, and irrigation practices within the watershed. Understanding this variability is crucial for tailoring water management strategies and optimizing resource allocation to meet the specific needs of different crops within the watershed using an advanced remote sensing (RS) approach.

Since vegetation cover within a watershed is not uniform, the aggregated Kc values inherently account for the diversity of crops and their varying growth stages. The use of NDVI-based approaches in large-scale watershed studies has been discovered in multiple studies. Fawzy et al. (2021) employed a remote sensing approach to estimate both daily and seasonal crop evapotranspiration. Their findings indicated that in 2018, the seasonal evapotranspiration distribution across the Nile Delta was relatively low, averaging 1406.8 mm per season, with values ranging from 0 to 2410 mm per season. This variation was primarily attributed to differences in cropping patterns, particularly the high water consumption of rice compared to other crops. Similarly, Senay et al. (2007) evaluated the performance of irrigated agriculture in Afghanistan using satellite-derived data. They utilized seasonal actual evapotranspiration (ETa) estimates across the entire basin as indicators to assess year-to-year variations in agricultural production. Additionally, Nyolei et al. (2019) estimated seasonal actual evapotranspiration across different agroecological zones (highland, midland, and lowland) using remote sensing. His study reported that from December 8, 2016, to March 8, 2017, the average seasonal evapotranspiration for crops in agricultural areas was 331 mm, with pixel values ranging between 152 mm and 476 mm. The significant variation in seasonal ET was attributed to differences in daily ET estimates across farms, influenced by variations in maize growth stages and the presence of other crops such as bananas, coffee, and fruit trees.

The projected crop water requirements (CWR), expressed as a percentage change from the reference period, are summarized in Table 5-3 for the baseline and each climate change scenario. These projections highlight potential future challenges for agricultural water management. Monthly CWR projections vary, with average increases ranging from very small change to 19 % from the mid- to late century, indicating a significant intensification in water demand due to climate change. Seasonal CWRs also exhibit an increase, ranging from 6% to 13%, with this trend being more pronounced under the SSP5-8.5 scenario, which is associated with higher greenhouse gas emissions and more severe climate impacts.

In summary, the increase in crop water requirements in the irrigated areas clearly indicates that the impact of climate change could increase CWR and negatively influence the yield of the crops unless their needs are met. Furthermore, the generation of CWR and the assessment of changes under climate change scenarios provide valuable insights for water resource management, agricultural planning, and adaptation strategies. By understanding the evolving water requirements of crops and anticipating future challenges, stakeholders can better prepare and implement sustainable measures to ensure food security and water resilience in the study area.

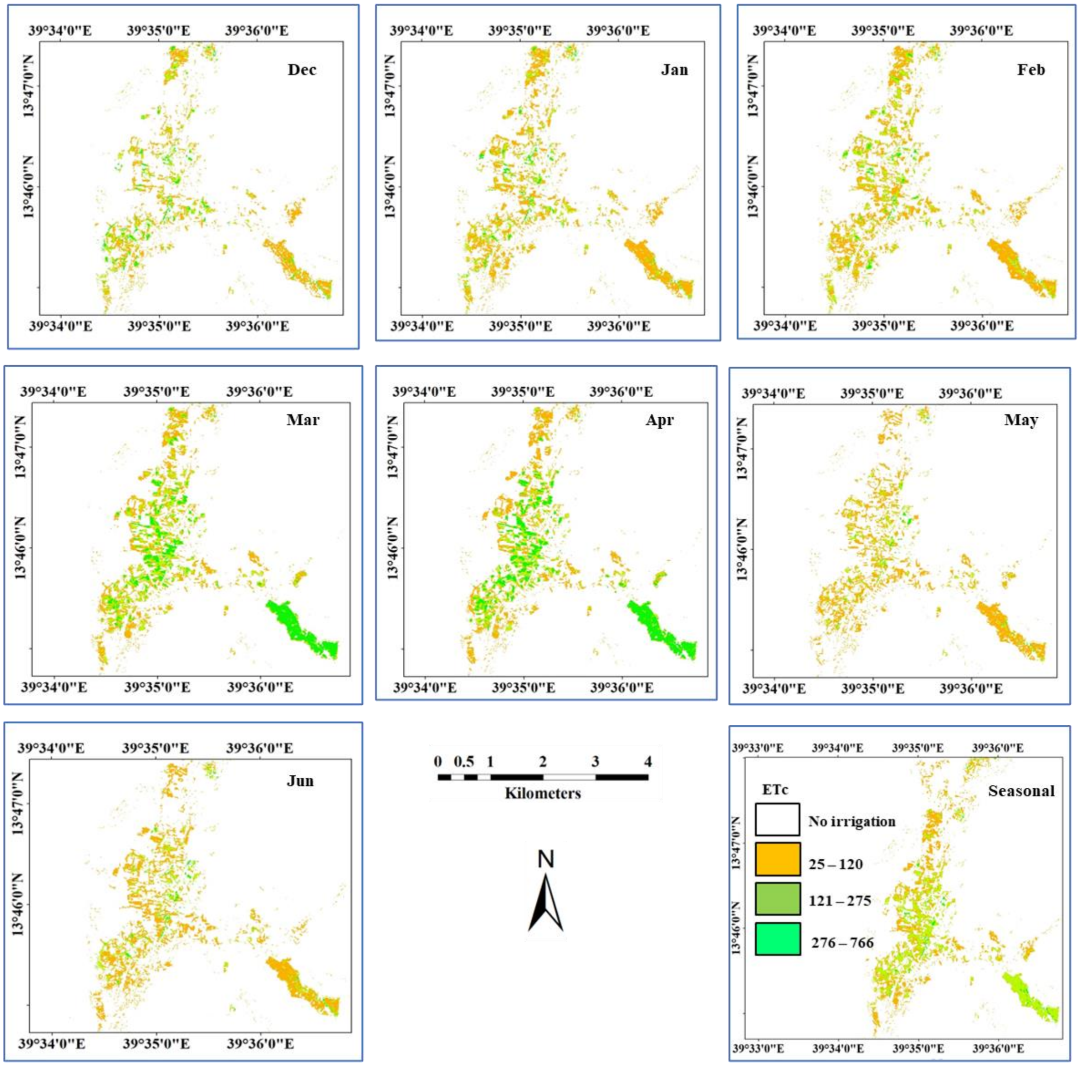


Figure 5-9: Spatial and temporal distribution of monthly and seasonal crop water requirements in the irrigated areas of the study area from December to June

Table 5-3: Monthly and seasonal CWR under reference and future climate change scenarios

			Crop water requirement in mm and percent change (%)							
			SSP2-4.5_MT		**SSP2-4.5_ET**		**SSP5-8.5_MT**		**SSP5-8.5_ET**	
Months	**Range**	**Baseline**	**mm**	**%**	**mm**	**%**	**mm**	**%**	**mm**	**%**
Dec	Min	4.35	4.85	12	4.87	12	4.92	13	5.09	17
	Max	80.9	90.4		90.6		91.7		94.8	
Jan	Min	3.82	4.21	10	4.31	13	4.31	13	4.56	19
	Max	96.2	105.9		108.4		108.4		114.7	
Feb	Min	3.48	3.54	2	3.70	7	3.64	5	3.84	11
	Max	116.3	118.3		123.9		121.9		128.5	
Mar	Min	4.02	4.14	3	4.05	1	4.07	1.2	4.22	5
	Max	163.1	168.2		164.4		165.0		171.3	
Apr	Min	3.96	4.10	4	4.27	8	4.22	7	4.51	14
	Max	152.2	157.6		164.1		162.3		173.4	
May	Min	4.10	4.45	8	4.61	12	4.57	11	4.83	18
	Max	124.6	135.1		140.1		138.9		146.6	
Jun	Min	1.28	1.31	2	1.30	1	1.29	0.2	1.34	4
	Max	32.8	33.5		33.0		32.9		34.2	
Seasonal	Min	25.02	26.6	6	27.1	8.4	27.03	8	28.4	13
	Max	766.2	808.9		824.6		821.0		863.5	

5.4 Conclusions and recommendations

The impact of climate change on agricultural water availability is influenced by a multitude of factors, but two primary climatic variables stand out as key determinants: rainfall and temperature. This is due to the control of other climatic parameters. In this study, the impact of climate change on crop water requirement was assessed using temperature. Although rainfall does not directly affect crop water requirements, it plays an indirect yet significant role in irrigation water requirement, agricultural water availability, and broader water resource management.

The major conclusions drawn from the study are:

- The analysis reveals an overall increasing trend in mean rainfall across most stations and scenarios, with varied magnitudes of change. This trend is observed across all time periods and is particularly notable in *Kiremt* rainfall, where increases range from +7% to +118% in most stations. Additionally, *Belg* rainfall also shows an increasing trend in most stations, further indicating a shift towards wetter conditions. However, the high variability of rainfall manifesting in both extreme events (droughts and floods) could pose challenges to agricultural productivity and water management systems, even in wetter conditions.
- Temperature projections show consistent increases in both maximum and minimum temperatures across time periods and scenarios. Variability among stations underscores the importance of local factors and microclimates in climate assessments. Illala station stands out with the lowest temperature changes, emphasizing the need for site-specific analysis.
- In line with increasing temperatures, ETo is projected to increase in both the mid- and end-term periods under all SSPs in all stations. Seasonal variations indicate higher increases in the *Kiremt* and the *Belg* seasons compared to the annual. Additionally, specific months such as June and May show the highest projected increases in ETo, emphasizing the need to grasp seasonal and peak monthly water demand for optimal resource management. Spatially, Edagahamus station consistently projects the highest increases across scenarios, seasons, and periods.
- The study projects significant increases in crop water requirements in response to climate change scenarios. The average predicted increases range from slight changes to 19% from mid- to end-of-century across the entire scheme or watershed, indicating a substantial

intensification of water demand driven by climate change. Seasonal crop water requirements also showed an increasing trend ranging from 6 to 13%. These increases underscore the pressing need to adapt water management strategies to balance rising crop water requirements with the complex interaction of temperature and rainfall trends.

- Changes in rainfall, temperatures, ETo, and CWR are more pronounced in end-term projections under SSP5-8.5 scenarios than in mid-term ones across all stations, indicating increased greenhouse gas emissions and more severe climate effects. This underscores the escalating impact of climate change over the century, highlighting the need for long-term water management and adaptation strategies.

Overall, the findings emphasize the need to comprehend and prepare for climate change's diverse impacts on rainfall, temperatures, and evapotranspiration. Proactive adaptation measures and ongoing research are crucial for managing the risks associated with changing precipitation patterns. Understanding local temperature variations is vital for addressing challenges like heat stress and ecosystem impacts. Additionally, the study highlights the dynamic nature of crop water requirement and the challenges posed by climate-induced increases in water demand. Stakeholders can use this information to develop targeted adaptation strategies for sustainable water management and agricultural productivity amidst a changing climate, enhancing preparedness and mitigation efforts.

Finally, it is crucial to recognize that the findings of this research hold significant practical implications for the formulation of long-term adaptation strategies aimed at ensuring sustainable crop production and effective management of water resources. These implications extend not only to the specific region under study but also resonate globally, offering valuable insights applicable to diverse agricultural landscapes facing similar climate challenges.

The following recommendations are drawn from the findings of the research study:

- Projections indicate a consistent rise in both maximum and minimum temperatures across various time periods and climate scenarios. This warming trend has a direct and significant impact on CWR, as higher temperatures increase evapotranspiration rates and exacerbate water stress on crops. To mitigate these effects and ensure sustainable agricultural productivity, it is crucial to implement targeted adaptation strategies that focus on reducing

CWR. These strategies may include the adoption of advanced irrigation technologies, such as drip and sprinkler systems, which minimize water losses and enhance water-use efficiency. Additionally, promoting agronomic practices like mulching, the use of drought-tolerant crop varieties, optimized planting schedules, and soil moisture conservation techniques can further contribute to reducing water demand.

- The study area is highly affected by recurring drought events, prompting many researchers to focus on developing adaptation strategies aimed at reducing the impacts of drought. However, projections of mean rainfall suggest a future trend toward wetter conditions accompanied by high variability. As a result, adaptation strategies should also include measures to address and mitigate the risks of potential flooding. While rainfall does not directly influence crop water requirements, it plays a crucial role in determining overall agricultural water availability, which indirectly impacts irrigation needs and water resource planning.
- Enhance access to timely and accurate climate information and forecasts to enable farmers and water managers to make informed decisions and adapt their practices to evolving drought and flooding phenomena.
- Encouraging collaboration among diverse stakeholders, including policymakers, researchers, and local communities, is essential for developing tailored adaptation strategies aimed to promote sustainable water management and agricultural productivity. Such collaborative efforts can significantly enhance preparedness and mitigation endeavors.
- Based on the findings of this study, several emerging issues require further exploration to enhance understanding and management of climate change and variability impacts. These include:
    - Investigate the role of emerging irrigation technologies, such as precision irrigation, soil moisture sensors, and remote sensing, in addressing future water demand under climate change.
    - Developing innovative solutions to mitigate flood risks in regions experiencing increasing rainfall trends while ensuring sufficient water availability for crops during dry spells.

- Assessing the impact of increasing extreme weather events, including droughts and floods, on agricultural systems in terms of productivity, water demand, and ecosystem sustainability.
- Investigating the integration of climate projections into comprehensive water resource management plans to ensure sustainability in regions facing droughts and increased rainfall variability.
- Developing systems that provide timely and accurate climate and water demand predictions to assist farmers and water managers in adapting to changing conditions.
- Exploring collaborative frameworks that engage policymakers, researchers, and local communities in creating region-specific adaptation plans that balance agricultural water use with overall resource sustainability.

References

Ahmad, M. J., Cho, G.-H., Kim, S.-H., Lee, S., Adelodun, B., & Choi, K.-S. (2021). Influence mechanism of climate change over crop growth and water demands for wheat-rice system of Punjab, Pakistan. *Journal of Water and Climate Change*, *12*(4), 1184-1202.

Alotaibi, M. (2023). Climate change, its impact on crop production, challenges, and possible solutions. *Notulae Botanicae Horti Agrobotanici Cluj-Napoca*, *51*(1), 13020-13020.

Assfaw, M. T., Neka, B. G., & Ayele, E. G. (2023). Modeling the impact of climate change on streamflow responses in the Kessem watershed, Middle Awash sub-basin, Ethiopia. *Journal of Water and Climate Change*, *14*(12), 4837-4859.

Awulachew, S. B., Erkossa, T., & Balcha, Y. (2011). *Irrigation and Water for Sustainable Development: Proceedings of the Second Forum December 15-16, 2008, Addis Ababa, Ethiopia*. IWMI.

Behailu, M., & Nata, T. (2005). Monitoring productivity of water in agriculture and interacting systems: the case of Tekeze/Atbara River Basin in Ethiopia.

Bellard, C., Bertelsmeier, C., Leadley, P., Thuiller, W., & Courchamp, F. (2012). Impacts of climate change on the future of biodiversity. *Ecology letters*, *15*(4), 365-377.

Berhe, A. G., Mesfin, H. S., Abraha, A., Abraha, G. G., Misgna, S. H., & Gebremicael, T. G. (2018). The impact of climate change on irrigation water requirement of Maize and Onion: the case of Gum-Selasa small-scale irrigation scheme, Tigray, Ethiopia.

Brunsell, N. A., & Gillies, R. R. (2002). Incorporating surface emissivity into a thermal atmospheric correction. *Photogrammetric engineering and remote sensing*, *68*(12), 1263-1270.

Daniel, H. (2023). Performance assessment of bias correction methods using observed and regional climate model data in different watersheds, Ethiopia. *Journal of Water and Climate Change*, *14*(6), 2007-2028.

Deryng, D., Conway, D., Ramankutty, N., Price, J., & Warren, R. (2014). Global crop yield response to extreme heat stress under multiple climate change futures. *Environmental Research Letters*, *9*(3), 034011.

Diro, G., Tompkins, A., & Bi, X. (2012). Dynamical downscaling of ECMWF Ensemble seasonal forecasts over East Africa with RegCM3. *Journal of Geophysical Research: Atmospheres*, *117*(D16).

Fawzy, H. E. D., Sakr, A., El-Enany, M., & Moghazy, H. M. (2021). Spatiotemporal assessment of actual evapotranspiration using satellite remote sensing technique in the Nile Delta, Egypt. Alexandria Engineering Journal, 60(1), 1421-1432.

Field, C. B., & Barros, V. R. (2014). *Climate change 2014–Impacts, adaptation and vulnerability: Regional aspects*. Cambridge University Press.

Gebrechorkos, S., Taye, M. T., Birhanu, B., Solomon, D., & Demissie, T. (2023). Future changes in climate and hydroclimate extremes in East Africa. *Earth's Future*, *11*(2), e2022EF003011.

Gebrehiwot, T., & van der Veen, A. (2013). Assessing the evidence of climate variability in the northern part of Ethiopia. *Journal of development and agricultural economics*, *5*(3), 104-119.

Gebrehiwot, T., Van der Veen, A., & Maathuis, B. (2011). Spatial and temporal assessment of drought in the Northern highlands of Ethiopia. *International Journal of Applied Earth Observation and Geoinformation*, *13*(3), 309-321.

Gebremedhin, Y., & Berhe, A. A. (2015). Impact of climate change on potato yield (Solanum tuberosum L.) at Mekelle areas, in northern Ethiopia. *World Journal of Agricultural Sciences*, *11*(2), 62-69.

Gebremeskel, G., & Kebede, A. (2018). Estimating the effect of climate change on water resources: Integrated use of climate and hydrological models in the Werii watershed of the Tekeze river basin, Northern Ethiopia. *Agriculture and Natural Resources*, *52*, 195-207.

Glenn, E. P., Neale, C. M., Hunsaker, D. J., & Nagler, P. L. (2011). Vegetation index-based crop coefficients to estimate evapotranspiration by remote sensing in agricultural and natural ecosystems. Hydrological Processes, 25(26), 4050-4062.

Hargreaves, G. H., & Samani, Z. A. (1985). Reference crop evapotranspiration from temperature. *Applied engineering in agriculture*, *1*(2), 96-99.

Hatfield, J. L., & Prueger, J. H. (2015). Temperature extremes: Effect on plant growth and development. *Weather and climate extremes*, *10*, 4-10.

Hordofa, A. T., Leta, O. T., Alamirew, T., & Chukalla, A. D. (2021). Spatiotemporal trend analysis of temperature and rainfall over Ziway Lake Basin, Ethiopia. *Hydrology*, *9*(1), 2.

Kahsay, K. D., Pingale, S. M., & Hatiye, S. D. (2018). Impact of climate change on groundwater recharge and base flow in the sub-catchment of Tekeze basin, Ethiopia. *Groundwater for Sustainable Development*, *6*, 121-133.

Kahsay, K. D., & Reda, K. W. Enhancing Water use Efficiency of Maize under Deficit Irrigation: the Case of Moisture Deficit Areas of Tigray, Ethiopia.

Kifle, M., & Gebretsadikan, T. (2016). Yield and water use efficiency of furrow irrigated potato under regulated deficit irrigation, Atsibi-Wemberta, North Ethiopia. *Agricultural water management*, *170*, 133-139.

Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P., & Naylor, R. L. (2008). Prioritizing climate change adaptation needs for food security in 2030. *Science*, *319*(5863), 607-610.

Mahmood, R., Pielke Sr, R. A., Hubbard, K. G., Niyogi, D., Dirmeyer, P. A., McAlpine, C., Carleton, A. M., Hale, R., Gameda, S., & Beltrán-Przekurat, A. (2014). Land cover changes and their biogeophysical effects on climate. *International Journal of Climatology*, *34*(4), 929-953.

Maraun, D., Wetterhall, F., Ireson, A., Chandler, R., Kendon, E., Widmann, M., Brienen, S., Rust, H., Sauter, T., & Themeßl, M. (2010). Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user. *Reviews of geophysics*, *48*(3).

Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S. L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., & Gomis, M. (2021). Climate change 2021: the physical science basis. *Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change*, *2*(1), 2391.

Mebrahtu, Y. (2021). Estimation of crop water requirement using CROPWAT model for onion and tomato: A case study of Raya Azebo District, Ethiopia. . *Journal of Biology, Agriculture and Healthcare*, *11(8)*. https://doi.org/https://doi.org/10.7176/JBAH/11-8-04.

Mebrahtu, Y., Mehari, H., Nurga, Y., & Tamiru, H. (2021). Estimation of crop water requirement using CROPWAT Model for maize, A case study of Raya Azebo District, Ethiopia. *Journal of Resources Development and Management*, *74*, 18-22.

Msongaleli, B. M., Rwehumbiza, F., Tumbo, S. D., & Kihupi, N. (2015). Impacts of climate variability and change on rainfed sorghum and maize: implications for food security policy in Tanzania.

Musie, M., Sen, S., & Srivastava, P. (2020). Application of CORDEX-AFRICA and NEX-GDDP datasets for hydrologic projections under climate change in Lake Ziway sub-basin, Ethiopia. *Journal of Hydrology: Regional Studies*, *31*, 100721.

Nicholson, S. E. (2017). Climate and climatic variability of rainfall over eastern Africa. *Reviews of geophysics*, *55*(3), 590-635.

Nicholson, S. E. (2018). The ITCZ and the seasonal cycle over equatorial Africa. *Bulletin of the American Meteorological Society*, *99*(2), 337-348.

Nigusse, A. G., & Adhanom, O. G. (2019). Flood hazard and flood risk vulnerability mapping using geo-spatial and MCDA around Adigrat, Tigray region, Northern Ethiopia. *Momona Ethiopian Journal of Science*, *11*(1), 90-107.

Nyolei, D., Nsaali, M., Minaya, V., van Griensven, A., Mbilinyi, B., Diels, J., ... & Kahimba, F. (2019). High resolution mapping of agricultural water productivity using SEBAL in a cultivated African catchment, Tanzania. Physics and Chemistry of the Earth, Parts A/B/C, 112, 36-49.

