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Historical and Future Climate Trends in East Gojjam Zone: A CMIP6-Based Analysis.

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BAHIR DAR UNIVERSITY

COLLEGE OF AGRICULTURAL AND ENVIRONMENTAL SCIENCES

Department of Natural Resource Management

M.Sc. Program

**Historical and Future Climate Trends in East Gojjam Zone: A CMIP6-Based
Analysis**

M.Sc. Thesis

By

Demis Shitaye

February 2025

Bahir Dar, Ethiopia



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M.Sc. Thesis

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Demis Shitaye

**A Thesis Submitted in Partial Fulfillment of the Requirements for the
Degree of Master of Science (M.Sc.) In “Environment and Climate Change”**

Department: Natural Resource Management

Program: Environment and climate change

Advisor: Solomon Addisu (PhD.)

February 2025

Bahir Dar, Ethiopia

THESIS APPROVAL SHEET

As a member of the Board of Examiners of the Master of Sciences (M.Sc.) thesis open defense examination, we have read and evaluated this thesis prepared by **Mr. Demis Shitaye** entitled **"Historical and Future Climate Trends in East Gojjam Zone: A CMIP6-Based Analysis"**. We hereby certify that; the thesis is accepted for fulfilling the requirements for the award of the degree of Master of Sciences (M.Sc.) in the **environment and climate change**.

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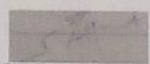
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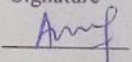
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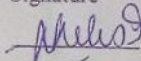
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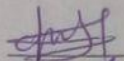
This is to certify that this thesis entitled "**Historical and Future Climate Trends in East Gojjam Zone: A CMIP6-Based Analysis**" submitted in partial fulfillment of the requirements for the award of the degree of Master of Science in "**Environment and Climate Change**" to the Graduate Program of College of Agriculture and Environmental Sciences, Bahir Dar University by Mr. **Demis Shitaye** (ID.No. BDU1401325) is an authentic work carried out by him under our guidance. The matter embodied in this thesis work has not been submitted earlier for the award of any degree or diploma to the best of our knowledge and belief.

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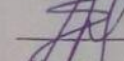
Name of the Student's

Solomon Addisu (PhD.)

Name of the Advisor



Signature



Signature

03/03/2025

date

05/03/2025

date

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LIST OF ACRONYMS/ABBREVIATIONS

CMIP6	Coupled Model Intercomparison Project Phase6
CRI	Comprehensive Rating Index
CV	Coefficient of variation
DAMIP	Detection and Attribution Model Intercomparison Project
DCPP	Decadal Climate Prediction Project
DTR	Diurnal Temperature Range
EGZSS	East Gojjam Zone Selected Stations
ENMI	Ethiopian National Meteorological Institute
ENSO	El Niño Southern Oscillation
ESGF	Earth System Grid Federation
GCM	Global Climate Model
GDP	Gross Domestic Product
GHG	Greenhouse gas
IAM	Integrated Assessment Model
IOD	Indian Ocean Dipole
IPCC	Intergovernmental panel on climate change
ITCZ	Inter Tropical Convergence Zone
KGE	Kling-Gupta Efficiency
m.a.s. l	Meter above sea level
MK	Mann–Kendall
NASA	National Aeronautic Space Administration
NMSA	National Meteorological Station Agency
NSE	Net Sutcliff Efficiency
PBIAS	Percent of bias
PCI	Precipitation Concentration Index
PPM	Parts Per Million
QBO	Quasi-Biennial Oscillation
r	Pearson correlation coefficient
RMSE	Root means square error
RCMs	Regional Climate Models
SAI	Standard Anomaly Index

SD	Standard deviation
SPI	Standard Precipitation Index
SSPs	Socioeconomic Pathways
SSTs	Sea Surface temperatures
Tmax	Maximum Temperature
Tmin	Minimum Temperature
UNDP	United Nations Development Program
UNFCCC	United Nations Framework Convention on Climate Change
WCRP	World Climate Research Program
WGCM	Working Group on Coupled Modeling
WMO	World Meteorological Organization

ABSTRACT

Climate change trends and variability, particularly in rainfall and temperature patterns, present significant challenges to understanding and mitigating environmental impacts. These challenges are particularly evident in regions like the East Gojjam Zone. Therefore, the current study was conducted to evaluate historical and project future climate trends in East Gojjam, North Eastern Ethiopia. The Mann-Kendall trend test was applied to analyze historical rainfall and temperature trends at both monthly and annual scales using climate data from four stations (Motta, D/Work, Dejen, and D/Markos). To examine rainfall variability the coefficient of variation, rainfall anomaly index, precipitation concentration index, and standard precipitation index were used. To evaluate and project CMhyd software was used to perform bias correction and extraction of simulated data for the historical period (1984 to 2014) and for future periods (2015 to 2100). The findings revealed that D/Work station has the highest rainfall variability, whereas, the remaining stations showed positive and negative rainfall anomaly indexes across the stations. The precipitation concentration index analysis revealed that most stations, except for D/Markos, experienced irregular rainfall distributions from 16 to 20. The standard precipitation index indicates a predominance of below-normal rainfall across all stations suggests increasing drought risks. All stations, except Motta, showed a significant increasing trend in mean annual rainfall. For future climate projections MIROC6 was the best-performing models for simulating rainfall and FGOLAS-g3 was selected for Tmax and Tmin simulation. After evaluating historical trends, the study assessed future climate projections to understand potential changes in rainfall and temperature under different SSP scenarios. The projections indicated that a potential decrease in annual rainfall for the Motta and D/Markos stations in the near term, whereas D/Work and Dejen were expected to increase. In the late century, a similar trend was observed, with expected decreases in annual rainfall for Motta and D/Markos, contrasted by increases for D/Work and Dejen. The temperature projections indicated a continuous increase in maximum and minimum temperatures across all stations under the five scenarios. The study underscores the need for localized climate model evaluations to enhance adaptation strategies. The findings provide critical insights for policymakers and stakeholders to develop climate-resilient interventions in East Gojjam.

Keywords; *Bias correction, Climate change, climate variability, Model Performance, Mann-Kendall trend, Rainfall variability, SSP scenarios.*

TABLE OF CONTENTS

ACKNOWLEDGMENT.....	iv
LIST OF ACRONYMS/ABBREVIATIONS.....	v
ABSTRACT	vii
TABLE OF CONTENTS.....	viii
LIST OF TABLES	x
LIST OF FIGURES	xi
LIST OF APPENDICES.....	xii
Chapter One: INTRODUCTION	1
1.1. Background and Justifications.....	1
1.2. Statement of the Problem	3
1.3. Objective.....	5
1.3.1. General objective	5
1.3.2. Specific objectives were to:	5
1.4. Research questions.....	5
1.5. Significance of the study	5
1.6. Scope and limitations of the study	6
Chapter Two: LITERATURE REVIEW.....	7
2.1. Definitions and Concepts of Climate Related Terms	7
2.2. Trends and variability in rainfall and temperature	9
2.3. Climate models and Global climate models	10
2.3.1. Coupled Model Intercomparison Project Phase 6 (CMIP6)	11
2.3.2. GCM performance metrics (statistical metrics)	12
2.4. Projection of future climate change.....	13
2.4.1. Shared socioeconomic pathways (SSPs)	13
2.5. Empirical literature on historical climate trends and variability.....	19
2.6. Empirical literature on the evaluation of climate models	20
2.7. Empirical literature on the projection of future climate change.....	21
Chapter Three: MATERIALS AND METHODS.....	23
3.1. Description of the study Area.....	23
3.2. Methods of data collection and sources	24
3.2.1. Observed and CMIP6 GCM datasets	24
3.3. Method of data analysis.....	27
3.3.1. Historical rainfall and temperature trend analysis	29
3.3.2. Variability analysis of rainfall data from 1984 to 2014	31

3.3.3. Performance metrics for the evaluation of GCMs.....	34
3.3.4. Future climate projection and trend analysis	37
Chapter Four: RESULTS AND DISCUSSIONS	39
4.1. Data Quality Check	39
4.1.1. Man–Kendall trend test of the pre-whitening procedure for the mean annual maximum and minimum temperature.	40
4.2. Variability analysis of seasonal and annual rainfall.....	41
4.2.1. Coefficient of variation	41
4.2.2. Standardized rainfall anomaly index (SRAI).....	43
4.2.3. Precipitation concentration index (PCI).....	45
4.2.3. Standard precipitation index (SPI).....	46
4.3. Trend analysis of monthly, annual, and seasonal average rainfall from 1984 to 2014	48
4.3.1. Trend analysis of annual and seasonal rainfall from 1984–2014.....	51
4.3.2. Trend analysis of the mean monthly maximum and minimum temperature (1984–2014).....	55
4.3.3. Trend analysis of the mean annual maximum and minimum Temperature from 1984–2014.	60
4.4. Performance of the CMIP6 GCMs for simulating rainfall	63
4.5. Performance of the CMIP6 GCMs for simulating the mean annual maximum and minimum temperature	66
4.6. Selection of best-performing models for future climate change analysis	71
4.7. Projections of future rainfall and temperature changes	72
Chapter Five: CONCLUSION AND RECOMMENDATIONS	79
5.1. Conclusion.....	79
5.2. Recommendations	80
References	81
APPENDIX	99

LIST OF TABLES

Table 3.1. Information on the eight CMIP6 models used in this study.	26
Table 3.2. Standard precipitation indices (SPIs) and their interpretation.	33
Table 3.3. The five performance metrics along with their equations and references.	36
Table 4.1. Mean annual maximum temperature MK trend test results of the pre-whitened procedure.....	41
Table 4.2. Mean annual minimum temperature of the Mann–Kendall trend test results of the prewhitened procedure.	41
Table 4.3. Seasonal and annual rainfall variability data in mm from 1984–2014.	43
Table 4.4. Years of the different PCI classes in the study area (1984 to 2014).	46
Table 4.5. MK trend test results for the monthly average rainfall (mm).	50
Table 4.6. The Mann–Kendall trend test results of mean annual and seasonal rainfall (mm).....	53
Table 4.7. MK trend test results of mean monthly maximum temperature from 1984–2014.	57
Table 4.8. MK trend test results of mean monthly minimum temperature from 1984–2014.	59
Table 4.9. Mann Kendall’s trend test results of mean annual maximum temperature.....	60
Table 4.10. Mann–Kendall trend test results for the mean annual minimum temperature.	61
Table 4.11. Performance metrics and ranking of GCMs for total annual rainfall using the CRI method.	64
Table 4.12. Performance metrics and ranking of GCMs for mean annual Tmax in (°C) through the CRI method.....	67
Table 4.13. Performance metrics and ranking of GCMs for mean annual Tmin in (°C) through the CRI method.....	69
Table 4.14. The average annual rainfall in the near-term (2031 to 2061) and long-term (2070 to 2100) periods at SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0 and SSP5-8.5 climate scenarios under the studied temporal scales compared with the observed annual.....	73
Table 4.15. The mean annual Tmax and Tmin (°C) in the near term (2031 to 2061) and (2070–2100) periods at SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0 and SSP5-8.5 climate scenarios under the studied temporal scales compared with the observed Tmax and Tmin	76

LIST OF FIGURES

Figure 3.1. Map of the study area	23
Figure 4. 1. Annual rainfall anomalies at the stations from 1984–2014.....	45
Figure 4. 2. The standardized precipitation index of the stations from 1984 to 2014.	48
Figure 4.3. MK trend test of the annual rainfall at the Motta, D/Work, Dejen, and D/Markos stations.	54
Figure 4.4. MK trend test of the mean annual Tmax at the Motta, D/Work, Dejen, and D/Markos Stations.....	61
Figure 4.5. MK trend test of the mean annual Tmin at the Motta, D/Work, Dejen, and D/Markos Stations.....	62
Figure 4. 6. Total annual RF of the CMIP6 GCMs with observed data at the Motta, D/Work, Dejen, and D/Markos Stations.	65
Figure 4.7. Mean annual Tmax of the CMIP6 GCMs with observed data at the Motta, D/Work, Dejen, and D/Markos Stations.	68
Figure 4.8. Mean annual Tmin of the CMIP6 GCMs with observed data at the Motta, D/Work, Dejen, and D/Markos Stations.	70
Figure 4.9. The projected annual Rainfall (2015–2100) under SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 climate change scenarios along with the observed rainfall (1984–2014) at the studied EGZ selected stations.....	74
Figure 4.10. The projected mean annual Tmax (2015 to 2100) under the SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 climate change scenarios along with the observed rainfall (1984 to 2014) at the selected stations in the studied EGZ.	77
Figure 4.11. The projected mean annual Tmin (2015 to 2100) under the SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 climate change scenarios along with the observed rainfall (1984 to 2014) at the selected stations in the studied EGZ.	78

LIST OF APPENDICES

Appendix 1: Description of studied meteorological stations over East Gojjam Zone.	99
Appendix 2: Annual rainfall autocorrelation coefficient values and plots.	99
Appendix 3: Mean annual maximum temperature autocorrelation coefficient values and plots.	100
Appendix 4: Mean annual minimum temperature autocorrelation coefficient values and plots.	101

Chapter One: INTRODUCTION

1.1. Background and Justifications

Climate change is the most sensitive issue and poses considerable danger to all life on Earth in this century (Thomson, 2009). It is one of the most difficult issues facing economies and communities today (Bryan *et al.*, 2010). Over the last century, the global average temperature has risen by 0.6°C. In Africa by the end of the 21st century, the temperature will rise from 3°C to 4°C (Bryan *et al.*, 2010). According to the Intergovernmental Panel on Climate Change's Fourth Assessment Report, the global average surface temperature is expected to rise by 1.8°C to 4°C by 2100 (IPCC, 2014a). An extreme weather or climate event is unusual for a particular location and time of year (Parry *et al.*, 2007). According to Easterling *et al.* (2000), extreme events can be divided into two main categories: (1) yearly extreme events or weather events, which are based on simple statistics such as very low or very high daily temperature and event-driven rainfall, and (2) more complex event-driven, extremes, e.g., droughts, floods, heat waves, and hurricanes, which do not necessarily occur every year at a given location. Climate change is considered one of the greatest challenges facing the world in the 21st century (Stevens *et al.*, 2021).

Regarding climate change and climate variability, Africa is the most susceptible continent (Challinor *et al.*, 2007). Due to their dependence on agricultural outputs, which are climate-sensitive, many African nations are vulnerable to climate change (Yesuf *et al.*, 2008). Climate variability and change are among the major environmental challenges of the 21st century (Canziani and Parry, 2007). There is strong evidence and understanding that climate change is occurring and is recognized as one of the greatest challenges (Meybeck *et al.*, 2012). In particular, climate change and variability are caused by either natural or anthropogenic activities (Saroar, 2016). To address this global environmental issue, the United Nations Framework Convention on Climate Change (UNFCCC) approved the Paris Agreement, which is a legally binding framework for addressing global climate change (Duyck, 2015). Climate change has become one of the most essential concerns in the field of sustainable development, and its impacts can be affected in different parts of the globe (Dioha and Kumar, 2020).

Most developing countries are affected by climate change because they largely depend on climate-sensitive sectors with low adaptive capacity (Mesfin *et al.*, 2020). The warming of our planet due to the emission of greenhouse gases is now unquestionable, and over the last century, the CO₂ atmospheric concentration has increased significantly and has, in turn, caused the average global temperature to increase by 0.74°C compared with that in the preindustrial era (UNFCCC, 2007). A majority of sub-Saharan countries, including Ethiopia, are highly impacted by the adverse effects of weather and climate extremes, resulting in low agricultural production and food insecurity (Amare and Simane, 2017). The climate of Ethiopia has changed over the last few decades, with temperatures increasing by approximately 0.37°C over the previous four decades (Gebrechorkos *et al.*, 2019). A coupled model intercomparison project (CMIP) is a vital tool to better understand past, present, and future climate change.

The Coupled Model Intercomparison Project (CMIP) is a project that evaluates the performance of GCMs in simulating past, present, and future climate change under different scenarios (Eyring *et al.*, 2016). CMIP6 is the latest version of the CMIP and has superior simulation capability and projection accuracy compared with previous versions (O'Neill *et al.*, 2016). CMIP6 involves several simulations of GCMs currently used to interpret past and future climate changes (Mandel and Lipovetsky, 2021). The latest GCMs improve spatial resolution, improve the parameterization scheme of physical processes, and increase the representativeness of climate change feedback. To study past, present, and future climate change, researchers have used three statistical approaches to develop future climatic scenarios: general circulation models (GCMs), synthetic climatic scenarios, and past climatic data (Tan *et al.*, 2017). GCMs are the most reliable, advanced, and effective tools for studying past and future climates (Raju and Kumar, 2020). However, uncertainties caused by the model structure, initial conditions, boundary conditions, calibration process, and other factors may still affect the GCM outputs (Navarro and Tapiador, 2024).

The major difference between the CMIP5 and CMIP6 future scenarios is that CMIP5 (RCP) projections are available based on 2100 radiative forcing values for four GHG concentration pathways (Long and Li, 2021). In contrast, CMIP6 uses socioeconomic pathways (SSPs), considered more realistic future scenarios (Almazroui *et al.*, 2020).

Another update of CMIP6 is the development and support of the intercomparison model, which focuses on biases, processes, and climate model feedback (Yukimoto *et al.*, 2019). The Coupled Model Intercomparison Project Phase Six (CMIP6) is the most recent update of the CMIP. CMIP6 models run several new and updated emission pathways that explore a much wider range of possible future outcomes than are included in CMIP5. CMIP6 represents a substantial expansion over CMIP5 in terms of the number of modeling groups participating, the number of future scenarios examined, and the number of different experiments conducted; the number of experiments that have been designed in CMIP6 is greater than that in CMIP5's earlier phases.

The physical processes of the CMIP6 models are more complex, and their resolutions are improved (Eyring *et al.*, 2016a). The CMIP6 GCMs are different from earlier generations in that they include high geographic resolutions, improved cloud microphysical process parameters, and additional earth system processes and components, including ice sheets and biogeochemical cycles (Eyring *et al.*, 2019). In this study, the East Gojjam Zone was selected for the rainfall and temperature trends and projections performance of CMIP6 models in the study area. Although few studies have been conducted on trends and variabilities in rainfall and temperature, CMIP6 model evaluations, and projections of future climate change in the region as discussed above, however still there is a gap that these studies did not address.

1.2. Statement of the Problem

Climate change poses significant threats to environmental, socioeconomic, and related sectors, including water resources, agriculture and food security, human health, and terrestrial biodiversity. Compared with the average climate conditions, climate extremes result in more profound changes, causing a great/substantial negative impacts on both human and natural systems (Tierney *et al.*, 2013). Trends in climate extremes present a serious risk to food security in many parts of the world, particularly in Sub-Saharan Africa being vulnerable (Krishnamurthy *et al.*, 2012). In Ethiopia, rain-fed agriculture accounts for approximately 96% of total crop production, making it highly susceptible to climate variability (Serdeczny *et al.*, 2017). Frequent high temperatures and unpredictable rainfall patterns often lead to natural disasters such as droughts, heavy rainfall, and flooding (Kotir, 2011).

Assessing historical climate trends and future projections for Ethiopia is complicated by the country's diverse topography, which ranges from sea level to elevations of 1290 to 3000 meters above sea level (Philip *et al.*, 2018). Rainfall patterns across Ethiopia are highly variable, with some regions experiencing only one rainy season while others have two or more (Dereje *et al.*, 2012). According to Rowell *et al.* (2015) identify Indian Ocean Sea Surface Temperatures (SSTs) as a significant driver of East African rainfall patterns over longer time scales. Based on Almazroui *et al.* (2021) increasing concentrations of greenhouse gases (GHGs) can lead to a significant increase in the intensity and frequency of climate extremes. The negative impacts of these climate extremes on global crop production and food security are far more common than their positive impacts (Moriondo *et al.*, 2011). However, understanding the dynamics and physics behind climate extremes remains a significant challenge (Funk *et al.*, 2019).

A study by (Belay *et al.*, 2021b) focused on the projected impacts of climate change on agriculture in Ethiopia, but it did not provide a comprehensive overview of observed climate trends and variabilities within the country. Changes in rainfall patterns may lead to severe water shortages and flooding, while rising temperatures can shift crop growing seasons, jeopardizing food security and increasing the risk of climate-related diseases such as malaria and dengue fever (IPCC, 2007a). It is essential to recognize that changes in precipitation and temperature are not uniform globally; significant spatial and temporal variations exist across different regions (Parry *et al.*, 2007).

Most studies in Ethiopia have primarily focused on mean climate trend analysis, which often overlooks unusual climate changes and their implications. Furthermore, existing research shows inconsistencies in reporting climate change impacts, lacking a coherent pattern or trend in rainfall across the country. Although numerous studies have assessed climate trends at global, regional, and local scales, there remains a gap in understanding the specific magnitudes of temperature and rainfall trends at a smaller scale, particularly in the East Gojjam Zone. To address this information gap, the current study aims to fill the above information gap by analyzing the trends and variability of climate elements, evaluating the performance of Coupled Model Intercomparison Project Phase Six (CMIP6) models, and projecting future climate scenarios for the East Gojjam Zone.

1.3. Objective

1.3.1. General objective

The general objective of this research was to evaluate climate models and analyze temperature and rainfall trends and variability in the study area.

1.3.2. Specific objectives were to:

- Analyze historical climate trends and variability for rainfall and temperature.
- Evaluate and rank historical simulations of CMIP6 GCMs for rainfall and temperature over the East Gojjam Zone (1984–2014) on an annual timescale.
- Project future climate change trends under CMIP6-SSP scenarios for the period 2031–2100.

1.4. Research questions

1. What are the historical climate trends and variability in rainfall and temperature over East Gojjam Zone from 1984 to 2014?
2. How are the accurate historical simulations of CMIP6 GCMs in simulating rainfall and temperature trends over the East Gojjam Zone (1984–2014) on an annual timescale?
3. What are the projected future climate change trends (temperature and rainfall) for the East Gojjam Zone under CMIP6-SSP scenarios from 2031 to 2100?

1.5. Significance of the study

This study will significantly contribute to academic research and policy-making by enhancing our understanding of climate change trends and variabilities from the perspective of rural communities. The findings will be instrumental in drafting and refining future environmental policies and action plans at the community level, fostering informed climate adaptation and mitigation strategies tailored to the unique socio-ecological context of the East Gojjam Zone. Furthermore, this research will serve as a valuable resource for stakeholders, including policymakers, local governments, and community organizations, facilitating collaborative efforts in addressing climate change challenges effectively.

1.6. Scope and limitations of the study

This study is geographically confined to selected stations in the East Gojjam Zone, which may limit its applicability to broader regions or diverse socio-ecological contexts. Thematically, the research focuses on evaluating climate models, analyzing historical trends and variabilities in rainfall and temperature, and projecting future climate trends. This focus is essential for understanding local climate dynamics and informing targeted climate adaptation and mitigation strategies tailored to the specific environmental and socio-economic conditions of the study area. The researcher has used only four stations' data. This is due to the absence of long-term recorded data in the stations and small number of stations in the zone and the uneven distribution of gauges stations.

Chapter Two: LITERATURE REVIEW

2.1. Definitions and Concepts of Climate Related Terms

Climate: Climate is usually defined as the “average weather” or more rigorously as the statistical average and variability of weather conditions over a period ranging from months to thousands or millions of years. The conventional period is 30 years, as defined by the World Meteorological Organization (WMO, 2007).

Weather: This is a short-term phenomenon that describes the atmosphere, daily air temperature, pressure, humidity, solar radiation, wind speed, and precipitation (IPCC, 2007c).

Climate variability: Variations in the mean state and other statistics (such as standard deviations, the occurrence of extremes, etc.) of the climate at all temporal and spatial scales beyond those of individual weather events. The differences are usually termed anomalies (Manyatsi *et al.*, 2010). Climate variability is the way climate fluctuates annually above or below a long-term average value (Timofeyeva-Livezey *et al.*, 2015).

Climate change: A change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties, which persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes, external forcings, or persistent anthropogenic changes in the composition of the atmosphere or land (IPCC and New York, 2007).

Trend: A trend is a significant change over time shown by a random variable (such as temperature and rainfall data) and is visible by statistical parametric and nonparametric procedures (Bihrat *et al.*, 2003).

Climate model: Climate models are fundamental tools for acquiring past and future climate information through the utilization of estimation techniques for land, ocean, atmosphere, and ice interactions (Randall *et al.*, 2007).

Scenario: This refers to a plausible and often simplified description of how the future may develop based on a coherent, internally consistent set of assumptions about driving forces and key relationships. Scenarios may be derived from projections, but are often based on additional information from other sources, sometimes combined with a narrative storyline.

There are no agreed definitions for climate variability and climate change. The definitions of these two terms have evolved. The World Meteorological Organization (WMO) refers to climate change as long-term changes in average weather conditions (Arguez and Vose, 2011). Climate change encompasses changes in climate patterns over time, which can arise from natural processes and human activities (IPCC, 2007b). The definitions of climate change consistently highlight the dual role of natural and anthropogenic factors in driving these changes.

On the other hand, climate variability refers to fluctuations in the average climate state and its statistical measures across various temporal and spatial scales. This distinction underscores the complexity of climate dynamics and the interplay between different influencing factors (IPCC, 2001). Variability includes more than individual weather events and may result from natural internal processes within the climate system or variations in natural or anthropogenic external forces (Tasokwa, 2011). Climate variability is a short-term fluctuation that occurs from year to year. The natural mode of climate variability associated with the El Niño Southern Oscillation (ENSO) as well as an increase in anthropogenic activities has greatly contributed to the observed changes in rainfall and temperature within the country (Diro et al., 2012; Rowell et al., 2015). Climate variability is the way climate fluctuates annually above or below a long-term average value (Dandesa *et al.*, 2017).

Similarly, the most important feature of sea surface temperature variability that can cause large-scale weather disruptions is El Niño and its counterpart La Niña, a nearly basin-wide warming and cooling of the equatorial Pacific Ocean known as ENSO (Goddard *et al.*, 2003). According to IPCC (2013), climate variability refers to shorter-term variations in climate, including fluctuations associated with, for example, teleconnection systems, El Niño (warming), or La Niña (cool) events, which are spatial and season-specific. Precipitation and temperature trend analyses at different spatial and temporal scales have been important during the past century because of the attention given to global climate change. Key factors contributing to climate change include high population growth rates; a growing dependence on fossil fuel-based technologies; and land use changes, particularly through urbanization, agriculture, and deforestation. These activities lead to increased concentrations of greenhouse gases and aerosols in the atmosphere (Maloney *et al.*, 2014).

2.2. Trends and variability in rainfall and temperature

According to the IPCC (2014b) Fifth Assessment Report, the seasonal mean temperature has increased in many areas of Ethiopia. According to the UNDP climate change country profiles, the average annual temperature of Ethiopia increased by 1.3°C between 1960 and 2006 (Mcsweeney *et al.*, 2010). Climate variability and change have significantly impacted the economic growth of the country, resulting in a 10% decline in its GDP from the proposed targets and increasing income inequality by 20% (Mideksa, 2010). The Ethiopian climate is characterized by a history of climate extremes, such as droughts and floods, and increases and decreases in temperature and precipitation, respectively.

Current climate variability is already imposing a significant challenge on Ethiopia by affecting food security, the water and energy supply, poverty reduction, and sustainable development efforts, as well as by causing natural resource degradation and natural disasters (Herzog, 2009). According to the Ethiopian Meteorological Institute (EMI, 2010), the average annual minimum temperature across the country has increased by approximately 0.25°C every 10 years, whereas the mean annual maximum temperature has increased by approximately 0.1°C every decade.

Rainfall trends over recent years in Ethiopia are less evident than temperature trends, and there are large variations in the direction and extent of changes across the region. An increase in rainfall in some locations for some seasons is observed but a decrease in rainfall is observed in other parts of the region and overall trends are weak and hard to detect (Nakawuka *et al.*, 2018). A trend analysis of annual rainfall in Ethiopia revealed that rainfall has remained more or less constant. When averaged over the whole country, a declining trend over the northern half of the country and southwestern Ethiopia (Belay *et al.*, 2017). Ethiopia has three rainy seasons, namely, June to September (called *Kiremt*), October to January (*Bega*), and February to May (*Belg*). The minimum temperature increased by 0.37 degrees Celsius per decade between 1951 and 2007 (NMI, 2010). The frequency of hot and night days also tends to increase trend during these years. While the average number of “cold days” decreased by 5.8% between 1960 and 2003, the average number of “cold” nights per year decreased by 11.2% (Ayal and Leal Filho, 2017).

2.3. Climate models and Global climate models

Climate models serve as essential instruments for understanding both historical and future climate dynamics. They employ estimation techniques to analyze the complex interactions among various components of the Earth's system, including land, ocean, atmosphere, and ice (Randall *et al.*, 2007). Climate models are the primary tools available for investigating the climate system's response to various forcings, making climate predictions on seasonal to decadal time scales, and making projections of future climate over the coming century and beyond. Therefore, evaluating the performance of these models, both individually and collectively, is crucial (Kreienkamp *et al.*, 2012). Climate models are important tools for understanding and predicting the complex Earth's climate. Several global climate models (GCMs) have been developed by several research centers in the world.

GCMs are complex mathematical models, that can simulate three dimensions, such as the Earth's atmosphere, ocean, and land surface (Harle *et al.*, 2002). Global climate models are mathematical frameworks that represent the physics of the climate system, including the atmosphere, ocean, land surface, and cryosphere (Randall *et al.*, 2007). The first successful attempt to numerically observe the general circulation of the atmosphere was conducted by Phillips (1956). The outputs of such models, which are large-scale representations of the atmosphere and its processes, have recently been improved by coupled atmosphere-ocean GCMs (AOGCMs) (Şen and Öztopal, 2013).

The climate scenario or emission scenario is the use of an indicator of what the future may look like over decades or centuries, given a set of assumptions, including land use change and future emissions of greenhouse gases (Ayalew, 2019; Belazreg *et al.*, 2023). GCMs are useful instruments that are often used to research the global climate system for the past, present, and future. Since 1995, scientists from many international institutes have been working to build GCMs to produce dependable and effective models for simulating climate systems (Edwards, 2011). The climate variables of GCMs are provided in grid cell format coverage of the globe (Eyring *et al.*, 2019).

The World Climate Research Programme (WCRP) Working Group on Coupled Modeling (WGCM) has compiled outputs from global climate modeling groups to facilitate climate model experiments under the Coupled Model Intercomparison Project (CMIP). Global climate models (GCMs) play a crucial role in simulating the Earth's climatic conditions.

They serve as vital tools for evaluating the impacts of different radiative forcings on the Earth's climate system, thereby enhancing our understanding of climate change dynamics (Dibaba *et al.*, 2019). For this reason, one of the main applications of GCMs is investigation to improve the understanding and knowledge of the climate system.

GCMs are characterized by uncertainties and the climates of mountain and coastal regions of the world (Fowler *et al.*, 2007). The uncertainties in the GCM simulation could stem from the spatial and temporal coarse resolution nature of the model, the initial model assumption, and the mathematical formulation considered in the model (Ahmadalipour *et al.*, 2018). Regardless of their uncertainty, GCMs are considered the most important tools for future climate projection (Vasiliades *et al.*, 2009). However, GCMs-based future climate variability and trend studies require performance evaluations of GCMs in simulating climate variables (Demessie *et al.*, 2023).

2.3.1. Coupled Model Intercomparison Project Phase 6 (CMIP6)

The Coupled Model Intercomparison Project Phase 6 (CMIP6) features updated versions of models that were part of earlier phases. This latest phase has introduced advanced simulations from state-of-the-art general circulation models (GCMs). Notably, CMIP6 has significantly expanded both the number and scope of experimental simulations, enhancing the extent of climate modeling research (Eyring *et al.*, 2016a). Recent simulations offer a valuable opportunity to assess the Earth's system response to radiative forcing changes throughout the 21st century. The updated models feature enhanced spatial resolution and improved physical parameterizations, leading to more accurate representations of critical Earth system processes, including biogeochemical cycles. Additionally, these models provide better insights into components such as ice sheets, thereby contributing to a more comprehensive understanding of climate dynamics (Stouffer *et al.*, 2017).

The evaluation of CMIP6 simulations over several regions suggests that the model outputs differ from those of earlier CMIP phases (Almazroui *et al.*, 2020). Some studies evaluated CMIP6 GCM historical runs across several parts of the globe, including South America (SA), Brazil, Thailand, Guatemala, and Ethiopia. Using long-term historical runs conducted a preliminary analysis was conducted to assess the performance of CMIP6 over southwestern China (Rivera and Arnould, 2020). The subset of models that most accurately depict the variability in precipitation in this area (Fan *et al.*, 2020) showed that although there was significant variation between the models and regions, the majority of

the CMIP6 models accurately replicated the spatial pattern of the climatological annual mean temperature over the global land surface. Additionally, even though CMIP6 showed less spatial variability than the observations did, it was nevertheless able to reflect the direction of trends in mean global surface temperatures throughout the years 1901 to 1940 (rising), 1941 to 1970 (cooling), and 1971 to 2014 (fast warming), as revealed by the observational data.

2.3.2. GCM performance metrics (statistical metrics)

Statistical metrics are normally used for assessing the differences between model simulations and observed datasets, and each metric can show the overall performance differently for model simulations (Gleckler *et al.*, 2008). Additionally, statistical metrics are often found in comparisons of climate simulation results between GCMs and observed datasets (Kamworapan and Surussavadee, 2019). Continuous statistical metrics have been employed over different study areas to evaluate the performance of precipitation and temperature at different spatial and temporal scales (Nashwan and Shahid, 2020). The continuous statistical indices most commonly employed by most studies are the root mean square error (RMSE), mean error (ME), mean absolute error (MAE), Pearson correlation coefficient (r), and coefficient of determination (R^2), Kling-Gupta efficiency (KGE), Nash Sutcliffe efficiency (NSE), percent bias (PBIAS), RMSE-observation standard deviation ratio (RSR) and mean square error (MSE) (Moriasi *et al.*, 2015).

The RMSE was used to compare the GCMs and reference data, to indicate the magnitudes of the errors in each grid cell. The ME and MAE measure the average magnitude of the error between the rainfall products and the ground-based observations. The major differences between ME and MAE are that ME can yield positive and negative results, whereas MAE only gives positive results (Tan and Santo, 2018). The RMSE, MAE, ME, and MSE values of 0.0 indicate a perfect fit between the temperature products and the observed dataset (Singh *et al.*, 2017). The study used several statistical metrics to evaluate model performance in simulating temperature and rainfall data. The root means square error (RMSE) and mean absolute error (MAE) are considered low when they are less than half the standard deviation of the measured data, indicating their appropriateness for model evaluation. The correlation coefficient (r) and the coefficient of determination (R^2) assess the linear relationship between the observed and simulated data, with R^2 values above 0.5 generally considered acceptable. However, both r and R^2 are sensitive to outliers

and may not effectively capture differences in model predictions. The Kling-Gupta efficiency (KGE) is introduced as a more robust alternative, integrating correlation, bias, and variability, particularly in the context of rainfall data with varying intensities. In contrast, the Nash–Sutcliffe efficiency (NSE) measures the fit of observed versus simulated data against a 1:1 line, with values between 0.0 and 1.0 indicating acceptable performance. The RMSE-observation standard deviation ratio (RSR) standardizes the RMSE, providing a combined error index. Finally, the percent bias (PBIAS) quantifies the tendency of models to overestimate or underestimate observed values, with an optimal value of 0.0 indicating accurate performance. Overall, the literature emphasizes the importance of using multiple statistical criteria for a comprehensive evaluation of model performance in temperature and rainfall simulations. For example, a study by (Alaminie *et al.*, 2021) Included the RMSE, NRMSE, PBIAS, NSE, and R^2 .

2.4. Projection of future climate change

Climate projections are typically presented for a range of plausible pathways, scenarios, or targets that capture the relationships between human choices, emissions, concentrations, and temperature changes. Some scenarios are consistent with continued dependence on fossil fuels, whereas others can be achieved only by deliberate actions to reduce emissions. The resulting range reflects the uncertainty inherent in quantifying human activities (including technological change) and their influence on climate.

2.4.1. Shared socioeconomic pathways (SSPs)

SSPs are climate change scenarios with projected socioeconomic global changes up to 2100 as defined in the IPCC Sixth Assessment Report on Climate Change in 2021. They are used to derive greenhouse gas emission scenarios with different climate policies (Petkovski *et al.*, 2023). SSPs provide narratives describing alternative socio-economic developments. The SSPs can be quantified with various integrated assessment models (IAMs) to explore possible future socioeconomic and climate pathways (Petkovski *et al.*, 2023). The latest scenarios utilized in the CMIP6 and featured in the IPCC Sixth Assessment Report (2021) are grounded in shared socio-economic pathways (SSPs). The most rigorous mitigation scenario aims to meet the Paris Agreement's target of limiting the global temperature rise to well below 2°C, with aspirations to restrict it to 1.5°C. SSP scenarios integrate new narratives about potential societal developments with previous representative concentration pathways (RCPs), which outline greenhouse gas and aerosol

concentration changes over time. The SSPs provide alternative narratives for global growth over the next century, independent of climate policy considerations. Although they do not directly quantify adaptation or mitigation efforts, they highlight the complexities and challenges of implementing such strategies, which are influenced by many factors such as population dynamics, regional cooperation, and technological advancements.

The Shared Socioeconomic Pathways (SSPs) were created through a collaborative community effort over several years. They outline global trends that present various challenges for climate change mitigation and adaptation. A conceptual framework was established to integrate the SSPs with Representative Concentration Pathways (RCPs) in climate simulations, facilitating comprehensive research on climate-related issues. This integration aims to enhance understanding and inform strategies for addressing climate change effectively (Van Vuuren *et al.*, 2014; O'Neill *et al.*, 2014; Kriegler *et al.*, 2014). The specific content of the SSPs was developed next (O'Neill *et al.*, 2016). These comprise five alternative narratives that describe the main characteristics of the pathways in qualitative terms (Shao *et al.*, 2015) as well as quantitative descriptions for key elements including population (Kc and Lutz, 2014), economic growth (Dellink *et al.*, 2017), and urbanization (Jiang and O'Neill, 2017).

The Shared Socioeconomic Pathways (SSPs) outline various potential futures for society in the context of climate change and policy. SSP1 and SSP5 present optimistic scenarios characterized by significant investments in education and health, alongside rapid economic growth and effective institutions. However, SSP5 is marked by a reliance on an energy-intensive, fossil-fuel-based economy, while SSP1 emphasizes a transition towards sustainable practices. In contrast, SSP3 and SSP4 depict more pessimistic trajectories, with minimal investment in education and health, a rapidly growing population, and escalating inequalities. SSP3 focuses on regional security priorities, while SSP4 highlights severe inequalities both within and between countries, resulting in heightened vulnerability to climate change impacts. SSP2 represents a middle-ground scenario, suggesting that societal trends will follow historical patterns without significant changes. Overall, the SSPs illustrate a spectrum of possible futures, influenced by varying levels of investment in human development and differing approaches to sustainability and inequality (O'Neill *et al.*, 2016).

Five distinct SSPs were developed, each of which is based on varying assumptions regarding human development indicators such as population growth, education levels, urbanization, GDP, economic growth, technological progress, and emission patterns. These SSPs are intended to complement an updated version of the RCPs, enhancing the understanding of future climate scenarios (Riahi et al., 2017). The new representative concentration pathways (RCPs) establish stabilized radiative forcings, which represent the balance between incoming solar radiation and outgoing energy from Earth by the end of the century. This balance informs the necessary climate change policies for achieving specific shared socioeconomic pathways (SSPs). The SSPs are grounded in five distinct narratives that outline various socioeconomic trajectories: sustainable development, regional rivalry, inequality, fossil-fueled development, and middle-of-the-road development. To ensure accurate future climate projections, it is essential to evaluate and validate climate models against reliable observational data, which helps assess their skill and uncertainty. The SSPs are based on five narratives that describe different levels of socioeconomic development: SSP1, SSP2, SSP3, SSP4, and SSP5, each representing a unique scenario for future socioeconomic development (Riahi et al., 2017).

SSP1 (Sustainability): This scenario reflects the low end of the range of future forcing pathways in the IAM literature and updates the RCP2.6 pathway. SSP1 was chosen because it has substantial land use change, particularly an increase in global forest cover. This scenario is particularly relevant from the Integrated Assessment Model (IAM) and Impact Adaptation Vulnerability (IAV) perspectives, as it presents a combination of low vulnerability and minimal challenges for both mitigation and adaptation efforts, alongside a low-forcing signal (O'Neill *et al.*, 2016). According to Van Vuuren et al. (2008), describe the possible developments in global energy use and production, land use, emissions, and climate changes following the SSP1 scenario. The results show that a combination of resource efficiency, preferences for sustainable production methods, and investment in human development could lead to a strong transition towards a more renewable energy supply, less land use, and lower anthropogenic greenhouse gas emissions in 2100 than in 2010, even in the absence of explicit climate policies.

The world transition towards sustainability is characterized by a commitment to inclusive development that adheres to environmental limits. There is an observable improvement in the management of global commons, which refers to shared resources that require

collective governance. Investments in education and health are accelerating demographic transitions, indicating a shift in population dynamics that supports sustainable development. Furthermore, the focus of economic growth is developing from simple financial metrics to a broader consideration of human well-being, suggesting a more holistic approach to assessing progress. This shift is accompanied by a concerted effort to reduce inequality within and between countries, reflecting a growing recognition of the importance of equitable development. Finally, consumption patterns are changing, with a trend toward lower material growth and reduced resource and energy intensity, aligning with sustainability goals (Rogelj *et al.*, 2018).

SSP2 (Middle of the Road): This scenario represents the medium part of the range of future forcing pathways and updates the RCP4.5 pathway. It is the middle challenge to mitigation and adaptation. The Shared Socioeconomic Pathway 2 (SSP2) was selected due to its moderate land use and aerosol pathways, making it less extreme compared to other SSPs. This choice is significant for the Detection and Attribution MIP (DAMIP) and the Decadal Climate Prediction Project (DCPP), as it aligns with their focus on intermediate societal vulnerability and forcing levels, thereby providing relevant insights for Integrated Assessment Models (IAM) and Impacts, Adaptation, and Vulnerability (IAV) research (Van Vuuren *et al.*, 2017).

The world follows a path in which social, economic, and technological trends do not shift markedly from historical patterns. Development and income growth are characterized by significant disparities among countries, with some countries achieving notable progress while others lag. Efforts by global and national institutions to meet sustainable development goals are ongoing but face challenges, resulting in slow advancement. Although there are instances of improvement, environmental systems continue to degrade, and there is a general decline in resource and energy consumption intensity. Global population growth is projected to be moderate and stabilize in the latter half of the century. Income inequality remains a persistent issue, with only gradual improvements and challenges related to societal and environmental vulnerabilities continuing to pose significant obstacles (Koomey *et al.*, 2019).

SSP3 (Regional rivalry): It is a high challenge to mitigation and adaptation. This scenario represents the medium to high end of the range of future forcing pathways. It fills a gap in CMIP5 forcing pathways that are particularly important because it represents a forcing

level that is similar to forcing in the SSP2 baseline scenario as well. Baseline scenarios are crucial for Integrated Assessment and Vulnerability (IAV) studies focused on quantifying "avoided impacts." These studies require a comparison between impacts in mitigation scenarios and those in unmitigated baseline scenarios (Bukovsky *et al.*, 2021).

The Shared Socioeconomic Pathway 3 (SSP3) has been selected due to its characteristics, including significant land use changes, particularly a reduction in global forest cover, and elevated non-CO₂ forcing emissions, especially sulfur dioxide (SO₂). This scenario is integral to the Land Use Model Intercomparison Project (LUMIP) and the Aerosol Chemistry Model Intercomparison Project (AerChemMIP), as it addresses critical questions regarding the sensitivity of regional climates to land use changes and aerosol emissions (O'Neill *et al.*, 2020). Furthermore, SSP3 is particularly relevant for Integrated Assessment Models (IAM) and Impact Adaptation Vulnerability (IAV) studies because it reflects a combination of high societal vulnerability and substantial forcing, making it a significant scenario for future climate impact assessments (Van Vuuren *et al.*, 2017).

This scenario identifies four key features of the scenario under discussion. Firstly, it highlights the significant costs associated with achieving ambitious climate targets. Secondly, it notes a medium-high forcing level in the reference scenario. Thirdly, there are high emissions of air pollutants, which warrant further analysis regarding their impacts and potential policy synergies. Lastly, the scenario indicates a decrease in forest area due to the rapid expansion of cropland and pasture land. Overall, the SSP3 scenario serves as a valuable framework for Integrated Assessment Models (IAM) and analyses related to impact, adaptation, and vulnerability (IAV), reflecting a pessimistic outlook influenced by socioeconomic and environmental factors. The insights derived from this scenario can enhance understanding of large-scale land use changes and their implications for environmental studies (Fujimori *et al.*, 2017).

The resurgence of nationalism, alongside concerns regarding competitiveness and security, has led countries to prioritize domestic and regional issues. This shift in focus has resulted in policies increasingly centered on national and regional security, often at the expense of broader development initiatives. As nations strive for energy and food security, investments in education and technological advancement have diminished. Economic growth remains sluggish, characterized by material-intensive consumption patterns, whereas social inequalities either persist or worsen. Population dynamics reveal low

growth in industrialized nations and high growth in developing countries. Additionally, the lack of international emphasis on environmental issues contributes to significant environmental degradation in certain regions (Koomey *et al.*, 2019).

SSP4 (Inequality): It is a low challenge to mitigation and a high challenge to adaptation. This scenario falls in the range of medium forcing pathways and updates the RCP6.0 pathway. SSP4 was chosen because together with SSP4-3.4 it could be used to investigate differences in impacts across global average forcing pathways even if the regional climate effects of land use and aerosols turn out to be strong. The SSP4 scenario highlights a growing divide between high-income and low-income communities, with the former experiencing continued prosperity and the latter facing limited economic growth, leading to increased inequalities. High-income groups, well-connected globally, are driving up demand for energy and food, with a notable shift towards electrification through nuclear and renewable sources. The impact of carbon pricing in this scenario varies by region, revealing differing responses to mitigation efforts. Additionally, the SSP4 mitigation strategies are marked by afforestation in high-income areas, contrasting with deforestation trends in low-income regions (Calvin *et al.*, 2019).

The growing inequalities in human capital investment, economic opportunity, and political power contribute to stratification within and between countries. This disparity results in a widening gap between societies engaged in knowledge and capital-intensive sectors and those reliant on low-tech, labor-intensive economies. As social cohesion diminishes, the likelihood of conflict and unrest increases. In the high-tech economy, technological development is robust, while the energy sector sees a diversification of investments, balancing carbon-intensive fuels and low-carbon energy sources. Environmental policies tend to prioritize local issues, primarily those benefiting middle and high-income areas (Shafeeqe and Luo, 2021).

SSP5 (Fossil-fueled development): This scenario represents the high end of the range of future pathways in the IAM literature and updates the RCP8.5 pathway. SSP5 was chosen for this forcing pathway because it is the only SSP scenario with emissions high enough to produce a radiative forcing of 8.5 W m^{-2} in 2100. The SSP5 scenario has rapid economic growth, very high levels of fossil fuel use, a doubling of food demand, and a tripling of energy demand and greenhouse gas emissions over the century, marking the upper end of the scenario literature in several dimensions. The SSP5 scenario provides a useful

reference point for climate impact and adaptation analysis at high levels of future climate change although climate policy in SSP5 could also significantly reduce emissions (Kriegler *et al.*, 2017).

It is a high challenge to mitigation and a low challenge to adaptation. This world places increasing trust in competitive markets, innovation, and participatory societies as essential drivers for sustainable development. It highlights the increasing integration of global markets and significant investments in health, education, and institutions aimed at enhancing human and social capital. However, this economic and social development is accompanied by the exploitation of fossil fuel resources and the adoption of resource-intensive lifestyles, contributing to rapid economic growth in the world. The text also mentions that while the global population is expected to peak and then decline in the 21st century, local environmental issues, such as air pollution, are being effectively managed (Shafeeqe and Luo, 2021).

2.5. Empirical literature on historical climate trends and variability

Studies conducted by Zenebe *et al.* (2011) revealed that Ethiopian agricultural production is predicted to decline by as much as 6% to 32.5% as a consequence of climate change impacts between 2030 and 2050 compared with the current outputs which will make the country dependent on food aid. According to Shawul *et al.* (2020) analyzed extreme rainfall indices and long-term rainfall variability in the upper Awash Basin, which showed a high spatial and temporal variability in rainfall and exhibited lower rainfall concentration in the basin. Previous studies have shown that climate variability and change have significantly affected the Ethiopian economy, particularly in the agricultural sector, which is rainfall-dependent and highly dominated by traditional agricultural practices (Mersha and van Laerhoven, 2018b).

A study conducted by Wagesho *et al.* (2013) on the annual and temporal variability of rainfall over Ethiopia revealed that the trend of annual and *Kiremt* rainfall significantly decreased in northern and western parts of Ethiopia, whereas the annual rainfall distribution tended to increase in the eastern parts of the country. A few studies conducted in the region have revealed the effects of rainfall variability on agricultural activities such as crop damage due to erratic rainfall, floods, drought occurrence, and incidences of pests and diseases (Eshetu *et al.*, 2020). Similarly, Wodaje *et al.* (2016) reported that there was considerable spatial rainfall variability in the region. Information on rainfall anomalies,

seasonal variations, and extreme rainfall and temperature trends across the study area is critically lacking. Undertaking trend analysis and variability of rainfall patterns is vital for the accurate prediction of climate extremes and for taking corresponding adaptation and mitigation measures (Field and Barros, 2014).

Various studies have shown declining trends in annual rainfall patterns in different parts of the country, whereas other studies have shown increasing rainfall trends (Benti and Abara, 2019, Shawul et al., 2020). Several studies on key climate trend indicators have also been conducted in Ethiopia by (Jury and Funk, 2013; Taye and Willems, 2012; Conway *et al.*, 2004; NMAE, 2007b; McSweeney *et al.*, 2008; Dereje *et al.*, 2012; Tesso *et al.*, 2012). Fewer differences in temporal and spatial scales were analyzed; these studies reported consistent warming trends in the maximum and minimum temperatures over the past few decades in Ethiopia. According to NMI (2007a), there was an increase of 0.1°C per decade for maximum temperature and 0.25 to 0.37°C per decade for minimum temperature trends.

According to the Ethiopian National Meteorological Institute (NMI, 2001) study of 42 meteorological stations, the country has experienced both dry and wet years over the last 50 years. A trend analysis of annual rainfall revealed that unpredictable and irregular rainfall patterns affected both crop and livestock production trends in the Southern Nation Nationalities and Peoples of Ethiopia (Belay *et al.*, 2021b). Araro *et al.* (2020) reported that changes in temperature trends within highlands and lowlands were both positive and negative, respectively. Asfaw *et al.* (2018) conducted a time series analysis of the rainfall amount and temperature in northern Ethiopia. The results revealed an increasing trend in drought years, with decreasing trends in both *Belg* and *Kiremt* rainfall patterns, whereas the temperature changes tended to increase. In a study conducted (Abebe, 2017), a decreasing rainfall trend has been observed in Ethiopia since the 1990s, and this decline has considerably affected agricultural production as well as water availability in the country.

2.6. Empirical literature on the evaluation of climate models

Performance evaluation and the selection of appropriate GCMs are vital. The effectiveness of eight selected CMIP6 GCMs in simulating the annual and seasonal rainfall observed over the Ethiopian Upper Blue Nile Basin from 1988 to 2014 was assessed (Mohammed,

2024a). Based on observational data from 1961 to 2014, the ability of 20 CMIP6 GCMs was evaluated to simulate surface air temperature climatology and variability over the Tibetan Plateau (Hu *et al.*, 2022). According to Alaminie *et al.* (2021), out of the 12 employed CMIP6 climate models, MRI-ESM2-0 for temperature and BCC-CSM-2MR for precipitation were selected based on their highest performance.

Based on the result of (Ayugi *et al.*, 2021) reported the mean surface temperatures via 13 CMIP6 climate models. Among those models, five performed best: FGOALS-g3, HadGEM-GC31-LL, MPI-ESM2-LR, CNRM-CM6-1, and IPSL-CM6A-LR. The best performing models identified in the study include GFDL-ESM4, CanESM5, CESM2-WACCM, MRI-ESM2-0, NorESM2-LM, UKESM1-0-LL, and CNRM-CM6-1 (Ngoma *et al.*, 2022). Among the 19 models, the three best models that simulated the temperature in Southwestern China were ACCESS-CM2, CMCC-CM2-SR5, and CMCC-ESM5 (Chengxiu *et al.*, 2022).

2.7. Empirical literature on the projection of future climate change

The Earth's climate is projected to be warmer and more variable from time to time (Collins *et al.*, 2016). According to the Intergovernmental Panel on Climate Change (IPCC), the average surface temperature of the world is expected to increase by 1.8°C to 4.0°C at the end of the twenty-first century (Bates, 2008). Summer precipitation is projected to increase at the end of the twenty-first century (Chen *et al.*, 2020). Increasing temperature is predicted to disturb the hydrologic cycle worldwide (Abebe and Kebede, 2017).

Based on the results of Benti and Abara (2019), a study in the Masha district in southern Ethiopia reported that the annual rainfall is expected to significantly decline in the next 35 years, whereas the annual mean temperature will increase. In the next 100 years, the average temperature in Ethiopia is projected to increase from 23.08°C from 1961-1990 to 26.92°C from 2070-2099 (WB, 2008). Jury and Funk (2013) reported similar declining trends in the southwestern region, and they further projected these trends to continue until 2050.

A study conducted by Alaminie *et al.* (2021) revealed that MRI-ESM2-0 for temperature and BCC-CSM2MR for precipitation were selected based on their highest performance. The MRI-ESM2-0 mean annual maximum temperature for the near (long)-term period

increases by 1.1 (1.5) °C, 1.3 (2.2) °C, 1.2 (2.8) °C, and 1.5 (3.8) °C under the four SSPs. On the other hand, the BCCCSM-2MR precipitation projections show a statistically insignificant increasing trend for the near (long)-term periods of 5.9 (6.1) %, 12.8 (13.7) %, 9.5 (9.1) %, and 17.1 (17.7) % under the four SSP scenarios. Relative to the reference period 1995 to 2014, the winter and summer precipitation in northern China is projected to increase at the end of the 21st century under SSP5-8.5, with a larger increase in the highest-ranked mean model ensemble projection compared to those in the all-mean model ensemble and lowest ranked mean model ensemble projections (Yang *et al.*, 2023).

Chapter Three: MATERIALS AND METHODS

3.1. Description of the study Area

Location: The study where, conducted in East Gojjam Zone (14,010km²) Amhara Region of Ethiopia 10.0°19' and 11.0°0' N latitude and 36. 0°-39° 0' E longitude. Debre Markos is the town of the zone and is 255 km from the Amhara Region of Bahir Dar city and 300 km from Addis Ababa. The zone is bordered by different neighbors in the south by the Oromia Region, on the west-by-west Gojjam, on the north by South Gondar, and the east by South Wollo; the bend of the Abay River defines the Zone's northern, eastern and southern boundaries (EGZAO, 2022).

The topography of the Zone is characterized by a complex topography made up of hills, rivers, valleys, and mountains. From Motta to Dejen midland plains, with several ups and downs, and from Machakel to Gozamen are the midland and slopping lands. Its elevation ranges from 800 to 4200 meters above sea level (m.a.s.l.). The average annual rainfall ranges from 800 to 1800 mm, and the mean annual temperature ranges between 7.5°C and 27°C (EGZAO, 2022).

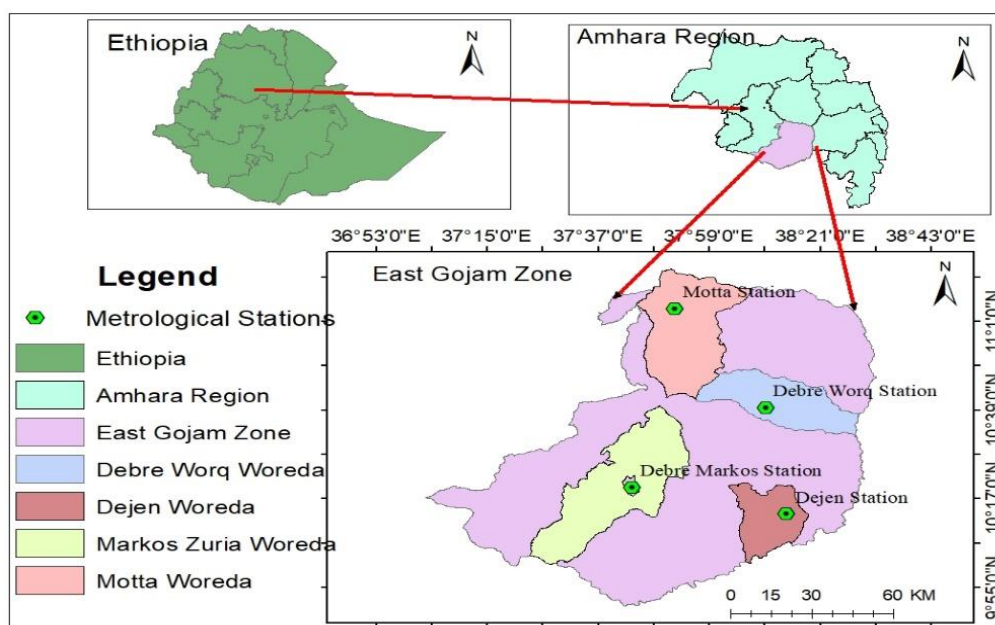


Figure 3.1. Map of the study area.