Peng, S., Wang, C., Li, Z., Mihara, K., Kuramochi, K., Toma, Y., & Hatano, R. (2023). Climate change multi-model projections in CMIP6 scenarios in Central Hokkaido, Japan. *Scientific Reports*, *13*(1), 230.

Pernicová, N., Urban, O., Čáslavský, J., Kolář, T., Rybníček, M., Sochová, I., Peñuelas, J., Bošeľa, M., & Trnka, M. (2024). Impacts of elevated CO2 levels and temperature on photosynthesis and stomatal closure along an altitudinal gradient are counteracted by the rising atmospheric vapor pressure deficit. *Science of the Total Environment*, *921*, 171173.

Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., Lobell, D. B., & Travasso, M. I. (2014). Food security and food production systems.

Rajabi, A., & Babakhani, Z. (2018). The study of potential evapotranspiration in future periods due to climate change in west of Iran. *International Journal of Climate Change Strategies and Management*, *10*(1), 161-177.

Reda, A. G., & Mamo, G. (2013). Detection of Climate Trends Over Ethiopia Using Geospatial Techniques. *Journal of Meteorology and Climate Science*, *11*(1), 10-17.

Reyes-González, A., Kjaersgaard, J., Trooien, T., Hay, C., & Ahiablame, L. (2018). Estimation of Crop Evapotranspiration Using Satellite Remote Sensing-Based Vegetation Index. Advances in Meteorology, 2018(1), 4525021.

Rosenzweig, C. E., Jones, J. W., Hatfield, J., Antle, J., Ruane, A., Boote, K., Thorburn, P., Valdivia, R., Porter, C., & Janssen, S. (2015). *Guide for regional integrated assessments: handbook of methods and procedures, Version 5.1*.

Rosenzweiga, C., Elliott, J., Deryng, D., Ruane, A., Müllere, C., Arneth, A., Boote, K., Folberth, C., Glotter, M., & Khabarov, N. (2014). Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. *Proceedings of the National Academy of Sciences of the United States of America*, *111*, 268-3273.

Rudraswamy, G., & Umamahesh, N. (2024). Investigating the impact of climate change on irrigation and crop water requirements of Bhadra and Tungabhadra command area: A CMIP-6 GCMs and CROPWAT 8.0 approach. *Water Supply*, *24*(2), 625-642.

Senay, G. B., Budde, M., Verdin, J. P., & Melesse, A. M. (2007). A coupled remote sensing and simplified surface energy balance approach to estimate actual evapotranspiration from irrigated fields. Sensors, 7(6), 979-1000.

Shafeeque, M., & Bibi, A. (2023). Assessing the impact of future climate scenarios on crop water requirements and agricultural water supply across different climatic zones of Pakistan. *Frontiers in Earth Science*, *11*, 1283171.

Shahidian, S., Serralheiro, R., Serrano, J., Teixeira, J., Haie, N., & Santos, F. (2012). *Hargreaves and other reduced-set methods for calculating evapotranspiration*. IntechOpen London.

Shiferaw, H. M., Gebremedhin, A., Gebretsadkan, T., & Zenebe, A. (2018). Modelling hydrological response under climate change scenarios using SWAT model: the case of Ilala watershed, Northern Ethiopia. *Modeling Earth Systems and Environment*, *4*, 437-449.

Sillmann, J., & Roeckner, E. (2008). Indices for extreme events in projections of anthropogenic climate change. *Climatic change*, *86*, 83-104.

Takele, G. S., Gebrie, G. S., Gebremariam, A. G., & Engida, A. N. (2022). Future climate change and impacts on water resources in the Upper Blue Nile basin. *Journal of Water and Climate Change*, *13*(2), 908-925.

Tasumi, M., Allen, R. G., & Trezza, R. (2006, October). Calibrating satellite-based vegetation indices to estimate evapotranspiration and crop coefficients. In Proceedings of the 2006 USCID water management conference, ground water and surface water under stress: competition, interaction, solutions, Denver. Proceedings… Denver, USA: USCID (pp. 103-112).

Taylor, R. G., Scanlon, B., Döll, P., Rodell, M., Van Beek, R., Wada, Y., Longuevergne, L., Leblanc, M., Famiglietti, J. S., & Edmunds, M. (2013). Ground water and climate change. *Nature climate change*, *3*(4), 322-329.

Tefera, A. S., Ayoade, J., & Bello, N. (2019). Drought occurrence pattern in tigray region, northern Ethiopia. *Journal of Applied Sciences and Environmental Management*, *23*(7), 1341-1348.

Trenberth, K. E. (2011). Changes in precipitation with climate change. *Climate research*, *47*(1-2), 123-138.

Tsegay, A., Raes, D., Geerts, S., Vanuytrecht, E., Abraha, B., Deckers, J., Bauer, H., & Gebrehiwot, K. (2012). Unravelling crop water productivity of tef (Eragrostis Tef (Zucc.) Trotter) through AquaCrop in northern Ethiopia. *Experimental Agriculture*, *48*(2), 222-237.

Woldemeskel, F., Sharma, A., Sivakumar, B., & Mehrotra, R. (2012). An error estimation method for precipitation and temperature projections for future climates. *Journal of Geophysical Research: Atmospheres*, *117*(D22).

Yeboah, K. A., Akpoti, K., Kabo-bah, A. T., Ofosu, E. A., Siabi, E. K., Mortey, E. M., & Okyereh, S. A. (2022). Assessing climate change projections in the Volta Basin using the CORDEX-Africa climate simulations and statistical bias-correction. *Environmental Challenges*, *6*, 100439.

Ziadat, F. M., & Taimeh, A. Y. (2013). Effect of rainfall intensity, slope, land use and antecedent soil moisture on soil erosion in an arid environment. Land Degradation & Development, 24(6), 582-590.

CHAPTER SIX

6. ANALYZING THE IMPACT OF CLIMATE CHANGE ON SURFACE RUNOFF IN EASTERN TIGRAY, NORTHERN ETHIOPIA

Abstract

Climate change is expected to significantly alter the global water cycle, affecting the availability and distribution of water, which poses a serious threat to water security. Hence, this study addresses the critical issue on how climate variability and change impact water resources, focusing on surface runoff in the study area. The study employs the Hydrological Engineering Centre-Hydrological Modelling System (HEC-HMS) to simulate future surface runoff using the latest climate projections from the Climate Modelling Intercomparison Project Phase Six (CMIP6). The model inputs include digital elevation models, land use and soil maps, and climate and hydrological data, which were carefully calibrated and validated using observed stream flow data. Results from the simulations indicate that under the SSP2-4.5 scenario, surface runoff is projected to decline significantly in most months during both the mid-term (2040-2069) and end-term (2070-2099) periods, with reductions ranging from 0.56% to nearly 26%. However, increases in runoff are expected in some months, particularly in February, March, July, and August, with increases ranging from 1% to 23% during the end of the century. Under the more extreme SSP5-8.5 scenario, surface runoff is generally expected to decrease during the mid-term period but to increase in most months during the end-term period. The results from the simulations indicate projected declines in surface runoff under SSP2-4.5 and variable patterns under SSP5-8.5. However, without adequate infrastructure to capture, store, and utilize this runoff, significant amounts may be lost through evaporation, infiltration, or excessive flow during peak months. In regions such as the study area, where water resource management is already constrained, reduced runoff could worsen water shortages for agriculture, domestic use, and other sectors. Conversely, the increases in runoff observed during specific months or under extreme scenarios may pose flooding risks if not effectively managed. These findings emphasize the necessity of developing and implementing adaptive water management systems, including water harvesting technologies (e.g., reservoirs, check dams, or rainwater harvesting), to enhance water storage during periods of excess runoff and ensure availability during dry periods. Effective water management is essential to addressing variability and mitigating both water shortages and flood risks.

Key words: Climate change, CMIP6, HEC-HMS, SSP2-4.5, SSP5-8.5, Surface runoff, Adaptive water management

6.1 Introduction

Climate variability and change impact on water resources is currently a key global research agenda (IPCC, 2007, 2013). It is anticipated that climate change will alter significantly the global water cycle through changes in temperature and precipitation (Sharma & Babel, 2013). This changes the overall magnitude, variability and timings of stream flow which affects the water balance of a watershed. This could cause an imbalance in water availability and poses a threat to water security. Hence, evaluating the likely impacts of climate variability and change on water resources availability is crucial towards planning sustainable management of water resources.

To estimate the surface water availability at watershed level, the Hydrological Engineering Centre-Hydrological Modeling System (HEC-HMS) has been widely used. Accordingly, HEC-HMS has been applied to study the impacts of climate change on water resources in different regions with a variety of climatic and physiographic characteristics (Ahmadi et al., 2022; Gramz et al., 2024; Hassaan et al., 2024; Masimba et al., 2022; Muleta & Marcell, 2023; Suryani et al., 2024).

Numerous studies have been conducted to estimate water balance components, including surface runoff, in various catchments of the Geba basin. Most of these studies employed the Water and Energy Transfer between Soil, Plants, and Atmosphere (WetSpa) hydrological model, often without integrating climate change models or scenarios (Gebreyohannes et al., 2013; Gebru & Tesfahunegn, 2020; Hailekiros et al., 2023; Meresa et al., 2019; Teklebirhan et al., 2012). Only a few studies have combined WetSpass with climate change projections (Goitom et al., 2012; Kidanemariam et al., 2021; Tesfaye et al., 2014a). Additionally, some researchers utilized the SWAT model to estimate various components of the water balance in different watersheds of the basin (Ashenafi, 2014; Hailu, 2016; Mekuriaw, 2019; Shiferaw et al., 2018). Other studies adopted alternative hydrological models, such as the J2000 hydrological model (Hailekiros et al., 2023) and the distributed hydrological model based on the Wflow_PCRaster/Python framework (Gebremicael et al., 2019).

However, the HEC-HMS model, which is widely used worldwide for hydrological simulations due to its versatility and reliability, has not been extensively applied in the Geba basin. Furthermore, the studies that incorporated climate models for surface runoff predictions largely relied on earlier climate models and scenarios, neglecting the advancements offered by the latest climate models such as CMIP6. This presents a significant research gap, as the use of outdated models may limit the accuracy and reliability of future water balance predictions.

While existing studies have contributed valuable insights into water balance estimation in the Geba basin, there is a lack of research integrating the HEC-HMS model with the latest CMIP6 climate models for surface runoff predictions. The HEC-HMS model's ability to simulate hydrological processes across diverse conditions makes it a promising tool for filling this gap (Sahu et al., 2023). By utilizing HEC-HMS in conjunction with CMIP6, this study aims to provide more accurate and up-to-date predictions of surface runoff under future climate scenarios, addressing a critical need for improved water resource planning and management in the region.

Moreover, the HEC-HMS model was chosen for its stability and robust performance in hydrological simulations. It is particularly valued for its ability to accurately simulate essential hydrological parameters such as rainfall-runoff processes, streamflow, infiltration, and evapotranspiration, using the available data. One of the key advantages of HEC-HMS is its flexibility in adapting to various watershed conditions, making it suitable for a wide range of hydrological studies, including flood forecasting, water availability assessment, and watershed management (Sahu et al., 2023).

In addition to its technical strengths, HEC-HMS is well-supported by an extensive array of resources. Numerous academic publications provide detailed methodologies, case studies, and validation examples, which are invaluable for researchers and practitioners alike. Moreover, there is a wealth of tutorials and instructional content available from different resources, offering step-by-step guidance on model setup, parameterization, calibration, and result interpretation.

In this study, the HEC-HMS model was specifically tested to simulate surface runoff under the latest climate projections provided by the Climate Modeling Intercomparison Project Phase Six (CMIP6). CMIP6 represents the most recent and comprehensive set of climate models, offering updated scenarios for future climate conditions, including temperature and precipitation patterns. By integrating these projections with the HEC-HMS model, the study aims to provide critical insights into how future climate variability may impact surface runoff and overall water availability.

These findings are expected to be highly valuable for various stakeholders, including water resource managers, urban planners, and policymakers. The results will help inform strategies for managing water resources in the face of changing climate conditions, enabling more resilient planning and adaptation measures. This study thus contributes to a better understanding of potential future hydrological scenarios and supports informed decision-making to address the challenges posed by climate change on water resources in the study area.

6.2 Material and Methods

To analyze surface water availability in the study area, Hydrological Engineering Centre-Hydrological Modeling System (HEC-HMS) model was used. The hydrological model uses inputs of current and future climate projections (precipitation, maximum and minimum temperature) to generate current and future surface runoff. Moreover, Spatial Digital Elevation Model (DEM), land use, soil maps and observed stream flow data are required for HEC-HMS model simulation. The stream flow data was used for model calibration and validation. The schematic frame work of the study is summarized in Fig. 6-1.

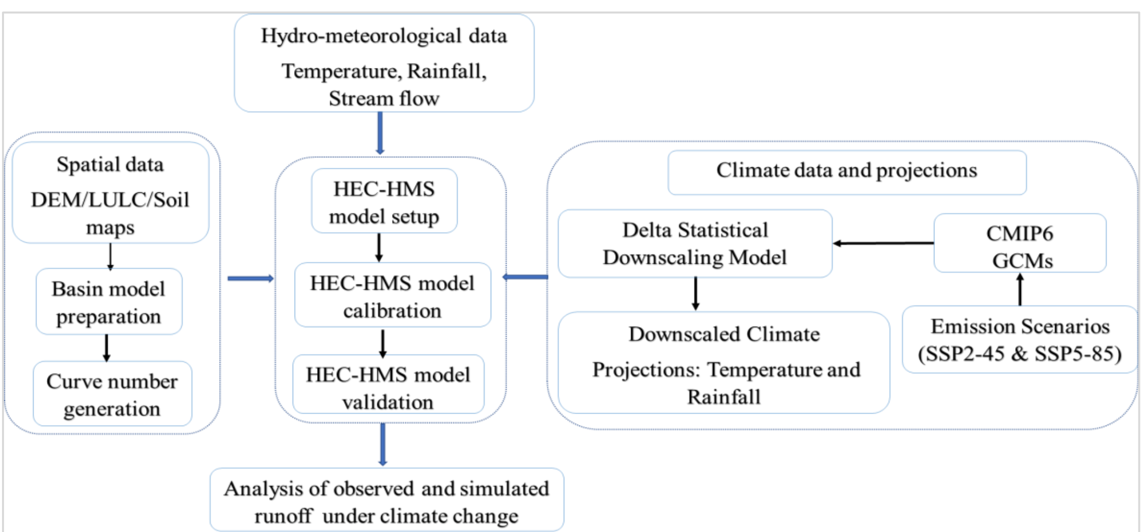


Figure 6-1: Schematic frame work of the study

6.2.1 Input data Requirements

The HEC-HMS model simulation relies on a comprehensive range of input datasets to ensure accurate representation of hydrological processes within the study area. These inputs include spatial data, such as a high-resolution Digital Elevation Model (DEM) to delineate watershed boundaries and analyze terrain drainage patterns, as well as land use maps and soil maps to characterize land cover and soil properties that influence runoff generation, infiltration, and evapotranspiration. Additionally, the model requires temporal data, including climate variables (e.g., precipitation and temperature) and hydrological data (e.g., streamflow) to calibrate and validate the simulation.

6.2.1.1 Spatial data input

The 30-meter resolution DEM from the Shuttle Radar Topography Mission (SRTM) was utilized to delineate watersheds and analyze drainage patterns of the terrain. Land use and soil maps were employed to define land cover and soil types, which influence the basin's hydrological processes. The SRTM 30-meter resolution DEM was sourced from the United States Geological Survey's Earth Explorer site (http://earthexplorer.usgs.gov/). Additionally, the land use and soil maps were derived from 30-meter resolution Landsat images using Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data, available at (http://data.ess.tsinghua.edu.cn/), and 250-meter resolution soil grids developed by the International Soil Reference and Information Centre (ISRIC) - World Soil Information (https://www.isric.org/), respectively.

6.2.1.2 Hydro-meteorological data

Meteorological data, such as minimum and maximum temperatures and precipitation, were collected from the Ethiopian National Meteorological Service Agency (NMSA). Additionally, hydrological data, specifically stream flow, is needed to calibrate and validate the model at the basin outlet. The Ethiopian Ministry of Water Resources provided stream flow data from 2004 to 2007, with 2004-2005 used for model calibration and 2006-2007 for validation. These years were chosen due to the relatively low number of missing stream flow values compared to other years.

6.2.1.3 Climate data downscaling and projections

The latest models from the Coupled Model Intercomparison Project Phase 6 (CMIP6) were used to project daily maximum and minimum temperature (tasmax and tasmin) and precipitation (pr) data. These models were specifically chosen for their consistency and high-resolution accuracy in East and sub-Saharan Africa (as shown in Table 5-1). By utilizing atmospheric data from 1985 to 2100, they offer a detailed outlook on future climatic conditions. Climate projections were analyzed under two SSP-RCP scenarios: SSP2-4.5 and SSP5-8.5, aimed at examining potential climate outcomes for both the mid-term (2040-2069) and end-term (2070-2099) periods, compared against a baseline period from 1980 to 2014. The detailed on climate downscaling and projection are presented in Chapter 5.

6.2.2 The Hydrological Engineering Centre-Hydrological Modeling System (HEC-HMS) model

This study utilized HEC-HMS version 4.11 for watershed development. The HEC-HMS software includes several model components, such as the basin model, meteorological model, control specifications, and distinct components for inputting data related to precipitation, temperature, evapotranspiration, streamflow, and other relevant variables.

6.2.2.1 Basin model

A basin model includes a schematic that can incorporate various objects such as sub-basins, routing reaches, junctions, sources, sinks, diversions, and reservoirs, and it stores details about the properties and interconnections of these objects (Fig. 6-2). Unlike earlier versions of HEC-HMS, this model was built directly within the software itself, eliminating the need for any external software.

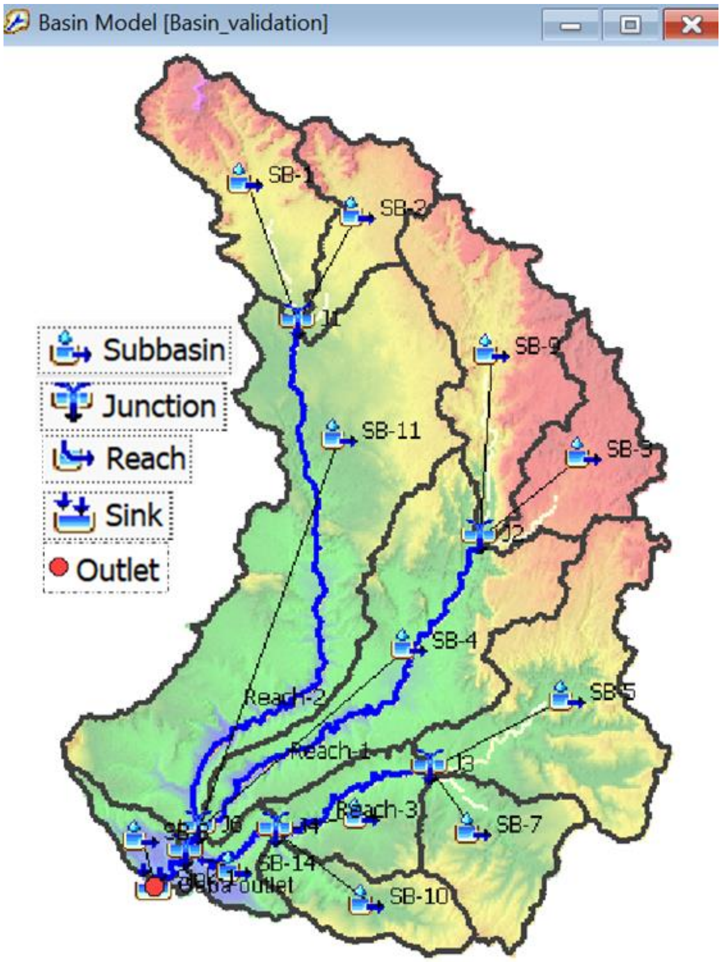


Figure 6-2: Basin model and terrain setup in HEC-HMS

6.2.2.2 Meteorological model

The meteorological model in HEC-HMS plays a vital role in defining and managing various climatic and atmospheric inputs necessary for hydrological simulations. This model enables users to specify and configure multiple meteorological elements that impact the hydrological processes within a watershed. Key elements include precipitation, temperature, evapotranspiration, sunshine and solar radiation, humidity, and snowmelt. In this study, methods within the meteorological model, such as the specified hyetograph for precipitation and specific evapotranspiration from seven different stations, were utilized.

6.2.2.3 Loss model

The loss models in HEC-HMS estimate runoff by calculating the volume of water lost through interception, infiltration, storage, evaporation, or transpiration, and then subtracting this from the total precipitation. In this study, the Soil Conservation Service-Curve Number (SCS-CN) loss method was chosen due to its simplicity, reliability, and minimal data requirements (Ponce & Hawkins, 1996). Developed by the USDA Soil Conservation Service in 1954, the SCS-CN method is widely used for estimating direct runoff, and it calculates precipitation excess based on soil type, land use, surface conditions, and antecedent moisture conditions (USDA, 1985), using equations 6.1-6.3.

$$P_e = \frac{(P - I_a)^2}{P - I_a + S} \qquad equation\ (6.1)$$

$$S = \frac{25400 - 254\, CN}{CN} \qquad equation\ (6.2)$$

$$I_a = 0.2\, S \qquad equation\ (6.3)$$

Where p_e is accumulated excess precipitation at time t, p is accumulated rainfall depth at time t, S is the potential maximum retention, CN is curve number, and I_a is initial abstraction

6.2.2.4 Routing in HEC-HMS

Despite the availability of multiple flood routing methods in the HEC-HMS model, the Muskingum method was chosen for this study because of its simplicity and low data requirements, and it has been widely applied in numerous hydrological studies (Fanta & Tadesse, 2022; Guduru et al., 2023; Salman & Hamdan, 2023; Salvati et al., 2024; Yilma & Kebede, 2023). This method provides an approximate way to compute the outflow hydrograph at the outlet using two input parameters: the flood wave's travel time (K) through the routing reach and the attenuation of the flood wave (X). These parameters are generally obtained through calibration using observed discharge data. In the Muskingum method, the K parameter represents the time it takes for a flood wave to travel through a reach, while the X parameter is a constant coefficient with values typically ranging between 0 and 0.5. These parameters can be estimated using observed inflow and outflow hydrographs, where K is determined by the time interval between similar points on both hydrographs, and X is estimated through a trial and error process.