Climate: In the Zone from Dejen to Motta, the area is characterized by a lower Weiina dega, and around Debre Markos, it is a lower dega agroclimatic zone. It receives average annual rainfall ranging from 800 to 1800 mm, and the mean annual temperature of the area ranges between a maximum of 29.0 °C and a minimum of 10.0 °C (EGZAO, 2022).

Soil types: The major types of soil in the East Gojjam Zone are, especially in Motta to Dejen, vertosols, and from Machakel to Gozamen nitisols. These types of soil are composed of organic and inorganic materials and are suitable for agricultural activities and other forms of economic activities (EGZAO, 2022).

Land use systems: The total area of the zone is estimated at 14,010 sq. km which is equivalent to 1.40 million hectares. However, the data from the Zone Office of Agriculture indicated the total land area at 1.46 million hectares which has been characterized by different land use patterns. In the Zone 45% of the total land is arable, 8% is irrigable arable land, 13% is forest land, 11% is grazing land, and 21% is barren land. The remaining land cover type is less than 2% (EGZAO, 2022).

3.2. Methods of data collection and sources

3.2.1. Observed and CMIP6 GCM datasets

To evaluate the effectiveness of CMIP6 GCMs, historical rainfall and temperature data collected from seven meteorological stations from 1984 to 2014 was obtained from the North West Amhara Meteorological Institute (NWAMI). The dataset includes daily observations of rainfall, maximum temperature, and minimum temperature over a 31-year baseline period. The choice of the three climatic parameters (rainfall, Tmax, and Tmin) was based on their influential role in the agricultural, forestry, health, and other sectors. In total, there are seven meteorological stations within the study area (EGZ), but only four-gauge stations were selected for detailed analysis such as Motta, D/Work, Dejen, and D/Markos stations. The selection of meteorological stations for data analysis in the East Gojjam Zone was based on the following criteria:

- **Completeness of Data:** The stations with minimal missing data were prioritized to ensure a consistent dataset.
- **Availability of Long-Term Records:** Stations with a long-term history of climate data were chosen to facilitate trend analysis and model validation.

- **Adherence to WMO Standards:** The stations needed to comply with the World Meteorological Organization (WMO) standards for reliable data collection and reporting.
- **Representation of Diverse Topography:** The stations were selected to represent the varied topography of the East Gojjam Zone, including hills, valleys, and plains, ensuring that the data captured different regional climate characteristics.
- **Minimal missing observations:** Only stations with a high number of valid observations and minimal gaps were selected for detailed analysis.

This structured approach ensures that the data used for model simulations are robust and reliable, facilitating accurate climate analysis in the region (Getachew, 2018a). It is a standard practice that a minimum of 30 years of data are required to conduct climatological studies (Wodaje *et al.*, 2016). In this study, the observed data from 1984 to 2014 were used to align the climate models from the CMIP6 GCMs.

To evaluate the performance of CMIP6 GCMs, the daily data with the variant label r1i1p1f1 were sourced from the Earth System Grid Federation (ESGF) database, which can be accessed at (<https://esgf-node.llnl.gov/search/cmip6>), which specifically targets variables such as rainfall (pr), maximum temperature (Tmax), and minimum temperature (Tmin). To ensure consistency in model performance evaluation, the first realization of the ensemble (r1i1p1f1) was utilized for both historical and future model runs, which helps minimize bias. The historical data duration ranges from 1984 to 2014, with some models encompassing 2015. The researcher utilized specific parameters to filter the data, including the source ID for GCMs, variable types, frequency of data collection, and experimental IDs for both historical and future scenarios (SSPs) with shared socioeconomic pathways. Each model variant labels were employed to identify individual ensemble members, which were categorized based on factors such as realizations, initialization schemes, different physics, and forcing indices. This structured approach facilitated a comprehensive analysis of climate trends over the specified period (Papalexiou *et al.*, 2020).

This study focuses on future climate projections and trend analysis via the data from the CMIP6 Earth System Grid Federation (ESGF) database. Various scenarios, including low forcing (SSP1-2.6), medium forcing (SSP2-4.5), medium to high forcing (SSP3-7.0), medium forcing (SSP4-6.0), and strong forcing (SSP5-8.5) are examined. The future

projections were analyzed from 2015 to 2100. This study specifically focuses on the years from 2031 to 2100 for future projections, aligning with the timeframe of gridded observation datasets. Additionally, the study summarizes essential information regarding the selected CMIP6 models, including model names, institutions, and atmospheric resolutions, providing a comprehensive overview of the datasets used in the analysis. In the present study, for each station above 31 years, gauge station data were used to investigate the recent CMIP6 model evaluation, projections of future climate change, trends, and variability in rainfall and temperature across the study area.

Table 3.1. Information on the eight CMIP6 models.

Number	CMIP6 Model	Institute	Country	Resolution (lon. by lat. in degrees)	Variant label
1	BCC-CSM2-MR	Beijing climate center	China	1.1°×1.1°	r1i1p1f1
2	FGOLAS-g3	University of Chinses Academy of sciences	China	2°×2.3°	r1i1p1f1
3	GFDL-CM4	Geophysical Fluid Dynamics Laboratory	USA	2.5°×2.0°	r1i1p1f1
4	MIROC6	Japan Agency for Marine-Earth Science and Technology	Japan	1.4°×1.4°	r1i1p1f1
5	MPI-ESM1-2-HR	Max-Planck-Institute fur Meteorology	Germany	0.9°×0.9°	r1i1p1e1
6	MPI-ESM1-2-LR	Max-Planck-Institute fur Meteorology	Germany	1.9°×1.9°	r1i1p1f1
7	MRI-ESM2-0	Metrological Research Institute	Japan	1.1°×1.1°	r1i1p1f1
8	NorESM2-MM	Norwegian Climate Service Center	Norwegian	2.5°×1.9°	r1i1p1f1

3.3. Method of data analysis

Many inconsistencies (missing data) exist in ground station data across most countries in Africa, both temporally and spatially (Sylla *et al.*, 2012). Missing data in the climate datasets were addressed through preliminary data quality control measures to detect errors (such as inconsistencies in temperature values). The analysis of long-term climate data from various stations revealed that the dataset was incomplete, requiring preliminary data quality control measures. These measures aimed to identify and rectify errors, such as minimum temperatures exceeding maximum temperatures or where both values were recorded as empty. To address the gaps in the dataset, the multivariate imputation by chained equations (MICE) algorithm was employed as a proxy method for imputing the missing climate data. This approach ensures a more reliable dataset for further analysis and research (Jing *et al.*, 2022), which is available via R statistical software. The Multivariate Imputation by Chained Equations (MICE) algorithm was selected for imputing missing values due to its ability to:

Impute missing data with high accuracy: MICE use observed data from all stations as predictors to estimate missing values, improving the reliability of the dataset.

Account for uncertainty: It provides multiple predictions for each missing value, allowing for the consideration of uncertainty in the imputation process.

Handle complex missing data: MICE can impute missing values in a multivariate dataset, making it suitable for the climate data with multiple variables (temperature, rainfall) and missing values.

Better than other methods: Compared to simpler imputation methods like inverse distance weighting (IDW) and multiple linear regression (MLR), MICE provide more accurate imputations, especially in cases of missing data across multiple stations or time periods (Turrado *et al.*, 2014). Outliers in daily rainfall and daily maximum and minimum temperatures were also detected via the quality control procedure RClimDex 1.3 (Song *et al.*, 2022). This study evaluated the historical simulations from seven CMIP6 global climate models focusing on rainfall data alongside six GCMs for temperature data. Performance evaluations and projections were conducted for these models from 1984 to 2014 and 2015 to 2100, considering the availability of observed datasets. A study by (Babaousmail *et al.*, 2023) evaluated the model performance of 15 CMIP6 GCMs, the study period covers from 1980 to 2014. Based on the availability of daily data and the model's best performance, the GCMs were selected in various regions of Ethiopia (Jury,

2015; Alaminie *et al.*, 2021, Gashaw *et al.*, 2024). The models were also chosen because they had been used more widely in various regions of Ethiopia in their previous version (CMIP5) (Jury, 2015; Worku *et al.*, 2018a). For example, BCC-CSM2-MR, MPI-ESM1-2-LR, and MRI-ESM2-0 were selected because of their best model performance in simulating the rainfall climatology of the Southern Bale Eco-Region (Gashaw *et al.*, 2024). The selection of FGOLAS-g3, MIROC6, MPI-ESM1-2-HR, and NorESM2-MM was based on their superior performance in rainfall and temperature projections for the South Asian countries (Almazroui *et al.*, 2020).

In a climate model, there is bias when if the statistical characteristics of projected values vary from the observed climate for the same period (Bakker and Van Den Hurk, 2011). Climate model bias is also defined as the large deviations between the observed and simulated output data based on the statistical findings (Wörner *et al.*, 2019). Accordingly, all statistical properties of the simulated values of the climate model output, like the mean, quartile, and standard deviation of a certain element are potentially biased. Therefore, different bias correction methods were applied to climate model outputs by other researchers at different times (Adera and Alfredsen, 2020).

In this study, to perform bias correction and extraction of GCM data for the historical period (1984 to 2014) and for future periods (2015 to 2100), **CMhyd** software was used. Under CMhyd, there are five types of rainfall bias correction methods: linear scaling, delta-change correction, precipitation local intensity scaling, power transformation of precipitation, and distribution mapping of precipitation bias correction methods. For temperature, there are three types of bias correction methods: linear scaling, delta-change correction (additive), and variance scaling. In this study, distribution mapping (DM) was applied for rainfall and temperature to enhance the accuracy of the data. Similarly, (Gurara *et al.*, 2023) distribution mapping (DM) bias correction method was applied, which better transfers the observed precipitation and temperature statistics to the raw RCM CORDEX-Africa RCP4.5 and RCP8.5 climate scenarios in the upper Wabe Shebelle basin Ethiopia.

CMhyd software is better at transferring observed rainfall and temperature statistics to raw GCM outputs across various shared socioeconomic pathways (SSPs), including SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 (Piani *et al.*, 2010). The bias correction was conducted through simulated results from these SSPs alongside data from local

meteorological stations in the East Gojjam Zone, which included Motta, D/Work, Dejen, and D/Markos. Ultimately, the study identified the best-performing CMIP6 models for analyzing historical climate trends and future projections for the specified stations.

3.3.1. Historical rainfall and temperature trend analysis

The nonparametric Mann–Kendall test is commonly employed to detect monotonic trends in the time series of hydrologic variables. The modified Mann-Kendall (MK) trend test is a prominent method for analyzing historical and future climate trends through time series data. This statistical approach is particularly effective in detecting trends in climate parameters such as rainfall and temperature. The Mann–Kendall trend test is recognized for its ability to identify monotonically increasing or decreasing trends, making it a valuable tool in climate research. Mann–Kendall (S) statistics are nonparametric statistical tests used for detecting trends in climatic parameters, and have several advantages over parametric tests because they are simple, robust, accommodate missing data, and insensitive to outliers (Ranasinghe and Piyadasa, 2017). It does not require the data to be normally distributed; it is appropriate for analyzing trends in data over time and has low sensitivity to abrupt breaks due to inhomogeneous time series (Ofgeha and Abshire, 2021). For this study, a statistical tool called (modified) R package software was used.

In meteorological records, the appearance of outliers is common; however, the non-parametric Mann–Kendall test is capable of fixing this problem because its statistic is based on the (+or-) signs rather than the values of the random variable, and therefore, the trends are less affected by the outliers (Birsan *et al.*, 2005). The result of the MK trend test may contain an error, if autocorrelation exists in the time series data. To avoid this problem, a pre-whitening procedure was performed to remove the autocorrelation in the time series. Autocorrelation or lagged correlations assess whether a time series depends on its past. However, if no significant level of serial autocorrelation at all lags, it needs to be performed without any modification. Following the serial autocorrelation test, the MK test from the Z-value and trend from Sen's slope (β) estimation were computed based on monthly, seasonal, and annual rainfall and temperature data. Therefore, the autocorrelation coefficient can be calculated through R software ACF () syntax. The ACF (X. lag. max=1, plot=FALSE) to a series x automatically calculates the lag-1 autocorrelation. The line gives the values beyond which the autocorrelations are significantly different from zero.

To identify the existence of significant autocorrelation within the time series calculated as follows:

$$\frac{-1-1.645*(N-2)^{0.5}}{N-1} \leq R \leq \frac{1+1.645*(N-2)^{0.5}}{N-1} \dots \text{Equation (1)}$$

Where N is the number of years and R is the autocorrelation coefficient.

The Mann–Kendall statistic (S) is the overall score for the time series data, which are then compared to a critical value to test whether the trend in rainfall or temperature is increasing, or decreasing or if no trend can be observed. The strength of the trend is proportional to the magnitude of the Mann–Kendall statistic. $\text{Sgn}(X_j - X_k)$ is an indicator function that results in values of 1, 0, or -1 according to the significance of $X_j - X_k$ where $j > k$, the function was calculated as follows:

The Mann–Kendall statistic (S) of the series x is given by test (Mann, 1945, Kendall, 1962).

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_j - X_i) \dots \text{Equation (2)}$$

where x_j and x_i are the annual values in years j and i , $j > i$, respectively, and

$$\text{sgn}(X_j - X_i) = \begin{cases} 1 & \text{if } X_j - X_i > 0 \\ 0 & \text{if } X_j - X_i = 0 \\ -1 & \text{if } X_j - X_i < 0 \end{cases} \dots \text{Equation (3)}$$

A score of $S = +1$ is awarded a positive value of S, indicating that the value in a time series has an increasing trend, whereas a score of $S = -1$ is awarded a negative value of S, indicating a decreasing trend; if the S value is 0, there is no trend. It is necessary to compute the probability associated with S and the sample size, n, to statistically quantify the significance of the trend.

The variance associated with S is calculated from (Mann, 1945, 1975).

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{k=1}^m t_k(t_k-1)(2t_k+5)}{18} \dots \text{Equation (4)}$$

where m is the number of tied groups and t_k is the number of data points in group k.

In cases where the sample size $n > 10$, the test statistic Z is calculated as follows:

$$Z = \frac{S-1}{\sqrt{\text{Var}(S)}} \text{ if } S > 0 \dots \text{Equation (5)}$$

$$Z = 0 \text{ if } S = 0 \dots \text{Equation (6)}$$

$$Z = \frac{S+1}{\sqrt{\text{Var}(S)}} \text{ if } S < 0 \dots \text{Equation (7)}$$

If the value of Z is negative, the trend is said to be a decreasing trend, whereas if the value of Z is positive, the trend is said to be an increasing trend. If the absolute value of $|z|$ is

greater than the confidence limit (1.96), there is no significant trend. If the absolute value of $|z|$ is less than the confidence limit (1.96), there is a significant trend. Additionally, if the p-value is greater than the level of significance at $\alpha=0.05$, there is no trend. However, if the p-value is less than the level of significance at $\alpha=0.05$, there is a significant trend. In this study, the desired value of α is 0.05, which indicates the level of confidence (Getachew, 2018b).

Theil Sen's slope estimator: was used to analyze the magnitudes from the mean of variation. It is an alternative, more robust, nonparametric estimate of the slope of a time series. In the nonparametric statistical tool, the magnitude of a trend that exists in the time series was estimated by a slope estimator (Hirsch *et al.*, 1982). β is the robust estimate of the trend magnitude. In other words, the slope estimator (β) is the median over all possible combinations of pairs for the whole dataset. A positive value of β indicates an 'upward trend', whereas a negative value of β indicates a 'downward trend' (Karpouzou *et al.*, 2010). During the computation of Sen's slope, all sets of slopes (dk) are calculated via each pair of X_i and X_j via Equation (5). The Sen slope (β_1) is subsequently calculated as the median of all slopes, dk , via Equation (6) (Pohlert, 2018). Each set of slopes (dk) is calculated as follows:

$$dk = \frac{x_j - x_i}{j - i} \dots \dots \dots \text{Equation (8)}$$

The Sens Slope (β_1) can be calculated by

$$\beta_1 = \text{median}(dk) = \text{median} \left(\frac{x_j - x_i}{j - i} \right) \dots \dots \dots \text{Equation (9)}$$

where i and j are indices for values of the variable X , for all $1 \leq i < j \leq n$.

3.3.2. Variability analysis of rainfall data from 1984 to 2014

Among methods of climate variability measures: the changes of historical (observed) climate variability are measured through different statistical analysis tools or techniques which include: coefficient of variation (CV), rainfall anomaly index (RAI), standardized precipitation index (SPI), and precipitation concentration index (PCI) (Hänsel *et al.*, 2016; Asfaw *et al.*, 2018; Esayas *et al.*, 2019). These statistical tools were calculated through the R software ("precintcon" R package).

Coefficient of variation (CV): serves as a significant statistical tool for analyzing climate variability, particularly in understanding how individual data points deviate from the mean. In this context, CV was employed to assess both seasonal and annual variations in

rainfall and temperature patterns. A higher CV value indicates greater spatial variability, whereas a lower value suggests less variability. This study focused on meteorological records from the Motta, D/Work, Dejen, and D/Markos Stations and examined the monthly, seasonal, and annual variations in rainfall and temperature data. This CV has been widely used by many scholars for the analysis of climatology data (Issahaku *et al.*, 2016). The classification of rainfall variability is based on the coefficient of variation (CV), as outlined by (Kassie, 2014). A CV of less than 20% signifies low variability in rainfall, a CV ranging from 20% to 30% indicates moderate variability, the CV between 30% and 40% represents high variability, and a CV from 40% to 70% indicates very high variability. Finally, a CV greater than 70% denotes extremely high variability. Hence, this classification illustrates that the higher the value of the CV is, the greater the variability of rainfall in the study area; conversely, a lower CV indicates less variability. The value of the CV can be calculated via:

$$CV = \frac{S}{\bar{X}_i} \times 100 \dots \dots \dots \text{Equation (10)}$$

Where CV is the coefficient of variation, S is the standard deviation and $\bar{X}_i$ is the mean of precipitation during the recording period.

The standardized rainfall anomaly index (SRAI): was used to calculate the negative and positive anomalies of rainfall fluctuations in a certain region and it was used to analyze the frequency and intensity of the precipitation. It has also been calculated to determine the dry and wet years on the records and is used to assess the frequency and severity of droughts (Alemu and Bawoke, 2020). This method helps to identify the drought period by determining the dry and wet years of the recording period (Asfaw *et al.*, 2018; Gleixner *et al.*, 2017). This index is calculated as follows:

$$Z = \frac{Xi - \bar{X}_i}{\sigma} \dots \dots \dots \text{Equation (11)}$$

where **Z** is the rainfall anomaly; **xi** is the annual rainfall for the historical record; $\bar{X}_i$ is the mean of the annual rainfall, and σ is the standard deviation of the annual rainfall for the historical observation of the time series. The SRAI value is classified as extremely wet ($Z > 2$), very wet ($1.5 \leq Z \leq 1.99$), moderately wet ($1 \leq Z \leq 1.49$), almost normal ($-0.99 \leq Z \leq 0.99$), moderately dry ($-1.49 \leq Z \leq -1$), very dry ($-1.99 \leq Z \leq -1.5$), and extremely dry ($Z \leq -2$) (Funk *et al.*, 2015).

The precipitation concentration index (PCI): was used to evaluate the distribution of annual rainfall. The PCI is used to indicate the hydrological risk of flood and drought events in the study area (De Luis *et al.*, 2000). It can be calculated as:

$$PCI = \frac{\sum_{i=1}^{12} P_i^2}{(\sum_{i=1}^{12} P_i)^2} \dots\dots\dots \text{Equation (12)}$$

where P_i represents the monthly precipitation in the month i PCI. A PCI value of <10 represents a uniform distribution of precipitation (low concentration); a PCI value ranging from 11–15 indicates a moderate rainfall concentration; a PCI value ranging from 16–20 represents an irregular distribution of rainfall in the area; and any value above 20 units indicates a strong irregular rainfall distribution across the area (Oliver, 1980b).

The standard precipitation index (SPI): is the most widely used method of drought index to detect and characterize meteorological drought (Karabulut, 2015). To quantify the rainfall deficiency at the observed time scale in a given district. The SPI can be calculated for different periods (1, 3, 6, 12, 24, and 48 months) (Svoboda *et al.*, 2012). In this study, 12 months or annual periods (SPI-12) were used. The SPI value was calculated as follows:

$$SPI_{ij} = \frac{X_{ij} - \mu_{ij}}{\alpha_{ij}} \dots\dots\dots \text{Equation (13)}$$

where SPI_{ij} represents an i th month at the j th period, X_{ij} is the total observed rainfall value for the i th month at the j th period, and μ_{ij} and α_{ij} represent the long-term mean and standard deviation of the i th month, and j th timescale of the selected period respectively. In the study conducted by (McKee *et al.*, 1993), the SPI has different output values ranging from -2.0 to 2.0.

Table 3.2. Standard precipitation indices (SPIs) and their interpretation.

SPI value	Interpretation
≥ 2.0	Extremely wet
1.5 to 1.99	Severely wet
1.0 to 1.49	Moderately wet
0.99 to -0.99	Near Normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
≤ -2.0	Extremely dry

3.3.3. Performance metrics for the evaluation of GCMs

The evaluation of the CMIP6 models was conducted with data from four selected stations in the East Gojjam Zone, covering the period from 1984 to 2014. Various performance metrics were employed to assess the performance of the GCM models. These statistical metrics compare the differences between model simulations and observed datasets, and each metrics can show the overall performance differently for model simulations (Gleckler *et al.*, 2008). Statistical metrics are often found in comparisons of climate simulation results between GCMs and observed datasets (Kamworapan and Surussavadee, 2019). This study involved the simulation of seven for rainfall and six for temperature general circulation models and the validation of annual observational data through four performance metrics to analyze rainfall, maximum, and minimum temperature data. Different performance metrics were commonly employed in comparing climate estimate results from models and observed datasets (Alemseged and Tom, 2015; Worku *et al.*, 2020; Liu *et al.*, 2023). In this study, four PMs were applied to compare the capabilities of CMIP6 GCMs with observed datasets from 1984 to 2014. The PMs were the root mean square error (RMSE), percent bias (PBIAS %), correlation coefficient (r), and Kling–Gupta efficiency (KGE). Table 3 shows the PMs equations employed in this research, with descriptions as below:

i. Root means square error (RMSE)

RMSE calculates the difference between CMIP6 GCM data and actual rainfall values. It is a statistical measure that quantifies the magnitude of the error between the GCM outputs and the observed data, making it a widely utilized index for assessing model accuracy. It is one of the commonly used error index statistics (Moriassi *et al.*, 2007). The range of RMSE values is 0 to ∞ , where a number close to zero signifies better performance (Yan *et al.*, 2023). However, the lower the RMSE is, the better the model performance. The lower the RMSE value is, the lower the error found in the simulation (Lovino *et al.*, 2018).

ii. Percent bias (PBIAS)

PBIAS serves as a critical metric for evaluating the accuracy of simulated data in comparison to observed data. A bias measure indicates positive or negative differences between the CMIP6 GCMs data and the observed data. When the PBIAS values are near zero, the CMIP6 GCMs perform better in replicating the observed rainfall data. The best value of PBIAS is 0, which signifies that the model's predictions align perfectly with actual observations. A negative PBIAS value suggests underestimation, whereas a

positive PBIAS value indicates overestimating the model data (Worku *et al.*, 2019). The selection of PBIAS as a recommended metric is grounded in its ability to highlight deficiencies in model performance. By providing a clear indication of bias, PBIAS allows researchers and practitioners to assess the reliability of their simulations and make necessary adjustments to improve model accuracy. Overall, PBIAS is a valuable tool for understanding the tendencies of simulation models concerning real-world data (Gupta *et al.*, 1999).

iii. Correlation coefficient (r)

It is employed to describe the degree of similarity between the simulated (CMIP6 GCM) and observed data. The value of the correlation coefficient (r) varies from 0.0 to 1.0 (Alemseged and Tom, 2015; Worku *et al.*, 2020; Mohamed and Saeed, 2022). Higher values indicate better agreement and lower values indicate less agreement. It is also an index of the degree of the linear relationship between the observed and simulated data.

iv. Kling–Gupta efficiency (KGE)

It is a statistical measure used to evaluate performance metrics by combining correlation, bias, and variability. The KGE was employed to evaluate the performance of the selected CMIP6 GCMs in replicating the observed rainfall datasets. KGE integrates variability in addition to correlation and bias to determine the relationship and biases in the average and changes of observed and CMIP6 GCM variables (Gupta *et al.*, 2009; Kling *et al.*, 2012). The score of KGE ranges from $-\infty$ to 1, with 1 indicating a perfect score and values larger than 0.4 indicating acceptable performance (Salehie *et al.*, 2023). Its value ranges from $-\infty$ to 1. One indicates good model performance (Knoben *et al.*, 2019). The KGE was developed by Kling as an improvement over the Nash-Sutcliffe efficiency (NSE) and correlation coefficient (R) (Worku *et al.*, 2018a).

Table 1.3. The five-performance metrics along with their equations and references.

Metrics and their equation	Best values	References
$RMSE = \frac{\sqrt{\sum_{i=1}^n (CMIP6 - \overline{obser})^2}}{n}$	0	(Nayef et al., 2024)
$PBIAS = \frac{\sum_{i=1}^n (CMIP6 - \overline{obser})}{\sum_{i=1}^n \overline{obser}} * 100$	0	(Worku et al., 2018b)
$r = \frac{\sum_{i=1}^n (CMIP6 - \overline{CMIP6}) - (\overline{obser} - \overline{obser})}{\sqrt{\sum_{i=1}^n (CMIP6 - \overline{CMIP6})^2 \sum_{i=1}^n (\overline{obser} - \overline{obser})^2}}$	1	(Mohammed, 2024)
$KGE = 1 - \sqrt{\sum_{i=1}^n \left((R - 1)^2 + \left(\frac{sdrCMIP6}{sdr \overline{obser}} - 1 \right)^2 + \left(\frac{\overline{CMIP6}}{\overline{obser}} - 1 \right)^2 \right)}$	1	(Kamruzzaman et al., 2021)

Notes: - CMIP6 is model data, obser is observed data, the bar over the variables denotes the average for 1984 to 2014, sdr obser is the standard deviation of observed data, sdrCMIP6 is the standard deviation of model data, and n represents the analysis period (31 years).

Therefore, these error metrics were calculated via Zoo and hydroGOF (R package) software. Hence, the overall ranking of the seven for rainfall and six for temperature CMIP6 GCMs were considered in all the statistical metrics (i.e., RMSE, PBIAS, r, and KGE) was performed following the comprehensive rating index (CRI) method, which has also been implemented in the previous studies (Guo *et al.*, 2021). Finally, to select the best-performing models, ranking was performed. In this study, the comprehensive rating index (CRI) was used. The CRI is known to effectively rank the overall performance of GCMs (Gashaw *et al.*, 2024). The formula is as follows in equation (1):

$$CRI = 1 - \frac{1}{n.m} \sum ranki \dots \dots \dots \text{Equation (14)}$$

Where n is the number of statistical performance measures used in this study for evaluating the models (4), m is the number of CMIP6 GCMs that are evaluated in the study (7), and Rank is the rank of the CMIP6 GCMs for each performance measure, which ranges from 1 to 7 for the best-performing model and low-performing model, respectively. A value of CRI closer to 1 indicates better performance of the model (Jia *et al.*, 2019). Finally, from those ranked CMIP6 models, the best-performing models were selected for future climate projection of the stations.

3.3.4. Future climate projection and trend analysis

This study focuses on future climate projections by analyzing mean annual maximum and minimum temperature and rainfall data over two distinct time intervals: a baseline period from 1984 to 2014 and a future period from 2015 to 2100. The analysis used distribution mapping, which is integrated within the climate model data for the hydrologic modeling (CMhyd) tool (Rathjens *et al.*, 2016). It was used for bias correction of best-performing GCM projections under different climate change scenarios. This study focused on bias correction of the best-performing CMIP6 general circulation models (GCMs) by utilizing data extracted for each station; hence, the bias correction process was performed by providing the daily observed historical (1984 to 2014), raw GCM historical (1984 to 2014), and future raw GCM (2015 to 2100) data of each station in the text file.

Future climate change analyses, as well as bias corrections of the global dataset, were performed mainly for the SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 climate change scenarios (Alaminie *et al.*, 2021). For each climate scenario, 30 year baseline period (1976 to 2005), 30 years interval projection scenarios (2041 to 2070 and 2071 to 2099), and three climate variables (maximum and minimum temperatures and rainfall) were used (Gurara *et al.*, 2023). In this study, analyses of future climate changes for the near future from (2031 to 2061) and long-term changes from (2070 to 2100) were conducted for the SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 climate scenarios across the EGZ selected stations. The focus on the period 2031 to 2100 for future projections is driven by the following reasons:

Alignment with gridded observation datasets: The timeframe of 2031 to 2100 aligns with the available gridded climate observation datasets, ensuring consistency between observed and projected climate data.

Medium to long-term impact assessment: This period provides sufficient time to assess the long-term impacts of climate change, which is critical for understanding trends in temperature and rainfall, especially in the context of agriculture and other climate-sensitive sectors. The SSPs (Shared Socioeconomic Pathways) scenarios, ranging from low to high emissions pathways (SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5), influence the climate.

These scenarios allow for the exploration of different future pathways, considering variables such as population growth, technological advancements, and mitigation efforts. The range of SSPs provides a comprehensive view of possible future climates under

different emission trajectories, enabling better planning for future climate impacts. According to Gebresellase et al. (2022), the analysis was carried out using 30 years for the baseline period (1981 to 2010), and 30 years interval projection scenario for the near term (2031 to 2060), and the long term (2061 to 2090). The SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 scenarios represent the low-forcing, medium-forcing, medium-to-high forcing, and high-end-forcing pathways, respectively. For example, (Alaminie *et al.*, 2021) bias corrections of a global dataset based on 18 CMIP6 GCMs produced data for SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios with data derived from bias corrections of a global dataset utilizing 18 CMIP6 general circulation models (GCMs). In the present study, the researchers included SSP4-6.0 to examine the projected climate changes between the SSP3-7.0 and SSP5-8.5 scenarios.

Chapter Four: RESULTS AND DISCUSSIONS

4.1. Data Quality Check

In this study, autocorrelation was calculated through RStudio via ACF () syntax as follows: ACF (x, lag.max=1) \$acf, to a series x automatically calculates the lag-1 autocorrelation. The lines represent the values beyond which the autocorrelations are significantly different from zero. A study conducted by (Adamowski and Bougadis, 2003) in Canada on the detection of trends in annual extreme rainfall revealed that stations with significant autocorrelation were prewhitened. The study conducted by (Yue and Wang, 2002) revealed significant autocorrelation in sample data can lead to misleading test results. Hence, in this study, the effect of autocorrelation was considered. The lag-1 serial correlation coefficient (ρ_1) and its upper and lower limits for the confidence interval at the 0.1 significance level for the total annual rainfall, mean annual Tmax and mean annual Tmin are presented for each station in the figure (series x1, x2, x3, and x4) in Appendices 2 and 3.

The analysis involved four meteorological stations, such as Motta, D/Work, Dejen, and D/Markos, to assess the presence of lag-1 serial correlation coefficients and identify trends in the specified climatic variables. The findings revealed that the total annual rainfall had serial correlation coefficient values of -0.068 for the Motta station, 0.1 for the D/Work station, 0.033 for the Dejen station, and -0.06 for the D/Markos station. In this case, the overall stations were not significantly correlated ($\alpha = 0.1$). Thus, the study concluded that there was no need to apply a trend-free pre-whitening procedure (TFPW).

As shown in Figure series x1, x2, x3, and x4 in Appendix 1, the pre-whitened procedure made the series independent and serially uncorrelated at the stations. The analysis of serial correlation coefficients for mean annual maximum temperatures reveals varying values across different stations. The mean annual maximum temperature of the serial correlation coefficient values was ($R = 0.28$) for the Motta station, ($R = 0.35$) for the D/Work station, ($R = 0.31$) for the Dejen station, and ($R = 0.47$) for the D/Markos station. In contrast, the mean annual minimum temperature of the serial correlation coefficient values was $R = 0.16$ for the Motta station, $R = 0.56$ for D/Work, $R = 0.7$ for the Dejen station, and $R = 0.42$ for the D/Markos station. These findings indicated that the D/Work and Dejen stations presented stronger correlations for minimum temperature than for maximum temperatures

across the four stations. In some stations were showed stronger and weaker serial correlation because of its local environmental factors and geographical characteristics.

The mean annual maximum temperature analysis indicated that, out of four stations, only D/Markos showed serial correlation. Whereas, except for Motta, the mean annual minimum temperature of all stations was shown serially correlated at a significance level of $\alpha = 0.1$. Consequently, the pre-whitened procedure was necessary only for the D/Markos station to address serial correlations in the MK test for the mean annual maximum temperature. Therefore, the D/Work, Dejen, and D/Markos stations were required for the prewhitened procedure for the mean annual minimum temperature. Figures 4.2 and 4.3 in Appendices 2 and 3 illustrate the significant serial correlations observed.

4.1.1. Man–Kendall trend test of the pre-whitening procedure for the mean annual maximum and minimum temperature.

The analysis of the mean annual maximum temperature trends in the East Gojjam Zone revealed significant findings from four selected stations. This study employed the pre-whitened Mann–Kendall trend test to assess the temperature data over various periods. Notably, two stations, Motta and D/Markos, showed statistically significant increasing trends in the mean annual maximum temperature. The results for Motta indicated a p-value of 0.01, a z-value of 2.53, a prewhitened Sens slope of 0.026, a Mann–Kendall statistic (S) of 143, and a Kendall’s tau of 0.33. Similarly, D/Markos showed a more pronounced trend, with a p-value of 0.0005, a z-value of 3.82, a prewhitened Sens slope of 0.035, a Mann–Kendall statistic (S) of 215, and Kendall’s tau of 0.49. Whereas, the result of D/Work and Dejen stations were showed non-significant trends (p-values of 0.83 and 0.5 respectively), because of its local factors, data quality and the length of the time series. Generally, a z-value of 3.82 for D/Markos indicates strongly significant increasing trends and steady warming trend over the observed period. The Kendall’s tau values (0.33 for Motta and 0.49 for D/Markos) indicated that moderate positive correlations.

Table 2.1. Mean annual maximum temperature MK trend test results of the pre-whitened procedure.

Stations	Z- value	Prewhitend Sen's slope	Sens slope	M.K stat(S)	Kendall's tau	p-value	α	Trend
Motta	2.53	0.026	0.03	143.0	0.33	0.01***	0.05	Significant
D/work	-0.21	-0.003	-0.01	-13.0	-0.03	0.83	0.05	Not significant
Dejen	0.68	0.01	0.02	39.0	0.09	0.5	0.05	Not significant
D/Markos	3.82	0.035	0.036	215.0	0.49	0.0005***	0.05	Significant

In the mean annual minimum temperature, only the D/Markos station was shown a statistically significant increasing trend, with a p-value of 0.0005, a z-value of 2.82, a pre-whitened Sens slope of 0.02, a Mann–Kendall statistic (S) of 159, and Kendall's tau of 0.37. These findings highlight the importance of monitoring temperature trends in the Zone, as they may have implications for climate change and local environmental conditions.

Table 4.2. Mean annual minimum temperature of the Mann–Kendall trend test results of the prewhitened procedure.

Stations	Z- value	Prewhitend Sen's slope	Sens slope	M.K stat(S)	Kendall's tau	p-value	α	Trend
Motta	1.035	0.014	0.018	59.0	0.14	0.30	0.05	Not significant
D/work	1.78	0.07	0.09	101.0	0.23	0.07	0.05	Not significant
Dejen	0.96	0.04	0.1	55.0	0.13	0.34	0.05	Not significant
D/Markos	2.82	0.02	0.03	159.0	0.37	0.005***	0.05	Significant

4.2. Variability analysis of seasonal and annual rainfall

4.2.1. Coefficient of variation

Analysis of the variability and trends of the main parameters of climate are rainfall and temperature, either on a monthly or seasonal basis or on an annual basis, which is highly important for informing policy and decision-makers trying to design a strategy either to adapt to or mitigate the adverse impacts of climate change in the community. The coefficient of variation (CV) is a tool of descriptive statistics widely used to classify the degree of variability, as a CV<20% indicates low variability, a CV between 20% and 30% indicates moderate rainfall variability, a CV between 30% and 40% indicates high

variability, a CV between 40% and 70% indicates very high variability and a CV>70% indicates extremely high variability in rainfall (Kassie, 2014).

The coefficient of variation of the seasonal and annual rainfall at the stations is presented in Table 4.3. The analysis of annual rainfall from four stations reveals significant rainfall patterns over the years. The maximum annual rainfall was 1684.57 mm in 2006, whereas the minimum was 597.5 mm in 1990. The mean annual rainfall for the stations from 1984 to 2014 varied, with Motta receiving 1212.09 mm, D/Work receiving 939.99 mm, Dejen receiving 1124.68 mm, and D/Markos receiving 1369.11 mm. Among the four stations, D/Work presented the highest CV (21.79%), with a standard deviation (204.84) for the mean annual rainfall. In this station may require more robust climate adaptation strategies, including development of water storage systems and drought-resistant crop varieties. However, the lowest value (CV=10.44%) was recorded at the D/Markos station. Because of the accuracy of CV for rainfall datasets are affected by wind, temperature, humidity, local factors such as geography and microclimates play a significant role in rainfall patterns.

The summer season, locally known as Kiremt (JJAS), was identified as the period with the highest rainfall, average between 680.14 mm and 1001.06 mm across the stations. During this season, the coefficient of variation was lower, indicating more stable rainfall patterns, particularly in Motta, Dejen, and D/Markos. The main rainy season contributes significantly to the annual totals, accounting for more than 72% of the total rainfall at each station. This study is similar to the findings of (Getachew, 2018a; Assefa and Mengistu, 2021b), who reported that summer is the main rainy season contributing the highest to the annual rainfall in different parts of the country.

The second-highest amount of mean seasonal rainfall (172.36, 174.69, 2012.31, and 234.8) was received during the spring season, locally known as Belg rain (FMAM), and the rainfall contributed 13.8%, 18.58%, 19.1%, and 17.15% at the Motta, D/Work, Dejen, and D/Markos stations, respectively. The highest percentage (CV=58.14%) was recorded at Motta, whereas the lowest percentage was recorded at D/Work (CV=37.53%). According to Getachew., (2018a) reported that the rainfall pattern in the Kiremt season was less variable than the rainfall pattern in the Belg season (February to May) in the southern Gonder Zone of the Amhara regional state of Ethiopia.

The winter was the season locally known as Bega rainfall (Oct, Nov, Dec, Jan), with the lowest amounts of mean seasonal rainfall (mean=151.05, 85.15, 71.02, and 133.24 mm), with a very high coefficient of variation recorded (CV=68.8%, 64.73%, 58.03%, and 57.42%, respectively) at all stations. At this time, the amount of rainfall was not as high as that in the summer and spring seasons. The result underscores the importance of seasonal rainfall forecasting and early warning systems. Generally, the higher seasonal variability was recorded during winter and spring seasons, at this time early alerts would allow farmers to adjust their practices or seeks alternative livelihoods in case of drought and floods. Regarding variability, low to very high levels of variability were recorded in the annual rainfall, whereas moderate to very high levels of variability were observed for the coefficient of variation in monthly rainfall.

Table 4.3. Seasonal and annual rainfall variability data in mm from 1984–2014.

Stations	Season	Mean (mm)	Maximum	Minimum	STDV	CV%	Rainfall contribution
Motta	Spring	172.36	406.2	63.3	42.53	58.14	13.8%
	Summer	925.48	1080.3	623.0	13.63	11.18	74.1%
	Winter	151.05	313.8	25.84	51.38	68.8	12.1%
	Annual	1248.89	1506.7	891.4	143.71	11.86	100%
D/work	Spring	174.69	301.55	38.5	65.56	37.53	18.58%
	Summer	680.14	1162.4	403.0	194	28.52	72.34%
	Winter	85.15	216.31	2.1	55.12	64.73	9.1%
	Annual	939.99	1392.25	597.5	204.84	21.79	100%
Dejen	Spring	212.31	665.43	87.0	113.766	53.58	19.1%
	Summer	841.35	1214.84	583.75	131.74	15.66	74.5%
	Winter	71.02	154.30	10.26	41.21	58.03	6.41%
	Annual	1124.68	1684.57	848.80	190.84	16.97	100%
D/Markos	Spring	234.8	452.41	96.40	94.55	40.27	17.15%
	Summer	1001.06	1180.18	780.40	107.71	10.76	73.12%
	Winter	133.24	315.58	30.40	76.51	57.42	9.73%
	Annual	1369.11	1679.40	1079.40	142.93	10.44	100%

4.2.2. Standardized rainfall anomaly index (SRAI)

The rainfall anomaly index was used to calculate the negative and positive anomalies of rainfall fluctuations in a certain region and to analyze the frequency and intensity of the rainfall. It helps to identify the drought period by determining the dry and wet years of the

recording period (Gleixner *et al.*, 2017; Asfaw *et al.*, 2018). The annual rainfall anomalies from 1984–2014 in the study area are presented in Figure 4.1. The analysis of rainfall anomalies revealed significant interannual variability in the observed time series. In this study, the highest positive anomalies were recorded at Motta in 1996(4.66), 2001(4.76), 2006(3.98), at D/Work in 1988(5.14), 2000(5.4), 2007(5.19), at Dejen in 2006(3.08), 2008(2.14), 2009(5.03), at and D/Markos in 1993(5.08), 1996(4.66), 2006(5.04), with values ranging from +2.14 to +5.4. Conversely, the highest negative anomalies were occurred at Motta in 1989(-5.99), 2009(-5.49), 2012(-3.29), at D/Work in 1990(-5.49), 2002(-4.93), 2014(-3.14) at Dejen in 1991(-3.4), 2002(-3.72), 2004(-3.45), and at D/Markos in 1984(-5.66), 1986(-4.51), 2012(-3.82) with values ranging from -3.29 to -5.99.

Drought years were identified at the studied stations; for example, Motta experienced negative anomalies in multiple years, including from 1987 to 1995 and 2000 to 2012. D/Work also showed significant drought from 1984 to 2014, and Dejen and D/Markos recorded similar patterns of negative anomalies and drought conditions during overlapping years. The findings suggest a correlation between these anomalies and El Niño events, indicating a broader climatic influence on rainfall patterns in the region. The years 1989, 1990, 2002, and 1984 experienced the highest negative anomalies due to the occurrence of El Niño, which affected the main livelihood of rural people in different parts of Ethiopia (Gebregiorgis *et al.*, 2019).

Recent studies have indicated that approximately twelve extreme historical droughts have been recorded in Ethiopia and affected the economic development of the country(Viste *et al.*, 2013; Mersha and van Laerhoven, 2018; Matewos, 2019). Drought incidents in Ethiopia negatively affect the livelihoods of millions of people. The major droughts in Ethiopia recorded in the last three decades were related to ENSO events. In Ethiopia, El Niño events in 1987, 1991, 2001, 2009, and 2015 coincided with extended drought conditions from April to November, which cover the main cropping season of the country.

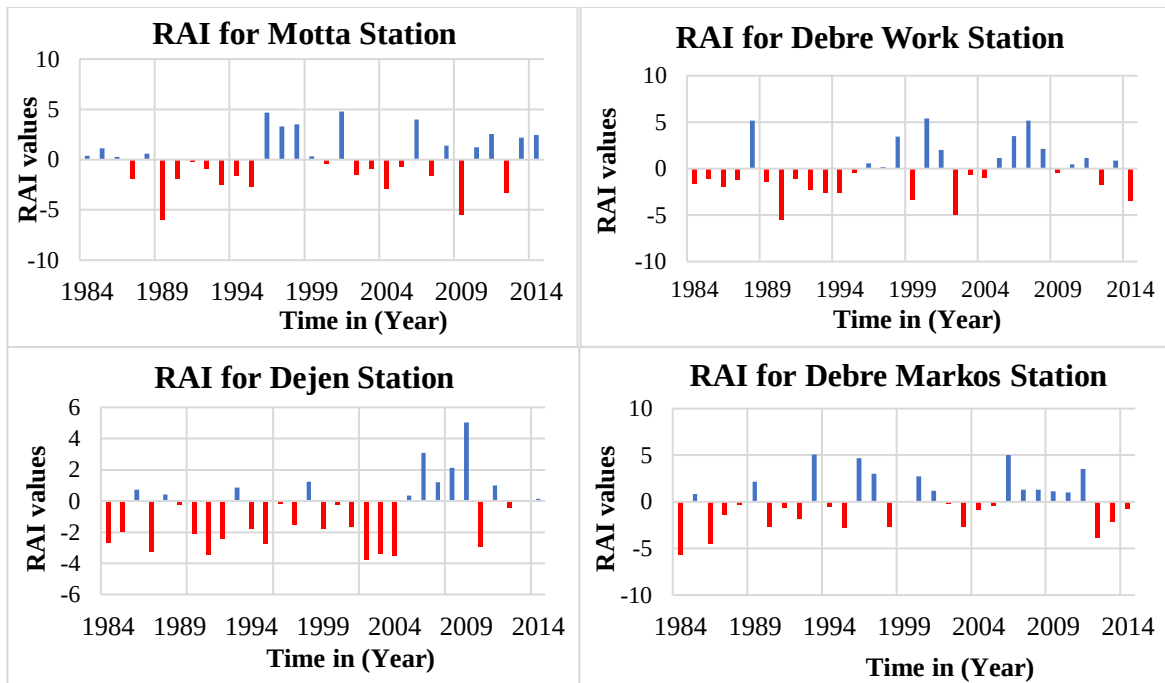


Figure 4. 1. Annual rainfall anomalies at the stations from 1984–2014.

4.2.3. Precipitation concentration index (PCI)

The precipitation concentration index was calculated based on a different class of PCI to measure the distribution of rainfall on an annual basis across the stations in the study area. The value of the PCI class, which is <10 , represents a uniform rainfall distribution; a PCI value ranging from 11–15 indicates a moderate rainfall distribution; a PCI value ranging from 16–20 represents an irregular rainfall distribution; and any value above 20 units indicates a strong irregular rainfall distribution across the area (Oliver, 1980a).

As presented in Table 4.4, the percentage rainfall distribution of Motta 22.58% was moderate, that of 64.52% was irregular, and that of 12.9% was strongly erratic. In D/Work, 38.71% was moderate, 41.94% was irregular, and 19.35% was strongly erratic. In Dejen, 32.26% was moderate, 64.52% was irregular, and 3.22% was strongly erratic. At D/Markos station, 51.61% of the events were moderate, 41.94% were irregular, and 6.45% were strongly erratic. In Motta and Dejen stations, the mean annual precipitation concentration index revealed a more irregular rainfall distribution compared to others. The results imply that areas like Motta and Dejen could face difficulties in planning agricultural activities because of the highly irregular rainfall distribution. Farming in such areas may need to incorporate more adaptive strategies, such as drought-tolerant crops or irrigation systems that can accommodate unpredictable rainfall patterns. In contrast, areas with more moderately distributed rainfall like D/Work and D/Markos might benefit from

more predictable farming systems, which can reduce the risks associated with extreme weather events. In Motta and D/Work the mean annual PCI showed more strongly erratic rainfall. Therefore, in those areas' farmers are able to adapt to more drought resistant varieties and fluctuating rainfall through crop scheduling.

Table 4.4. Years of the different PCI classes in the study area (1984 to 2014).

Stations	PCI class	Categories	Number of years	Percentage (%)
Motta	<10	Uniform	no (0)	no (0)
	11 - 15	moderate	7(1985,1986,1993,1997,2005,2014)	22.58%
	16 – 20	irregular	20	64.52%
	>20	strong erratic	4 (1995,2003,2010,2012)	12.9%
D/Work	<10	Uniform	no (0)	no (0)
	11 – 15	moderate	12	38.71%
	16 – 20	irregular	13	41.94%
	>20	strong erratic	6 (1988,1994,1999,2002,2004,2013)	19.35%
Dejen	<10	Uniform	no (0)	no (0)
	11 – 15	moderate	10	32.26%
	16 – 20	irregular	20	64.52%
	>20	strong erratic	1 (2003)	3.22%
D/Marko s	<10	Uniform	no (0)	no (0)
	11 – 15	moderate	16	51.61%
	16 – 20	irregular	13	41.94%
	>20	strong erratic	2 (2009,2012)	6.45%

4.2.3. Standard precipitation index (SPI)

The SPI is the most widely used method for determining drought indices to detect and characterize meteorological drought (Karabulut, 2015). This study aimed to quantify the rainfall deficiency across various stations in a specific district, and utilizing standardized precipitation index (SPI) values to assess wet and dry years. The findings indicate significant variability in rainfall patterns, with some years classified as extremely wet (≥ 2), severely wet (1.5 to 1.99, moderately wet (1 to 1.49), near normal (0.99 to -0.99), moderately dry (-1 to -1.49), severely dry (-1.5 to -1.99) or extremely dry (≤ -2).

At the Motta station, extremely wet years were recorded in 2001 and 2006, whereas severely wet conditions were noted for several years from 1996 to 2014. Conversely, the station also experienced moderately dry years in the late 1980s and early 2000s, with severely dry years occurred in the late 1980s and 2009 to 2010 and extremely dry years were occurred (1989,1990, 2009 and 2010). For the D/Work station, extremely wet years were observed in 2001, 2007, and 2008, with a range of severely wet (1988, 1989,1998,2000,2001), and moderately wet years from 1988 to 2008. The station also faced moderately dry conditions in the late 1980s and early 2000s, alongside instances of severe dryness in the early 1990s and extremely dry years were occurred only in 1991. The Dejen station reported that the extremely wet years in 2009 and 2010, with several severely wet years noted in 2007 and 2010. Moderately dry years were recorded intermittently from the mid-1980s to the early 2000s, whereas extremely dry years were not documented. At the D/Markos station, extremely wet years were identified in 1993, 1996, and 2001, with a series of severely wet years from 1993 to 2010. Moderately dry years were observed throughout the 1980s and 1990s, with severe dryness recorded in the mid-1980s and early 1990s and extremely dry years occurred in 1985, 1988, and 1995.

Overall, the analysis revealed that the majority of years across the studied stations showed below-normal rainfall distributions. These results agree with recent studies showing that the frequency of the drought cycle has changed over time in Ethiopia (Belay *et al.*, 2021). From the SPI findings presented in Figure 4.2, it is evident that most of the drought years were associated with El Nino events, whereas wet years coincided with La Nina years. For example, the recent 2015 year caused by the El Nino event was considered one of the driest years in the history of Ethiopia, and the Belg and Kiremt seasons were highly affected. As a result, crops fail in the field, livestock die, and millions of people remain food insecure (Viste *et al.*, 2013; Gidey *et al.*, 2018).

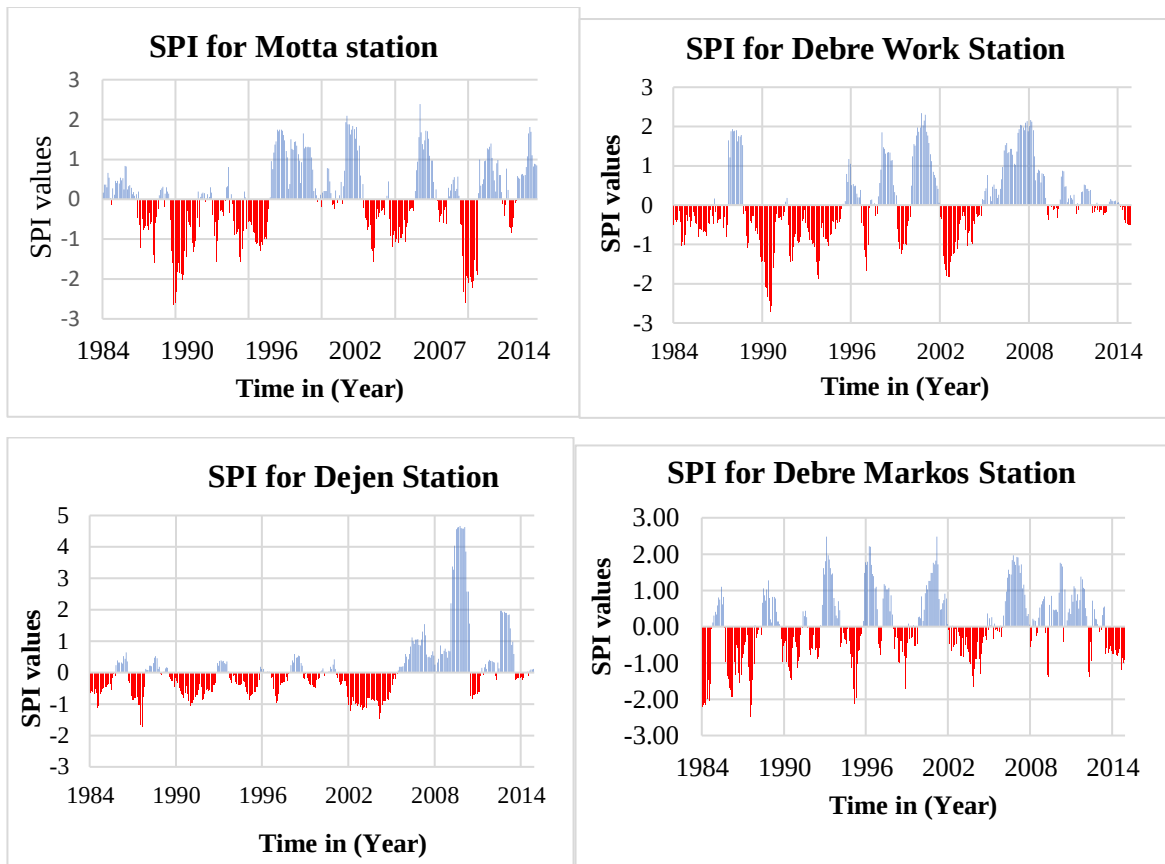


Figure 4. 2. The standardized precipitation index of the stations from 1984 to 2014.

4.3. Trend analysis of monthly, annual, and seasonal average rainfall from 1984 to 2014

The Mann–Kendall (MK) trend analysis provides a robust tool for assessing long-term rainfall trends, identifying both statistically significant increases and decreases at various stations. The study clearly shows significant temporal variability in rainfall across months, suggesting regional differences in how rainfall patterns have evolved from 1984 to 2014. The slope and P-value were used for the determination of trends. The monthly analyses of the meteorological stations were computed based on the availability and reliability of the observed gauge stations. The analysis of the monthly rainfall trends in the East Gojjam Zone utilized data from four meteorological stations such as Motta, D/Work, Dejen, and D/Markos. The study revealed statistically significant increasing trends in the monthly average rainfall at some stations and some months (Table 4.5).

Significant increases in rainfall were recorded at several stations during particular months. For example: at the Motta station, a statistically significant increasing trend was observed in November, with a p-value of 0.05 and a slope of 0.8. D/Work station exhibited a

significant increasing trend in July, with a p-value of 0.002 and a slope of 4.98. The Dejen station showed statistically increasing trends in March, June, August, and November, with the corresponding p-values and slopes indicating significant trends. In particular, the D/Markos station recorded an increase in September, with a p-value of 0.013 and a slope of 3.35. On the other hand, both the Motta and Dejen stations verified statistically significant decreasing trends in February, with Motta showing a p-value of 0.0047 and a slope of -0.27, whereas Dejen had a p-value of 0.024 and a slope of -0.29. Generally, areas like D/Work and Dejen, with significant increases in rainfall during certain months (e.g., July and June), may benefit from enhanced rainfall for crops that need abundant water during these periods. The potential causes contributing to the observed increasing rainfall in these months (June and July) can be tied to larger climate shifts such as changes in atmospheric patterns and regional climate phenomena. However, the decreasing trends in February suggests that farmers in Motta and Dejen might face challenges due to reduce early-year rainfall, which could affect crop germination or early stage of growth. Motta and Dejen, which exhibit both increasing and decreasing rainfall trends, highlight the challenges for agricultural resilience, suggesting that farmers need to adjust practices to cope with these fluctuations. The finding of this study result revealed that there were rainfall variability patterns in the region.

Table 4.5. MK trend test results for the monthly average rainfall (mm).