6.2.2.5 Transform Model

The Transform Model in HEC-HMS is designed to convert excess precipitation into direct runoff within a watershed. In this research, the Soil Conservation Service (SCS) Unit Hydrograph method was selected to estimate runoff. The key input for this method is lag time (T_{lag}), which is affected by the time of concentration (T_c). Both lag time and time of concentration are crucial in determining how quickly a watershed responds to rainfall events. These parameters were calculated using equations 6.4 and 6.5. These factors impact the peak flow and timing of runoff, which are vital for flood prediction and watershed management. The SCS Unit Hydrograph method is popular due to its simplicity and adaptability to various watershed conditions (NRCS, 2004a).

$$T_c = 0.0195 * \frac{L^{0.77}}{S^{0.385}} \qquad equation\ (6.4)$$

Where T_c is the time of concentration in min, L is length of reach in meter (m), and S is the slope in (m/m)

$$T_{lag} = 0.6 * T_C \qquad equation\ (6.5)$$

Where T_{lag} is the lag time in min, T_c is time of concentration in min

6.2.2.6 Canopy storage and surface depressions storage

Canopy interception is a key storage component in subbasin elements. It refers to the amount of precipitation captured by trees, shrubs, and grasses. The maximum canopy storage depends on the type of vegetation (Table 6-1). Surface storage, on the other hand, is the portion of precipitation that bypasses the canopy and accumulates in small surface depressions. The maximum surface storage is determined by the catchment slope (Table 6-2). Both initial canopy storage and surface storage are set to 0% at the beginning of the simulation, as the period starts after a no rain condition. The maximum canopy storage and surface storage per storm event, both expressed in millimeters (mm), represent the depth of water that can be held by vegetation and the amount of water that collects on the land surface, respectively. The maximum storage values are adapted from (Fleming & Neary, 2004) and (Bennett, 1998).

Table 6-1: Maximum canopy storage based on vegetation type

Type of vegetation	Max. canopy storage (mm/storm)
General vegetation	1.27
Grasses and deciduous trees	2.032
Trees and Coniferous Trees	2.54

Adapted from Fleming and Neary (2004) and Bennett (1998)

Table 6-2: Maximum surface storage based on slope

Description	Slope (%)	Surface storage (mm/storm)
Paved impervious areas	NA	3.2-6.4
Steep, smooth slopes	>30	1.0
Moderate to gentle slopes	5-30	12.7-6.4
Flat, furrowed land	0-5	50.8

Adapted from Fleming and Neary (2004) and Bennett (1998)

6.2.3 Model calibration and validation

The Ethiopian Ministry of Water Resources provided stream flow data from 2004 to 2007, with 2004-2005 used for model calibration and 2006-2007 for validation. Optimization of the model was conducted at the basin outlet, specifically at the Geba station near Mekelle. This station was selected due to its strategic location, which allows for accurate monitoring of stream flow and better representation of the basin's hydrological conditions.

6.2.4 Statistical evaluation

The model's performance was evaluated using several metrics, including Nash-Sutcliffe (NSE) or Model Efficiency or Coefficient of Efficiency (E), Coefficient of Determination (R^2), and Percent Bias (PBIAS) (equations 6.6-6.8) . The summary of these performance ratings is based on the criteria established by Moriasi et al. (2007) (see Table 6-3).

Coefficient of efficiency (E) (Nash & Sutcliffe, 1970)

$$E = 1 - \left[\frac{\sum_{i=1}^{N}(Oi - Si)^2}{\sum_{i=1}^{N}(Oi - \bar{O})^2}\right] \qquad (equation\ 6.6)$$

Where E is Coefficient of efficiency, Oi Observed value, Si simulated value, $\bar{O}$ mean observed value and N is the number of observations. It ranges from -∞ to 1.0, with optimal value of 1.0

Coefficient of determination (R^2)

$$R^2 = \frac{\sum_{i=1}^{N}(Oi - \bar{O})(Si - \bar{S})}{\sqrt{\sum_{i=1}^{N}(Oi - \bar{O})^2} \cdot \sqrt{\sum_{i=1}^{N}(Si - \bar{S})^2}} \qquad (eqution\ 6.7)$$

Where R^2 is Coefficient of determination, Oi Observed value, Si simulated value, $\bar{O}$ mean observed value $\bar{S}$ mean simulated value and N is the number of observations. It ranges from 0.0 to 1.0, with optimal value of 1.0.

Percent Bias (PBIAS)

$$PBIAS = 100\% \left(\frac{\sum_{i=1}^{N}(Oi - Si)}{\sum_{i=1}^{N} Oi}\right) \qquad (eqation\ 6.8)$$

Where PBIAS is Percent Bias, *Oi Observed value, Si simulated value*

Table 6-3: Summary of statistical performance ratings based Moriasi et al. (2007)

Performance Rating	**NSE**	**R^2**	**PBIAS**
Very Good	$0.65<NSE\leq1.00$	$0.65<R^2\leq1.00$	PBIAS< ±15
Good	$0.55<NSE\leq0.65$	$0.55<R^2\leq0.65$	±15≤PBIAS<±20
Satisfactory	$0.40<NSE\leq0.55$	$0.40<R^2\leq0.55$	±20≤PBIAS<±30
Unsatisfactory	NSE ≤0.40	$R^2\leq0.40$	PBIAS≥±30

6.3 Results and Discussion

6.3.1 Land use land cover classifications

The 2009 LULC classification derived using the maximum livelihood-supervised image classification procedure results, depicted in Fig. 6-3, identify six main land cover types: bare land, forest, cultivated areas, shrubland, urban area, and water bodies. The land-use map indicates that over 41% of the study area is dominated by cultivation. Bare land and shrubland each account for nearly 25% of the area, while the remaining portions are comprised of forest, built up areas including village settlements, and water bodies. Classification accuracy was improved using 396 ground truth data points collected via GPS during previous field visits. The classification reveals a highly diverse pattern of land use across the basin, which has significant implications for hydrological modeling, water resource management, and climate impact assessments.

The diverse land-use pattern reflects the complex interaction between human activities and natural systems within the watersheds. Furthermore, the dominance of agriculture and bare land suggests intense pressure on land resources, which could lead to environmental degradation if not managed sustainably (Bewket, 2003; Teferi et al., 2013).

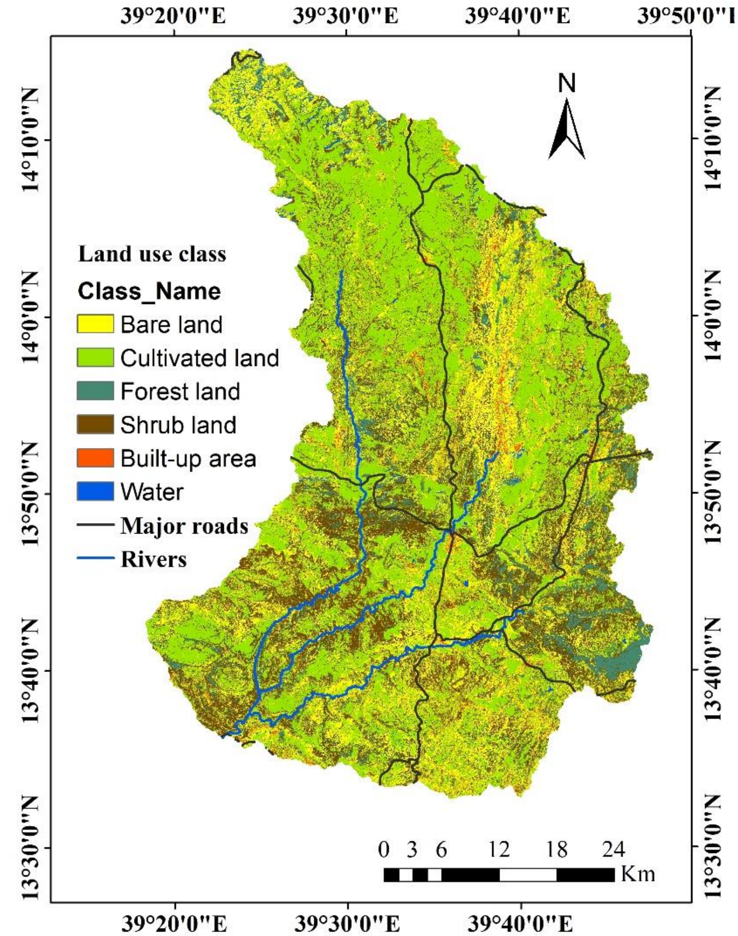


Figure 6-3: Land use land cover map of the study area

6.3.2 Soil texture and Hydrological Soil Group (HSG)

In this study, the classification of Hydrologic Soil Groups (HSG) was determined using soil texture data obtained from ISRIC soil grids. The classification process involved matching soil texture characteristics with the standard HSG criteria outlined by the USDA Natural Resources Conservation Service (NRCS, 2004b). Fig. 6-3 and Table 6-4 provide an overview of soil texture, HSG classification, and the percentage distribution of each group. Based on their hydrological properties: (i) Group A has a low tendency for surface runoff and a high capacity for water infiltration, (ii) Group B exhibits moderate surface runoff potential and infiltration rates, (iii) Group C is characterized by high surface runoff potential and low infiltration capacity, and (iv)

Group D has a very high surface runoff potential with minimal infiltration capacity (NRCS, 2004b).

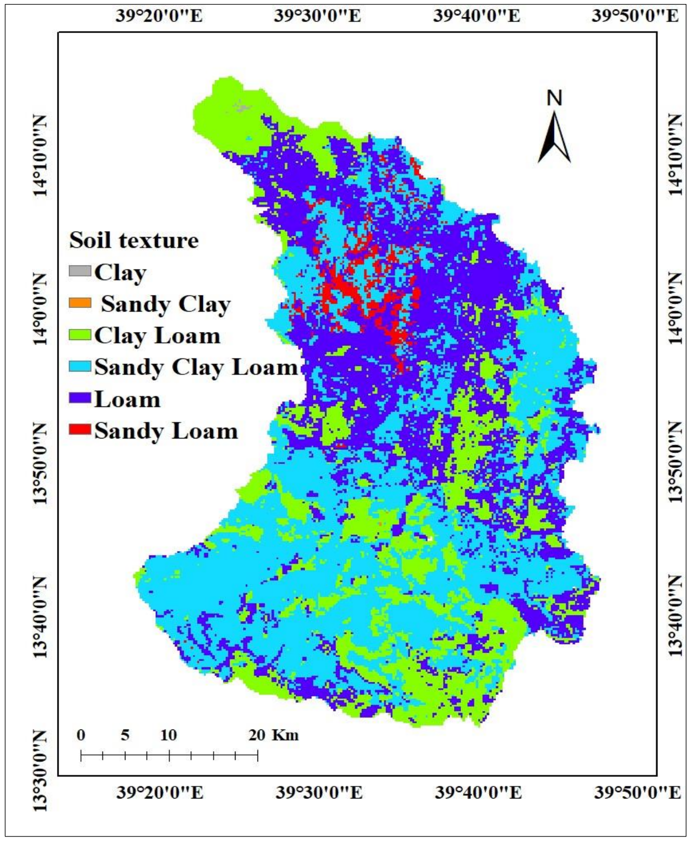


Figure 6-4: Soil texture class with ISRIC 250 m resolution (https://www.isric.org/)

The study area mainly consists of Sandy Clay Loam, Loam, and Clay Loam soils, each with unique hydrologic characteristics. Sandy Clay Loam (Group C) has low infiltration rates and a layer that restricts water movement, which leads to a higher potential for surface flow. Loam (Group B) has moderate infiltration rates, is well-drained, and has a balanced texture, resulting in moderate water transmission and a lower potential for surface flow. Clay Loam (Group D) has very low infiltration rates and a high potential for surface flow, and it is prone to water retention due to its clay content.

Table 6-4: Hydrological Soil Group (HSG), soil texture and percent of coverage

Soil texture	HSG	Area (km^2)	Percent
Clay	D	0.97	0.04
Sandy Clay	D	0.20	0.01
Clay Loam	D	538.06	22.18
Sandy Clay Loam	C	1027.57	42.36
Loam	B	798.23	32.91
Sandy Loam	A	60.71	2.50

In the study area, Group D soils are the most prevalent, accounting for 22.18% (Clay Loam) and 42.36% (Sandy Clay Loam). These soil types exhibit low infiltration rates, leading to a heightened potential for surface runoff. This condition increases the likelihood of soil erosion, limits groundwater recharge, and raises the risk of flash flooding (Kuok et al., 2023; Odoh et al., 2024). Therefore, implementing soil conservation and water management strategies tailored to specific HSGs is crucial. For instance, contour farming, terracing, and the use of vegetative cover are effective in reducing runoff on Group D soils. In contrast, Group C soils could benefit from practices that enhance organic matter to improve infiltration, while Group B soils require management strategies that maintain their natural balance, supporting moderate infiltration and water retention (Huffman et al., 2013; Morgan, 2009).

6.3.3 Grid Curve Number, Storage (S) and Initial Abstraction (Ia)

The grid curve number is derived by combining Hydrological Soil Group (HSG) data with Land Use/Land Cover (LULC) information. To create the gridded curve number map as shown in Fig. 6-5, the original 30-meter LULC data is resampled to a 250-meter resolution to align with the resolution of the HSG. This re-gridding process ensures consistency between the datasets, enabling accurate calculation and mapping of curve number values, which are vital for estimating runoff in hydrological models (Dwivedi & Tripathi, 2020). Mismatched resolutions can lead to errors in runoff estimation, whereas proper alignment ensures both consistency and reliability (Gassman et al., 2007; Tan et al., 2015).

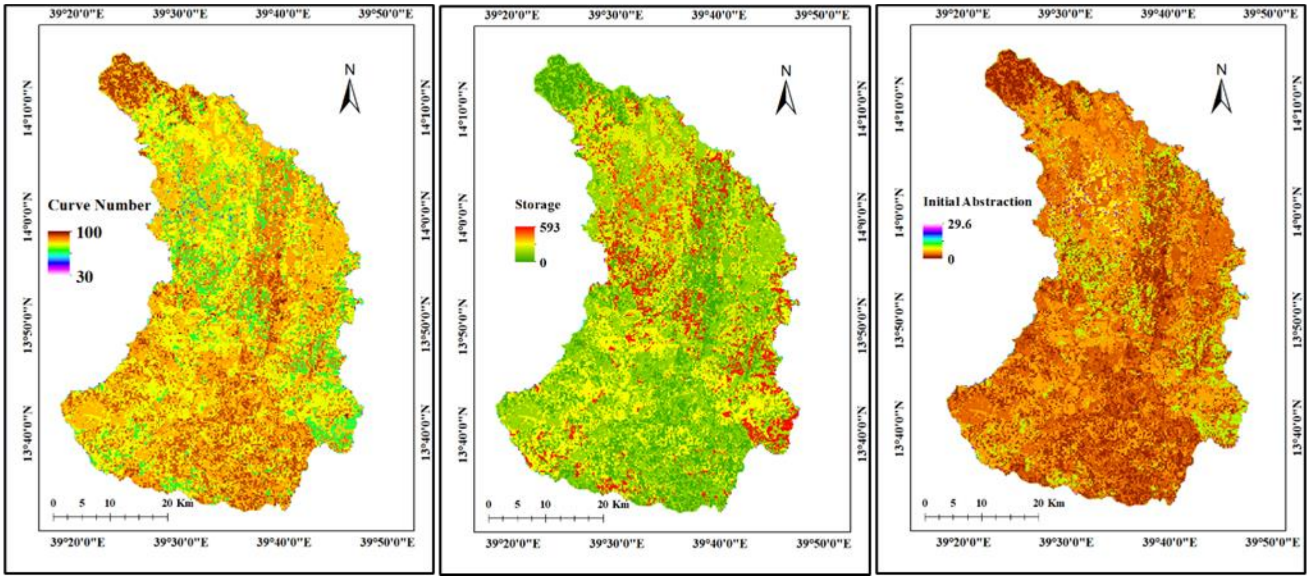


Figure 6-5: Grid Curve Number, Storage (mm) and Initial Abstraction (mm)

Additionally, spatial storage and initial abstraction values are calculated from the gridded curve number as shown in Fig. 6-5. The spatial storage values in the study area show considerable variation, ranging from zero to a maximum of 593. Similarly, initial abstraction values, which indicate the amount of water absorbed before runoff begins, range from zero to 29.6. A clear relationship exists between storage and initial abstraction: areas with higher storage values typically have higher initial abstraction values, meaning they can absorb more water before runoff occurs. These areas usually have lower curve number values, signifying a lower potential for surface runoff due to their greater retention and infiltration capacity (Brandão et al., 2024).

Hydrological models that employ the curve number (CN) method, such as HEC-HMS, are particularly sensitive to CN parameterization. The CN value is a key determinant of runoff depth generated by a given rainfall event. Even minor changes in CN values can result in substantial variations in simulated runoff, which directly impact flood forecasting, irrigation planning, and reservoir operations (Ponce & Hawkins, 1996). Therefore, understanding the spatial variability of storage, initial abstraction, and curve number is crucial for evaluating runoff potential and supporting informed decision-making in water resource management and flood risk mitigation (Hawkins et al., 2008; NRCS, 2004a)

6.3.4 Model Calibration and Validation

Calibration and validation are fundamental stages in hydrological modeling, essential for improving model accuracy and ensuring reliable predictions. Calibration involves adjusting model parameters to achieve the best alignment between simulated and observed data, while validation tests the model's ability to predict outcomes using an independent dataset under varying conditions (Duda et al., 2012; Trucano et al., 2006). These processes are vital in reducing uncertainties and establishing confidence in the model's performance (Dahabreh et al., 2017).

In this study, the calibration focused on optimizing key parameters such as the Curve Number (CN), canopy storage, surface depression storage, and Muskingum routing coefficients (K and X). These parameters significantly affect surface runoff generation, storage, and flow routing, making their optimization critical for accurately simulating the basin's hydrological processes. The calibration process was iterative, using observed streamflow data from representative monitoring station to ensure close alignment between simulated and observed flow.

The calibrated parameters for sub-basins and river reaches are summarized in Table 6-5. These parameters represent the configuration that achieved the most accurate simulation of hydrological processes within the basin.

Table 6-5: Final calibrated parameters for sub-basins and reaches in the model

Element	Model parameters					
	Initial CN	Optimized CN	Canopy storage (mm)	Surface depression storage (mm)	Muskingum K (hr)	Muskingum X
SB1	74.45	76	0.50	2.50	-	-
SB2	82.04	74	0.75	4.00	-	-
SB3	81.12	82	1.00	3.00	-	-
SB4	73.62	40	0.50	3.00	-	-
SB5	75.40	41	1.20	2.50	-	-
SB7	77.85	38	1.00	3.00	-	-
SB8	76.65	72	0.50	3.00	-	-
SB9	78.92	40	2.30	2.85	-	-
SB10	74.36	32	1.20	3.00	-	-
SB11	78.78	40	1.20	2.85	-	-
SB12	77.67	82	1.00	2.85	-	-
SB14	81.64	82	2.00	2.50	-	-
Reach-1	-	-	-	-	93.52	0.001
Reach-2	-	-	-	-	107.42	0.035
Reach-3	-	-	-	-	51.932	0.020
Reach-4					39.32	0.214
Reach-5	-	-	-	-	89.11	0.158
Reach-6	-	-	-	-	0.945	0.254

The spatial variability in the calibrated parameters reflects the heterogeneity of hydrological processes across sub-basins. Differences in Curve Numbers and storage capacities indicate variations in land use, soil types, and surface characteristics. Similarly, the Muskingum routing parameters for river reaches highlight the effects of flow attenuation and storage along river channels.

The calibration process employed both manual and automated optimization techniques. Objective functions such as the "sum of squared residuals" and "mean of squared residuals" were instrumental in achieving optimal parameter configurations. Automated calibration provided efficiency and objectivity in addressing complex optimization challenges, while manual calibration incorporated expert insights to further refine the model (Arnold et al., 2012; Boyle et al., 2000).

Observed flow data from the Mekelle gauge station in the upper Geba Basin (January 1, 2004 – December 31, 2005) was used for calibration, while independent data (January 1, 2006 – December 31, 2007) was used for validation. This dual-phase approach ensured the model's robustness in simulating hydrological conditions across different datasets (Fig. 6-6).

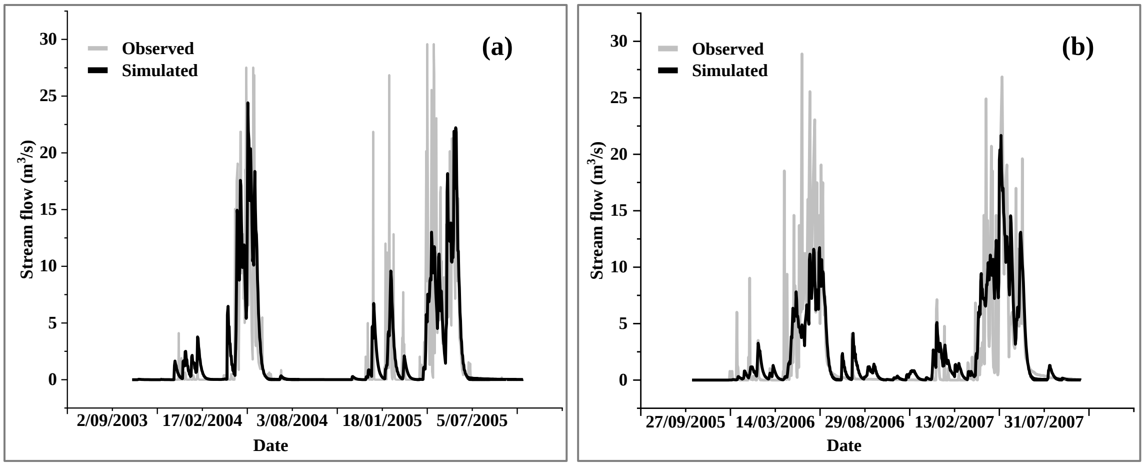


Figure 6-6: Hydrographs of observed and simulated daily flow for the calibration period (a) and validation period (b) at the Geba near Mekelle gauge station.