Month	MK trend test	Motta	D/Work	Dejen	D/Markos
Jan.	Z-value	0.29	0.34	-1.45	0.83
	Sen's slope	0.0	0.0	-0.085	0.138
	MK stat (S)	18.0	21.0	-86.0	50.0
	P-value	0.77	0.73	0.15	0.40
Feb.	Z-value	-2.83	-1.84	-2.265	-1.04
	Sen's slope	-0.27	-0.19	-0.29	-0.19
	MK stat (S)	-165.0	-107.0	-113.0	-62.0
	P-value	0.0047***	0.066	0.024**	0.30
Mar.	Z-value	1.68	0.36	2.12	0.65
	Sen's slope	0.0	0.19	1.24	0.325
	MK stat (S)	73.0	22.0	126.0	39.0
	P-value	0.09*	0.72	0.034**	0.52
Apr.	Z-value	0.37	0.56	0.0	-0.136
	Sen's slope	0.26	0.55	-0.026	-0.10
	MK stat (S)	23.00	34.0	-1.0	-9.0
	P-value	0.7	0.57	1.0	0.89
May.	Z-value	-0.41	0.34	0.102	0.58
	Sen's slope	-0.52	0.52	0.18	0.59
	MK stat (S)	-25.00	21.0	7.0	35.0
	P-value)	0.68	0.73	0.92	0.56
Jun.	Z-value	0.068	1.037	2.18	-0.65
	Sen's slope	0.124	0.93	1.80	-0.60
	MK stat (S)	5.00	62.0	129.0	-39.0
	P-value	0.95	0.3	0.03**	0.52
Jul.	Z-value	0.068	3.06	0.2	-0.068
	Sen's slope	0.09	4.98	0.24	-0.120
	MK stat (S)	5.00	181.0	13.0	-5.0
	P-value	0.95	0.002***	0.84	0.95
Aug.	Z-value	1.84	1.67	2.31	0.0
	Sen's slope	2.85	2.14	2.07	-0.058
	MK stat (S)	109.0	99.0	137.0	-1.0
	P-value	0.06	0.096	0.02**	1.0
Sept.	Z-value	1.36	-0.36	0.99	2.48
	Sen's slope	1.64	-0.25	0.82	3.35
	MK stat (S)	81.0	-22.0	59.0	147.0
	P-value	0.17	0.72	0.32	0.013***
Oct.	Z-value	0.27	0.22	0.97	1.27
	Sen's slope	0.41	0.095	0.54	0.91
	MK stat (S)	17.0	14.0	58.0	76.0
	P-value	0.79	0.83	0.33	0.2
Nov.	Z-value	1.9	0.70	2.14	1.31
	Sen's slope	0.80	0.117	0.23	0.42
	MK stat (S)	113.0	42.0	127.0	78.0
	P-value	0.05**	0.48	0.03**	0.19
Dec.	Z-value	-1.088	0.05	-0.77	-0.33
	Sen's slope	0.00	0.0	-0.038	0.0
	MK stat (S)	-63.0	4.0	-46.0	-20.0
	P-value	0.28	0.96	0.44	0.74

4.3.1. Trend analysis of annual and seasonal rainfall from 1984–2014

The Mann–Kendall trend test was conducted via R Studio to analyze the rainfall and temperature trends from 1984 to 2014 in the East Gojjam Zone. The analysis focused on total annual rainfall, mean annual maximum, and minimum temperature. The key statistical outputs included the MK trend statistic (Z), Sen's slope (β), the MK statistic (S), Kendall's tau, and the p-value, which are essential for determining the trends in rainfall and temperature. The MK test revealed whether there were increasing or decreasing trends in the data. A z-value exceeding the 1.96 confidence limit indicates a significant trend, whereas a value below this threshold suggests an insignificant trend. The p-value further assessed the significance of the trends, with a value less than 0.05 leading to the rejection of the null hypothesis, indicating the presence of a trend. On the other hand, with a p-value greater than 0.05, the null hypothesis suggests no trend.

Overall, the findings indicated that varying trends in total annual rainfall and temperature, with some stations showing positive trends, others showing negative trends, and some shows no trend. This analysis provides valuable insights into climatic changes in the East Gojjam Zone over the specified period. Except for Motta, all the stations showed a significant increasing trend. The statistical analysis indicated that these stations had p-values below the 0.05 significance level, confirming the presence of a statistically significant increasing trend in rainfall. Specifically, D/Work presented a slope of 7.11 mm/year, Dejen presented a slope of 7.56 mm/year, and D/Markos presented a slope of 6.17 mm/year. In contrast, Motta station did not show a statistically significant trend, with a p-value above the 0.05 threshold.

Generally, the findings indicated that the three stations experienced a notable increasing trend in annual rainfall, while the Motta station showed no significant trend in rainfall likely due to local geographical or environmental factors. These could include its altitude, topography, or proximity to moisture sources, which may influence rainfall patterns differently than at other stations. Local weather system or microclimates might also play role in reducing the overall trends, and making it less responsive to broader regional climatic changes. In D/Work, Dejen, and D/Markos, the total annual rainfall results showed statistically significant increasing trends, as the computed p-value was less than the level of significance at $\alpha = 0.05$, which implies that the null hypothesis was rejected.

These results are in agreement with the findings of (Belay *et al.*, 2021a), who examined the trends in the annual rainfall distribution in southern Ethiopia noted that the annual rainfall had a statistically insignificant increasing trend from 1995 to 2014. However, at the Motta station, the total annual rainfall result showed a statistically insignificant increasing trend, as the computed p-value ($p > 0.05$ and slope=3.13) was greater than the level of significance at $\alpha = 0.05$, which implies that the null hypothesis was accepted. As shown in Table 4.6, as the computed p-value was greater than the level of significance at $\alpha = 0.05$, no trend was observed at the Motta station, and as the computed p-value was less than the level of significance at $\alpha = 0.05$, a trend was observed at the Debre Work, Dejen, and Debre Markos stations.

The seasonal rainfall analysis of the trends in Table 4.6 below the summer season (June, July, August, and September) revealed a statistically significant increasing trend only at the D/Work station, with p-values and slopes ($p < 0.05$ and slope=6.69) at the 5% level of significance. Conversely, other stations, such as the Motta, Dejen, and D/Markos stations, did not show statistically significant increasing or decreasing trends across all seasons. The significant seasonal differences in rainfall trends at D/Work, especially in the summer months may be influenced by factors such as monsoon patterns, seasonal wind shifts, and local topography. These factors can affect the amount and distribution of rainfall during the summer. The seasonal changes could also be linked to broader climatic shifts like the Indian ocean dipole or El Nino phenomena, which influence regional weather patterns, including rainfall variability and intensity in East Africa.

Table 4.6. The Mann–Kendall trend test results of mean annual and seasonal rainfall (mm).

Stations	Season	Mean (mm)	Z-value	Sens slope	M.K stat (S)	Rainfall contribution (%)	p-value	α	Trend
Motta	Spring	172.36	-0.85	-1.29	-51.00	13.8%	0.4	0.05	No
	Summer	925.48	0.61	1.84	37.00	74.1%	0.54	0.05	No
	Winter	151.05	1.4	2.39	83.00	12.1%	0.16	0.05	No
	Annual	1248.89	0.92	3.13	55.00	100%	0.08	0.05	No
D/work	Spring	174.69	0.71	1.03	43.00	18.58%	0.48	0.05	No
	Summer	680.14	2.00	6.99	119.00	72.34%	0.04**	0.05	Significant
	Winter	85.15	-0.41	-0.35	-25.00	9.1%	0.68	0.05	No
	Annual	939.99	1.97	7.1	117.00	100%	0.048**	0.05	Significant
Dejen	Spring	212.31	0.17	0.28	11.00	19.1%	0.87	0.05	No
	Summer	841.35	1.94	5.33	115.00	74.5%	0.05**	0.05	No
	Winter	71.02	1.63	1.49	97.00	6.41%	0.1	0.05	No
	Annual	1124.68	1.97	6.38	117.00	100%	0.03**	0.05	Significant
D/Markos	Spring	234.8	0.58	0.21	35.00	17.15%	0.56	0.05	No
	Summer	1001.06	1.56	0.93	93.00	73.12%	0.12	0.05	No
	Winter	133.24	1.55	0.38	93.00	9.73%	0.12	0.05	No
	Annual	1369.11	1.97	6.17	117.00	100%	0.048**	0.05	Significant

* As the computed p-value is greater than the significance level, $\alpha = 0.05$, one cannot reject the null hypothesis H_0 .

** As the computed p-value is lower than the significance level, $\alpha = 0.05$ rejects the null hypothesis H_0 .

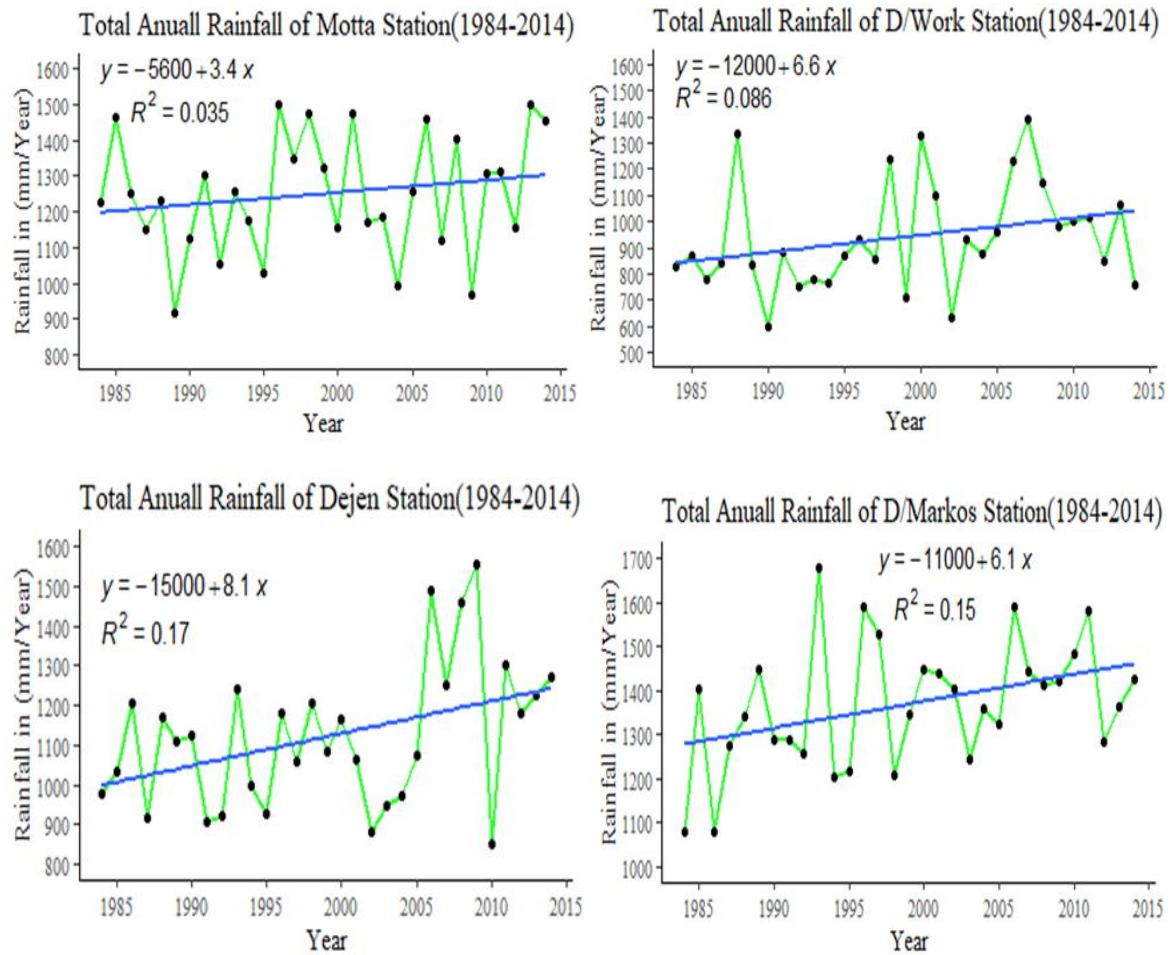


Figure 4.3. MK trend test of the annual rainfall at the Motta, D/Work, Dejen, and D/Markos stations.

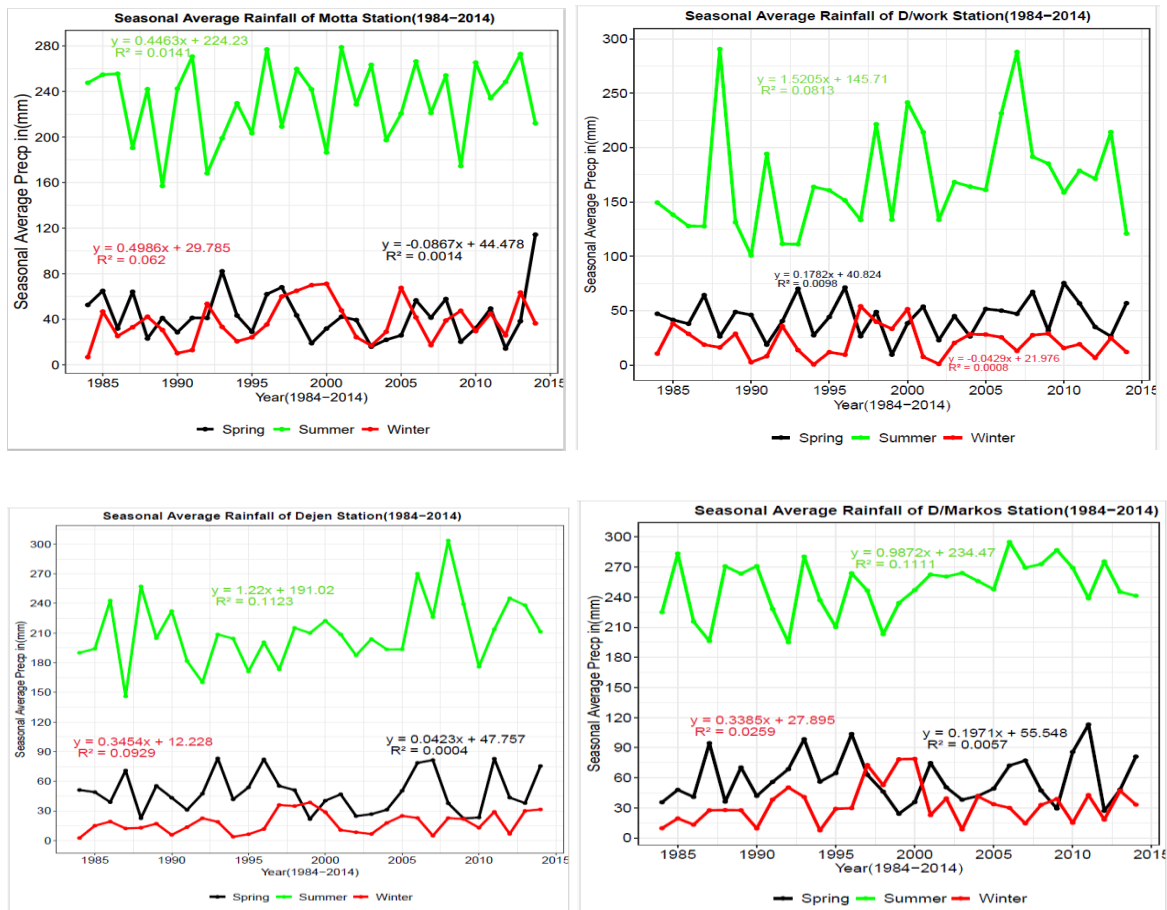


Figure 4.3. MK trend test of the seasonal rainfall at the Motta, D/Work, Dejen, and D/Markos stations.

4.3.2. Trend analysis of the mean monthly maximum and minimum temperature (1984-2014).

An analysis of the monthly mean maximum and minimum temperature data was performed to detect the variability and trends in the temperature in the study area at different times. Table 4.7 shows the monthly mean maximum temperature and its trend in the periods under examination. The results of the MK test for the monthly mean maximum temperature at the stations showed statistically significant increasing trends only at the Motta and D/Markos stations: at the Motta station, months such as February, August, and September presented p values and slopes ($p < 0.01$ and slope=0.047, $p < 0.05$ and slope=0.028, $p < 0.01$ and slope=0.028, respectively). For the D/Markos station months, such as February, June, July, and September, the p-value and slope were $p < 0.01$, slope=0.058, $p < 0.01$, slope=0.06, $p < 0.01$, slope=0.04, $p < 0.05$, and slope=0.022 respectively. However, only the D/Work station showed statistically significant decreasing

trends in the monthly mean maximum temperature in October and December, with p-values and slopes ($p < 0.05$ and slope = -0.48, $p < 0.05$ and slope = -0.05, respectively). The remaining months were not statistically significant.

Table 4.7. MK trend test results of mean monthly Tmax from 1984–2014.

Month	MK trend test	Motta	D/work	Dejen	D/Markos
Jan.	Z-value	1.29	-1.51	1.68	1.30
	Sen's slope	0.033	-0.03	0.032	0.022
	MK stat (S)	77.00	-90.00	100.0	78.00
	P-value	0.19	0.13	0.09	0.19
Feb.	Z-value	2.84	0.68	1.75	3.23
	Sen's slope	0.047	0.017	0.043	0.058
	MK stat (S)	168.00	41.00	104.00	191.00
	P-value	0.0045***	0.49	0.08	0.001***
Mar.	Z-value	1.105	-0.085	1.83	2.29
	Sen's slope	0.024	-0.0004	0.057	0.044
	MK stat (S)	66.00	-6.00	109.00	136.00
	P-value	0.27	0.93	0.06	0.022
Apr.	Z-value	1.17	0.476	1.44	2.17
	Sen's slope	0.026	0.011	0.049	0.06
	MK stat (S)	70.00	29.00	86.00	129.00
	P-value	0.24	0.63	0.14	0.03
May.	Z-value	1.29	0.612	0.5	1.2
	Sen's slope	0.038	0.013	0.016	0.036
	MK stat (S)	77.00	37.00	31.00	72.00
	P-value)	0.19	0.54	0.6	0.22
Jun.	Z-value	1.67	0.21	0.034	2.9
	Sen's slope	0.034	0.0037	0.0005	0.06
	MK stat (S)	99.00	13.00	3.00	172.00
	P-value	0.096	0.84	0.97	0.0037***
Jul.	Z-value	1.8	-0.9	-1.12	3.298
	Sen's slope	0.026	-0.018	-0.031	0.04
	MK stat (S)	107.00	-54.00	-67.00	195.00
	P-value	0.07	0.37	0.26	0.00097***
Aug.	Z-value	2.31	-1.12	-1.6	2.24
	Sen's slope	0.028	-0.019	-0.036	0.02
	MK stat (S)	137.00	-67.00	-95.00	133.00
	P-value	0.02**	0.26	0.11	0.024***
Sept.	Z-value	3.35	-0.66	-0.58	1.956
	Sen's slope	0.028	-0.009	-0.0057	0.022
	MK stat (S)	198.00	-40.00	-35.00	116.00
	P-value	0.0008***	0.5	0.56	0.05**
Oct.	Z-value	0.99	-1.92	0.748	1.3
	Sen's slope	0.018	-0.048	0.0094	0.024
	MK stat (S)	59.00	-114.00	45.00	78.00
	P-value	0.32	0.05**	0.45	0.19
Nov.	Z-value	0.7	-1.83	0.3	1.14
	Sen's slope	0.01	-0.039	0.0038	0.02
	MK stat (S)	42.00	-109.00	19.00	68.00
	P-value	0.49	0.06	0.76	0.25
Dec.	Z-value	-0.748	-2.29	-0.187	0.78
	Sen's slope	-0.014	-0.048	-0.0036	0.011
	MK stat (S)	-45.00	-136.00	-12.00	47.00
	P-value	0.45	0.02**	0.85	0.43

As demonstrated below in Table 4.8, for the mean monthly minimum temperature from four stations, three of them were statistically significant increasing trends, namely, the D/Work, Dejen, and D/Markos stations observed. In D/Work station months such as February, April to August, and October to December, the p-value and slope are $p=0.03$ and $\text{slope}=0.11$, $p<0.01$, $\text{slope}=0.09$, $p<0.01$, $\text{slope}=0.079$, $p<0.05$, $\text{slope}=0.074$, $p<0.01$, $\text{slope}=0.093$, $p<0.01$, $\text{slope}=0.07$, $p<0.01$, $\text{slope}=0.189$, $p<0.01$, $\text{slope}=0.131$ and $p<0.05$, $\text{slope}=0.13$, respectively. In Dejen station, months such as January, February, and March presented p-values and slopes ($p<0.01$, $\text{slope}=0.2$, $p<0.01$, $\text{slope}=0.21$ and $p<0.05$, $\text{slope}=0.118$, respectively). D/Markos station months, such as January, February, June, July, August, September, and October, presented p values and slopes ($p<0.05$, $\text{slope}=0.039$, $p<0.01$, $\text{slope}=0.047$, $p<0.01$, $\text{slope}=0.029$, $p<0.01$, $\text{slope}=0.036$, $p<0.01$, $\text{slope}=0.026$, $p<0.01$, $\text{slope}=0.047$ and $p<0.01$, $\text{slope}=0.021$, respectively). However, the mean monthly minimum temperature trends had shown that, in all the months at all the stations, no statistically significant decreasing trends were observed. Thus, in this study, the minimum temperature increased more than the maximum temperature. This study agreed with that of (Assefa and Mengistu, 2021b), who reported that the average annual minimum temperature increases faster than the average maximum temperature.

Table 4.8. MK trend test results of mean monthly Tmin from 1984–2014.

Month	MK trend test	Motta	D/work	Dejen	D/Markos
Jan.	Z-value	0.37	1.55	2.43	2.057
	Sen's slope	0.017	0.088	0.2	0.039
	MK stat (S)	23.00	92.00	144.00	122.00
	P-value	0.7	0.12	0.015**	0.04**
Feb.	Z-value	1.1	2.14	2.79	2.619
	Sen's slope	0.032	0.11	0.2	0.047
	MK stat (S)	66.00	127.00	165.00	155.00
	P-value	0.27	0.03**	0.005***	0.0088***
Mar.	Z-value	-0.22	1.27	2.31	1.78
	Sen's slope	-0.005	0.07	0.118	0.023
	MK stat (S)	-14.00	76.00	137.00	106.00
	P-value	0.83	0.2	0.02**	0.074
Apr.	Z-value	-0.37	2.4	1.67	1.699
	Sen's slope	-0.0086	0.088	0.092	0.028
	MK stat (S)	-23.00	142.00	99.00	101.00
	P-value	0.7	0.01***	0.096	0.089
May.	Z-value	-0.7	2.38	1.699	1.78
	Sen's slope	-0.02	0.079	0.074	0.028
	MK stat (S)	-42.00	141.00	101.00	106.00
	P-value)	0.49	0.017***	0.089	0.074
Jun.	Z-value	0.39	2.23	0.7649	3.35
	Sen's slope	0.005	0.074	0.038	0.029
	MK stat (S)	24.00	132.00	46.00	198.00
	P-value	0.7	0.026**	0.44	0.0008***
Jul.	Z-value	1.17	2.65	1.24	4.18
	Sen's slope	0.018	0.093	0.0448	0.036
	MK stat (S)	70.00	157.00	74.00	247.00
	P-value	0.24	0.008***	0.21	0.00003***
Aug.	Z-value	1.088	2.498	1.768	3.079
	Sen's slope	0.01	0.07	0.049	0.026
	MK stat (S)	65.00	148.00	105.00	182.00
	P-value	0.28	0.012**	0.077	0.002***
Sept.	Z-value	0.9	1.82	1.58	3.86
	Sen's slope	0.019	0.062	0.055	0.03
	MK stat (S)	54.00	108.00	94.00	228.00
	P-value	0.37	0.07	0.11	0.0001***
Oct.	Z-value	0.714	2.82	1.665	3.025
	Sen's slope	0.03	0.189	0.086	0.047
	MK stat (S)	43.00	167.00	99.00	179.00
	P-value	0.48	0.0048***	0.095	0.0025***
Nov.	Z-value	1.58	2.33	1.938	1.75
	Sen's slope	0.047	0.131	0.152	0.021
	MK stat (S)	94.00	138.00	115.00	104.00
	P-value	0.11	0.019**	0.05**	0.08
Dec.	Z-value	0.63	1.97	1.39	-0.085
	Sen's slope	0.011	0.13	0.12	-0.002
	MK stat (S)	38.00	117.00	83.00	-6.00
	P-value	0.53	0.048**	0.16	0.93
Mean annual	Z-value	1.38	2.74	2.175	3.79
	Sen's slope	0.019	0.09	0.10	0.028
	MK stat (S)	82.00	162.00	129.00	224.00
	P-value	0.17	0.006***	0.029	0.00015***

4.3.3. Trend analysis of the mean annual maximum and minimum Temperature from 1984–2014.

What could be the implications of

The trend analysis of mean annual maximum and minimum temperature data for 31 years at the Motta, D/Work, Dejen, and D/Markos stations were analyzed from 1984 to 2014 reveals significant warming trends at some stations, especially in Motta and D/Markos, with significant increases in both maximum and minimum temperatures. While D/Work and Dejen showed increasing trends, they are not statistically significant at the 5% significance level for maximum temperature, though they do show significant warming for minimum temperatures. In Motta and D/Markos showed significant temperature increase, but D/Work and Dejen do not showed significant trends, because local factors, such as elevation, topography, and proximity to water bodies, may influence the variability of temperature trends across different stations. Areas with more urbanization or deforestation may experience more pronounced temperature increases. The findings highlight regional variability in temperature changes across the stations. As shown in Table 4.9, the mean annual maximum temperature trend test results for the Motta and D/Markos stations showed significant increasing trends, with p-values and slopes ($p=0.002$, slope=0.03, and $p=0.00009$, slope=0.036) significant at the 99% confidence level ($\alpha = 0.01$). Figure 4.4 below shows that the mean annual maximum temperature trends of Motta and D/Markos stations were shown significantly an increasing trend at 1% ($\alpha = 0.01$). However, D/Work station was showed decreasing trend. The significant temperature increases could be affected agricultural productivity due to higher temperatures leading to heat stress on crops. Water availability could also be impacted, as increased temperatures may lead to higher evaporation rates.

Table 4.9. Mann Kendall's trend test results of mean annual maximum temperature.

Stations	Z-value	Sen's slope	M.K stat(S)	Kendall's tau	p-value	α	Trend
Motta	3.06	0.03	181.0	0.389	0.002***	0.05	Significant
D/work	-0.88	-0.013	-53.0	-0.114	0.37*	0.05	No significant
Dejen	0.95	0.016	57.0	0.123	0.34*	0.05	No significant
D/Markos	3.91	0.036	231.0	0.497	0.00009***	0.05	Significant

* As the computed p-value is greater than the significance level $\alpha = 0.05$, one cannot reject the null hypothesis H_0 .

** As the computed p-value is lower than the significance level $\alpha = 0.05$ reject the null hypothesis H_0 .

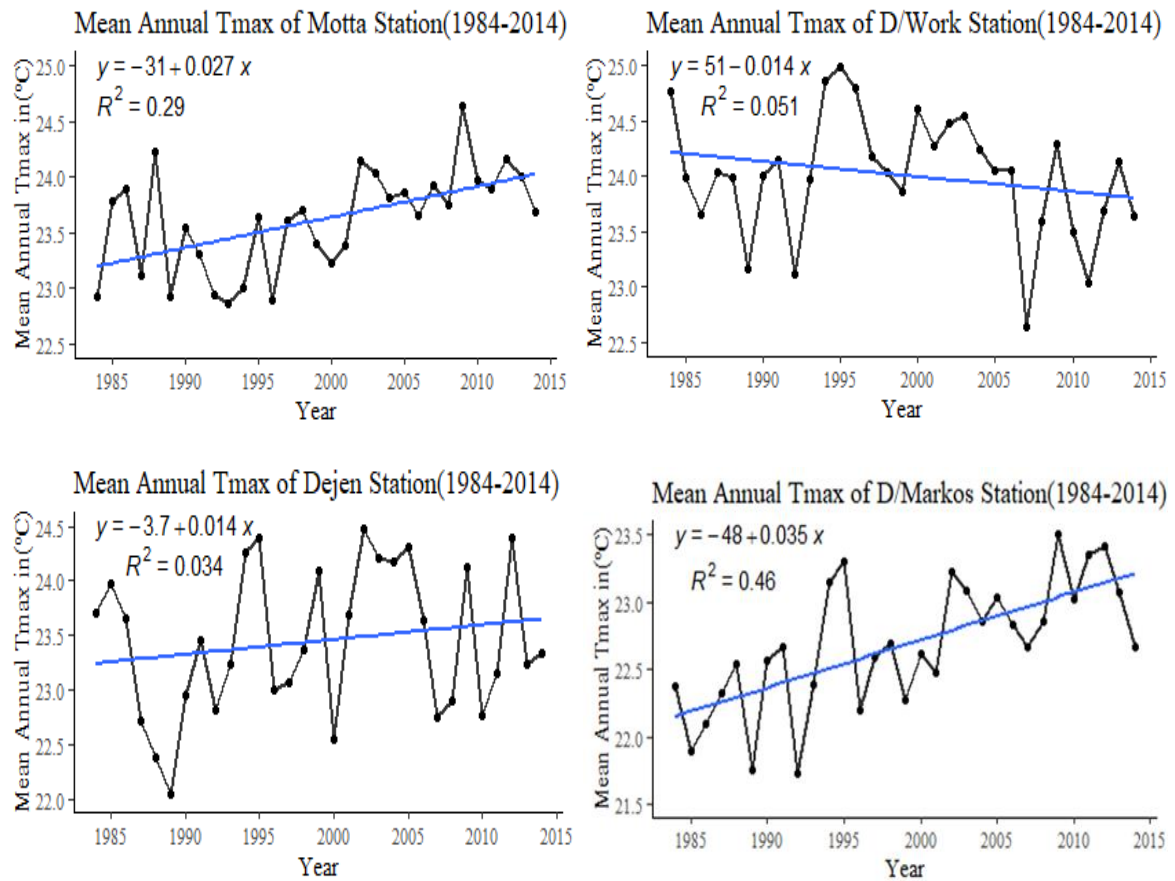


Figure 4.4. MK trend test of the mean annual Tmax at the Motta, D/Work, Dejen, and D/Markos Stations.

The trends of the mean annual minimum temperature data were statistically significant at the D/Work, Dejen, and D/Markos stations, with p-values and slopes ($p=0.006$, slope=0.019, $p=0.029$, slope=0.11 and $p=0.00015$, slope=0.028) being significant at 1%, 5%, and 10% levels of significance, respectively. In Figure 4.5 below, the mean annual minimum temperature trends were shown significant increasing trends at D/Work, Dejen, and D/Markos stations.

Table 4.10. Mann–Kendall trend test results for the mean annual minimum temperature.

Stations	Z-value	Sen's slope	M.K stat(S)	Kendall's tau	p-value	α	Trend
Motta	1.36	0.019	81.0	0.174	0.17	0.05	Insignificant
D/work	2.74	0.09	162.0	0.348	0.006***	0.05	Significant
Dejen	2.175	0.11	129.0	0.277	0.029**	0.05	Significant
D/Markos	3.79	0.028	224.0	0.482	0.00015***	0.05	Significant

* As the computed p-value is greater than the significance level $\alpha = 0.05$, one cannot reject the null hypothesis H_0 .

** As the computed p-value is lower than the significance level $\alpha = 0.05$ rejects the null hypothesis H_0 .

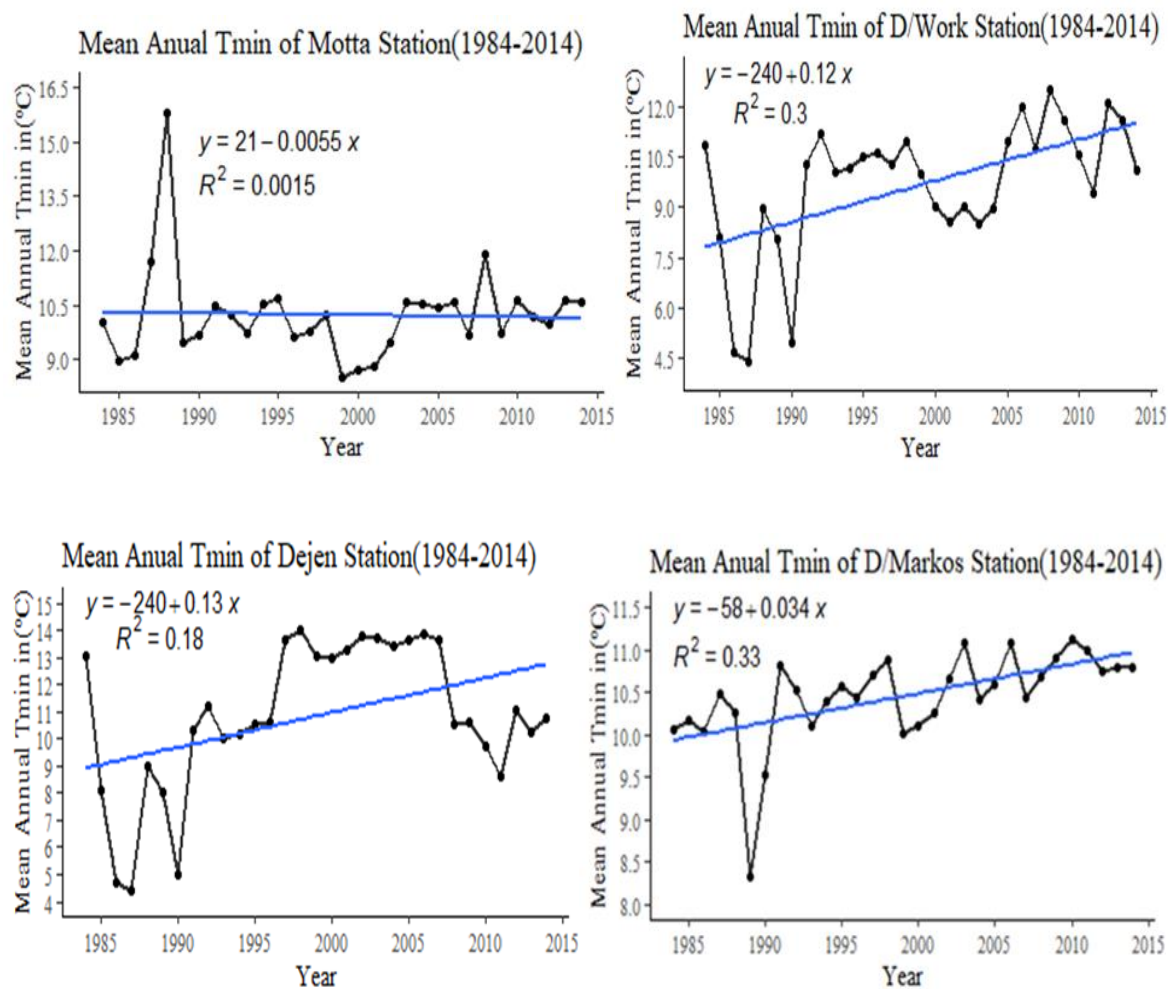


Figure 4.5. MK trend test of the mean annual Tmin at the Motta, D/Work, Dejen, and D/Markos Stations.

4.4. Performance of the CMIP6 GCMs for simulating rainfall

This study investigated the capacity of the CMIP6 model to reproduce the observed daily, monthly, and annual rainfall (Eyring *et al.*, 2019). Suggests that appropriate model evaluation entails performance measures for the mean state, patterns, fluctuations, essential physical operations, and potential emergent limitations. In Table 4.11 showed that the rankings of the seven GCMs for all the stations reported using the CRI method. The statistical metric evaluation was accomplished via the CMIP6 model simulations from 1984 to 2014 for the total annual rainfall calculated for all GCMs. In the present study, an evaluation of total annual rainfall was conducted based on RMSE, PBIAS, r , KGE, and CRI. The climate models underestimate the observed variables, when the model values are lower than the observed values, whereas overestimation is recorded, when the model values are higher than the observed values.

The performance of seven CMIP6 GCMs in terms of long-term total annual rainfall with observed data across the selected stations in the EGZ is presented in Figure 8, and the results show clearly the difference between the observations and models. The GCMs were ranked based on the values of the performance measures via the CRI. When the values of the CRI are highest, the model is best performed. Among the seven CMIP6 GCMs, MIROC6, MPI-ESM1-2-HR, and MPI-ESM1-2-LR were the best-performing (highest-ranked GCMs) for long-term annual rainfall across all stations, namely, Motta, D/work, Dejen, and D/Markos. However, the poor-performance CMIP6 GCM models, such as the BCC-CSM2-MR, GFDL-CM4, MRI-ESM2-0, and NorESM2-MM GCMs, at all stations (i.e., Motta, Debre Work, Dejen, and Debre Markos) also shown underestimated of the total annual rainfall, except MIROC6. The findings indicated that the models contain varying extents of estimation bias at different stations in the zone.

In figure 4.6 among the least performed GCMs, in each station such as: - Motta (BCC-CSM2-MR and NorESM2-MM), D/Work (NorESM2-MM), on Dejen and D/Markos the similar GCMs (GFDL-CM4, MRI-ESM2-0, and NorESM2-MM) were overestimated, whereas the others were underestimated. However, all the best performing models were underestimated at all stations.

Table 4.11. Performance metrics and ranking of GCMs for total annual rainfall using the CRI method.

Stations	CMIP6 Models	RMSE	PBIAS	KGE	R	CRI	Rank
Motta	1.BCC-CSM2-MR	88.66	1.5	0.42	0.75	0.23	6 th
	2. GFDL-CM4	98.16	0	0.28	0.72	0.29	5 th
	3. MIROC6	54.62	0	0.78	0.88	0.86	1 st
	4.MPI-ESM1-2-HR	64.11	0	0.69	0.85	0.69	3 rd
	5.MPI-ESM1-2-LR	62.57	0	0.71	0.85	0.74	2 nd
	6. MRI-ESM2-0	74.48	0	0.59	0.81	0.51	4 th
	7. NorESM2-MM	189.49	0.9	-1.67	0.46	0.03	7 th
D/Work	1.BCC-CSM2-MR	69.6	0	0.45	0.72	0.34	6 th
	2. GFDL-CM4	69.48	0	0.45	0.73	0.4	5 th
	3. MIROC6	51.91	0	0.69	0.83	0.86	1 st
	4.MPI-ESM1-2-HR	57.7	0	0.62	0.8	0.66	3 rd
	5.MPI-ESM1-2-LR	56.76	0	0.63	0.8	0.74	2 nd
	6. MRI-ESM2-0	63.44	0	0.54	0.76	0.51	4 th
	7. NorESM2-MM	171.51	0.1	-2.3	0.38	0	7 th
Dejen	1.BCC-CSM2-MR	86.92	-0.6	0.47	0.73	0.43	5 th
	2. GFDL-CM4	104.17	0	0.24	0.64	0.26	6 th
	3. MIROC6	69.33	0	0.66	0.82	0.83	1 st
	4.MPI-ESM1-2-HR	74.6	0	0.61	0.79	0.71	2 nd
	5.MPI-ESM1-2-LR	77.77	0	0.58	0.77	0.6	3 rd
	6. MRI-ESM2-0	86.15	0	0.48	0.73	0.49	4 th
	7. NorESM2-MM	208.03	0.9	-2.02	0.36	0	7 th
D/Markos	1.BCC-CSM2-MR	87.91	1.4	0.42	0.75	0.31	5 th
	2. GFDL-CM4	108.24	0	0.12	0.68	0.29	6 th
	3. MIROC6	57.79	0	0.75	0.87	0.86	1 st
	4.MPI-ESM1-2-HR	69.37	0	0.64	0.82	0.63	3 rd
	5.MPI-ESM1-2-LR	66.6	0	0.67	0.83	0.74	2 nd
	6. MRI-ESM2-0	87.76	0	0.42	0.74	0.49	4 th
	7. NorESM2-MM	193.02	1.0	-1.77	0.43	0.029	7 th

Note that rank is given based on CRI, and 1st and 7th rank indicate the best and poorest performing models, respectively.



Figure 4. 6. Total annual RF of the CMIP6 GCMs with observed data at the Motta, D/Work, Dejen, and D/Markos Stations.

4.5. Performance of the CMIP6 GCMs for simulating the mean annual maximum and minimum temperature

The performance of CMIP6 GCMs for simulating mean annual maximum (Tmax) minimum temperature (Tmin) across multiple stations (Motta, D/Work, Dejen, and D/Markos) has been assessed using performance metrics like RMSE, PBIAS, KGE, and R with results indicated varied level of model performance. FGOLAS-g3 consistently ranks as the best performing model, providing the most reliable simulations, while models like MPI-ESM1-2-HR and MRI-ESM2-0 showed poorer performance, particularly at D/Work and D/Markos stations. These insights are crucial for selecting appropriate models for future temperature projections. In Tables 4.12 and 4.13 present the statistical metric evaluations achieved by the CMIP6 model simulations from 1984 to 2014 for the mean annual maximum and minimum temperature calculated for all GCMs and the ranking of the GCMs derived using the CRI method. A graphical comparison of the studied GCMs for simulating long-term mean annual Tmax and Tmin distributions of the studied GCMs and observed data over the EGZ-selected stations as illustrated in Figures 4.7 and 4.8.

Based on this study in Table 4.12, the best-performing models (the highest-ranking GCMs) for the mean annual Tmax were FGOLAS-g3, MIROC6, and MPI-ESM1-2-HR at all stations. At Motta and D/Markos stations, the FGOLAS-g3 and MIROC6 GCMs showed an overestimation of the mean annual Tmax, whereas, the MPI-ESM1-2-HR model was underestimated. At D/Work and Dejen stations, the MPI-ESM1-2-HR and MIROC6 GCMs were shown overestimated, whereas the FGOLAS-g3 was underestimated. Also, the mean annual Tmax of the least-performing models was underestimated at all stations.

For the mean annual Tmin in Table 4.13, the best-performing models were FGOLAS-g3, MIROC6, and MRI-ESM2-0. Because the FGOLAS-g3 and MPI-ESM1-2-HR shows the highest consistency across various performance metrics and it has a more accurate and reliable representation of in both Tmax and Tmin. Whereas other models were showed poor performance, because it may struggle with local factors like topography or seasonal to specific certain stations, leading to overestimations or underestimations of temperature. And this showed that except, for FGOLAS-g3 at the D/Markos station all models were showed underestimated at all stations in both the best and least performing models. Therefore, the performance of the remaining models was poorly performed (least ranked

GCMs), because these models are the coarser temporal resolutions of the climate models. By identifying the best-performing models, like FGOLAS-g3, MIROC6, MPI-ESM1-2-HR, and MRI-ESM2-0, this analysis can guide future projections of Tmax and Tmin, ensuring that more reliable models are used for climate adaptation strategies in the region. Generally, first, second, and third-ranked GCMs were best selected for future projections of Tmax and Tmin of the mean model ensemble (MME).

Table 4.12. Performance metrics and ranking of GCMs for mean annual Tmax in (°C) through the CRI method.

Stations	CMIP6 Models	RMSE	PBIAS	KGE	R	CRI	Rank
Motta	1.FGOLAS-g3	1.39	-0.1	0.59	0.8	0.80	1st
	2. GFDL-CM4	1.48	0	0.53	0.78	0.57	6 th
	3. MIROC6	1.8	0	0.31	0.73	0.17	3 rd
	4.MPI-ESM1-2-HR	1.97	0	0.58	0.8	0.6	2 nd
	5. MPI-ESM1-2-LR	1.5	0	0.52	0.78	0.5	4 th
	6. MRI-ESM2-0	1.55	0	0.49	0.76	0.3	5 th
D/Work	1.FGOLAS-g3	1.49	0	0.41	0.70	0.57	3 rd
	2. GFDL-CM4	1.48	0	0.42	0.72	0.7	6 th
	3. MIROC6	1.97	0	-0.03	0.59	0.17	2 nd
	4.MPI-ESM1-2-HR	1.47	0	0.43	0.73	0.83	1st
	5. MPI-ESM1-2-LR	1.65	0	0.28	0.66	0.43	4 th
	6. MRI-ESM2-0	1.69	0	0.24	0.64	0.3	5 th
Dejen	1.FGOLAS-g3	1.55	0	0.62	0.81	0.83	1st
	2. GFDL-CM4	1.62	0	0.59	0.80	0.43	4 th
	3. MIROC6	1.56	0	0.62	0.81	0.8	2 nd
	4.MPI-ESM1-2-HR	1.56	0	0.62	0.81	0.8	2 nd
	5. MPI-ESM1-2-LR	1.67	0	0.56	0.78	0.3	5 th
	6. MRI-ESM2-0	1.8	0	0.49	0.75	0.17	6 th
D/Markos	1.FGOLAS-g3	1.34	0	0.71	0.86	0.83	1st
	2. GFDL-CM4	1.42	0	0.67	0.84	0.57	6 th
	3. MIROC6	2.98	0	0.13	0.36	0.17	3 rd
	4.MPI-ESM1-2-HR	3.26	0	-0.04	0.21	0.80	2 nd
	5. MPI-ESM1-2-LR	3.19	0	0.01	0.26	0.47	4 th
	6. MRI-ESM2-0	3.05	0	0.09	0.32	0.30	5 th

Note that Rank is given based on CRI, and the 1st and 6th ranks indicate the best and poorest performing models, respectively.

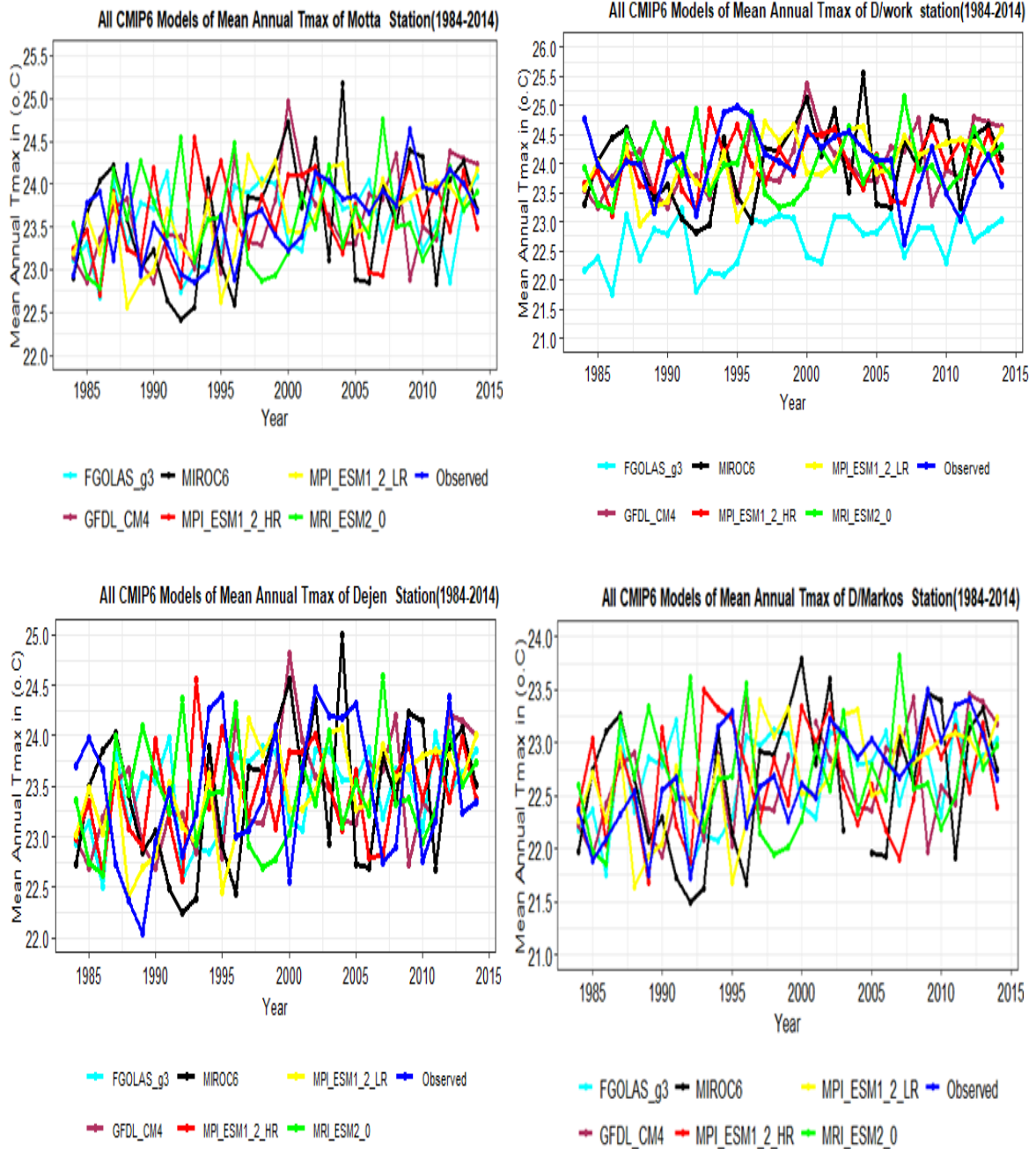


Figure 4.7. Mean annual Tmax of the CMIP6 GCMs with observed data at the Motta, D/Work, Dejen, and D/Markos Stations.

Table 4.13. Performance metrics and ranking of GCMs for mean annual Tmin in (°C) through the CRI method.

Stations	CMIP6 Models	RMSE	PBIAS	KGE	R	CRI	Rank
Motta	1.FGOLAS-g3	1.83	-0.1	0.34	0.6	0.7	2 nd
	2. GFDL-CM4	1.89	0	0.29	0.58	0.4	4 th
	3. MIROC6	1.81	0	0.35	0.61	0.80	1 st
	4.MPI-ESM1-2-HR	1.99	0	0.21	0.55	0.27	5 th
	5.MPI-ESM1-2-LR	2.12	0	0.11	0.49	0.13	6 th
	6. MRI-ESM2-0	1.86	0	0.31	0.59	0.53	3 rd
D/Work	1.FGOLAS-g3	2.65	-0.1	0.12	0.37	0.57	3 rd
	2. GFDL-CM4	2.68	-0.1	0.11	0.36	0.43	4 th
	3. MIROC6	2.63	0	0.14	0.38	0.70	2 nd
	4.MPI-ESM1-2-HR	2.83	0	0	0.29	0.10	6 th
	5.MPI-ESM1-2-LR	2.76	0	0.05	0.33	0.23	5 th
	6. MRI-ESM2-0	2.62	0	0.14	0.39	0.77	1st
Dejen	1.FGOLAS-g3	2.95	-0.1	0.15	0.39	0.83	1st
	2. GFDL-CM4	3.12	-0.1	0.05	0.25	0.43	4 th
	3. MIROC6	2.98	0	0.13	0.36	0.63	2 nd
	4.MPI-ESM1-2-HR	3.26	0	-0.04	0.21	0.1	6 th
	5.MPI-ESM1-2-LR	3.19	0	0.01	0.26	0.23	5 th
	6. MRI-ESM2-0	3.05	0	0.09	0.32	0.5	3 rd
D/Markos	1.FGOLAS-g3	0.98	0	0.48	0.74	0.83	1st
	2. GFDL-CM4	1.2	0	0.22	0.64	0.30	5 th
	3. MIROC6	1.06	0	0.39	0.69	0.70	2 nd
	4.MPI-ESM1-2-HR	1.17	0	0.26	0.67	0.43	4 th
	5.MPI-ESM1-2-LR	1.34	0	0.04	0.61	0.17	6 th
	6. MRI-ESM2-0	1.08	0	0.37	0.69	0.60	3 rd

Note that rank is given based on CRI, and the 1st and 6th ranks indicate the best and poorest performing models, respectively.

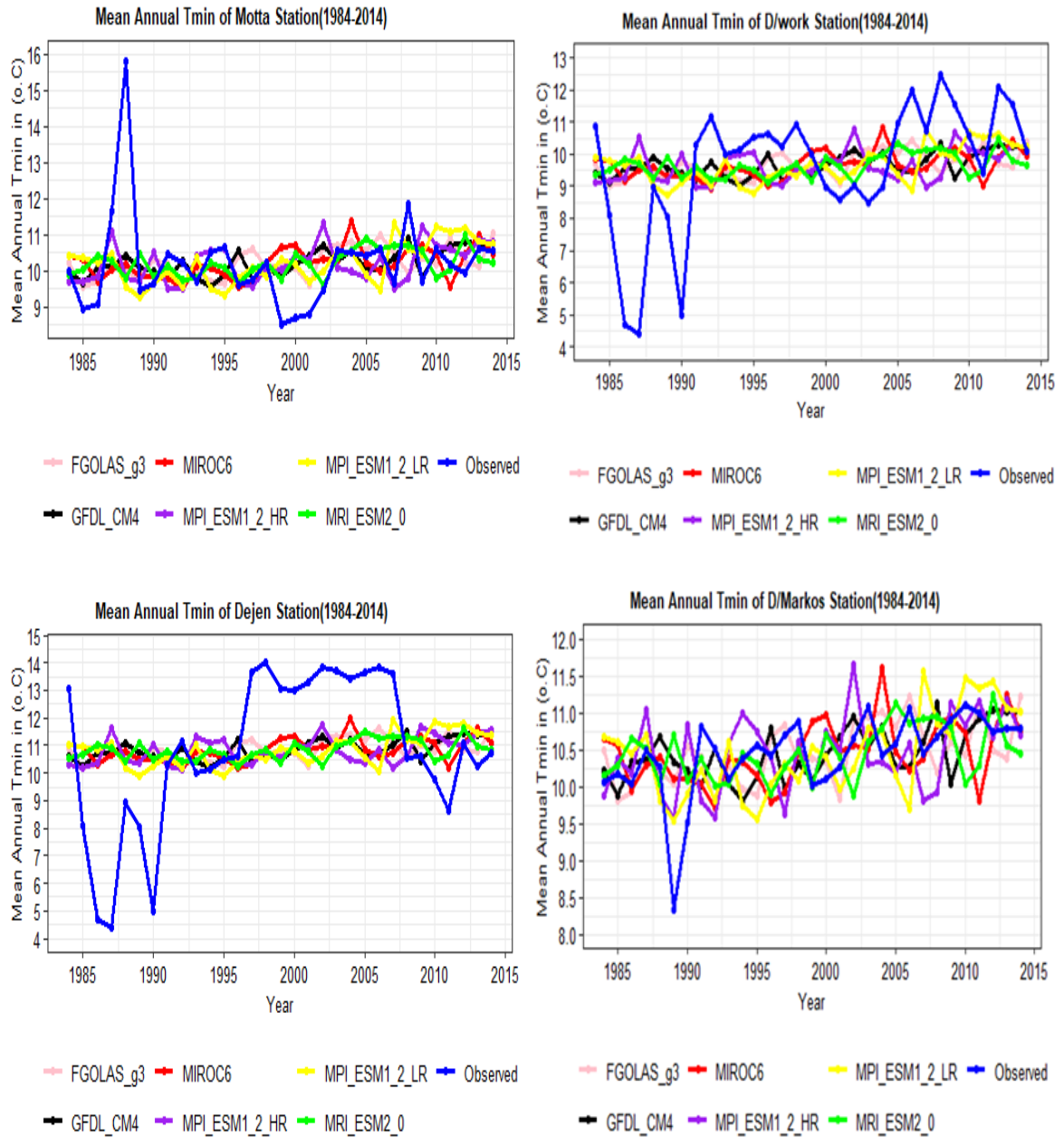


Figure 4.8. Mean annual Tmin of the CMIP6 GCMs with observed data at the Motta, D/Work, Dejen, and D/Markos Stations.

4.6. Selection of best-performing models for future climate change analysis

As stated earlier, MIROC6, MPI-ESM1-2-HR, and MPI-ESM1-2-LR shown consistently better performance in simulating annual rainfall at all stations. The FGOLAS-g3, MPI-ESM1-2-HR, and GFDL-CM4 models had shown consistently better performance for the Motta, D/Work, and D/Markos stations, and at the Dejen station the models such as: - FGOLAS-g3, MIROC6 and MPI-ESM1-2-HR were shown consistently better performance for simulating the mean annual Tmax. FGOLAS-g3, MIROC6, and MRI-ESM2-0 had shown consistently better performance in simulating the mean annual Tmin at all stations. Therefore, this study was evaluated the performance of the individual best-performing models as well as the mean ensemble model (MME) of the three best-performing models were shown above in Tables 4.11, 4.12 and 4.13, which were chosen for rainfall, Tmax, and Tmin.