The model’s reliability was evaluated using statistical performance metrics, including Nash-Sutcliffe Efficiency (NSE), the coefficient of determination (R^2), and percent bias (PBIAS). These metrics provide complementary insights: NSE evaluates simulation accuracy, R^2 measures consistency between observed and simulated data, and PBIAS quantifies systematic bias (Krause et al., 2005; Waseem et al., 2017).

During calibration, the observed and simulated daily peak discharges in the basin were 29.6 m^3/s and 21.5 m^3/s, respectively. For the validation period, the observed peak discharge was 28.9 m^3/s, while the simulated value was 21.7 m^3/s. As shown in Table 6-6, the observed peak flows consistently exceeded the simulated values, indicating that the model underestimated peak flows during both calibration and validation periods.

The observed and simulated average annual flow volumes were 124.7 Mm^3 and 130.1 Mm^3, respectively, during calibration, and 140.7 Mm^3 and 141.4 Mm^3 during validation. These results suggest a minor overestimation of total flow volumes by the model, as highlighted in Table 6-6.

Table 6-6: Observed and simulated peak discharge and total volume for model calibration and validation.

	Years	**Total outflow***				**Performance measures**		
		Peak discharge (m^3/s)		Volume (Mm^3)				
		Observed	Simulated	Observed	Simulated	NSE	PBIAS	R^2
Calibration	2004 – 2005	29.6	21.5	124.7	130.1	48.4	-7.82	48
Validation	2006 – 2007	28.9	21.7	140.7	141.4	61.0	-2.86	61

*Daily outflow over the year from Geba near Mekelle gauge station

Statistical evaluation of the model's performance revealed a Nash-Sutcliffe Efficiency (NSE) of 0.484 and a coefficient of determination (R^2) of 0.48 for the calibration period. For the validation period, the NSE and R^2 values improved to 0.61 and 0.61, respectively (Table 6-6). Moreover, the percent bias (PBIAS) for the simulations remained within the acceptable range, further confirming the model's reliability. Based on the performance benchmarks established by Moriasi et al. (2007) (Table 6-3), these evaluation metrics indicate that the model's performance was satisfactory during calibration and good during validation.

The HEC-HMS model utilized in this study incorporates surface storage processes that effectively reduce peak discharges by temporarily retaining runoff in depressions, floodplains, and other storage features before gradually releasing it. This mechanism lessens the intensity of peak flows without significantly altering the overall runoff volume. In certain instances, the total flow volume may be slightly overestimated due to prolonged water retention and delayed outflow (Feldman, 2000; Chu & Steinman, 2009). Furthermore, hydrological factors such as infiltration, channel flow routing, and evapotranspiration play a critical role in redistributing runoff, leading to a smoother hydrograph while maintaining or marginally increasing cumulative discharge over time (USACE, 2016). Similar findings were reported by Belay & Tassew (2024) and Mohammed & Fuli (2020), who noted an underestimation of peak flows and a slight overestimation of total runoff volume when applying the HEC-HMS model to simulate rainfall-runoff processes. Consequently, the model provides a reliable representation of hydrological processes in the Geba Basin and is well-suited for applications in water resource planning and management.

6.3.5 Simulation of future surface runoff

After optimizing the rainfall-runoff model, it was used to simulate future surface runoff for the basin under projected mid-term (2040-2069) and end-term (2070-2099) climate scenarios using the delta method, with the reference period being 1980-2014 (Fig. 6-7) and Annex 3. The results indicate that under the SSP2-4.5 scenario, surface runoff is expected to decrease in most months during the mid-term period, with the exception of March. The decline in surface runoff ranges from 0.74% in February to nearly 26% in November. For the end-term period under SSP2-4.5, most months show a decrease in surface runoff ranging from 0.56% to 17%, although January, February, March, and August are projected to experience increases between 1% and 23%, with the smallest increase in August and the largest in February. Several studies in northern Ethiopia, using various emission scenarios and time frames, have also indicated a declining trend in future surface runoff in their respective study areas (e.g., Gebremeskel & Kebede, 2018b; Kahsay et al., 2018; Shiferaw et al., 2018; Takele et al., 2022).

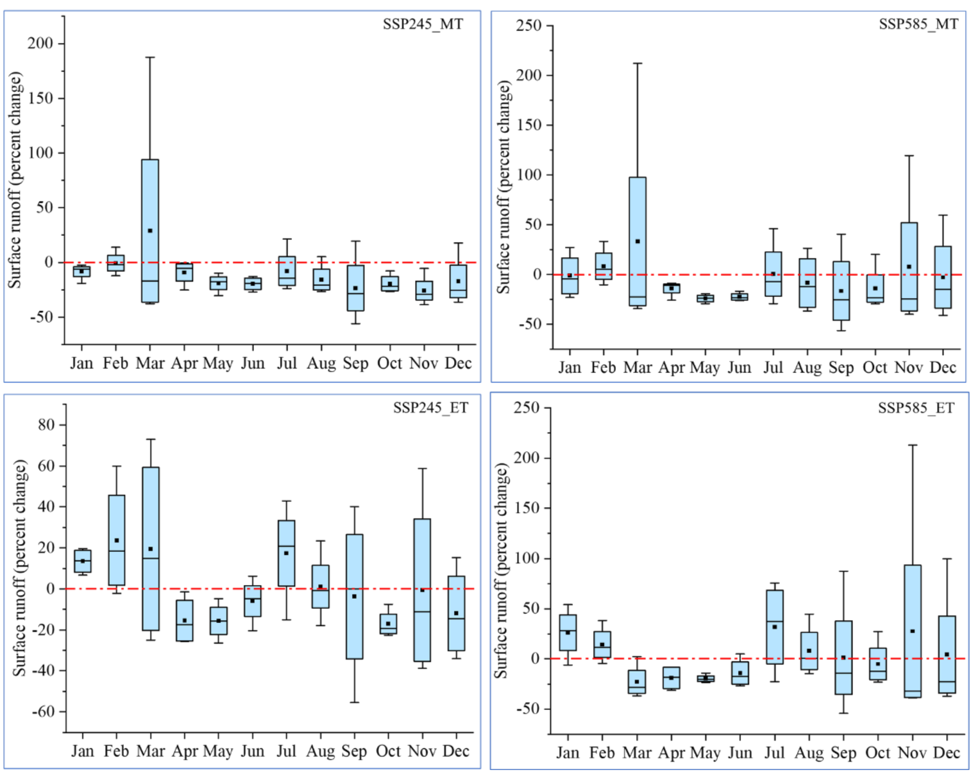


Figure 6-7: Monthly surface runoff change under SSP245 and SSP585 in mid and end-term periods from the reference period (1980-2014).

Under the worst-case scenario, SSP5-8.5, surface runoff is expected to decrease in most months during the mid-term period, ranging from 1.29% to 24%. However, February, March, July, and November are projected to experience an increases in stream flow, ranging from 0.4% to 33%. In contrast, for the end-term period under SSP5-8.5, most months are projected to have increased surface runoff ranging from 1.22% to 31.8%, while March, April, May, June, and October are expected to experience declines ranging from 5.1% to 22.8%. Overall, the SSP245 scenario for both the mid-term and end-term periods and the SSP5-8.5 scenario for the mid-term period project declining trends in surface runoff, while the SSP5-8.5 scenario for the end-term period shows an increase in most months.

The projected changes in surface runoff under different climate scenarios have significant implications for water resources management, particularly in the context of climate change. The decline in surface runoff, especially under the SSP2-4.5 scenario, suggests potential water shortages during critical periods, which could affect water supply for agriculture, drinking water, and industrial use. This decline may also impact the health of aquatic ecosystems and reduce the availability of water for hydropower generation, leading to energy shortages (De Oliveira et al., 2017; Pagán et al., 2016).

The increase in surface runoff projected in some months under the SSP5-8.5 scenario could lead to increased risk of flooding, which would require enhanced flood management strategies, including the construction of more robust infrastructure and the implementation of effective early warning systems. Moreover, the variability in runoff between different scenarios and periods highlights the need for flexible and adaptive water management strategies that can respond to both droughts and floods. This includes investing in sustainable water storage and distribution systems, promoting water conservation practices, and developing policies that can accommodate the uncertainties posed by climate change. Additionally, collaboration between local, regional, and national authorities will be crucial to ensure the equitable distribution and efficient use of water resources in the face of these challenges.

6.3 Conclusion and Recommendations

This study offers valuable insights into the hydrological characteristics and the potential impacts of climate change on surface runoff in the study area. The results highlight a significant variability in surface runoff under different climate scenarios. Under the SSP2-4.5 scenario, a declining trend in surface runoff is projected during most months for both mid-term (2040-2069) and end-term (2070-2099) periods, raising concerns about water shortages and their implications for agriculture, domestic supply, and ecosystem health. In contrast, the SSP5-8.5 scenario indicates mixed trends, with some months showing increased runoff that could heighten the risk of flooding, particularly during the end-term period. These findings emphasize the urgent need for adaptive strategies to manage water resources effectively in the face of these projected changes.

To address the challenges posed by the projected variability in surface runoff, the following recommendations are proposed:

- Develop and implement flexible, integrated water resource management strategies to address both the risks of declining runoff (e.g., droughts) and potential flooding. These strategies should prioritize long-term sustainability and resilience to climate variability.
- Invest in climate-resilient infrastructure, including sustainable water storage systems, improved irrigation networks, and robust flood mitigation measures. This will enhance water supply reliability during dry periods and reduce flood risks during high runoff months.

References

Ahmadi, A., Jalali, J., & Mohammadpour, A. (2022). Future runoff assessment under climate change and land-cover alteration scenarios: a case study of the Zayandeh-Roud dam upstream watershed. *Hydrology Research*, *53*(11), 1372-1392.

Arnold, J. G., Moriasi, D. N., Gassman, P. W., Abbaspour, K. C., White, M. J., Srinivasan, R., Santhi, C., Harmel, R., Van Griensven, A., & Van Liew, M. W. (2012). SWAT: Model use, calibration, and validation. *Transactions of the ASABE*, *55*(4), 1491-1508.

Ashenafi, A. A. (2014). *Modeling hydrological responses to changes in land cover and climate in Geba River Basin, Northern Ethiopia*

Belay, A. A., & Tassew, B. G. (2024). GIS-based application of hydrological modelling in the Borkena Catchment, Ethiopia. *Hydrology Research*, *56*(1), 1-12.

Bennett, T. H. (1998). *Development and application of a continuous soil moisture accounting algorithm for the Hydrologic Engineering Center Hydrologic Modeling System (HEC-HMS)*. University of California, Davis.

Bewket, W. (2003). *Towards integrated watershed management in highland Ethiopia: the Chemoga watershed case study*. Wageningen University and Research.

Boyle, D. P., Gupta, H. V., & Sorooshian, S. (2000). Toward improved calibration of hydrologic models: Combining the strengths of manual and automatic methods. *Water resources research*, *36*(12), 3663-3674.

Brandão, A. R. A., Schwamback, D., Ballarin, A. S., Ramirez-Avila, J. J., Vasconcelos, J. G., & Oliveira, P. T. (2024). Toward a Better Understanding of Curve Number and Initial Abstraction Values from a Global Watershed Dataset Perspective. *Available at SSRN 4795307*.

Chu, X., & Steinman, A. (2009). Event and continuous hydrologic modeling with HEC-HMS. Journal of Irrigation and Drainage Engineering, 135(1), 119-124.

Dahabreh, I. J., Wong, J. B., & Trikalinos, T. A. (2017). Validation and calibration of structural models that combine information from multiple sources. *Expert review of pharmacoeconomics & outcomes research*, *17*(1), 27-37.

De Oliveira, V. A., de Mello, C. R., Viola, M. R., & Srinivasan, R. (2017). Assessment of climate change impacts on streamflow and hydropower potential in the headwater region of the Grande river basin, Southeastern Brazil. *International Journal of Climatology*, *37*(15), 5005-5023.

Duda, P. B., Hummel, P. R., Donigian Jr, A. S., & Imhoff, J. C. (2012). BASINS/HSPF: Model use, calibration, and validation. *Transactions of the ASABE*, *55*(4), 1523-1547.

Dwivedi, K., & Tripathi, M. (2020). Preparation of Curve Number Map for hydrologic simulation using GIS and HEC-Geo-HMS Model. *Int. J. Curr. Microbiol. Appl. Sci*, *9*, 3264-3270.

Fanta, S. S., & Tadesse, S. T. (2022). Application of HEC–HMS for runoff simulation of Gojeb Watershed, Southwest Ethiopia. *Modeling Earth Systems and Environment*, *8*(4), 4687-4705.

Feldman, A. D. (2000). Hydrologic modeling system HEC-HMS: technical reference manual. US Army Corps of Engineers, Hydrologic Engineering Center.

Fleming, M., & Neary, V. (2004). Continuous hydrologic modeling study with the hydrologic modeling system. *Journal of hydrologic engineering*, *9*(3), 175-183.

Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). The soil and water assessment tool: historical development, applications, and future research directions. *Transactions of the ASABE*, *50*(4), 1211-1250.

Gebremeskel, G., & Kebede, A. (2018). Estimating the effect of climate change on water resources: Integrated use of climate and hydrological models in the Werii watershed of the Tekeze river basin, Northern Ethiopia. *Agriculture and Natural Resources*, *52*, 195-207.

Gebremicael, T., Mohamed, Y., & Van der Zaag, P. (2019). Attributing the hydrological impact of different land use types and their long-term dynamics through combining parsimonious hydrological modelling, alteration analysis and PLSR analysis. *Science of the Total Environment*, *660*, 1155-1167.

Gebreyohannes, T., De Smedt, F., Walraevens, K., Gebresilassie, S., Hussien, A., Hagos, M., Amare, K., Deckers, J., & Gebrehiwot, K. (2013). Application of a spatially distributed water balance model for assessing surface water and groundwater resources in the Geba basin, Tigray, Ethiopia. *Journal of Hydrology*, *499*, 110-123.

Gebru, T. A., & Tesfahunegn, G. B. (2020). GIS based water balance components estimation in northern Ethiopia catchment. *Soil and Tillage Research*, *197*, 104514.

Goitom, H., Smedt, F. D., Yohannes, T. G., Walraevens, K., Gebrehiwot, K., Bauer, H., & Deckers, J. (2012). Modeling Climate Change Impact in the Geba Basin, Ethiopia.

Gramz, M., Batchi, M., El Bouziani, J., Azagane, M. H., El-boukhari, A., Nafii, A., & Elharrari, Y. (2024). Impact of climate change on surface water resources in arid zones-the case of the Ykem watershed in the central plateau of Morocco. E3S Web of Conferences,

Guduru, J. U., Jilo, N. B., Rabba, Z. A., & Namara, W. G. (2023). Rainfall-runoff modeling using HEC-HMS model for Meki River watershed, rift valley basin, Ethiopia. *Journal of African Earth Sciences*, *197*, 104743.

Hailekiros, K., Gebreyohannes, T., Hussein, A., & Brhane, H. (2023). Water Balance Components Estimation using WetSpass Model: A Case study of Mekelle Area, Tigray, Ethiopia. *Physical Science International Journal*, *27*(3), 27-37.

Hailu, G. K. (2016). *Assessment of Hydrological Impacts of Land Cover Changes and Climate Variability in the Geba Catchment, Ethiopia* National Institute of Technology Karnataka, Surathkal].

Hassaan, H. A., Rauf, A. U., Ghumman, A. R., Khan, S., & Aamir, E. (2024). Assessment of climate change impact on inflows to Amandara headwork using HEC-HMS and ANNs. *Journal of Umm Al-Qura University for Engineering and Architecture*, 1-18.

Hawkins, R. H., Ward, T. J., Woodward, D. E., & Van Mullem, J. A. (2008). Curve number hydrology: State of the practice.

Huffman, R. L., Fangmeier, D. D., Elliot, W. J., Workman, S. R., & Schwab, G. (2013). *Soil and water conservation engineering*. American Society of Agricultural and Biological Engineers St. Joseph, MI.

IPCC. (2007). *Climate change 2007: Impacts, adaptation and vulnerability* (Genebra, Suíça, Issue.

IPCC. (2013). *The physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change.* ((No Title), Issue.

Kahsay, K. D., Pingale, S. M., & Hatiye, S. D. (2018). Impact of climate change on groundwater recharge and base flow in the sub-catchment of Tekeze basin, Ethiopia. *Groundwater for Sustainable Development*, *6*, 121-133.

Kidanemariam, S., Goitom, H., & Desta, Y. (2021). Coupled application of R and WetSpa models for assessment of climate change impact on streamflow of Werie Catchment, Tigray, Ethiopia. *Journal of Water and Climate Change*, *12*(3), 916-936.

Krause, P., Boyle, D., & Bäse, F. (2005). Comparison of different efficiency criteria for hydrological model assessment. *Advances in geosciences*, *5*, 89-97.

Kuok, K. K., Chiu, P. C., Rahman, M. R., Said, K. A. b. M., & Chin, M. Y. (2023). Evaluation of total infiltration and storage capacities for different soil types in Sarawak using SWMM. *Discover Water*, *3*(1), 18.

Masimba, O., Gumindoga, W., Mhizha, A., & Rwasoka, D. T. (2022). Impacts of climate change on streamflow and reservoir inflows in the Upper Manyame sub-catchment of Zimbabwe. *Water SA*, *48*(4), 359–368-359–368.

Mekuriaw, T. (2019). Evaluating impact of land-use/land-cover change on surface runoff using Arc SWAT model in sore and Geba Watershed, Ethiopia. *Journal of environment and earth science*, *9*(10), 6-17.

Meresa, E., Girmay, A., & Gebremedhin, A. (2019). Water Balance Estimation Using Integrated GIS-Based WetSpass Model in the Birki Watershed, Eastern Tigray, Northern Ethiopia. *Physical Science International Journal*, *22*(3), 1-17.

Mohammed, J. I., & Fuli, A. B. (2020). Application of HEC-HMS for the Assessment of Water Availability in Fincha and Didessa Sub-basin, Ethiopia.

Morgan, R. P. C. (2009). *Soil erosion and conservation*. John Wiley & Sons.

Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*, *50*(3), 885-900.

Muleta, T. N., & Marcell, K. (2023). Rainfall-runoff modeling and hydrological responses to the projected climate change for upper Baro Basin, Ethiopia. *American Journal of Climate Change*, *12*(2), 219-243.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I—A discussion of principles. *Journal of Hydrology*, *10*(3), 282-290.

NRCS, U. (2004a). National engineering handbook: Part 630—hydrology. *USDA Soil Conservation Service: Washington, DC, USA*, 11-15.

NRCS, U. (2004b). National Engineering Handbook: Part 630—Hydrology. Chapter 9: Hydrologic Soil-Cover Complexes. *United States Department of Agriculture-Natural Resources Conservation Service*.

Odoh, B. I., Nwokeabia, N. C., & CallistaIgwebudu, N. (2024). Assessment of urbanization impacts on soil erosion and groundwater recharge in Enugu, Southeastern Nigeria. *International Journal of Science and Research Archive*, *12*(2), 1558-1572.

Pagán, B. R., Ashfaq, M., Rastogi, D., Kendall, D. R., Kao, S.-C., Naz, B. S., Mei, R., & Pal, J. S. (2016). Extreme hydrological changes in the southwestern US drive reductions in water supply to Southern California by mid century. *Environmental Research Letters*, *11*(9), 094026.

Ponce, V. M., & Hawkins, R. H. (1996). Runoff curve number: Has it reached maturity? *Journal of hydrologic engineering*, *1*(1), 11-19.

Sahu, M. K., Shwetha, H. R., & Dwarakish, G. S. (2023). State-of-the-art hydrological models and application of the HEC-HMS model: a review. *Modeling Earth Systems and Environment*, *9*(3), 3029-3051.

Salman, Q. M. K., & Hamdan, A. N. A. (2023). Runoff Estimation for the Central Region of the Lesser Zab River Watershed Using the SCS-Curve Number Method and GIS. *Journal of Ecological Engineering*, *24*(9).

Salvati, A., Moghaddam Nia, A., Salajegheh, A., Shirzadi, A., Shahabi, H., Ahmadisharaf, E., Han, D., & Clague, J. J. (2024). A systematic review of Muskingum flood routing techniques. *Hydrological Sciences Journal*, *69*(6), 810-831.

Sharma, D., & Babel, M. S. (2013). Application of downscaled precipitation for hydrological climate-change impact assessment in the upper Ping River Basin of Thailand. *Climate dynamics*, *41*, 2589-2602.

Shiferaw, H. M., Gebremedhin, A., Gebretsadkan, T., & Zenebe, A. (2018). Modelling hydrological response under climate change scenarios using SWAT model: the case of Ilala watershed, Northern Ethiopia. *Modeling Earth Systems and Environment*, *4*, 437-449.

Suryani, N., Pawattana, C., Lohpaisankrit, W., & Muangthong, S. (2024). Assessing the impact of climate change on surface runoff of the Ubolratana Reservoir, Thailand. IOP Conference Series: Earth and Environmental Science,

Takele, G. S., Gebrie, G. S., Gebremariam, A. G., & Engida, A. N. (2022). Future climate change and impacts on water resources in the Upper Blue Nile basin. *Journal of Water and Climate Change*, *13*(2), 908-925.