The result revealed that the mean model ensemble (MME) of the three best-performing rainfall models (i.e., MIROC6, MPI-ESM1-2-HR, and MPI-ESM1-2-LR) had shown better performance than any of the individual models (Table 4.11). The mean model ensemble of the three Tmax models (FGOLAS-g3, MPI-ESM1-2-HR, and GFDL-CM4) also showed the best performance compared with the performance of the individual models in Table 4.12. For Tmin, the mean model ensemble of the three best-performing models (FGOLAS-g3, MIROC6, and MRI-ESM2-0) showed better performance than that of the performance of the individual models (Table 4.13). Therefore, in this study, the mean model ensemble of the three best-performing models were used for rainfall, Tmax, and Tmin for future climate change analysis.

According to Gashaw *et al.* (2024), using the ensemble mean of the three best-performing rainfall models (i.e., BCC-CSM2-MR, CNRM-CM6-1, and MRI-ESM2-0) have shown superior performance to that of any of the individual models. Similarly, (Zarrin and Dadashi-Roudbari, 2021) used the ensemble mean of the best-performing climate models for simulating rainfall over Iran. According to Ajibola *et al.* (2020) reported that the ensemble mean had outperformed the individual models for simulating annual rainfall over West Africa. Therefore, in this study, the performance of the ensemble mean of the three models was better than that of the individual models for simulating Rainfall, Tmax, and Tmin at the studied temporal scales. Generally, this study highlights the necessity of

evaluating the ensemble mean of different best-performing model combinations to obtain better simulations.

4.7. Projections of future rainfall and temperature changes

The projected average annual rainfall amounts of Motta, D/Work, Dejen, and D/Markos for the two future climate horizons under the five scenarios compared with the baseline period are indicated in Table 4.14. The findings of this study revealed that among the four stations, Motta showed the highest reduction (-7%) in annual rainfall in the near future (2031 to 2061) under the SSP1-2.6 scenario. In contrast, D/Work was shown the highest increment (36%) in the SSP5-8.5 scenarios compared with the other stations.

In the late-century period (2070 to 2100), the highest reduction (-6%) was expected at Motta and D/Markos under the SSP1-2.6. Whereas, the highest increment (41%) was projected at D/Work under the SSP5-8.5 scenario. In the near term, the average annual rainfall over Motta and Debre Markos stations was projected to decrease in the four SSP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP4-6.0); however, the average annual rainfall was increased in the SSP5-8.5 scenarios at Motta and D/Markos by 3% and 1% respectively. Whereas, the projected average annual rainfall was increased by 32%, 33%, 34%, 33%, and 36% under SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 scenarios at the D/Work station respectively and at the Dejen station also increased by +0.4%, 3%, 6%, 5% and 10% under SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 scenarios in the near-term periods.

On the other hand, during the late-century period, the mean annual rainfall over D/Work and Dejen was expected to increase in all scenarios. At the D/Work station the annual rainfall increased by 27%, 33%, 38%, 37%, and 41% under SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5, respectively, and the Dejen station was increased by 2%, 4%, 12%, 9%, and 15% under SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5, respectively. In general, according to the model result, D/Work and Dejen experienced an increase in annual rainfall in both the near-future and late-century periods in the five studied scenarios, whereas Motta and D/Markos stations showed a decrease in the annual rainfall in all scenarios except SSP5-8.5 (Table 4.14).

Generally, the finding of this study revealed that the annual rainfall was projected to decrease from -0.09% to -7% intervals at the Motta and D/Markos stations in the near-

term periods (2031 to 2061) under the SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP4-6.0 scenarios whereas, on the SSP5-8.5 scenario was projected to increase by +3% and 1% respectively. However, D/Work and Dejen stations were projected to increase from +2% to +41% under all SSPs. In the late-century period (2070 to 2100), at D/Work and Dejen stations showed an increase from +2% to +41% under all scenarios, whereas, Motta station decreased by -3% and -6% at SSP1-2.6 and SSP2-4.5 respectively and increased by 8%, 3%, and 12% at SSP3-7.0, SSP4-6.0, and SSP5-8.5. At D/Markos station all SSPs were decreased by -6%, -3%, -0.4%, and -2% except, SSP5-8.5. From four stations D/Work was shown as the highest percentage increase at all SSPs.

Table 4.14. The average annual rainfall in the near-term (2031 to 2061) and long-term (2070 to 2100) periods at SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0 and SSP5-8.5 climate scenarios under the studied temporal scales compared with the observed annual rainfall.

Stations	Scenarios	Average annual rainfall changes in (mm)		
		Observed	2031-2061	2070-2100
Motta	SSP1-2.6	1248.89	1164.56(-7%)	1178.96(-6%)
	SSP2-4.5	1248.89	1198.40(-4%)	1210.00(-3%)
	SSP3-7.0	1248.89	1247.27(-0.09%)	1343.25(+8%)
	SSP4-6.0	1248.89	1215.87(-3%)	1284.66(+3%)
	SSP5-8.5	1248.89	1289.47(+3%)	1395.79(+12%)
D/work	SSP1-2.6	939.99	1245.17(+32%)	1197.02(+27%)
	SSP2-4.5	939.99	1252.17(+33%)	1246.49(+33%)
	SSP3-7.0	939.99	1260.75(+34%)	1301.32(+38%)
	SSP4-6.0	939.99	1255.03(+33%)	1284.66(+37%)
	SSP5-8.5	939.99	1274.32(+36%)	1327.22(+41%)
Dejen	SSP1-2.6	1173.84	1178.95(+0.4%)	1192.62(+2%)
	SSP2-4.5	1173.84	1212.43(+3%)	1219.34(+4%)
	SSP3-7.0	1173.84	1242.89(+6%)	1322.82(+12%)
	SSP4-6.0	1173.84	1233.99(+5%)	1283.02(+9%)
	SSP5-8.5	1173.84	1294.55(+10%)	1359.87(+15%)
D/Markos	SSP1-2.6	1369.11	1284.45(-6%)	1288.33(-6%)
	SSP2-4.5	1369.11	1312.87(-4%)	1330.18(-3%)
	SSP3-7.0	1369.11	1349.45(-2%)	1364.02(-0.4%)
	SSP4-6.0	1369.11	1334.72(-3%)	1347.23(-2%)
	SSP5-8.5	1369.11	1383.38(+1%)	1413.47(+3%)

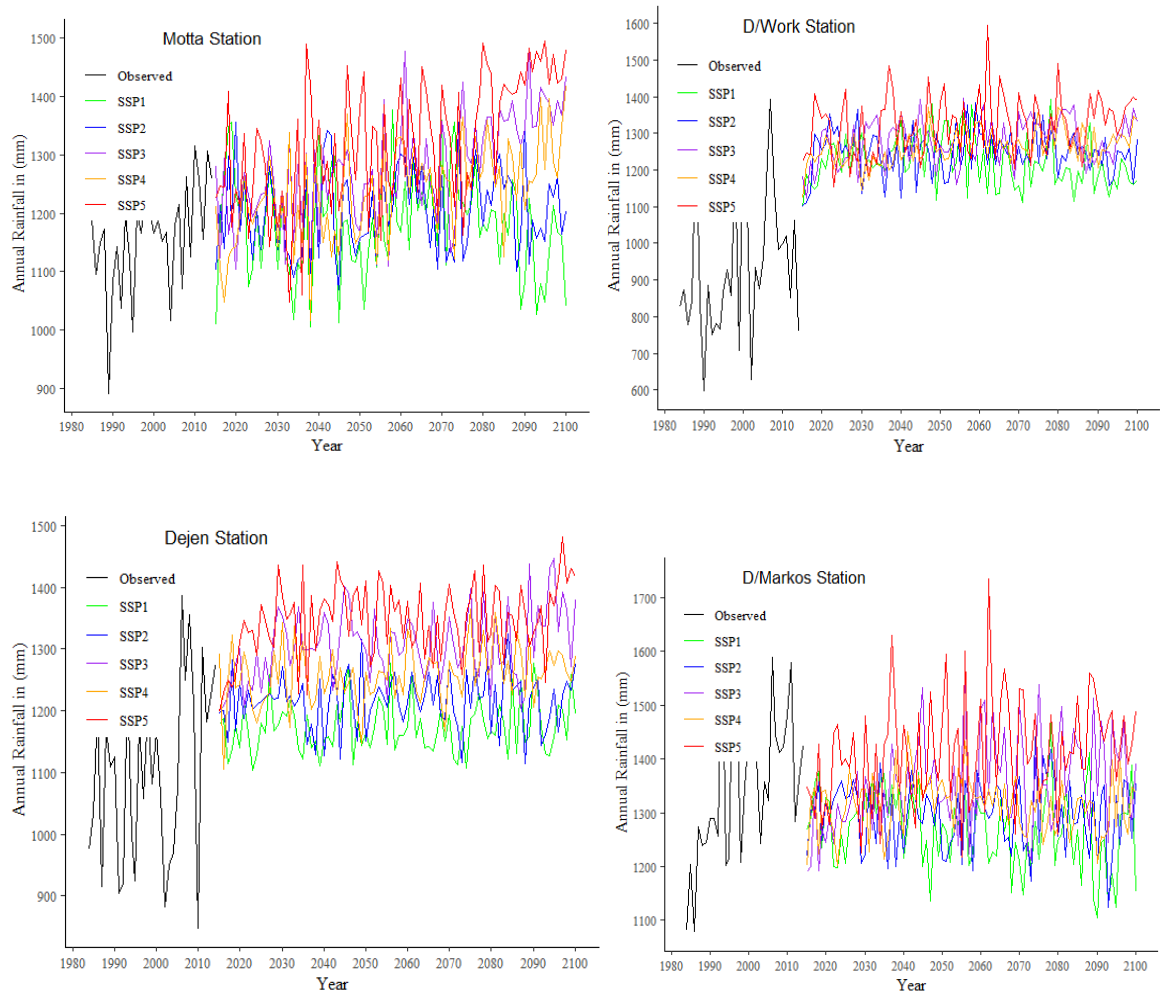


Figure 4.9. The projected annual Rainfall (2015–2100) under SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 climate change scenarios along with the observed rainfall (1984–2014) at the studied EGZ selected stations.

The projected mean annual Tmax and Tmin over the Motta, D/work, Dejen, and D/Markos stations were calculated during the near-future and late-century periods in Table 4.15. At Motta, D/Work, Dejen, and D/Markos reported that, the projected changes in Tmax from 1.72°C to 2.34°C, 1.45°C to 1.97°C, 3.75°C to 4.29°C, and 3.35°C to 3.8°C, respectively, in the near-future period (2031 to 2061). In the late century period (2070 to 2100), the projected changes in Tmax at the Motta, D/Work, Dejen, and D/Markos stations were increased from 1.78°C to 4.15°C, 1.51°C to 4.05°C, 3.83°C to 6.08°C, and 3.3°C to 5.3°C, respectively. However, for Tmin, the projected temperature changes at the Motta, D/Work, Dejen, and D/Markos stations during the near-future period increased from 5.31°C to 5.98°C, 5.74°C to 6.61°C, 4.61°C to 5.28°C, and 4.95°C to 5.62°C, respectively. In the

late century period (2070 to 2100), the projected changes in T_{min} at the Motta, D/Work, Dejen, and D/Markos stations increased from 5.34°C to 7.93°C, 5.77°C to 8.38°C, 4.63°C to 7.23°C, and 4.98°C to 7.57°C, respectively.

Among all the stations in the near-future period, Motta showed the highest projected increase in the maximum temperature change from 1.72°C to 2.34°C (0.62°C), whereas D/Markos showed the lowest projected increase in the maximum temperature change from 3.3°C to 3.8°C (0.5°C). In the late century, Dejen showed the highest projected increase in T_{max} change from 1.51°C to 4.05°C (2.54°C), whereas D/Markos showed the lowest projected increase in T_{max} change from 3.3°C to 5.3°C (2°C). For T_{min}, the highest projected change in the near term was increased by 5.74°C to 6.61°C (0.87°C) at D/Work, whereas the remaining stations showed the lowest projected changes increased by 0.67°C. In the late-century periods, D/Work showed the highest projected increase in T_{min} changes from 3.16°C to 5.77°C (2.61°C), whereas Motta and D/Markos showed the lowest projected increase in T_{min} changes from 5.34°C to 7.93°C (2.59) and 4.98°C to 7.57°C (2.59°C) respectively. Generally, the findings also revealed that the increase in T_{min} was greater than the increase in T_{max} at all the studied SSPs across the study area. In general, the smallest temperature (T_{max} and T_{min}) changes in all five studied future climate scenarios were projected at SSP1-2.6, whereas the highest temperature change was projected at SSP5-8.5. This study similar with (Assefa and Mengistu, 2021) revealing that the increase in T_{min} is higher than the increase in T_{max} in the studied SSPs. The projected increases in T_{max} and T_{min} in this study are associated with other studies in Ethiopia (Gashaw *et al.*, 2024). For example, (Alaminie *et al.*, 2021) reported the projected increases in T_{max} and T_{min} in the Upper Blue Nile Basin of Ethiopia during 2031 to 2060 and 2071 to 2100 periods at the four SSPs.

Table 4.15. The mean annual Tmax and Tmin (°C) in the near term (2031 to 2061) and (2070–2100) periods at SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0 and SSP5-8.5 climate scenarios under the studied temporal scales compared with the observed Tmax and Tmin.

Stations	Scenarios	Mean annual Tmax			Mean annual Tmin.		
		Observed	2031-2061	2070-2100	Observed	2031-2061	2070-2100
Motta	SSP1-2.6	23.61	25.33(+1.72)	25.39(+1.78)	10.09	15.40(+5.31)	15.43(+5.34)
	SSP2-4.5	23.61	25.55(+1.94)	26.33(+2.72)	10.09	15.66(+5.57)	16.20(+6.11)
	SSP3-7.0	23.61	25.60(+1.99)	27.12(+3.51)	10.09	15.86(+5.77)	17.32(+7.23)
	SSP4-6.0	23.61	25.52(+1.91)	26.36(+2.75)	10.09	15.74(+5.65)	16.70(+6.61)
	SSP5-8.5	23.61	25.86(+2.34)	27.76(+4.15)	10.09	16.07(+5.98)	18.02(+7.93)
D/work	SSP1-2.6	24.01	25.46(+1.45)	25.52(+1.51)	9.66	15.40(+5.74)	15.43(+5.77)
	SSP2-4.5	24.01	25.67(+1.66)	26.74(+2.73)	9.66	15.88(+6.22)	16.16(+6.50)
	SSP3-7.0	24.01	25.74(+1.73)	27.22(+3.21)	9.66	16.02(+6.36)	17.32(+7.66)
	SSP4-6.0	24.01	25.86(+1.85)	26.47(+2.46)	9.66	15.74(+6.08)	16.68(+7.02)
	SSP5-8.5	24.01	25.98(+1.97)	28.06(+4.05)	9.66	16.27(+6.61)	18.04(+8.38)
Dejen	SSP1-2.6	23.44	27.19(+3.75)	27.27(+3.83)	10.83	15.44(+4.61)	15.46(+4.63)
	SSP2-4.5	23.44	27.21(+3.77)	27.92(+4.48)	10.83	15.70(+4.87)	16.24(+5.41)
	SSP3-7.0	23.44	27.36(+3.92)	28.84(+5.4)	10.83	15.91(+5.08)	17.38(+6.55)
	SSP4-6.0	23.44	27.45(+4.01)	28.36(+4.92)	10.83	15.79(+4.96)	16.71(+5.88)
	SSP5-8.5	23.44	27.73(+4.29)	29.52(+6.08)	10.83	16.11(+5.28)	18.06(+7.23)
D/Markos	SSP1-2.6	22.68	26.03(+3.35)	25.98(+3.30)	10.45	15.40(+4.95)	15.43(+4.98)
	SSP2-4.5	22.68	25.69(+3.01)	26.26(+3.58)	10.45	15.66(+5.21)	16.27(+5.82)
	SSP3-7.0	22.68	26.26(+3.58)	27.70(+5.02)	10.45	15.86(+5.41)	17.32(+6.87)
	SSP4-6.0	22.68	26.15(+3.47)	26.94(+4.26)	10.45	15.74(+5.29)	16.65(+6.20)
	SSP5-8.5	22.68	26.48(+3.80)	27.98(+5.30)	10.45	16.07(+5.62)	18.02(+7.57)

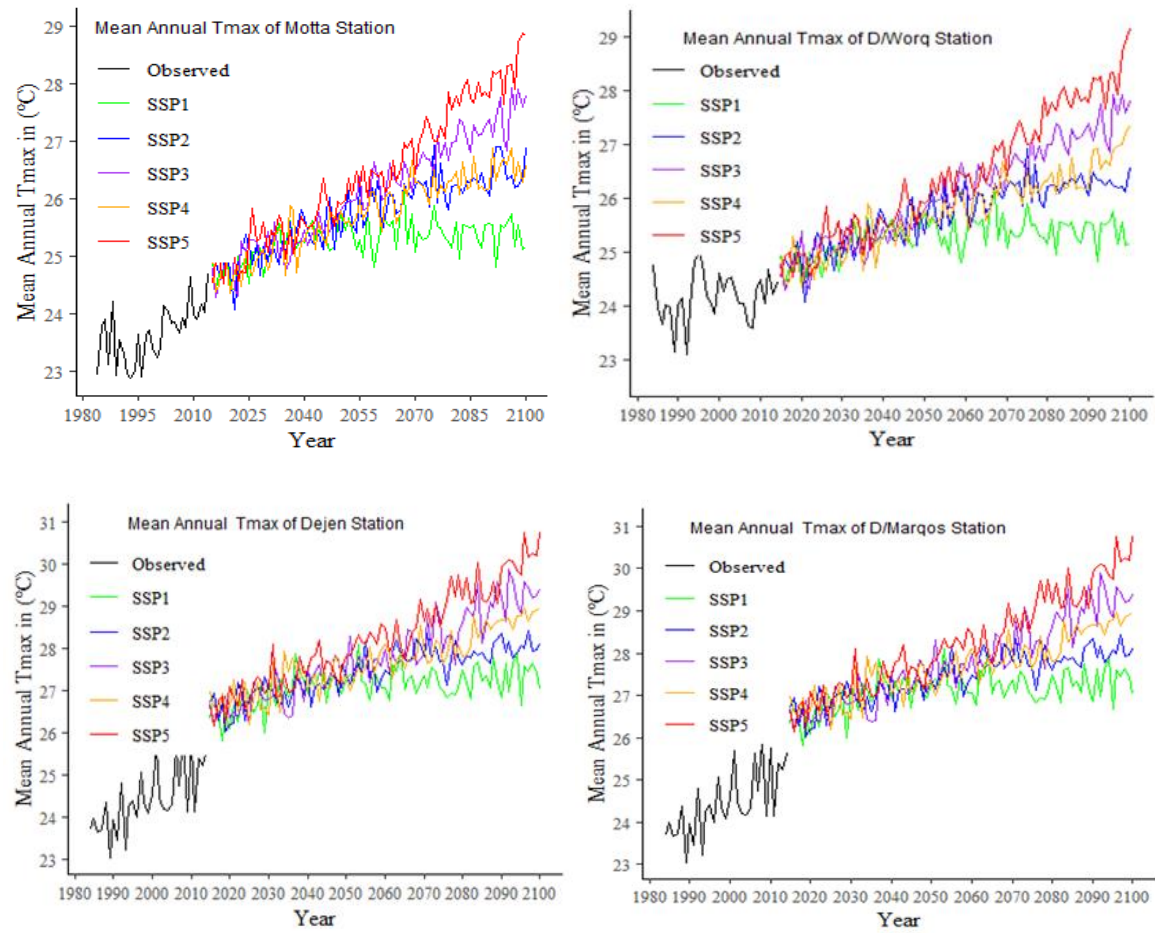


Figure 4.10. The projected mean annual Tmax (2015 to 2100) under the SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 climate change scenarios along with the observed rainfall (1984 to 2014) at the selected stations in the studied EGZ.

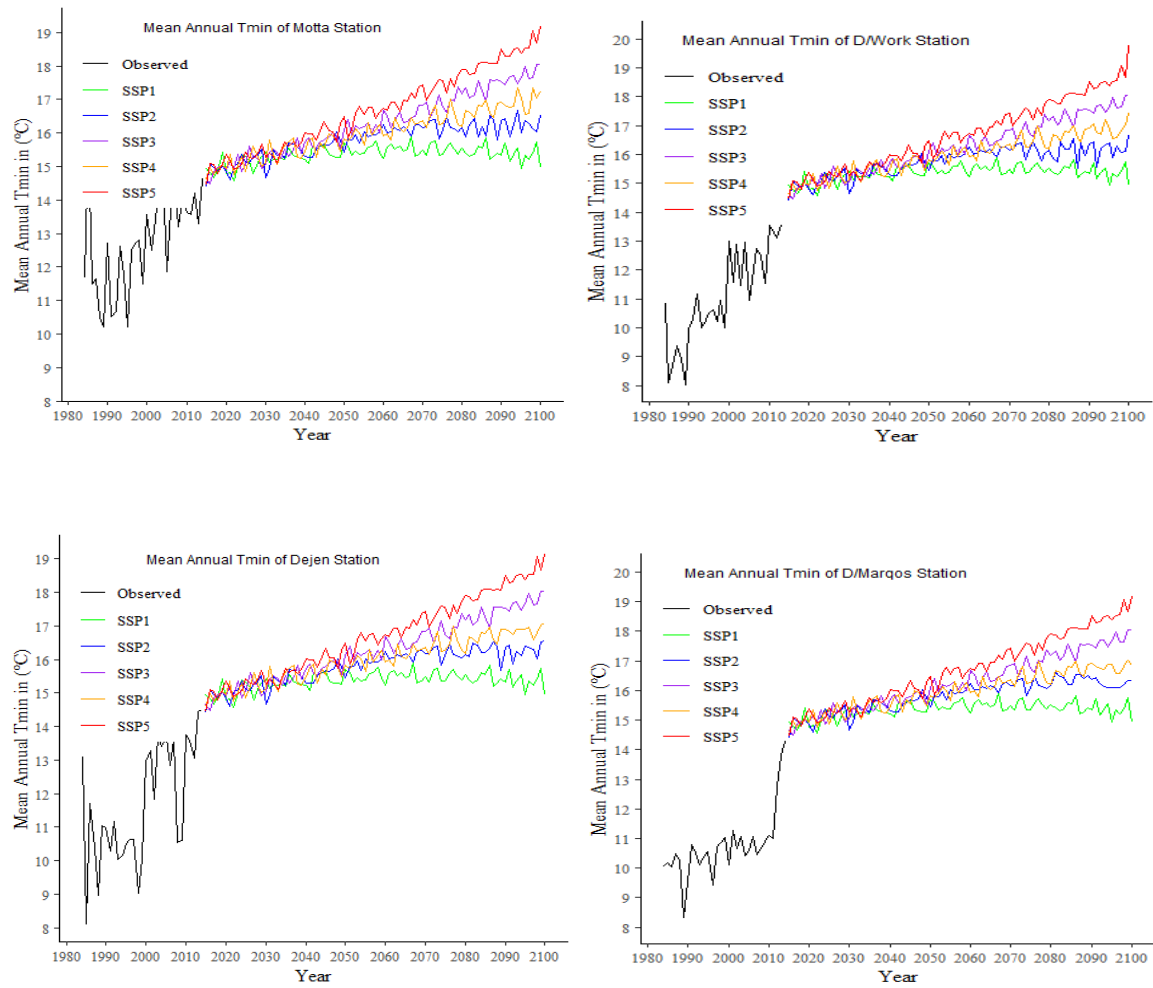


Figure 4.11. The projected mean annual T_{min} (2015 to 2100) under the SSP1-2.6, SSP2-4.5, SSP3-7.0, SSP4-6.0, and SSP5-8.5 climate change scenarios along with the observed rainfall (1984 to 2014) at the selected stations in the studied EGZ.

Chapter Five: CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

The analysis of the 31-year total annual rainfall data from four representative ground-based meteorological stations in the study area revealed a coefficient of variation (CV) ranging from 10.44 to 21.79%. Among the four stations considered, D/Work had a 21.79% coefficient of variation (moderate variability). However, the remaining stations showed less than 20% and low variability. The Mann–Kendall trend test analysis of the four stations showed an increasing trend in annual rainfall. However, except for D/Work, the Tmax values of all the stations showed an increasing trend, and except for Motta, the Tmin values of all the stations showed an increasing trend.

The results generally revealed that MPI-ESM1-2-HR, MPI-ESM1-2-LR, and MIROC6 had better performance in simulating annual rainfall. FGOLAS-g3, MPI-ESM1-2-HR, and MIROC6 exhibited better performance for Tmax, and FGOLAS-g3, MIROC6, and MRI-ESM2-0 exhibited better performance in simulating Tmin at the studied temporal scales. Hence, the ensemble means of MPI-ESM1-2-HR, MPI-ESM1-2-LR, and MIROC6 were used for the rainfall change analysis in the five scenarios. This study used the ensemble mean of the three best-performing climate models (FGOLAS-g3, MPI-ESM1-2-HR, and MIROC6) for simulating future Tmax and the ensemble mean of the three best-performing climate models (FGOLAS-g3, MPI-ESM1-2-HR, and MRI-ESM2-0) for simulating Tmin.

Climate change analysis for the near-future and late-century periods was undertaken in all scenarios after bias correction of the selected ensemble mean for rainfall, Tmax, and Tmin. The findings of the study revealed that in both the near-future and late-century periods, Tmax and Tmin had shown increasing trends at most stations. The rainfall pattern increased in the late century periods at most stations.

5.2. Recommendations

Based on these findings, the following possible solutions might be appropriate to address in future improvements:

- Based on the result of this study, the MIROC6 GCM model demonstrated the best performance for rainfall simulations across all stations, it is recommended to prioritize MIROC6 for future climate modeling and investigations in the study area. This model's accuracy in simulating rainfall can significantly enhance the reliability of future climate projections.
- The observed projected trends in both Tmax and Tmin revealed an increasing trend particularly for near-future and late-century periods, call for the urgent development of climate adaptation strategies. These strategies should target key sectors such as agriculture, water resources, agro/pastoralist communities, and the conservation of endemic wildlife. Implementing adaptive measures in these areas will help mitigate the adverse effects of rising temperatures and changing climate conditions.
- This study was carried out on annual temporal scales, which may limit the granularity of climate trends. Future research should consider incorporating daily and monthly spatial scales to provide more detailed insights into seasonal and monthly variations in temperature and precipitation. This will help improve the accuracy and relevance of climate projections for local-level planning and decision-making.

References

- Abebe, E. & Kebede, A. 2017. Assessment of climate change impacts on the water resources kof megech river catchment, Abbay basin, Ethiopia. *Open Journal of Modern Hydrology*, 7, 141-152.
- Abebe, G. J. D. i. b. 2017. Long-term climate data description in Ethiopia. 14, 371-392.
- Adamowski, K. & Bougadis, J. 2003. Detection of trends in annual extreme rainfall. *Hydrological Processes*, 17, 3547-3560.
- Adera, A. G. & Alfredsen, K. T. 2020. Climate change and hydrological analysis of Tekeze River Basin Ethiopia: Implication for potential hydropower production. *Journal of Water and Climate Change*, 11, 744-759.
- Ahmadalipour, A., Moradkhani, H. & Rana, A. 2018. Accounting for downscaling and model uncertainty in fine-resolution seasonal climate projections over the Columbia River basin. *Climate dynamics*, 50, 717-733.
- Ajibola, F. O., Zhou, B., Tchalim Gnitou, G. & Onyejuruwa, A. 2020. Evaluation of the performance of cmip6 high resmip on West African precipitation. *Atmosphere*, 11, 1053.
- Alaminie, A. A., Tilahun, S. A., Legesse, S. A., Zimale, F. A., Tarkegn, G. B. & Jury, M. R. 2021. Evaluation of past and future climate trends under cmip6 scenarios for the ubnb (abay), Ethiopia. *Water*, 13, 2110.
- Alemseged, T. H. & Tom, R. 2015. Evaluation of regional climate model simulations of rainfall over the upper blue Nile basin. *Atmospheric research*, 161, 57-64.
- Alemu, M. M. & Bawoke, G. T. 2020. Analysis of spatial variability and temporal trends of rainfall in Amhara region, Ethiopia. *Journal of Water and Climate Change*, 11, 1505-1520.
- Almazroui, M., Saeed, F., Saeed, S., Ismail, M., Ehsan, M. A., Islam, M. N., Abid, M. A., O'Brien, E., Kamil, S., Rashid, I. U. J. E. S. & Environment 2021. Projected changes in climate extremes using cmip6 simulations over six regions. 5, 481-497.
- Almazroui, M., Saeed, S., Saeed, F., Islam, M. N. & Ismail, M. 2020. Projections of precipitation and temperature over the South Asian countries in cmip6. *Earth Systems and Environment*, 4, 297-320.
- Amare, A. & Simane, B. J. J. A. S. T. B. 2017. Assessment of household food security in the face of climate change and variability in the upper blue-nile of Ethiopia. 7, 285-300.