Tan, M. L., Ficklin, D. L., Dixon, B., Yusop, Z., & Chaplot, V. (2015). Impacts of DEM resolution, source, and resampling technique on SWAT-simulated streamflow. *Applied Geography*, *63*, 357-368.

Teferi, E., Bewket, W., Uhlenbrook, S., & Wenninger, J. (2013). Understanding recent land use and land cover dynamics in the source region of the Upper Blue Nile, Ethiopia: Spatially explicit statistical modeling of systematic transitions. *Agriculture, ecosystems & environment*, *165*, 98-117.

Teklebirhan, A., Dessie, N., & Tesfamichael, G. (2012). Groundwater recharge, evapotranspiration and surface runoff estimation using WetSpass modeling method in Illala catchment, northern Ethiopia. *Momona Ethiopian Journal of Science*, *4*(2), 96-110.

Tesfaye, S., Raj, A. J., & Geberesamuel, G. (2014). Assessment of climate change impact on the hydrology of Geba Catchment, Northern Ethiopia. *American Journal of Environmental Engineering*, *4*(2), 25-31.

Trucano, T. G., Swiler, L. P., Igusa, T., Oberkampf, W. L., & Pilch, M. (2006). Calibration, validation, and sensitivity analysis: What's what. *Reliability Engineering & System Safety*, *91*(10-11), 1331-1357.

U.S. Army Corps of Engineers (USACE). (2016). Hydrologic Modeling System HEC-HMS Version 4.2, User's Manual. Davis, CA: Hydrologic Engineering Center.

USDA, S. (1985). National engineering handbook, supplement A, section 4. *US Department of Agriculture, Washington DC*.

Waseem, M., Mani, N., Andiego, G., & Usman, M. (2017). A review of criteria of fit for hydrological models. *International Research Journal of Engineering and Technology (IRJET)*, *4*(11), 1765-1772.

Yilma, Z. L., & Kebede, H. H. (2023). Simulation of the rainfall–runoff relationship using an HEC-HMS hydrological model for Dabus Subbasin, Blue Nile Basin, Ethiopia. *H2Open Journal*, *6*(3), 331-342.

CHAPTER SEVEN

7. EVALUATING WATER DEMAND AND EFFICIENCY SCENARIOS FOR PROJECTED WATER SUPPLY OPTIONS

Abstract

This study employs the Stockholm Environment Institute's Water Evaluation and Planning (WEAP) system to assess the impacts of various water demand scenarios on surface water resources in the study area. The WEAP model simulates both water supply and demand across multiple sectors, including domestic, livestock, industrial, commercial, and agricultural irrigation. The analysis is scenario-based, using 2017 as a baseline and projecting up to 2055 (2040–2069). Four scenarios were analyzed to evaluate the dynamics of future water demand and availability. The basis for all scenarios lies in assessing the key drivers influencing water demand and supply, including current water use inefficiencies, socio-economic growth, climate change impacts, and adaptive management strategies: (i) Baseline Scenario: this scenario reflects current water demand across various sectors, with agriculture accounting for the largest share (61%). By 2055, total water demand is projected to increase by 81%, highlighting inefficiencies in water use, (ii) Scenario II: assuming no climate change impacts, this scenario considers growth in water demand, projecting increases of 86.6%, 92.5%, and 98.3% by 2055 due to population growth, which drives higher domestic, industrial, and commercial needs, alongside a 10%, 20%, and 30% expansion of irrigated agriculture, respectively, (iii) Scenario III: incorporating the impacts of climate change, this scenario projects a reduction in surface water availability of up to 12% and more than a twofold increase in unmet water demand by 2055, (iv) Scenario IV: introducing improved irrigation efficiency (90%) significantly reduces agricultural water demand. However, increasing pressures from other sectors still lead to an overall rise in total water demand by 52% in the baseline scenario and averaged 65.3% without irrigation expansion. With a 30% irrigation expansion during the mid-term, demand rose to 69%, averaging 84% under climate change scenarios. Addressing water scarcity in the study area will require integrated water resource management that balances water conservation efforts in agriculture with growing demands from other sectors. Future strategies should prioritize improving irrigation efficiency, expanding water storage and harvesting systems, and utilizing groundwater resources. Sustainable water management is critical for ensuring long-term water security and preserving ecosystems.

Key words: Climate change impacts, Integrated water resource management (IWRM), Scenario-based analysis, Water supply and demand, WEAP model

7.1 Introduction

Climate change is widely recognized as a critical driver of global water scarcity, intensifying pressures caused by rapid population growth, urbanization, and economic development on finite water resources (Lee et al., 2023; Mendelsohn, 2016; Schlosser et al., 2014). Projections indicate that the gap between water demand and supply will continue to widen, heightening competition among agriculture, industry, domestic consumption, and ecological needs (Molle et al., 2012). This growing imbalance underscores the urgent need for research into the impacts of climate change on water availability, particularly in regions already experiencing chronic water stress. Developing adaptive water management strategies and evidence-based policies to address these challenges is critical (Kahil et al., 2015).

The Water Evaluation and Planning (WEAP) model, developed by the Stockholm Environment Institute, has proven to be a valuable tool for analyzing and managing complex water systems. It adopts a scenario-based approach to simulate hydrological processes, assess water supply and demand, and evaluate the impacts of both climate variability and anthropogenic changes (Abera & Ayenew, 2021; Husain & Rhyme, 2021). By integrating natural hydrological processes with socioeconomic factors, WEAP facilitates comprehensive water resource planning, enabling the evaluation of sustainable water allocation strategies under dynamic climate conditions. Its wide application across various regions has demonstrated its potential to enhance long-term climate resilience and support informed policy interventions for sustainable water management (Hadri et al., 2022).

Numerous studies in Ethiopia have employed the WEAP model to assess water availability and management. For example, Goshime et al. (2021) examined the effects of short- and long-term water resource developments on interconnected lakes in the Central Rift Valley, concluding that increasing water demand could disrupt the water balance, leading to significant water level declines and unmet demand. Teklu et al. (2020) used WEAP to simulate the hydrology of the Awash River Basin, successfully calibrating and validating the model with observed streamflow data. Similarly, Abera and Ayenew (2021) demonstrated the model's ability to represent hydrological dynamics in the Ketar sub-basin through statistical performance evaluation.

Alemu and Dioha (2020) explored the influence of population growth and improved living standards on water demand in Addis Ababa, projecting a 48% increase in unmet demand between 2015 and 2030. Laelago et al. (2020) used WEAP to assess long-term water allocation strategies in the Bilate River catchment, proposing optimal resource allocation scenarios to maximize benefits while maintaining ecological sustainability and mitigating water scarcity during peak periods. Kemal and Adeba (2021) evaluated the surface water potential of the Dabus sub-basin, analyzing current and future water demand under various scenarios. Collectively, these studies illustrate WEAP's utility in holistic water resource assessments across Ethiopia, enabling strategic planning to address future water challenges while balancing competing demands.

The study area, located in the semi-arid Tigray region of northern Ethiopia, is particularly vulnerable to water stress. This vulnerability is compounded by increasing water demands driven by population growth, urbanization, and competing sectoral needs. Additionally, the region experiences high susceptibility to climate variability and change, evidenced by shifts in precipitation patterns, prolonged droughts, and rising evapotranspiration rates (Berhe et al., 2018; Meles et al., 1997; Takele et al., 2022). These climatic changes are expected to exacerbate water scarcity, posing significant challenges to sustainable water management.

Previous research on climate change impacts on water resources in the Tigray region has primarily focused on the supply-side dynamics of water availability (Kahsay et al., 2018; Shiferaw et al., 2018; Tesfaye et al., 2014a; Tesfaye et al., 2019). While these studies provide valuable insights, they often neglect the demand side of the water balance, which is equally essential for effective water resource management. A comprehensive understanding of both supply and demand is crucial for developing accurate projections and practical solutions for future water management.

This study aims to evaluate the effects of climate change on both water availability and demand within selected watersheds while formulating adaptive strategies for sustainable water resource management. Specifically, the objectives are: (i) to assess the current water balance in the study area, incorporating both supply and demand components; (ii) to project future water availability and demand under various climate change scenarios using the WEAP model; (iii) to optimize water allocation strategies that reconcile competing sectoral demands while preserving ecological integrity; and (iv) to propose effective adaptation measures to enhance water security and resilience against climate variability and change.

7.2 Methods

This study used the WEAP model to assess water supply and demand under different scenarios. The schematic framework (Fig. 7-1) integrates hydrological and water allocation components to simulate surface water availability and distribution. Water supply is estimated using simulated runoff data from the HEC-HMS model, while water demand is analyzed based on sectoral requirements, including irrigation, domestic use, livestock, commercial activities, industrial needs, and environmental requirements. Scenario-based analysis was conducted to evaluate the impact of changing climate and socioeconomic factors on water availability, enabling a comprehensive assessment of future water resource sustainability in the study area.

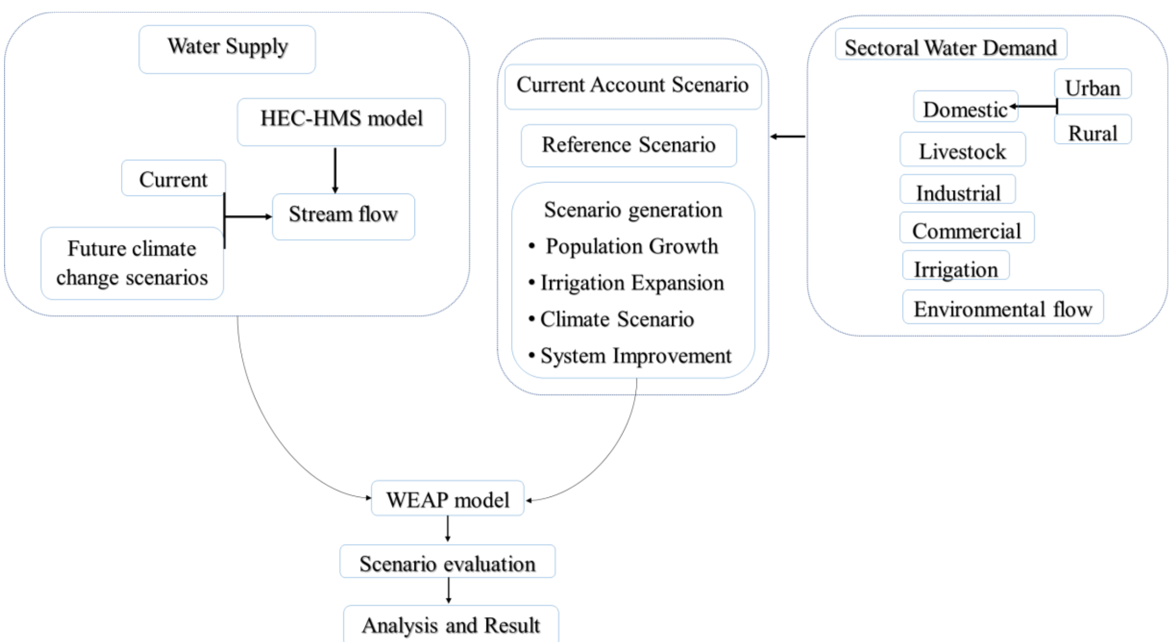


Figure 7-1: Schematic framework and model configuration of the WEAP model

7.2.1 WEAP Model

The WEAP model was employed to simulate both the supply and demand of water in the area. It is a widely used tool for water resource modeling, applied across various regions for planning and management (Adgolign et al., 2016; Ali et al., 2014; Hum & Talib, 2016). The model operates on the principle of a water balance, meaning it accounts for all inputs and outputs in a system, making it applicable to both simple and complex water systems, such as municipal supplies and transboundary river basins (SEI, 2023).

The WEAP model supports an integrated approach to water development by balancing supply-side issues (e.g., stream flows, groundwater) with demand-side management, including water use efficiency, re-use strategies, and water allocation. It allows for comprehensive simulation of both natural processes (e.g., runoff, evapotranspiration) and human-engineered systems (e.g., reservoirs, ground water pumping).

7.2.2 WEAP model data input and parameterization

7.2.2.1 Study area schematization

The study area was outlined, and its boundaries were established by incorporating the watershed shapefile, which was created using ArcGIS software. This map was utilized for implementing various water demand sectors, including domestic, livestock, industrial, commercial, and environmental flow needs (Fig. 7-2).

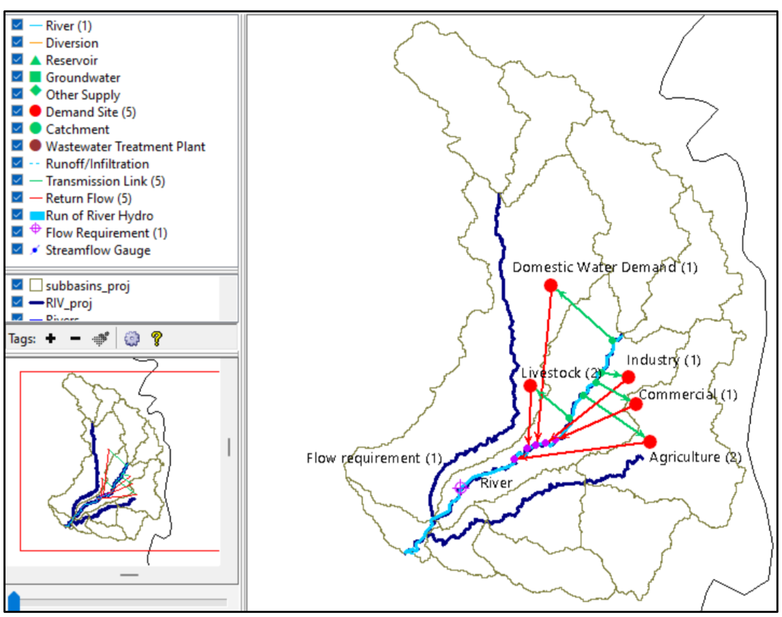


Figure 7-2: WEAP schematic view of demand sites in the study area

7.2.2.2 Sectoral demand inputs

Domestic Water Demand (DWD)

This study used population projections from the 2017 census data as the baseline to model current and future water demand. (CSA, 2014). Following Admasu et al. (2011), a population growth rate of 2.52% was applied to estimate the projected population through the mid-term period of 2050 (2040-2069). Additionally, per capita water consumption was calculated in accordance with recommendations from the Ethiopian Ministry of Water Resources (EMWR), which suggests daily water consumption of 30 to 50 liters per person for urban centers and 15 to 25 liters per person for rural areas.

Livestock Water Demand (LWD)

The Food and Agriculture Organization of the United Nations FAO (2006) has estimated the drinking water requirements for livestock. At an air temperature of 25°C, the daily water consumption per animal is as follows: cattle consume 25 liters, goats 9.6 liters, sheep 12.9 liters, and camels 41.8 liters. Additionally, 100 chickens require 33.1 liters of water each day. Furthermore, according to the Central Statistical Agency (CSA, 2017), the Eastern Zone has a total livestock population of 2.4 million, which includes 465,556 cattle, 678,582 sheep, 214,265 goats, 1,046 horses, 883 mules, 142,817 donkeys, 842 camels, and 872,948 poultry. Consequently, future livestock water demand was estimated based on the current total animal population and the average annual growth rate of livestock, which is 6.12%. This growth rate varies by species, with cattle experiencing the lowest growth rate at 3.8%, and camels the highest at 9.4% (Bachewe et al., 2018).

Commercial and Industrial Water Demand

The water requirements of commercial and institutional users, including hospitals, clinics, offices, bars, shops, restaurants, and hotels, must be taken into account. According to the Ethiopian Ministry of Water Resources (EMWR), 5% of the domestic water demand (DWD) should be allocated for small to medium-sized towns, while larger towns require 10%. Large towns are defined as those with a population of 50,000 or more, medium towns have populations between

10,000 and 50,000, and small towns have populations ranging from 2,500 to under 10,000. Additionally, industrial water demand was estimated at 30% of DWD of large and medium towns and 10% of DWD for small towns.

Irrigation Water Demand (IWD)

The irrigation water demand in the study area was estimated by integrating multiple factors, including the extent of irrigated areas derived from land use/land cover data, crop water requirement, effective rainfall, and irrigation efficiency (equation 7.1). The effective rainfall (ER) considered in this study is the portion of the rainfall effectively used by the plant and it can be estimated using the method of dependable rainfall. Dependable rainfall is one of the several methods available to calculate ER in CropWat model (equation 7.2 and 7.3). The empirical formula of dependable rainfall is developed by Water Service of FAO, based on the analysis carried out in arid and sub humid climates (Wane & Nagdeve, 2014).

$$IWD = \frac{(CWR - ER) * A}{IE} \qquad equation\ 7.1$$

Where CWR is crop water requirement (mm), ER is effective rainfall, A is the irrigated area (hectares), and IE is the irrigation efficiency (%)

$$ER = 0.6P_{tot} - 10 \quad for\ P \leq 70\ mm \qquad equation\ 7.2$$

$$ER = 0.6P_{tot} - 24 \quad for\ P > 70\ mm \qquad equation\ 7.3$$

Where ER is effective rainfall (mm) and P_{tot} is total rainfall (mm)

The irrigation efficiency for different schemes was determined through field data collection and a literature review. Local experts at the zonal and district levels were consulted for field irrigation efficiency measurements. Based on this, irrigation dams in the area were categorized as either good or poor performance. Two dams were selected for conveyance efficiency assessments. The selected areas included: (i) Hawzen: Frelekatit and May-mamuk; (ii) Wukro: Korir and Hezateafras (the latter being non-operational due to gate problem); (iii) Atsbi: Ruba-Felege and Haresaw; and (iv) Agulae/Birki: Grindahao, the only functioning dam in the area. Discharge measurements were taken at the inlets and outlets of primary, secondary, and tertiary canals using a current meter, and the efficiencies of these canals were multiplied to determine the overall conveyance efficiency. The field application efficiency was also assumed to be 60% (table 7-1). The total irrigation efficiency was calculated using equation 7.4.

$$E = \frac{CE \times AE}{100} \qquad equation\ 7.4$$

Where E is Scheme irrigation efficiency, CE is Conveyance Efficiency, AE is Application Efficiency

Table 7-1: Indicative values of the field application efficiency (AE)

Irrigation methods	**Field application efficiency**
Surface irrigation (border, furrow, basin)	60%
Sprinkler irrigation	75%
Drip irrigation	90%

Source: (Brouwer et al., 1989)

Environmental Flow Requirement (EFR)

Environmental Flow Requirement (EFR) is the allocation of water specifically for the environment to maintain ecosystem health in rivers and water bodies. Unlike consumptive uses such as agriculture and industry, EFR is non-consumptive and helps sustain aquatic biodiversity, habitat conservation, and water quality. EFR plays a critical role in water resource management and benefits species, navigation, recreation, and ecosystem functions.

The amount of EFR needed can vary by region and river system. For example, Smakhtin et al. (2004) suggest that 20–30% of mean annual runoff is a good starting point for environmental flows, while Tennant (1976) recommends 25% as a moderate threshold for maintaining basic ecological functions. Dyson et al. (2003) also support a similar range for ecosystem maintenance. In this study, the EFR is set at 25% of mean annual runoff, which is a common threshold used in water management to ensure downstream water quality, support wildlife, and maintain other societal needs (Tennant, 1997). Sustainable water management, including EFR, helps balance human demands with ecosystem preservation, promoting long-term environmental health.

7.2.2.3 Scenario generation/ development

Scenario development is a crucial method for exploring different possible future conditions that may impact a system (Carter et al., 2001). In this study, the WEAP model was designed based on several scenarios, using the year 2017 as the baseline and projecting through the mid-term period of 2050 (2040-2069).

Scenario I: *Baseline Scenario (2017)*

This scenario reflects the water demand for the year 2017, serving as the foundation for all subsequent scenario analyses. The selection of 2017 as the reference year was based on the availability of sectoral water demand projections for domestic use up to that point, along with detailed data on livestock water consumption. It captures the current state of the water system, providing a comprehensive assessment of water consumption across various sectors. In this scenario, water demand is evaluated across key sectors including domestic use, livestock needs, commercial and institutional activities, industrial consumption, and agricultural irrigation. The analysis offers an understanding of the present water demand patterns, establishing a reference point for evaluating future scenarios and water management strategies. This baseline scenario is crucial for identifying inefficiencies, potential vulnerabilities, and opportunities for improvement within the water system.

Scenario II: *No climate change impact, but growth of water demand by all sectors*

This scenario examines future water demand under the assumption that climate change will not directly affect water availability. However, it considers the anticipated growth in water demand across all sectors. Three key factors are integrated into this scenario: population growth, increased water demand from industrial and commercial sectors alongside domestic water demand, and the expansion of irrigated agriculture expansion.

This scenario projects a human population growth rate of 2.52% per year until 2050 (2040–2069). Livestock water demand is expected to grow at an average annual rate of 6.12. Industrial and commercial water demands are calculated alongside increases in domestic water demand (DWD), following the guidelines set by the Ethiopian Ministry of Water Resources (EMWR). Additionally, the area under irrigation is expected to rise from 10% to 30%. This scenario provides a comprehensive view of how demographic and economic factors, rather than climate change, drive future water demand across various sectors.

Scenario III: *Climate change impact and growth in water demand across all sectors*

This scenario builds upon Scenario II by incorporating the effects of climate change on future water availability, alongside the projected growth in water demand across all sectors. In addition to population growth and increased agricultural irrigation, this scenario takes into account potential changes in water resources due to climate change. It specifically uses the latest Shared Socioeconomic Pathways (SSPs) to model how climate conditions may evolve over the mid-term period (2040–2069).

Scenario IV: *Climate change impact, growth in water demand across all sectors, and 90% irrigation efficiency improvement by 90%*

This scenario builds on the previous scenarios by introducing a significant improvement in irrigation efficiency, recognizing that the agricultural sector is the largest consumer of freshwater resources. Globally, agriculture accounts for approximately 70% of freshwater use (Pimentel et al., 2004), making it a critical target for water-saving measures. In this scenario, irrigation efficiency is projected to improve to 90%, focusing on increasing field application efficiency through advanced irrigation technologies like drip irrigation, as described by Brouwer et al. (1989).

By increasing irrigation efficiency to 90%, water losses due to evaporation, runoff, and inefficient distribution are minimized, allowing more effective use of water for crop production. This improvement is crucial, given that agriculture not only consumes a significant portion of water but also faces growing demand due to population increases, food security needs, and expanded irrigated areas.

Additionally, this scenario considers how climate change, coupled with rising water demand across domestic, industrial, commercial, and livestock sectors, affects water availability. It assesses how increased efficiency in irrigation can help offset some of the pressures from both socio-economic growth and environmental changes, ensuring more sustainable water management in the long term.

7.3 Results and Discussion

7. 3.1 Surface water availability (monthly and annual stream flow)

Due to the unavailability of sufficient observed streamflow data for the Geba basin, simulated surface runoff data was utilized to assess the hydrology of the region. Specifically, the HEC-HMS model was employed to simulate runoff for the period 1980 to 2014, and the calibrated outputs were subsequently integrated into the WEAP model for comprehensive water resource analysis. The modeling results indicated that the mean annual surface water availability in the basin is approximately 147 million cubic meters (Mm³) (Table 7-2).

In comparison, Gebreyohannes et al. (2013) conducted a simulation of surface runoff for three sub-watersheds within the Geba Basin using the spatially distributed water balance model, WetSpass**,** for the period 1968 to 2003. Their findings estimated the annual surface runoff to be 44 Mm³ for Suluh, 58 Mm³ for Genfel, and 39 Mm³ for Agulae, resulting in a total runoff of 141 Mm³. These results are comparable to those obtained using HEC-HMS, providing further evidence of the basin's surface water potential.

Table 7-2: Monthly and annual stream flow data of Geba near Mekelle station (1980-2014)

Months	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**	**Annual**
Stream flow (Mm^3)	0	0.1	4.5	8.1	6.6	2.9	56.2	60.2	6.5	0.4	1.3	0.2	146.9

The monthly streamflow distribution (Table 7-2) reveals substantial seasonal variability, with the majority of runoff occurring during the rainy season (July and August), which accounts for over 85% of the annual flow. In contrast, the dry months experience little to no surface runoff. These findings underscore the importance of precise hydrological modeling in data-scarce regions, enabling reliable water resource assessments to support effective planning and management (Nath et al., 2024).

Variations in runoff estimates between models such as HEC-HMS, WetSpass, and others are often attributed to differences in spatial resolution, input data quality, and the underlying assumptions of each model. However, the similarity in total surface water availability estimates across these models highlights the Geba Basin's strong dependence on rainfall. This reliance further underscores the critical need for watershed management practices to control runoff, improve water retention, and promote sustainable water use for irrigation and domestic purposes (Meshesha & Khare, 2019).

7.3.2 Water demand by all sectors

Domestic Water Demand (DWD)

The demand for domestic water supply across the watersheds is centered on both urban and rural populations, as shown in Table 7-3. Total annual water consumption was estimated using population projections based on the 2017 census from the Central Statistical Agency (CSA) and the daily consumption guidelines established by the Ethiopian Ministry of Water Resources (EMWR). According to the calculations, urban areas have an annual water demand of 3.24 million cubic meters (Mm^3), while rural areas, with their significantly larger populations, require a total of 4.14 Mm^3 per year.

Table 7-3: Total urban and rural population and annual water consumption

District/city	Urban	Water use (Mm^3/yr)	Rural	Water use (Mm^3/yr)
Saesi Tsada-Emba-District	31326	0.46	133256	0.97
Ganta Afeshum-District	6023	0.09	94199	0.69
Hawzen-District	12525	0.18	122331	0.89
Kilte Awlalo-District	7961	0.12	105135	0.77
Atsbi Wonberta-District	18447	0.27	112128	0.82
Adigrat	95358	1.39	-	-
Wukro	50080	0.73	-	-
Total	221,720	3.24	567,049	4.14

Sources: CSA (2014); EMWR (2002)

Urban centers such as Adigrat and Wukro account for more than 65% of the total urban water consumption. This high demand is attributed to their larger population sizes and relatively higher per capita water usage compared to smaller towns. Despite lower per capita water use in rural areas, their collective water demand exceeds urban consumption due to the significantly larger rural population. The districts of Saesi Tsada-Emba**,** Hawzen**,** and Atsbi Wonberta exhibit the highest rural water consumption levels, consistent with their population sizes. Smaller rural populations, such as those in Ganta Afeshum**,** contribute proportionally less to the overall rural water demand.

Livestock Water Demand (LWD)

The demand for water by livestock was determined using the livestock population census conducted by the Central Statistical Agency (CSA). The average daily water consumption per animal was sourced from the Food and Agriculture Organization of the United Nations (FAO, 2006) and subsequently converted to an annual basis Based on these calculations, the total annual water consumption for livestock in the study area is estimated to be 9.6 million cubic meters (Mm^3) per year (Table 7-4).

Table 7-4: Livestock population and annual water consumption

Livestock	Population	Actual average (liter/animal/day)	Water use (Mm^3/yr)
Cattle	465,556	25	4.25
Goat	214,265	9.6	0.75
Sheep	678,582	12.9	3.20
Camel	842	41.8	0.01
Chicken (100 heads)	872,948	33.1	0.11
Horses	1046	-	-
Mules	883	16	0.01
Donkey	142,817	16	0.83
		Total	9.59

Sources: CSA (2017); Sileshi et al. (2003)

Table 7-4 provides detailed information on the livestock population, average daily water consumption per animal, and the corresponding total annual water use. Cattle and sheep are the primary contributors to livestock water demand, consuming 4.25 Mm^3 and 3.20 Mm^3 Mm^3 of water per year, respectively. Chickens, goats, camels, donkey, mules, and other livestock collectively account for the remaining water use.

These findings emphasize the significant role of cattle and sheep in total water demand, highlighting their importance in water resource planning for livestock in the study area. This assessment reinforces the need to analyze livestock water consumption as a key component of developing sustainable water management strategies (Cook et al., 2009).

Commercial and industrial water demand

There is no direct data available on commercial and industrial water usage for the study area. However, it can be estimated based on domestic water demand. Using guidelines from the Ethiopian Ministry of Water Resources (EMWR), Adigrat and Wukro are classified as large cities, while other locations are considered small to medium-sized towns. For estimating commercial water demand, consumption in Adigrat and Wukro is set at 10% of the total daily domestic water demand, while for smaller towns, it is 5% (Table 7-5). This leads to an estimated total commercial water usage of approximately 0.3 million cubic meters per year.

For industrial water consumption, large cities are assumed to use 30% of the total water (amounting to 0.64 million cubic meters annually), while small and medium towns are estimated to consume 10%, equivalent to 0.11 million cubic meters per year. Altogether, the industrial water demand is estimated at 0.75 million cubic meters annually.

Table 7-5: Annual water consumption in million cubic meters for commercial and industrial sectors

		Water use (Mm^3/yr)	
	Urban population	Commercial/Institutional	Industrial
Small and Medium towns	76282	0.06	0.11
large cities	145438	0.21	0.64
	Total	0.27	0.75

The analysis highlights that large cities, such as Adigrat and Wukro, dominate both commercial and industrial water consumption due to their higher population and urban activities. Small and medium towns contribute less but still require careful consideration in water resource planning.

In total, the combined commercial and industrial water demand for the study area amounts to 1.02 Mm³ per year**.** This underscores the importance of integrating commercial and industrial needs into comprehensive water resource management strategies to ensure sustainable allocation and use.

Irrigation Water Demand (IWD)

The irrigated area, based on land use and land cover (LULC) changes, was estimated to be 11, 216 hectares. This is closely aligned with a study on irrigation coverage for vegetables between 2020 and 2022, before and after the conflict in the Tigray region that reported 10,958 hectares of lands were irrigated in the Eastern zone of Tigray (Mwambi et al., 2024). The irrigation water demand (IWD) was determined using crop water requirement, irrigated area, and irrigation efficiency (equation 13), with an irrigation efficiency of 44% derived from the calculations shown in the appendix. Table 7-6 presents the monthly and seasonal IWR values, with monthly IWR ranging from approximately 4 to 18 million cubic meters. June has the lowest IWR due to crop senescence, while March had the highest demand. The total calculated seasonal IWR was calculated to be 84.2 million cubic meters.

Table 7-6: Monthly and seasonal irrigation water requirement

Month	*CWR (mm)	*ER (mm)	*Net I (CWR - ER) (mm)	*Ig (mm)	Area (ha)	*V (m3)	*IWR (V, Mm³)
Dec	42.63	11.04	31.59	71.80	11216.85	8053188	8.05
Jan	50.01	7.23	42.78	97.23	11216.85	10905837	10.91
Feb	59.89	0.00	59.89	136.11	11216.85	15267662	15.27
Mar	83.56	0.00	83.56	189.91	11216.85	21301818	21.30
Apr	78.08	34.40	43.68	99.27	11216.85	11135273	11.14
May	64.35	12.70	51.65	117.39	11216.85	13167052	13.17
Jun	17.05	0.00	17.05	38.75	11216.85	4346529	4.35
Seasonal	395.61	65.37	330.19	750.43	11216.85	84174811.4	84.18

*CWR: Crop Water Requirement, ER: Effective Rainfall, NI: Net Irrigation, Ig: Gross Irrigation, V: Volume, IWR: Irrigation Water Requirement

Conveyance efficiency at canal inlets and outlets across various dam sites ranged from 75% to 91% (Appendix 2), with the overall conveyance efficiency estimated at 74%. This indicates significant water loss during transport from the source to the field, due to factors such as leakage, evaporation, and seepage along the canals. Furthermore, with 60% field application efficiency for furrow irrigation (Brouwer et al., 1989), the overall scheme efficiency was calculated to be 44%. This reflects substantial water wastage. To address this, improvements in both conveyance and field application efficiency are necessary, which could involve upgrading canal infrastructure, adopting more efficient irrigation techniques, and implementing better water management practices. Addressing these water losses is critical for boosting water use efficiency, expanding irrigated areas, and improving crop production (Kang'au et al., 2011; Luyun Jr et al., 2021).

7.3.3 Modeling of water demand in current scenario

The current model scenario was developed using 2017 demand data and simulated streamflow data, showing a total water supply of 146.9 million cubic meters (Mm^3) at the Geba outlet near Mekelle. The basin supports five primary types of water consumers: domestic, agricultural, livestock, industrial, and commercial, with an additional 25% allocated for environmental flows, as outlined in Table 7-7. Of these, agriculture is the dominant consumer, utilizing 84.20 Mm^3 annually, which represents 60.61% of the total water usage. Domestic consumption amounts to 7.38 Mm^3, making up 5.31%, while livestock accounts for 9.59 Mm^3 (6.90%). The industrial and commercial sectors exhibit relatively low levels of water use, with industry consuming 0.75 Mm^3 (0.54%) and commercial activities accounting for 0.27 Mm^3 (0.19%). Environmental flow requirements are significant, totaling 36.73 Mm^3 and contributing 25% to the overall water demand. In total, the annual water consumption across all sectors is 138.92 Mm^3, highlighting the importance of efficient water allocation and management to meet the diverse needs of the basin's users while ensuring sustainable resource utilization.

Table 7-7: Water consumption by various sectors in the current account

Sectors	Consumption by sector Mm^3/yr	Percent share
Domestic	7.38	5.31
Agriculture	84.20	60.61
Livestock	9.59	6.90
Industry	0.75	0.54
Commercial	0.27	0.19
Environmental Flow Requirement	36.73	25.00
Total consumption	**138.92**	

7.3.4 Scenario analysis and water demand allocation

Modeling of water demand in reference scenario

The Reference Scenario (2018–2069) projects future water demands under the assumption of no new policy interventions, focusing solely on population growth for humans and livestock. Human population growth is estimated at a rate of 2.52% per year, while the livestock population is expected to grow at a higher rate of 6.12%. Agricultural water demand is assumed to remain constant throughout the study period. Table 7-8 summarizes the projected water consumption across various sectors.

Table 7-8: Projected water consumption with population growth (Mm^3)

Sector	2017	2025	2035	2045	2055 (2040-2069)	2055 Unmet demand
Agriculture	84.20	84.20	84.20	84.20	84.20	
Commercial	0.27	0.34	0.44	0.56	0.72	
Domestic	7.38	12.31	15.79	20.25	25.97	
Industry	0.75	0.94	1.21	1.55	1.99	
Livestock	9.59	19.59	35.48	64.27	116.40	
Environmental flow	36.73	36.73	36.73	36.73	36.73	
Total	138.92	154.11	173.85	207.56	266.01	
Available surface water	146.90					**-119.11 (81.1%)**

According to the analysis, water demand is expected to increase significantly due to population growth. By 2055, total water demand will rise to 266.01 million cubic meters (Mm^3), representing an 81% increase from the baseline year of 2017 (138.92 Mm^3). The largest growth is seen in livestock water demand, which is projected to increase from 9.59 Mm^3 in 2017 to 116.40 Mm^3 by 2055. Domestic water demand also shows a substantial rise, from 7.38 Mm^3 in 2017 to 25.97 Mm^3 by 2055.

Meanwhile, industrial and commercial water demands are expected to grow steadily, reaching 1.99 Mm^3 and 0.72 Mm^3, respectively, by 2055. Environmental flow requirements remain constant at 36.73 Mm^3 throughout the period, while agricultural water demand is maintained at 84.20 Mm^3 annually.

Despite the projected increases in demand, available surface water remains constant at 146.9 Mm^3. By 2055, unmet water demand is estimated to reach approximately 119.11 Mm^3, accounting for 81.1% of the projected total demand. This highlights the severe stress on water resources anticipated under this scenario, emphasizing the need for proactive water management strategies. Without interventions such as improved water-use efficiency, technological innovations, or policy changes, balancing the growing demands across sectors will become increasingly challenging. These findings provide a baseline for evaluating alternative scenarios and identifying sustainable solutions to address the anticipated water scarcity.

Modelling water demand in reference scenario and expansion of irrigated area

In this scenario, the modelling of water demand incorporates the expansion of irrigated areas alongside population growth. The analysis reveals a substantial rise in annual water consumption across all sectors. By mid-century, water usage is projected to exceed available surface water by 86.6%, 92.5%, and 98.3% under scenarios of irrigated area expansion by 10%, 20%, and 30%, respectively. This demonstrates the strong correlation between irrigation expansion and increased water demand, as shown in Table 7-9.

With a 10% expansion of irrigated areas, agricultural water demand grows to 92.62 million cubic meters (Mm^3) by 2055, compared to 84.20 Mm^3 in 2017. Total water consumption rises from 138.92 Mm^3 in 2017 to 274.44 Mm^3 by 2055, resulting in an unmet demand of 127.54 Mm^3, or 86.6% above the available surface water supply of 146.90 Mm^3. When irrigated areas expand by

20%, agricultural water demand reaches 101.04 Mm³ by 2055. Total water demand rises to 282.86 Mm³, leading to an unmet demand of 135.96 Mm³, or 92.5% above the available water supply. Under the 30% irrigation expansion scenario, agricultural water demand increases to 109.46 Mm³ by 2055. Total water demand reaches 291.28 Mm³, resulting in an unmet demand of 144.38 Mm³, or 98.3% above the available water supply.

Table 7-9: Projected water demand with population growth and irrigation expansion in different years

	2017	**2025**	**2035**	**2045**	**2055**	2055 Unmet demand
Agriculture (Expansion by 10%)	84.20	92.62	92.62	92.62	92.62	
Commercial	0.27	0.34	0.44	0.56	0.72	
Domestic Water Demand	7.38	12.31	15.79	20.25	25.97	
Industry	0.75	0.94	1.21	1.55	1.99	
Livestock	9.59	19.59	35.48	64.27	116.40	
Environmental flow	36.73	36.73	36.73	36.73	36.73	
Total	**138.92**	**162.54**	**182.27**	**215.98**	**274.44**	
Available surface water	146.90					**-127.5 (86.6%)**
	2017	2025	2035	2045	**2055**	
Agriculture (Expansion by 20%)	84.20	101.04	101.04	101.04	101.04	
Commercial	0.27	0.34	0.44	0.56	0.72	
Domestic Water Demand	7.38	12.31	15.79	20.25	25.97	
Industry	0.75	0.94	1.21	1.55	1.99	
Livestock	9.59	19.59	35.48	64.27	116.40	
Environmental flow	36.73	36.73	36.73	36.73	36.73	
Total	**138.92**	**170.96**	**190.69**	**224.40**	**282.86**	
Available surface water	146.90					**-135.9 (92.5%)**
	2017	2025	2035	2045	2055	
Agriculture (Expansion by 30%)	84.20	109.46	109.46	109.46	109.46	
Commercial	0.27	0.34	0.44	0.56	0.72	
Domestic Water Demand	7.38	12.31	15.79	20.25	25.97	
Industry	0.75	0.94	1.21	1.55	1.99	
Livestock	9.59	19.59	35.48	64.27	116.40	
Environmental flow	36.73	36.73	36.73	36.73	36.73	
Total	**138.92**	**179.38**	**199.11**	**232.82**	**291.28**	
Available surface water	146.90					**-144.4 (98.3%)**

This analysis underscores the potential pressure on water resources as both population growth and irrigation expansion drive water demand to unsustainable levels. Without proactive water management strategies, technological innovations, and efficiency improvements, the increased competition for water across sectors will pose significant challenges.

These findings emphasize the urgent need for adaptive water resource management practices, including optimizing irrigation systems, adopting water-saving technologies, and prioritizing equitable water allocation, to ensure sustainable water use while supporting agricultural productivity and economic growth.

Modelling water demand under future climate change scenarios

Surface water availability in the Geba basin is anticipated to decrease in mid-term climate change scenarios due to reduced stream flows. Projections indicate a 12% reduction in stream flow under SSP2-4.5 and a 5% reduction under SSP5-8.5, leading to declines in surface water availability to approximately 130 million cubic meters (Mm^3) and 140.3 Mm^3, respectively, compared to the baseline of 147 Mm^3. These reductions are expected to intensify water scarcity, particularly when combined with irrigation expansion and rising demand across various sectors. Table 7-10 outlines projections of unmet water demand under climate change scenarios with varying levels of irrigation expansion.

Without any expansion of irrigation, unmet water demand is expected to rise significantly by 2055, reaching 136.01 Mm^3 (104.6%) under SSP2-4.5 and 125.71 Mm^3 (89.6%) under SSP5-8.5. These figures indicate that even without increasing irrigated areas, the strain on water resources will be substantial.

If irrigated areas are expanded by 10%, unmet water demand increases further. Under SSP2-4.5, it is projected to reach 144.43 Mm^3 (111.1%), while under SSP5-8.5, it will rise to 134.13 Mm^3 (95.6%). This highlights the additional stress that even moderate irrigation expansion places on water resources. A 20% expansion in irrigation leads to even higher unmet demand levels. Projections suggest an increase to 152.85 Mm^3 (117.6%) under SSP2-4.5 and 142.55 Mm^3 (101.6%) under SSP5-8.5. This demonstrates how increasing irrigation further exacerbates water scarcity, especially in scenarios with more significant climate-induced reductions in water availability. The highest unmet demand occurs with a 30% expansion in irrigated areas, which pushes demand to 161.27 Mm³ (124.1%) under SSP2-4.5 and 150.97 Mm³ (107.6%) under SSP5-8.5. These figures underscore the severe pressure that expanded irrigation will place on already limited water supplies under future climate scenarios.

Table 7-10: Water demand under climate change scenarios

Irrigation expansion	Scenarios		Unmet demand (Mm3)/ % change	
			2017	Mid-term (2055)
			138.92	266.01
without expansion	Available surface water	146.9	7.98 (5.4%)	-119.01 (81.1%)
	SSP2-4.5_MT	130		-136.01(104.6%)
	SSP5-8.5_MT	140.3		-125.71(89.6%)
			138.92	274.43
10%	Available surface water	146.9	7.98 (5.4%)	-127.53(86.1%)
	SSP2-4.5_MT	130		-144.43(111.1%)
	SSP5-8.5_MT	140.3		-134.13(95.6%)
			138.92	282.85
20%	Available surface water	146.9	7.98 (5.4%)	-135.95(92.6%)
	SSP2-4.5_MT	130		-152.85(117.6%)
	SSP5-8.5_MT	140.3		-142.55(101.6%)
			138.92	291.27
30%	Available surface water	146.9	7.98 (5.4%)	-144.37(98.3%)
	SSP2-4.5_MT	130		-161.27(124.1%)
	SSP5-8.5_MT	140.3		-150.97(107.6%)

The combined effects of climate change and irrigation expansion will intensify competition for water resources, placing further strain on the already limited supply in the region. Without timely and proactive measures, unmet water demand is likely to more than double, emphasizing the urgent need for sustainable water management strategies to address these interconnected challenges.

Modelling water demand with improved irrigation efficiency

In this scenario, water consumption was modelled by assuming an increase in irrigation efficiency to 90% (Table 7-11). This improvement led to a substantial reduction in irrigation water use, decreasing consumption by over 100%, from 84.2 million cubic meters (Mm³) to 41.2 Mm³.

Despite this halving of irrigation water demand, overall water demand across all sectors rose by nearly 52% in the baseline scenario (available surface water supply), and averaged 65.3% under two scenarios without irrigation expansion. When considering a 30% irrigation expansion during the mid-term period, this increase climbed further, reaching nearly 69% and averaging 84%.

These figures highlight that while improvements in irrigation efficiency significantly reduce agricultural water use, rising demand in other sectors may counterbalance these savings. Agriculture plays a significant role in overall water consumption, but the increasing water demands from industrial and domestic sectors will continue to be challenges.

Table 7-11: Water consumption by sectors with improved irrigation efficiency

Irrigation expansion	Scenarios		Unmet demand (Mm3)/ % change	
			2017	2055
			138.92	223.02
without expansion	Available surface water	146.9	7.98 (5.4%)	-76.12 (51.8%)
	SSP2-4.5_MT	130		-93.02 (71.6%)
	SSP5-8.5_MT	140.3		-82.72 (58.9%)
			138.92	231.43
10%	Available surface water	146.9	7.98 (5.4%)	-84.53 (57.5%)
	SSP2-4.5_MT	130		-101.43 (78.0%)
	SSP5-8.5_MT	140.3		-91.13 (65.0%)
			138.92	239.85
20%	Available surface water	146.9	7.98 (5.4%)	-92.95 (63.3%)
	SSP2-4.5_MT	130		-109.85 (84.5%)
	SSP5-8.5_MT	140.3		-99.55 (71.0%)
			138.92	248.27
30%	Available surface water	146.9	7.98 (5.4%)	-101.37 (69.0%)
	SSP2-4.5_MT	130		-118.27 (91.0%)
	SSP5-8.5_MT	140.3		-107.97 (77.0%)

Additionally, this trend emphasizes that water conservation in one sector can be outweighed by growing pressures from others, and addressing future water scarcity will require a holistic approach that accounts for sectoral trade-offs, environmental sustainability, and economic development. An integrated water resource management (IWRM) approach that takes into account cross-sectoral interactions into account will be crucial in mitigating these challenges and ensuring equitable water distribution (Julio et al., 2021). In addition to constructing surface water harvesting systems, tapping into groundwater resources becomes increasingly crucial to meet the growing water demands across various sectors, and under different future climate change scenarios. Overall, efficient use of both surface and ground water sources will be vital for maintaining water security and supporting long-term development.

7.4 Conclusion and Recommendations

The study highlights both the current and projected water demand in the study area, focusing on various sectors including domestic, agricultural, livestock, industrial, and commercial water usage. Surface water availability is estimated at approximately 147 million cubic meters annually, with agricultural demands representing the largest share of water consumption, followed by domestic and livestock needs. Model simulations, which take into account future scenarios such as population growth, irrigation expansion, and climate change, indicate significant increases in water demand across all sectors. Specifically, the expansion of irrigated areas and climate change projections are expected to lead to a rise in unmet water demand, with some scenarios suggesting a potential doubling of water requirements. While improvements in irrigation efficiency can reduce agricultural water consumption, increasing demands from other sectors exacerbate overall water scarcity. This underscores the importance of Integrated Water Resource Management (IWRM) and the need for strategic water conservation, particularly through both surface and groundwater sources.

To tackle the challenges arising from the anticipated increase in water demand in the study area, the following recommendations are suggested:

- Given the projected increase in water demand, it is essential to implement Integrated Water Resource Management (IWRM) strategies that account for the interconnections between various sectors. This includes optimizing water use in agriculture, improving irrigation techniques, and effectively managing domestic, industrial, and livestock demands.
- While improvements in irrigation efficiency can significantly reduce water consumption, it is crucial to balance agricultural water savings with the rising demands from other sectors. Expanding the adoption of advanced irrigation technologies, such as drip and

sprinkler systems, will help mitigate water wastage and enhance overall water use efficiency.

- Upgrading canal infrastructure and improving conveyance efficiencies will reduce water losses during transport. Additionally, investments in better water storage and distribution systems will enhance water availability for all sectors, especially during dry periods.
- With the potential decline in surface water availability due to climate change, tapping into groundwater resources and implementing surface water harvesting systems are crucial for meeting future water demands. However, groundwater use must be managed sustainably to prevent depletion.

References

Abera, D., & Ayenew, T. (2021). Evaluation of the WEAP model in simulating subbasin hydrology in the Central Rift Valley basin, Ethiopia. *Ecological processes*, *10*(1), 41.

Adgolign, T. B., Rao, G. S., & Abbulu, Y. (2016). WEAP modeling of surface water resources allocation in Didessa Sub-Basin, West Ethiopia. *Sustainable Water Resources Management*, *2*, 55-70.

Admasu, A., Kiros, M., & Memhur, A. (2011). Baseline survey report of Tigray Region on WASH. *Tigray, Ethiopia*.

Alemu, Z. A., & Dioha, M. O. (2020). Modelling scenarios for sustainable water supply and demand in Addis Ababa city, Ethiopia. *Environmental Systems Research*, *9*, 1-14.

Ali, M., Saadon, A., Abd Rahman, N., & Khalid, K. (2014). An assessment of water demand in malaysia using water evaluation and planning system. InCIEC 2013: Proceedings of the International Civil and Infrastructure Engineering Conference 2013,

Bachewe, F. N., Minten, B., Tadesse, F., & Taffesse, A. S. (2018). *The evolving livestock sector in Ethiopia: Growth by heads, not by productivity* (Vol. 122). Intl Food Policy Res Inst.

Berhe, A. G., Mesfin, H. S., Abraha, A., Abraha, G. G., Misgna, S. H., & Gebremicael, T. G. (2018). The impact of climate change on irrigation water requirement of Maize and Onion: the case of Gum-Selasa small-scale irrigation scheme, Tigray, Ethiopia.

Brouwer, C., Prins, K., & Heibloem, M. (1989). Irrigation water management: irrigation scheduling. *Training manual*, *4*, 66.

Carter, T. R., La Rovere, E. L., Jones, R., Leemans, R., Mearns, L., Nakicenovic, N., Pittock, A., Semenov, S., Skea, J., & Gromov, S. (2001). Developing and applying scenarios. *Climate change*, *200*, 145-190.

Cook, S. E., Andersson, M. S., & Fisher, M. J. (2009). Assessing the importance of livestock water use in basins. *The Rangeland Journal*, *31*(2), 195-205.

CSA. (2014). *Federal Democratic Republic of Ethiopia central statistical agency population projection of Ethiopia for all regions at Wereda level from 2014–2017* (Addis Ababa: Central Statistical Agency, Issue.

CSA. (2017). *Agricultural Sample Survey 2014/2015 (2008 EC). Report on Are a and Production of Crops (Private Peasant Holdings, Mehere Season). Centra l Statistical agency, Ethiopia, Addis Ababa*.

Dyson, M., Bergkamp, G., & Scanlon, J. (2003). Flow: the essentials of environmental flows. *IUCN, Gland, Switzerland and Cambridge, UK*, 20-87.

FAO. (2006). *FAOLivestock's Long. ShadowEnvironmental issues and options* (FAO: Rome, Italy, Issue.

Gebreyohannes, T., De Smedt, F., Walraevens, K., Gebresilassie, S., Hussien, A., Hagos, M., Amare, K., Deckers, J., & Gebrehiwot, K. (2013). Application of a spatially distributed water balance model for assessing surface water and groundwater resources in the Geba basin, Tigray, Ethiopia. *Journal of Hydrology*, *499*, 110-123.

Goshime, D. W., Haile, A. T., Rientjes, T., Absi, R., Ledésert, B., & Siegfried, T. (2021). Implications of water abstraction on the interconnected Central Rift Valley Lakes sub-basin of Ethiopia using WEAP. *Journal of Hydrology: Regional Studies*, *38*, 100969.

Hadri, A., Saidi, M. E. M., El Khalki, E. M., Aachrine, B., Saouabe, T., & Elmaki, A. A. (2022). Integrated water management under climate change through the application of the WEAP

model in a Mediterranean arid region. *Journal of Water and Climate Change*, *13*(6), 2414-2442.
Hum, N. N. M. F., & Talib, S. A. (2016). Modeling water supply and demand for effective water management allocation in Selangor. *Jurnal Teknologi*, *78*(5-5).
Husain, S. A., & Rhyme, N. H. M. (2021). Decision Support Method for Agricultural Irrigation Scenarios Performance Using WEAP Model. *Theoretical, Modelling and Numerical Simulations Toward Industry 4.0*, 99-106.
Julio, N., Figueroa, R., & Ponce Oliva, R. D. (2021). Water resources and governance approaches: Insights for achieving water security. *Water*, *13*(21), 3063.
Kahil, T., Dinar, A., & Albiac, J. (2015). Water management and cooperation under climate change. Global Water Forum,
Kahsay, K. D., Pingale, S. M., & Hatiye, S. D. (2018). Impact of climate change on groundwater recharge and base flow in the sub-catchment of Tekeze basin, Ethiopia. *Groundwater for Sustainable Development*, *6*, 121-133.
Kang'au, S. N., Home, P., & Gathenya, J. (2011). Farm water use efficiency assessment for smallholder pumped irrigation systems in the arid and semi-arid areas of Kenya. *Agricultural Engineering International: CIGR Journal*, *13*(4).
Kemal, B., & Adeba, D. (2021). Surface water potential assessment and water demand evaluation (A case of dabus watershed, blue Nile basin). *Computational Water, Energy, and Environmental Engineering*, *10*(4), 155-168.
Laelago, D., Tekleab, S., & Dananto, M. (2020). Modeling long-term water allocation and analysis of alternative strategic scenarios in the catchment area of Bilate River, Rift Valley Lakes Basin, Ethiopia. *Ethiopian Journal of Water Science and Technology*, *3*, 73-93.
Lee, H., Calvin, K., Dasgupta, D., Krinner, G., Mukherji, A., Thorne, P., Trisos, C., Romero, J., Aldunce, P., & Barrett, K. (2023). *Climate change 2023: synthesis report. Contribution of working groups I, II and III to the sixth assessment report of the intergovernmental panel on climate change*. The Australian National University.
Luyun Jr, R., Galoso, J. R., Reyes, R. D., & Duka, M. (2021). Assessment of the Water Use Efficiencies of Selected Laterals and Paddy Fields at the Upper Pampanga River Integrated Irrigation System (UPRIIS), Philippines. *Philippine Journal of Agricultural and Biosystems Engineering*, *17*(2).
Meles, K., Maria, A., Tesfamichael, N., Sunil, S., Francis, K., & Lynne, M. (1997). Coping with low and erratic rainfall in the Eastern zone of Tigray.
Mendelsohn, R. (2016). Adaptation, climate change, agriculture, and water. *Choices*, *31*(3), 1-7.
Meshesha, T. W., & Khare, D. (2019). Towards integrated water resources management considering hydro-climatological scenarios: an option for sustainable development. *Environmental Systems Research*, *8*, 1-12.
Molle, F., Vallée, D., Brugère, C., Facon, T., Margat, J., Salamé, L., Le-Huu, T., Trondalen, J. M., & Faurès, J.-M. (2012). Managing competition for water and the pressure on ecosystems. In *The United Nations World Water Development Report 3* (pp. 150-159). Routledge.
Mwambi, M., Hruy, G., Boset, A. M., Singh, R., Schmitter, P., & Legesse, W. B. (2024). A rapid assessment of vegetable and irrigation systems in Tigray, Ethiopia, before and after the 2020-2022 conflict.

Nath, N. K., Das, P., Mishra, L. R., Kumar, A., Suryawanshi, S. L., & Gautam, V. K. (2024). Hydrological Modeling and Simulation for Water Resource Assessment. In *Integrated Management of Water Resources in India: A Computational Approach: Optimizing for Sustainability and Planning* (pp. 43-58). Springer.

Pimentel, D., Berger, B., Filiberto, D., Newton, M., Wolfe, B., Karabinakis, E., Clark, S., Poon, E., Abbett, E., & Nandagopal, S. (2004). Water resources: agricultural and environmental issues. *BioScience*, *54*(10), 909-918.

Schlosser, C. A., Strzepek, K., Gao, X., Fant, C., Blanc, É., Paltsev, S., Jacoby, H., Reilly, J., & Gueneau, A. (2014). The future of global water stress: An integrated assessment. *Earth's Future*, *2*(8), 341-361.

SEI. (2023). *WEAP (Water Evaluation and Planning system): a tool for sustainable water analysis. Stockholm environment Institute.*

Shiferaw, H. M., Gebremedhin, A., Gebretsadkan, T., & Zenebe, A. (2018). Modelling hydrological response under climate change scenarios using SWAT model: the case of Ilala watershed, Northern Ethiopia. *Modeling Earth Systems and Environment*, *4*, 437-449.

Sileshi, Z., Tegegne, A., & Tsadik, G. T. (2003). Water resources for livestock in Ethiopia: Implications for research and development. *Integrated water and land management research and capacity building priorities for Ethiopia*, *66*.

Smakhtin, V., Revenga, C., & Döll, P. (2004). A pilot global assessment of environmental water requirements and scarcity. *Water international*, *29*(3), 307-317.

Takele, G. S., Gebrie, G. S., Gebremariam, A. G., & Engida, A. N. (2022). Future climate change and impacts on water resources in the Upper Blue Nile basin. *Journal of Water and Climate Change*, *13*(2), 908-925.

Teklu, S., Soliman, A. H., & El-Zawahry, A. (2020). Testing the WEAP hydrologic model for awash basin, ethiopia "soil moisture module with watershed demand approach". *Civil Environ. Res*, *12*, 59-74.

Tennant, D. L. (1976). Instream flow regimens for fish, wildlife, recreation and related environmental resources. *Fisheries*, *1*(4), 6-10.

Tesfaye, S., Raj, A. J., & Geberesamuel, G. (2014). Assessment of climate change impact on the hydrology of Geba Catchment, Northern Ethiopia. *American Journal of Environmental Engineering*, *4*(2), 25-31.

Tesfaye, S., Taye, G., Birhane, E., & van der Zee, S. E. (2019). Observed and model simulated twenty-first century hydro-climatic change of Northern Ethiopia. *Journal of Hydrology: Regional Studies*, *22*, 100595.

Wane, S., & Nagdeve, M. (2014). Estimation of evapotranspiration and effective rainfall using CROPWAT.

CHAPTER EIGHT

8. SYNTHESIS

8.1 Introduction

Climate change and variability pose significant challenges to the management of water resources and the sustainability of agricultural productivity, particularly in arid and semi-arid regions such as Eastern Tigray in Northern Ethiopia. This region relies heavily on rainfall for its agricultural activities; however, rising temperatures, erratic rainfall patterns, and prolonged droughts have substantially disrupted water availability and crop production cycles. These disruptions threaten food security and the livelihoods of communities that depend on subsistence farming and rainfed agriculture.

Despite its considerable irrigation potential, the study area faces severe constraints arising from limited surface water resources and the escalating impacts of climate change. Future climate scenarios predict alterations in precipitation patterns, temperature increases, and heightened evapotranspiration rates, which further jeopardize water availability and crop productivity. Addressing these challenges necessitates an integrated approach to assess current and future water demands, crop water requirements, and resource availability to inform sustainable water management strategies.

This research aims to evaluate the impacts of climate change and variability on the availability of water resources, the dynamics of crop growing seasons, and crop water requirements, and crop water requirements in Eastern Tigray, Northern Ethiopia. The study also aims to contribute to sustainable water resource management strategies that enhance resilience to climate-related challenges. The results presented in Chapters 3 to 7 effectively address these research objectives. Specifically, Chapters 3 and 4 focus on analyzing trends and variability of key climate parameters (temperature and precipitation) and crop growing season characteristics using 30 year of historical data from 1980 to 2009, as well as future climate change scenarios for the mid (2040-2069) and end terms (2070-2099), by using Representative Concentration Pathways (RCPs) 4.5 and 8.5 from CMIP5. Through this examination of trends, variability, and anticipated future changes, these chapters significantly enhance the understanding of the uncertainties surrounding rainfall patterns, temperature fluctuations, and crop growing season characteristics, thereby promoting knowledge-based agricultural management.

The study area demonstrates considerable potential for irrigation; however, the future of crop production remains uncertain and challenging due to existing scarce water resources and ongoing climate change. Chapter 5 focuses on accurately assessing the spatio-temporal variability of crop water requirements under climate change scenarios, utilizing latest approach and data from CMIP6. Chapter 6 further investigates the surface water potential of the study area, aiming to provide insights into how climate variability and change will impact surface water resources in the future. By understanding water availability in the study area, water supply and demand potential were examined.

Moreover, Chapter 7 presents the analysis of the various water use scenarios under future climate conditions in the study area using the Water Evaluation and Planning System (WEAP), a widely used tool for water allocation and management. By analyzing the balance between water supply and demand, this research seeks to offer actionable recommendations for the sustainable management of water resources in the study area. The insights derived from this analysis will aid in developing adaptive strategies to ensure the long-term availability of water for both agricultural and non-agricultural purposes in the face of climate change.

Lastly, Chapter 8 presents the synthesis of the main research results of the different Chapters from 3 to 7. Accordingly, Section 8.2 provides a summary of the main findings while Section 8.3 outlines adaptation strategies and policy implications, and Sections 8.4, 8.5, and 8.6 address the limitations of the current study, issues for further research, and concluding remarks, respectively.

The research employs a comprehensive methodological framework integrating climate modelling, hydrological simulation, and water resource analysis to ensure robust and reliable results. Climate model datasets from the Climate Modelling Intercomparison Projects (CMIPs) enable accurate assessment of historical trends and future projections. The HEC-HMS model, calibrated with simulated surface runoff data, provides a credible analysis of surface water availability in selected watersheds. Additionally, the WEAP model simulates water supply and demand scenarios under varying climate and socio-economic conditions, offering a dynamic perspective on water resource management. Its strength lies in evaluating alternative strategies by incorporating climatic, hydrological, and socio-economic variables.

The methodological robustness is enhanced through the triangulation of data sources, the calibration and validation of models, and the application of scenario-based analyses. These approaches ensure that uncertainties are minimized, and the results are scientifically sound, providing a strong foundation for the formulation of adaptive strategies and policy recommendations.

8.2 Summary of main findings

8.2.1 Trends of temperature, rainfall, and crop growing season characteristics

Assessing long-term trends in temperature, rainfall, and crop-growing seasons is key to understanding climate uncertainties and managing agriculture, irrigation, and water resources in the region. In Eastern Tigray, rainfall trends increased in monthly, annual, and *Kiremt* (main rainy season), while *Belg* (short rainy season) rainfall generally declined. However, most stations showed no significant long-term changes, indicating variability without a clear trend. In contrast, temperature trends were clearer, with maximum and minimum temperatures rising significantly on annual and *Belg* time scales, though *Kiremt* season temperatures showed no significant trend. Homogeneity tests confirmed these results, with Tmax increasing and Tmin decreasing during *Kiremt*.

Change point detection analysis found consistent rainfall patterns across stations but showed varying change points for temperature between 1984 and 2000. This variability is likely due to population growth, urbanization, and frequent droughts, influencing warming trends.

There was high variability in Kiremt season rainfall (21–31%) and in the duration of dry spells (25–43%) during the observed period. The length of the growing period (LGP) ranged from 68 to 90 days, indicating a limited time frame for crops to mature.

The analysis of crop-growing seasons revealed significant inter-annual variability during the *kiremt* season, a short length of growing period (LGP), and a high risk of soil moisture deficits during the peak rainfall season due to extended dry spells. These results highlight the necessity for adaptive strategies in the study area. Rising temperatures and decreasing *Belg* rainfall present challenges to traditional farming practices, underscoring the need for sustainable water and crop management to mitigate these climate impacts.

8.2.2 Projected changes of key climate parameters and crop growing season characteristics

The impacts of climate change are becoming increasingly evident across various sectors worldwide. Therefore, it is essential to evaluate its effects on key climate variables such as temperature, rainfall, and evapotranspiration, along with the characteristics of the crop growing season. This assessment is crucial for supporting small-scale farmers who rely on rainfed agriculture. By quantifying these effects, farmers can make more informed decisions regarding crop variety selection, as well as effectively plan their planting and harvesting schedules and management strategies.

The results indicate a general increase in annual and summer (*Kiremt*) rainfall in most monitoring stations. However, the *Belg* rainfall season has exhibited a declining trend, with some positive changes noted under RCP4.5 during the mid-term period. In contrast, both maximum and minimum temperatures are expected to continue rising, correlating with a consistent increase in reference evapotranspiration across all stations.

Additionally, the analysis reveals a significant reduction in the length of the growing period (LGP), which is anticipated to shorten in the future. The LGP is projected to shorten by 5.5% to 19% from the mid to the end of the century. This decline is particularly expected under RCP8.5, due to both a delayed onset and an earlier cessation of the rainy season. These changes are driven by high variability in precipitation patterns and potential evapotranspiration. As a result, farmers will need to be more selective in choosing early-maturing and drought-tolerant crop varieties, as those requiring an LGP greater than 90 days may become unviable in future climate scenarios without appropriate adaptation strategies.

8.2.3 Spatio-temporal crop water requirement under present and climate change scenarios

Accurate insights into the spatial and temporal changes in crop water requirements under climate change scenarios are essential for assessing crop water productivity. This study examines how climate change and variability impact crop water requirements in the study area. For climate change assessment, we used data from the latest Coupled Model Intercomparison Project-Phase 6 (CMIP6) under two representative concentration pathways (SSP2-4.5 and SSP5-8.5), covering a baseline period from 1980–2014 and future periods from 2040–2069 and 2070–2099.

Results indicate that precipitation will likely increase in most stations across scenarios, signalling a shift toward wetter conditions and high variability. However, rising temperatures are expected to amplify the climate-driven changes in evapotranspiration and crop water needs, with reference evapotranspiration projected to increase in mid- and end-century periods under all SSP scenarios, leading to higher monthly crop water requirements.

These findings highlight the need to grasp the complex effects of climate change on rainfall, temperature, and evapotranspiration. Proactive adaptation and continued research are essential for managing variable precipitation patterns and preparing for growing water demands. Addressing local temperature shifts is critical to mitigate heat stress and ecosystem impacts. Tailored adaptation strategies will enable stakeholders to enhance water management and agricultural resilience amid climate uncertainty, supporting effective preparedness and mitigation efforts.

8.2.4 Future surface runoff under climate change scenarios

This study evaluates the anticipated effects of climate change on water resources, focusing specifically on surface runoff in selected watersheds of the eastern Tigray region of northern Ethiopia. Utilizing the HEC-HMS hydrological model alongside CMIP6 climate projections, the research reveals substantial changes in runoff patterns across different climate scenarios and time frames. Under the SSP2-4.5 scenario, surface runoff is projected to decrease during most months in both the mid-term (2040-2069) and end-term (2070-2099) periods, with reductions ranging from 0.56% to as high as 25.8%. However, increases are expected in select months, particularly in February, March, July, and August. In contrast, under the extreme SSP5-8.5 scenario, surface runoff is generally expected to decline during the mid-term but rises during most months in the end-term, suggesting significant seasonal variability.

These projected changes in runoff have critical implications for water resource management in the region. Under the SSP2-4.5 scenario, the reduction in runoff could lead to water shortages, affecting key sectors such as agriculture, drinking water supply, and industrial usage. Additionally, the decrease in surface water availability could strain aquatic ecosystems and diminish the potential for hydropower generation, thereby risking energy shortages. On the other hand, the increased runoff anticipated in the end-term of the SSP5-8.5 scenario could elevate flood risks, making enhanced flood management strategies essential. This would necessitate investments in resilient infrastructure and the development of effective early warning systems to minimize potential damages.

Given the variability in runoff projections across different climate scenarios, this study underscores the necessity of flexible and adaptive water management approaches. To address both droughts and floods, it is crucial to prioritize sustainable water storage solutions, promote conservation practices, and establish policies that are robust to climate uncertainties. Moreover, the study highlights the importance of collaborative efforts across local, regional, and national levels to ensure water resources are distributed equitably and used efficiently, particularly in the context of increasing climate risks. This integrated approach is essential to build resilience against future climate impacts on water resources.

8.2.5 Investigating water supply and demand dynamics

This study evaluated the impacts of various water demand scenarios and surface water resources within the study area using the Stockholm Environment Institute's Water Evaluation and Planning (WEAP) system. WEAP models both supply and demand across key sectors: domestic, livestock, industrial, commercial, and agricultural irrigation. Using 2017 as a baseline, the scenario-based analysis projects trends through 2050 (2040-2069), examining several possible future scenarios:

Baseline Scenario: Assumed the current water demand across sectors, identifying agriculture as the largest consumer (61%). It projects an 81% increase in total water demand across all sectors by 2055, emphasizing inefficiencies in water usage.

Scenario II: Assumed no climate change but account for projected increase water demand resulting from a 10%, 20%, and 30% expansion of irrigated land, in addition to the baseline scenario's projected demand. As a result, total water demand increases by 86.6%, 92.5%, and 98.3%, respectively, by 2055.

Scenario III: Considering climate change, this scenario anticipates a reduction in surface water availability of up to 12% and a more than double of unmet water demand by 2055.

Scenario IV: With improved irrigation efficiency, agricultural water demand reduced, but demands from other sectors rise and still contribute to an overall increase, emphasizing the need for integrated water management.

Overall, water demand is expected to rise sharply, driven by future population growth, economic development, and expansion irrigation. Climate change further intensifies water scarcity. While improved irrigation efficiency can reduce agricultural water use, added pressures from other sectors it limit its overall effect, underscoring the necessity of a comprehensive water management strategy. Addressing water scarcity in the area will require an integrated water resource management (IWRM) approach that balances agricultural water conservation with the needs of multiple sectors, considering the increasing demands over time. Future strategies should prioritize improving irrigation efficiency, expanding surface water storage and harvesting systems, and sustainable tapping mechanism of groundwater resources to ensure long-term water security and ecosystem preservation.

8.3 Adaptation strategies and policy implications

According to the IPCC (2007), adaptation to climate change is defined as adjustments to prepare for expected climate variability and change to moderate the harmful effect and exploit its beneficial opportunities. Based on this concept, possible adaptation strategies related to the risks associated with crop and water management in the study area are explored here. Findings of this research reveal that climate models project not only a significant increase in average temperatures from mid-century to end-century but also indicate a heightened and variable precipitation pattern. Consequently, it is imperative to develop adaptation strategies to address the warming temperatures and increased precipitation variability anticipated in the future. These adaptation strategies for the study area encompass the following: responses to climate change and variability on the supply side, responses on the demand side, and policy interventions for effective water management.

8.3.1 Responses on the water supply side

The study's findings reveal projected declines in surface runoff under SSP2-4.5 and variable patterns under SSP5-8.5. Specifically, surface runoff is expected to decrease during the mid-term period of SSP5-8.5 but increase during most months in the end-term period. These shifts highlight the dual challenges of water scarcity and potential flooding, necessitating comprehensive adaptation strategies to enhance water availability and reliability.

Key measures include expanding water storage capacity through technologies such as reservoirs, check dams, and rainwater harvesting systems to capture excess runoff and ensure availability during dry periods. Enhancing on-farm water conservation practices, such as soil moisture retention techniques and efficient irrigation methods, is equally critical. Additionally, integrated approaches for sustainable utilization of both surface and groundwater resources should be prioritized, along with implementing pollution control measures to maintain water quality.

To ensure resilience against climate variability, it is imperative to focus on equitable resource allocation, transparent water governance, and timely distribution of water to all users, especially smallholder farmers. Investments in modern water storage and distribution infrastructure, such as lined canals and drip irrigation systems, can significantly improve water-use efficiency and sustainability in agricultural practices.

Furthermore, the increase in runoff observed during specific months or under extreme scenarios poses a heightened risk of flooding, which calls for proactive flood management strategies. These may include constructing flood control structures, reinforcing natural drainage systems, and developing early warning systems to minimize the adverse impacts of extreme runoff events. Integrating these measures into adaptive water management systems can help mitigate both water shortages and flood risks, ensuring a reliable and sustainable water supply for agriculture, domestic use, and ecosystems in the face of a changing climate.

8.3.2 Responses on the water demand side

The study highlights significant increases in water demand across all sectors, such as domestic, industrial, and agricultural driven by population growth, economic development, and the expansion of irrigated agriculture. These pressures are further exacerbated by climate change. This underscores the need for integrated, efficient, and equitable water management practices to ensure water security and support resilient agricultural systems under escalating climate risks.

Addressing water demand amidst climate variability and change requires a comprehensive and multi-sectoral approach that prioritizes enhancing water use efficiency and sustainability. This involves promoting strategies to increase water productivity while simultaneously reducing water wastage. Key measures include implementing advanced water-saving irrigation technologies, such as drip and sprinkler systems, to minimize evaporation and conveyance losses, as well as adopting in-situ soil moisture conservation techniques like mulching and contour farming to improve water retention.

Additionally, integrating early-maturing and drought-tolerant crop varieties into agricultural systems can reduce water requirements, while irrigation scheduling tailored to crop water needs can optimize water usage. Such practices help farmers adapt to unpredictable rainfall patterns and extended dry spells. Participatory approaches involving multiple stakeholders, including farmers, policymakers, and water managers, are vital to identify and implement context-specific adaptation strategies.

Moreover, managing conflicts over water resources requires robust institutional frameworks that ensure equitable access and resolve disputes. Safeguarding environmental integrity is equally crucial, as preserving ecosystems such as wetlands and river systems helps sustain the hydrological cycle and buffer against extreme climatic events.

In conclusion, addressing escalating water demand necessitates a blend of technological, institutional, and community-based approaches to promote efficient water use, resolve resource conflicts, and enhance agricultural and water management systems. These efforts will be crucial in building resilience against climate variability and ensuring sustainable water resources for future generations.

8.3.3 Policy responses to climate change and variability

Addressing water scarcity in the context of climate change and variability requires a multifaceted approach encompassing various policy interventions and initiatives. It is imperative to implement policies aimed at enhancing water management and conservation practices to mitigate the impacts of water scarcity. This involves the formulation and enforcement of regulations targeting the reduction of water pollution and unsustainable groundwater withdrawal practices. Furthermore, there is a critical need to prioritize the reallocation of water resources from low-value to high-value uses, ensuring optimal utilization in agriculture, industry, and domestic sectors.

Enhancing the resilience and adaptive capacity of local farmers is of paramount importance and can be achieved through the implementation of tailored adaptation plans. This includes providing support for capacity-building initiatives, improving access to climate information and early warning systems, and fostering collaborative efforts among various stakeholders. Strengthening coordination and cooperation among government agencies, local communities, and other relevant actors is essential for effective policy implementation and adaptation planning.

Moreover, policy adjustments and investments in infrastructure and management practices are crucial to facilitating climate change adaptation on a broader scale. This may involve the development of climate-resilient infrastructure, such as water storage facilities, irrigation systems, and flood control measures, to enhance water security and resilience to extreme weather events. Additionally, promoting sustainable land use practices, watershed management initiatives, and ecosystem-based adaptation strategies can contribute to enhancing resilience to climate change impacts while fostering socio-economic development and environmental sustainability.

8.4 Scope and limitation of the study

This study utilized a multidisciplinary approach, integrating elements of climate science, water resource management, agriculture, and related fields. While the primary focus is on assessing surface water potential in the region, it does not encompass an evaluation of groundwater resources. Including groundwater analysis could have offered a more comprehensive understanding of overall water availability in the study area. Nevertheless, the scope of the study remains limited to surface water availability.

Additionally, the study utilized five selected General Circulation Models (GCMs) that have been commonly applied in various climate change impact studies in East Africa, and specifically in northern Ethiopia, as part of CMIP5. However, with the recent publication of CMIP6, which recommends the use of higher-resolution modelling tools, not all GCMs from CMIP5 were available. For instance, the Community Climate System Model (CCSM4), which is still under development, does not have complete maximum and minimum temperature data. Consequently, this study considered only four GCMs that are available in both CMIP5 and CMIP6.

8.5 Issues for further research

Future studies could significantly enhance this investigation by incorporating groundwater assessments, providing a more comprehensive understanding of the overall water resources in the study area. Groundwater plays a crucial role in sustaining agricultural productivity and meeting water demand, particularly in areas where surface water is limited.

Moreover, contemporary research increasingly incorporates machine learning and deep learning techniques to simulate climate change impacts and trends. These advanced computational methods have the potential to improve the accuracy of climate predictions and enhance the capacity to analyze large datasets. Future researchers could focus on integrating these innovative approaches into climate studies, as they can help uncover complex patterns and relationships within climate data that traditional methods may overlook. By leveraging machine learning and deep learning, researchers can develop more robust models that better inform adaptation and mitigation strategies, ultimately contributing to improved resilience against climate-related challenges.

8.6 Final remarks

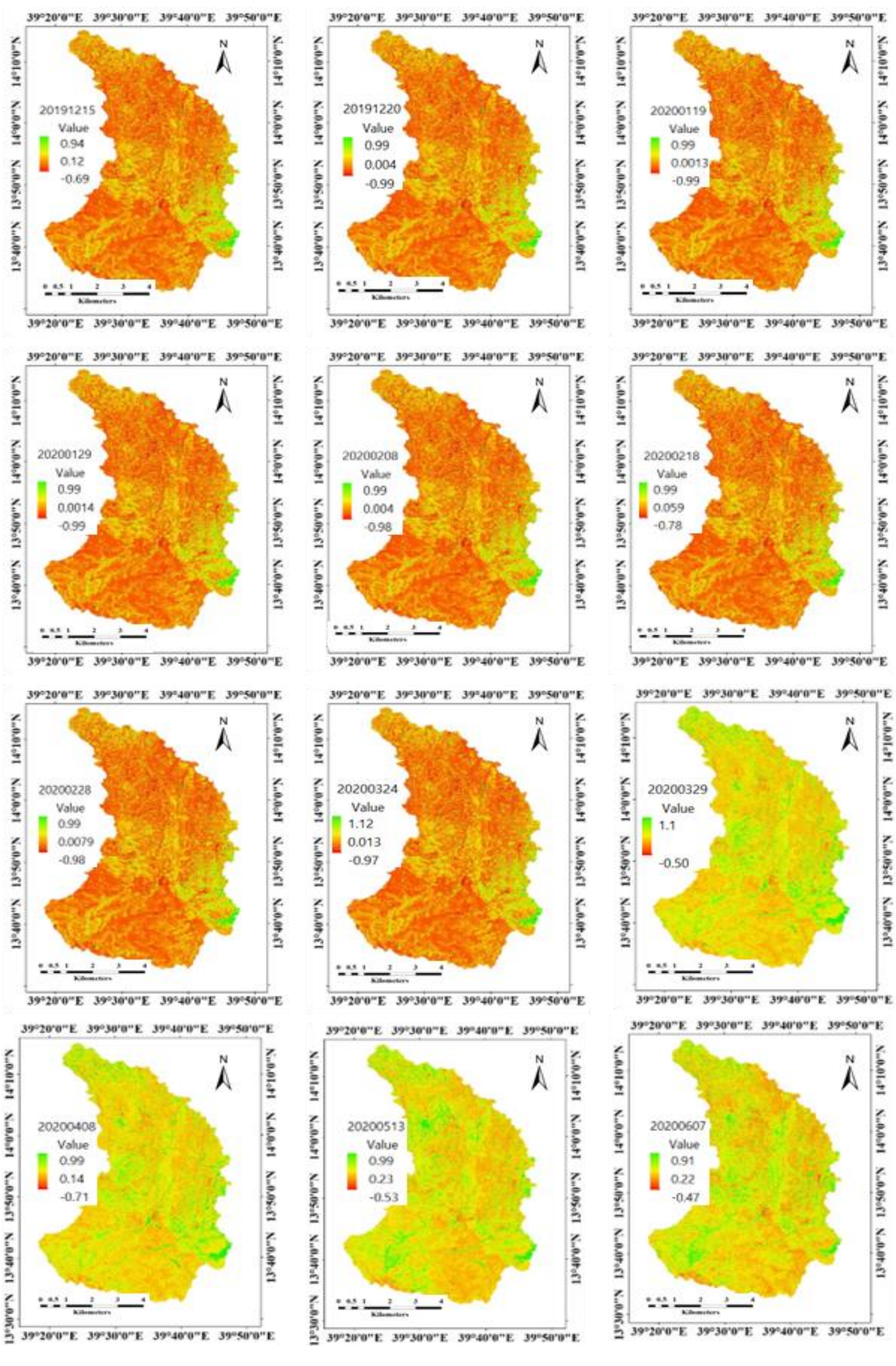
In summary, the findings and recommendations articulated in this dissertation lay a robust ground for future research endeavours, extending their applicability to other regions within the country. While it is important to recognize the challenges that may accompany the proposed areas for further investigation, pursuing these opportunities is expected to generate valuable insights for stakeholders and policymakers alike.

By embracing these research opportunities, deepening our understanding of the complex impacts of climate change on both crop production and water resource availability is required. This knowledge will facilitate the development of targeted strategies aimed at enhancing resilience and sustainability in agricultural practices and water management systems. Furthermore, the integration of multidisciplinary approaches, as demonstrated in this study, is crucial for addressing the multifaceted challenges posed by climate variability.

Ultimately, advancing research in this area not only supports local and national efforts to adapt to climate change but also contributes to broader global sustainability goals. By fostering collaboration among researchers, policymakers, and communities, is possible to ensure that the strategies developed are both effective and grounded in the realities of the regions affected. Through concerted efforts, is possible to build a more resilient agricultural sector and sustainable water resource management system that can withstand the ongoing challenges posed by climate change.

9. ANNEX

Annex 1: Spatial and temporal NDVI maps of the whole study area from December 2019 to June *2020*



Annex 2: Conveyance efficiency of selected dams in the study area

Name	Canal width (cm)	Canal depth (cm)	time (sec)	Rev	Area (cm2)	Area (m2)	Rev/min	V(m/s)	Discharge (m3/s)	CE (%)	Canal type	Mean CE (%)
Korir	53.00	12.00	30.00	117.00	636.00	0.06	234.00	1.54	0.098			
	51.00	12.00	30.00	115.00	612.00	0.06	230.00	1.52	0.093	94.58	1º	
	27.00	24.00	30.00	73.00	648.00	0.06	146.00	0.96	0.062			78.90
	27.00	20.00	30.00	73.00	540.00	0.05	146.00	0.96	0.052	83.33	2º	
Grindaho	1000.00	10.00	30.00	18.00	10000.00	1.00	36.00	0.24	0.238			
	1000.00	10.00	30.00	16.00	10000.00	1.00	32.00	0.21	0.211	88.89	1º	
	57.00	14.00	31.00	24.00	798.00	0.08	46.45	0.31	0.024			70.40
	52.00	16.00	30.00	20.00	832.00	0.08	40.00	0.26	0.022	86.88	2º	
	66.00	20.00	30.00	33.00	1320.00	0.13	66.00	0.44	0.057			
	66.00	20.00	30.00	30.00	1320.00	0.13	60.00	0.40	0.052	90.91	2º	
Millennium	70.00	47.00	30.00	49.67	3290.00	0.33	99.33	0.66	0.216			
	68.00	28.00	30.00	65.00	1904.00	0.19	130.00	0.86	0.163	75.74	1º	65.40
	38.00	20.00	30.00	64.33	760.00	0.08	128.67	0.85	0.065			
	34.00	20.00	30.00	62.00	680.00	0.07	124.00	0.82	0.056	86.23	2º	
Mai-Mamuk	40.00	18.00	30.00	38.50	720.00	0.07	77.00	0.51	0.037			
	35.00	19.00	30.00	34.00	665.00	0.07	68.00	0.45	0.030	81.57	1º	82.00
Haresaw	40.00	20.00	30.00	18.00	800.00	0.08	36.00	0.24	0.019			
	48.00	16.00	30.00	14.00	768.00	0.08	28.00	0.18	0.014	74.67	1º	59.25
	42.00	18.00	30.00	15.00	756.00	0.08	30.00	0.20	0.015			
	45.00	15.00	30.00	13.33	675.00	0.07	26.67	0.18	0.012	79.37	2º	
Ruba-Feleg	40.00	17.00	30.00	14.00	680.00	0.07	28.00	0.18	0.013			
	36.00	13.00	30.00	18.00	468.00	0.05	36.00	0.24	0.011	88.49	1º	88.00
											Total CE	73.99

Annex 3: Projected surface runoff under SSP2-45 and SSP5-85 in mid and end term periods

Table 10.1: Projected surface runoff under SSP2-45 (Mid-term)

Months	Observed	GFDL-ESM2M	HadGEM2-ES	MIROC6	MPI-ESM-MR	Average_GCMs
1	0.38	0.35	0.35	0.30	0.37	0.34
2	0.60	0.58	0.59	0.53	0.68	0.59
3	52.23	34.12	150.15	52.55	32.46	67.32
4	93.38	69.72	85.03	91.31	92.72	84.70
5	76.74	69.07	53.34	63.97	62.09	62.12
6	33.46	29.13	24.41	25.92	28.19	26.91
7	649.99	494.80	789.33	532.41	578.49	598.76
8	696.63	732.92	510.83	532.14	574.54	587.61
9	74.69	89.16	32.87	50.74	55.96	57.18
10	5.07	4.67	3.79	4.15	3.72	4.08
11	15.11	10.56	9.27	10.76	14.27	11.22
12	2.46	1.76	1.57	1.91	2.90	2.03

Table 10.2: Projected surface runoff under SSP2-45 (End-term)

Months	Observed	GFDL-ESM2M	HadGEM2-ES	MIROC6	MPI-ESM-MR	Average_GCMs
1	0.38	0.44	0.40	0.41	0.45	0.43
2	0.60	0.63	0.59	0.79	0.96	0.74
3	52.23	75.99	90.35	44.08	39.16	62.40
4	93.38	92.00	69.56	84.34	69.55	78.86
5	76.74	62.73	73.04	66.60	56.49	64.71
6	33.46	32.43	35.52	26.63	31.29	31.47
7	649.99	765.49	928.51	552.25	806.01	763.07
8	696.63	859.62	572.74	689.44	692.34	703.53
9	74.69	104.64	33.25	84.36	65.07	71.83
10	5.07	4.69	3.93	4.00	4.20	4.20
11	15.11	10.31	9.25	16.56	23.98	15.02
12	2.46	1.82	1.62	2.39	2.84	2.17

Table 10.3: Projected surface runoff under SSP5-85 (Mid-term)

Months	Observed	GFDL-ESM2M	HadGEM2-ES	MIROC6	MPI-ESM-MR	Average_GCMs
1	0.38	0.40	0.32	0.29	0.48	0.37
2	0.60	0.60	0.80	0.54	0.66	0.65
3	52.23	34.27	163.05	43.40	37.45	69.54
4	93.38	69.19	85.21	83.28	82.97	80.16
5	76.74	61.86	54.23	57.31	59.66	58.26
6	33.46	27.80	24.63	25.06	26.14	25.91
7	649.99	644.30	558.02	458.91	949.43	652.67
8	696.63	880.17	440.97	491.95	734.61	636.93
9	74.69	104.97	32.58	47.76	63.58	62.22
10	5.07	4.02	3.76	3.58	6.08	4.36
11	15.11	10.08	12.71	9.06	33.18	16.26
12	2.46	1.80	2.38	1.45	3.93	2.39

Table 10.4: Projected surface runoff under SSP5-85 (End-term)

Months	Observed	GFDL-ESM2M	HadGEM2-ES	MIROC6	MPI-ESM-MR	Average_GCMs
1	0.38	0.50	0.46	0.35	0.58	0.47
2	0.60	0.69	0.64	0.57	0.83	0.68
3	52.23	35.72	53.44	39.09	32.94	40.30
4	93.38	67.46	64.16	85.27	85.88	75.69
5	76.74	58.74	61.60	65.81	60.41	61.64
6	33.46	29.78	35.09	25.52	24.56	28.74
7	649.99	736.35	1141.10	501.41	1048.61	856.87
8	696.63	1007.44	650.74	594.27	753.12	751.39
9	74.69	140.05	34.15	65.76	62.46	75.61
10	5.07	4.75	4.14	3.90	6.45	4.81
11	15.11	11.19	9.23	9.37	47.28	19.27
12	2.46	2.11	1.69	1.55	4.92	2.57