- Araro, K., Legesse, S. A., Meshesha, D. T. J. E. S. & Environment 2020. Climate change and variability impacts on rural livelihoods and adaptation strategies in southern Ethiopia. 4, 15-26.
- Arguez, A. & Vose, R. S. J. B. o. t. A. M. S. 2011. The definition of the standard WMO climate normal: The key to deriving alternative climate normals. 92, 699-704.
- Asfaw, A., Simane, B., Hassen, A., Bantider, A. J. W. & extremes, c. 2018. Variability and time series trend analysis of rainfall and temperature in northcentral Ethiopia: A case study in Woleka sub-basin. 19, 29-41.
- Assefa, D. & Mengistu, M. 2021a. Time series trend and variability analysis of temperature and rainfall in the west Shewa zone of Oromia. *Ethiopia*.
- Assefa, D. & Mengistu, M. 2021b. Time series trend and variability analysis of temperature and rainfall in the west Shewa zone of Oromia, Ethiopia.
- Ayal, D. Y. & Leal Filho, W. J. J. o. A. E. 2017. Farmers' perceptions of climate variability and its adverse impacts on crop and livestock production in Ethiopia. 140, 20-28.
- Ayalew, D. W. 2019. *Evaluating the potential impact of climate change on the hydrology of ribb catchment, Blue Nile basin, Ethiopia*.
- Ayugi, B., Ngoma, H., Babaousmail, H., Karim, R., Iyakaremye, V., Sian, K. T. L. K. & Ongoma, V. 2021. Evaluation and projection of mean surface temperature using cmip6 models over East Africa. *Journal of African Earth Sciences*, 181, 104226.
- Babaousmail, H., Ayugi, B. O., Ojara, M., Ngoma, H., Oduro, C., Mumo, R. & Ongoma, V. 2023. Evaluation of cmip6 models for simulations of diurnal temperature range over Africa. *Journal of African Earth Sciences*, 202, 104944.
- Bakker, A. & Van Den Hurk, B. 2011. *Bias correction and resampling of racmo output for the hydrological modeling of the rhine*, KNMI De Bil, The Netherlands.
- Bates, B. 2008. Climate change and water. *Technical Paper of the Intergovernmental Panel on Climate Change*, 200.
- Belay, A., Demissie, T., Recha, J. W., Oludhe, C., Osano, P. M., Olaka, L. A., Solomon, D. & Berhane, Z. 2021a. Analysis of climate variability and trends in southern Ethiopia. *Climate*, 9, 96.
- Belay, A., Demissie, T., Recha, J. W., Oludhe, C., Osano, P. M., Olaka, L. A., Solomon, D. & Berhane, Z. J. C. 2021b. Analysis of climate variability and trends in southern Ethiopia. 9, 96.

- Belay, A., Recha, J. W., Woldeamanuel, T., Morton, J. F. J. A. & Security, F. 2017. Smallholder farmers' adaptation to climate change and determinants of their adaptation decisions in the central Rift Valley of Ethiopia. 6, 1-13.
- Belazreg, N. E. H., Hasbaia, M., Şen, Z. & Ferhati, A. 2023. Historical evaluation and future projections of monthly precipitation and temperature under cmip6 GCMs, case of Hodna basin (central Algeria). *Arabian Journal of Geosciences*, 16, 39.
- Benti, F. & Abara, M. J. C. T. J. o. S. A. 2019. Trend analyses of temperature and rainfall and their response to global CO2 emission in Masha, southern Ethiopia. 34, 67-75.
- Bihrat, Ö., Bayazit, M. J. T. j. o. e. & sciences, e. 2003. The power of statistical tests for trend detection. 27, 247-251.
- Birsan, M.-V., Molnar, P., Burlando, P. & Pfaundler, M. J. J. o. h. 2005. Streamflow trends in Switzerland. 314, 312-329.
- Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S. & Herrero, M. T. 2010. Coping with climate variability and adapting to climate change in Kenya: Household and community strategies and determinants.
- Bukovsky, M. S., Gao, J., Mearns, L. O. & O'Neill, B. C. 2021. Ssp-based land-use change scenarios: A critical uncertainty in future regional climate change projections. *Earth's Future*, 9, e2020EF001782.
- Calvin, K., Patel, P., Clarke, L., Asrar, G., Bond-Lamberty, B., Cui, R. Y., Di Vittorio, A., Dorheim, K., Edmonds, J. & Hartin, C. 2019. Gcam v5. 1: Representing the linkages between energy, water, land, climate, and economic systems. *Geoscientific Model Development*, 12, 677-698.
- Canziani, O. F. & Parry, M. L. 2007. Climate change 2007: Impacts, adaptation, and vulnerability. Contribution of Working Group ii to the fourth assessment report of the Intergovernmental Panel on Climate Change (IPCC).
- Challinor, A., Wheeler, T., Garforth, C., Craufurd, P. & Kassam, A. 2007. Assessing the vulnerability of food crop systems in Africa to climate change. *Climatic change*, 83, 381-399.
- Chen, X., Wang, L., Niu, Z., Zhang, M. & Li, J. 2020. The effects of projected climate change and extreme climate on maize and rice in the Yangtze River basin, china. *Agricultural and Forest Meteorology*, 282, 107867.
- Cheng-xiu, J., Chao, J. & Xi-yue, Z. 2022. Evaluation and projection of temperature in southwestern China by cmip6 models. *Chinese Journal of Agrometeorology*, 43, 597.

- Collins, W. D., Davis, S. J., Bales, R., Burney, J., McCarthy, R., Rignot, E., Torre, W. & Victor, D. 2016. Chapter 3. Science and pathways for bending the curve. *Collabra*, 2, 17.
- Conway, D., Mould, C. & Bewket, W. J. I. J. o. C. A. J. o. t. R. M. S. 2004. Over one century of rainfall and temperature observations in Addis Ababa, Ethiopia. 24, 77-91.
- Dandesa, T., Korecha, D., Nigatu, L. & Cheneka, B. J. E. S. A. I. J. 2017. Assessment of climatic variability and development of localized climate prediction method for livestock production in Borana area, southern Ethiopia. 13, 137.
- De Luis, M., Raventós, J., González-Hidalgo, J., Sánchez, J. & Cortina, J. J. I. J. o. C. A. J. o. t. R. M. S. 2000. Spatial analysis of rainfall trends in the region of Valencia (east Spain). 20, 1451-1469.
- Dellink, R., Chateau, J., Lanzi, E. & Magné, B. 2017. Long-term economic growth projections in the shared socioeconomic pathways. *Global Environmental Change*, 42, 200-214.
- Demessie, S. F., Dile, Y. T., Bedadi, B., Gashaw, T. & Tefera, G. W. 2023. Evaluations of regional climate models for simulating precipitation and temperature over the Guder sub-basin of upper blue Nile basin, Ethiopia. *Modeling Earth Systems and Environment*, 9, 4455-4476.
- Dereje, A., Kindie, T., Girma, M., Birru, Y. & Wondimu, B. J. A. J. o. A. R. 2012. Variability of rainfall and its current trend in Amhara region, Ethiopia. 7, 1475-1486.
- Dibaba, W. T., Miegel, K. & Demissie, T. A. 2019. Evaluation of the Cordex regional climate model performance in simulating climate conditions of two catchments in the upper blue Nile basin. *Dynamics of Atmospheres and Oceans*, 87, 101104.
- Dioha, M. O. & Kumar, A. J. A. 2020. Exploring greenhouse gas mitigation strategies for agriculture in Africa: The case of Nigeria. 49, 1549-1566.
- Diro, G., Tompkins, A. & Bi, X. J. J. o. G. R. A. 2012. Dynamical downscaling of ECMWF ensemble seasonal forecasts over East Africa with RegCM3. 117.
- Duyck, S. J. Y. o. i. e. l. 2015. The Paris climate agreement and the protection of human rights in a changing climate. 26, 3-45.
- Easterling, D. R., Meehl, G. A., Parmesan, C., Changnon, S. A., Karl, T. R. & Mearns, L. O. J. s. 2000. Climate extremes: Observations, modeling, and impacts. 289, 2068-2074.

- Edwards, P. N. 2011. History of climate modeling. *Wiley Interdisciplinary Reviews: Climate Change*, 2, 128-139.
- Esayas, B., Simane, B., Teferi, E., Ongoma, V. & Tefera, N. J. A. i. M. 2019. Climate variability and farmers' perception in southern Ethiopia. 2019.
- Eshetu, Z., Gebre, H., Lisanework, N. J. A. J. o. E. S. & Technology 2020. Impacts of climate change on sorghum production in northeastern Ethiopia. 14, 49-63.
- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J. & Taylor, K. E. 2016a. Overview of the coupled model intercomparison project phase 6 (cmip6) experimental design and organization. *Geoscientific Model Development*, 9, 1937-1958.
- Eyring, V., Cox, P. M., Flato, G. M., Gleckler, P. J., Abramowitz, G., Caldwell, P., Collins, W. D., Gier, B. K., Hall, A. D. & Hoffman, F. M. 2019. Taking climate model evaluation to the next level. *Nature Climate Change*, 9, 102-110.
- Eyring, V., Gleckler, P. J., Heinze, C., Stouffer, R. J., Taylor, K. E., Balaji, V., Guilyardi, E., Joussaume, S., Kindermann, S. & Lawrence, B. N. 2016b. Towards improved and more routine Earth system model evaluation in cmip. *Earth System Dynamics*, 7, 813-830.
- Fan, X., Duan, Q., Shen, C., Wu, Y. & Xing, C. 2020. Global surface air temperatures in cmip6: Historical performance and future changes. *Environmental Research Letters*, 15, 104056.
- Field, C. B. & Barros, V. R. 2014. *Climate change 2014—impacts, adaptation, and vulnerability: Regional aspects*, Cambridge University Press.
- Fowler, H., Ekström, M., Blenkinsop, S. & Smith, A. 2007. Estimating change in extreme European precipitation using a multimodel ensemble. *Journal of Geophysical Research: Atmospheres*, 112.
- Fujimori, S., Hasegawa, T., Masui, T., Takahashi, K., Herran, D. S., Dai, H., Hijioka, Y. & Kainuma, M. 2017. Ssp3: Aim implementation of shared socioeconomic pathways. *Global Environmental Change*, 42, 268-283.
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L. & Hoell, A. 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific data*, 2, 1-21.
- Funk, C., Peterson, P., Peterson, S., Shukla, S., Davenport, F., Michaelsen, J., Knapp, K. R., Landsfeld, M., Husak, G. & Harrison, L. J. J. o. C. 2019. A high-resolution

- 1983–2016 t max climate data record based on infrared temperatures and stations by the climate hazard center. 32, 5639-5658.
- Gashaw, T., Worqlul, A. W., Taye, M. T., Lakew, H. B., Seid, A., Ayele, G. & Hailelassie, A. 2024. Performance evaluations of cmip6 model simulations and future projections of rainfall and temperature in the Bale eco-region, southern Ethiopia. *Theoretical and Applied Climatology*, 1-24.
- Gebrechorkos, S. H., Hülsmann, S. & Bernhofer, C. J. I. J. o. C. 2019. Changes in temperature and precipitation extremes in Ethiopia, Kenya, and Tanzania. 39, 18-30.
- Gebregiorgis, D., Rayner, D. & Linderholm, H. W. 2019. Does the iod independently influence seasonal monsoon patterns in northern Ethiopia? *Atmosphere*, 10, 432.
- Gebresellase, S. H., Wu, Z., Xu, H. & Muhammad, W. I. 2022. Evaluation and selection of cmip6 climate models in the upper Awash Basin (uba), Ethiopia: Evaluation and selection of cmip6 climate models in the upper Awash basin (uba), Ethiopia. *Theoretical and Applied Climatology*, 149, 1521-1547.
- Getachew, B. 2018a. Trend analysis of temperature and rainfall in south Gonder zone, Amhara Ethiopia. *Journal of Degraded and Mining Lands Management*, 5, 1111.
- Getachew, B. 2018b. Trend analysis of temperature and rainfall in south Gonder zone, Ethiopia. *Journal of degraded and mining lands management* 5(2): 2502-2458.
- Gidey, E., Dikinya, O., Sebego, R., Segosebe, E. & Zenebe, A. 2018. Modeling the spatiotemporal meteorological drought characteristics using the standardized precipitation index (spi) in Raya and its environs, northern Ethiopia. *Earth Systems and Environment*, 2, 281-292.
- Gleckler, P. J., Taylor, K. E. & Doutriaux, C. 2008. Performance metrics for climate models. *Journal of Geophysical Research: Atmospheres*, 113.
- Gleixner, S., Keenlyside, N., Viste, E. & Korecha, D. J. C. D. 2017. The el niño effect on Ethiopian summer rainfall. 49, 1865-1883.
- Goddard, L., Barnston, A. G. & Mason, S. J. J. B. o. t. A. M. S. 2003. Evaluation of the IRI's "net assessment" seasonal climate forecasts: 1997–2001. 84, 1761-1782.
- Guo, H., Bao, A., Chen, T., Zheng, G., Wang, Y., Jiang, L. & De Maeyer, P. 2021. Assessment of cmip6 in simulating precipitation over arid central Asia. *Atmospheric Research*, 252, 105451.

- Gupta, H. V., Kling, H., Yilmaz, K. K. & Martinez, G. F. 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modeling. *Journal of Hydrology*, 377, 80-91.
- Gupta, H. V., Sorooshian, S. & Yapo, P. O. 1999. Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of Hydrologic Engineering*, 4, 135-143.
- Gurara, M. A., Jilo, N. B. & Tolche, A. D. 2023. Modeling climate change impact on the streamflow in the upper Wabe Bridge watershed in wabe Shebele River basin, Ethiopia. *International Journal of River Basin Management*, 21, 181-193.
- Hänsel, S., Schucknecht, A., Matschullat, J. J. T. & climatology, a. 2016. The modified rainfall anomaly index (rai)—is this an alternative to the standardized precipitation index (spi) in evaluating future extreme precipitation characteristics? 123, 827-844.
- Harle, K., Heijnis, H., Henderson-Sellers, A., Sharmeen, S. & Zahorowski, W. 2002. Human activity and climate variability project: Annual report 2001. EGZAO 2022.
- Herzog, T. J. W. R. I. 2009. World greenhouse gas emissions in 2005. 7, 2009.
- Hirsch, R. M., Slack, J. R. & Smith, R. A. J. W. r. r. 1982. Techniques of trend analysis for monthly water quality data. 18, 107-121.
- Hu, Q., Hua, W., Yang, K., Ming, J., Ma, P., Zhao, Y. & Fan, G. 2022. An assessment of temperature simulations by cmip6 climate models over the Tibetan plateau and differences with cmip5 climate models. *Theoretical and Applied Climatology*, 148, 223-236.
- IPCC 2001. Climate change impacts, adaptation, and vulnerability. IPCC Working Group ii, third assessment report. Cambridge, Cambridge University Press.
- IPCC 2007a.
- IPCC 2007b. Fourth assessment report of the, m.L. Parry, o.F. Canziani, j.P. Palutikof, p.J. Van der Linden and c.E. Hanson Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- IPCC 2007c. (Intergovernmental Panel Climate Change). 2007: The physical science basis: Contribution of working group I to the fourth assessment. Cambridge university press, Cambridge, united kingdom and new york, USA.
- IPCC 2013. Summary for policymakers. In: Climate change 2014: Impacts, adaptation, and vulnerability. Part a: Global and sectoral aspects. Contribution of Working

- Group ii to the fifth assessment report of the Intergovernmental Panel on Climate Change.
- IPCC 2014a.
- IPCC 2014b. Summary for policymakers. In: Climate change 2014: Impacts, adaptation, and vulnerability. Part a: Global and sectoral aspects. Contribution of Working Group ii to the fifth assessment report of the Intergovernmental Panel on Climate Change.
- IPCC, C. C. J. C. U. P., Cambridge, United Kingdom & New York, N., USA 2007. The physical science basis. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on climate change. 996, 113-119.
- Issahaku, A. R., Champion, B. B., Edziyie, R. J. E. & Science, S. 2016. Rainfall and temperature changes and variability in the upper east region of Ghana. 3, 284-294.
- Jia, K., Ruan, Y., Yang, Y. & Zhang, C. 2019. Assessing the performance of cmip5 global climate models for simulating future precipitation change in the Tibetan plateau. *Water*, 11, 1771.
- Jiang, L. & O'Neill, B. C. 2017. Global urbanization projections for the shared socioeconomic pathways. *Global Environmental Change*, 42, 193-199.
- Jing, X., Luo, J., Wang, J., Zuo, G. & Wei, N. 2022. A multi-imputation method to deal with hydro-meteorological missing values by integrating chain equations and random forest. *Water Resources Management*, 36, 1159-1173.
- Jury, M. R. 2015. Statistical evaluation of cmip5 climate change model simulations for the Ethiopian highlands. *International Journal of Climatology*, 35.
- Jury, M. R. & Funk, C. J. I. J. o. C. 2013. Climatic trends over Ethiopia: Regional signals and drivers. 33, 1924-1935.
- Kamruzzaman, M., Shahid, S., Islam, A. T., Hwang, S., Cho, J., Zaman, M. A. U., Ahmed, M., Rahman, M. M. & Hossain, M. B. 2021. Comparison of cmip6 and cmip5 model performance in simulating historical precipitation and temperature in Bangladesh: A preliminary study. *Theoretical and Applied Climatology*, 145, 1385-1406.
- Kamworapan, S. & Surussavadee, C. 2019. Evaluation of cmip5 global climate models for simulating climatological temperature and precipitation for southeast Asia. *Advances in meteorology*, 2019, 1067365.
- Karabulut, M. J. J. o. A. L. 2015. Drought analysis in antakya-kahramanmaraş graben, turkey. 7, 741-754.

- Karpouzou, D., Kavalieratou, S. & Babajimopoulos, C. J. E. W. 2010. Trend analysis of precipitation data in the Pieria region (Greece). 30, 30-40.
- Kassie, B. T. 2014. *Climate variability and change in Ethiopia: Exploring impacts and adaptation options for cereal production*, Wageningen University and Research.
- Kc, S. & Lutz, W. 2014. Demographic scenarios by age, sex, and education correspond to the SSP narratives. *Population and Environment*, 35, 243-260.
- Kendall, M. G. 1962. Rank correlation methods.
- Kling, J. R., Mullainathan, S., Shafir, E., Vermeulen, L. C. & Wrobel, M. V. 2012. Comparison friction: Experimental evidence from medicare drug plans. *The quarterly journal of economics*, 127, 199-235.
- Knoben, W. J., Freer, J. E. & Woods, R. A. 2019. Inherent benchmark or not? Comparing Nash–Sutcliffe and Kling–Gupta efficiency scores. *Hydrology and Earth System Sciences*, 23, 4323-4331.
- Koomey, J., Schmidt, Z., Hummel, H. & Weyant, J. 2019. Inside the black box: Understanding key drivers of global emission scenarios. *Environmental Modelling & Software*, 111, 268-281.
- Kotir, J. H. 2011. Climate change and variability in sub-Saharan Africa: A review of current and future trends and impacts on agriculture and food security. *Environment, Development and Sustainability*, 13, 587-605.
- Kreienkamp, F., Huebener, H., Linke, C. & Spekat, A. 2012. Good practice for the usage of climate model simulation results discussion paper. *Environmental Systems Research*, 1, 1-13.
- Kriegler, E., Bauer, N., Popp, A., Humpenöder, F., Leimbach, M., Strefler, J., Baumstark, L., Bodirsky, B. L., Hilaire, J. & Klein, D. 2017. Fossil-fueled development (ssp5): An energy and resource intensive scenario for the 21st century. *Global environmental change*, 42, 297-315.
- Kriegler, E., Edmonds, J., Hallegatte, S., Ebi, K. L., Kram, T., Riahi, K., Winkler, H. & Van Vuuren, D. P. 2014. A new scenario framework for climate change research: The concept of shared climate policy assumptions. *Climatic Change*, 122, 401-414.
- Liu, Z., Yang, D., Wang, Y., Lu, M. & Li, R. 2023. Eggn: Graph structure learning based on evolutionary computation helps more in graph neural networks. *Applied Soft Computing*, 135, 110040.
- Long, S.-M. & Li, G. 2021. Model uncertainty in the projected Indian summer monsoon precipitation change under low-emission scenarios. *Atmosphere*, 12, 248.

- Lovino, M. A., Müller, O. V., Berbery, E. H. & Muller, G. V. 2018. Evaluation of cmip5 retrospective simulations of temperature and precipitation in northeastern Argentina.
- Maloney, E. D., Camargo, S. J., Chang, E., Colle, B., Fu, R., Geil, K. L., Hu, Q., Jiang, X., Johnson, N. & Karnauskas, K. B. J. J. o. C. 2014. North American climate in cmip5 experiments: Part iii: Assessment of twenty-first-century projections. 27, 2230-2270.
- Mandel, I. & Lipovetsky, S. 2021. Climate change report ipcc 2021—a chimera of science and politics. *Available at SSRN 3913788*.
- Mann, H. B. a. K., M.G 1945, 1975. Nonparametric tests against trend. *Econom. J. Econom. Soc.* 1945, 13, 245–259. [Crossref] 60. Kendall, m.G. Rank correlation methods; Charles Griffin & co. Ltd.: London, UK, 1975.
- Mann, H. B. J. E. J. o. t. e. s. 1945. Nonparametric tests against trend. 245-259.
- Manyatsi, A., Mhazo, N., Masarirambi, M. J. R. J. o. E. & Sciences, E. 2010. Climate variability and change as perceived by rural communities in Swaziland. 2, 164-169.
- Matewos, T. 2019. Climate change-induced impacts on smallholder farmers in selected districts of Sidama, southern Ethiopia. *Climate*, 7, 70.
- McKee, T. B., Doesken, N. J. & Kleist, J. The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology*, 1993. Boston, MA, USA, 179-183.
- Mcsweeney, C., New, M., Lizcano, G. & Lu, X. J. B. o. t. A. M. s. 2010. The UNDP climate change country profiles: Improving the accessibility of observed and projected climate information for studies of climate change in developing countries. 91, 157-166.
- McSweeney, C., New, M. & Lizcano, G. J. P. f. c. 2008. UNDP climate change country profiles: Ethiopia.
- Mersha, A. A. & van Laerhoven, F. 2018a. The interplay between planned and autonomous adaptation in response to climate change: Insights from rural Ethiopia. *World Development*, 107, 87-97.
- Mersha, A. A. & van Laerhoven, F. J. W. D. 2018b. The interplay between planned and autonomous adaptation in response to climate change: Insights from rural Ethiopia. 107, 87-97.

- Mesfin, D., Simane, B., Belay, A., Recha, J. W. & Schmiedel, U. J. C. 2020. Assessing the adaptive capacity of households to climate change in the central rift valley of Ethiopia. 8, 106.
- Meybeck, A., Lankoski, J., Redfern, S., Azzu, N. & Gitz, V. Building resilience for adaptation to climate change in the agriculture sector. Proceedings of a joint Fao/OECD workshop, Rome, Italy, 23-24 April 2012. Building resilience for adaptation to climate change in the agriculture sector. Proceedings of a Joint FAO/OECD Workshop, Rome, Italy, 23-24 April 2012., 2012. Food and Agriculture Organization of the United Nations (FAO).
- Mideksa, T. K. J. G. E. C. 2010. Economic and distributional impacts of climate change: The case of Ethiopia. 20, 278-286.
- Mohamed, R. & Saeed, S. 2022. Relationship between leadership style and job satisfaction among physicians working in greater male hospitals. *International Journal of Social Research & Innovation*, 6, 1-30.
- Mohammed, J. A. 2024a. Performance evaluation and ranking of cmip6 global climate models over the upper blue Nile (Abbay) basin of Ethiopia. *Natural Hazards Research*.
- Mohammed, S. A. 2024b. Numerical comparison by using some criteria to estimate the two parameters of the exponentiated exponential distribution. *Iraqi Journal of Science*.
- 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, 885-900.
- Moriasi, D. N., Gitau, M. W., Pai, N. & Daggupati, P. 2015. Hydrologic and water quality models: Performance measures and evaluation criteria. *Transactions of the ASABE*, 58, 1763-1785.
- Moriondo, M., Giannakopoulos, C. & Bindi, M. 2011. Climate change impact assessment: The role of climate extremes in crop yield simulation. *Climatic change*, 104, 679-701.
- Nakawuka, P., Langan, S., Schmitter, P. & Barron, J. J. G. f. s. 2018. A review of trends, constraints, and opportunities of smallholder irrigation in East Africa. 17, 196-212.
- Nashwan, M. S. & Shahid, S. 2020. A novel framework for selecting general circulation models based on the spatial patterns of climate. *International Journal of Climatology*, 40, 4422-4443.

- Navarro, A. & Tapiador, F. J. 2024. Climate classification systems for validating earth system models. *Environmental Research: Climate*, 3, 042001.
- Nayef, B. H., Abdullah, S. N. H. S. & Mohammed, M. 2024. Deep learning function implications for handwritten character recognition using improved mean square error function. *Baghdad Science Journal*.
- Ngoma, H., Ayugi, B., Onyutha, C., Babaousmail, H., Lim Kam Sian, K. T., Iyakaremye, V., Mumo, R. & Ongoma, V. 2022. Projected changes in rainfall over Uganda based on cmip6 models. *Theoretical and Applied Climatology*, 149, 1117-1134.
- NMAE 2007a. Ma(National Meteorological Agency, Ethiopia). 2007. Initial national communication of Ethiopia to the United National Framework Convention on Climate Change (UNFCCC).Addis Ababa, Ethiopia.
- NMAE 2007b. Nma(National Meteorological Agency, Ethiopia). 2007. Initial national communication of Ethiopia to the United National Framework Convention on Climate Change (UNFCCC).Addis Ababa, Ethiopia.
- NMAES 2001. Names (National Meteorological Agency, Ethiopia). 2001. Initial national communication of Ethiopia to the United National Framework Convention on Climate Change (UNFCCC).Addis Ababa, Ethiopia.
- NMSA 2010. National meteorological station agents.
- O'Neill, B. C., Tebaldi, C., Van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F. & Lowe, J. 2016. The scenario model intercomparison project (scenario map) for cmip6. *Geoscientific Model Development*, 9, 3461-3482.
- O'Neill, B. C., Carter, T. R., Ebi, K., Harrison, P. A., Kemp-Benedict, E., Kok, K., Kriegler, E., Preston, B. L., Riahi, K. & Sillmann, J. 2020. Achievements and needs for the climate change scenario framework. *Nature Climate Change*, 10, 1074-1084.
- 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.
- Ofgeha, G. Y. & Abshire, M. W. 2021. Spatio-temporal variability and trends in rainfall and temperature in Anger watershed, southwestern Ethiopia. *Journal of Applied Geospatial Information*, 5, 462-472.

- Oliver, J. E. 1980a. Monthly precipitation distribution: A comparative index. *The Professional Geographer*, 32, 300-309.
- Oliver, J. E. J. T. P. G. 1980b. Monthly precipitation distribution: A comparative index. 32, 300-309.
- Papalexiou, S. M., Rajulapati, C. R., Clark, M. P. & Lehner, F. 2020. Robustness of cmip6 historical global mean temperature simulations: Trends, long-term persistence, autocorrelation, and distributional shape. *Earth's Future*, 8, e2020EF001667.
- Parry, M. L., Canziani, O., Palutikof, J., Van der Linden, P. & Hanson, C. 2007. *Climate change 2007-impacts, adaptation, and vulnerability: Working group ii contribution to the fourth assessment report of the ipcc*, Cambridge University Press.
- Petkovski, V., Miloskeska, S. K. & Arsov, S. 2023. Two different scenarios were proposed which show different temperature rises and two different precipitation forecasts, all generally inclined towards the downgrade effect on both of the indicators. Rise in temperature and change in climate can affect the region given that the biggest industry sectors are sensitive to climate changes. *Економски развој*, 96.
- Philip, S., Kew, S. F., van Oldenborgh, G. J., Otto, F., O'Keefe, S., Haustein, K., King, A., Zegeye, A., Eshetu, Z. & Hailemariam, K. J. J. o. C. 2018. Attribution analysis of the Ethiopian drought of 2015. 31, 2465-2486.
- Piani, C., Weedon, G., Best, M., Gomes, S., Viterbo, P., Hagemann, S. & Haerter, J. 2010. Statistical bias correction of global simulated daily precipitation and temperature for the application of hydrological models. *Journal of Hydrology*, 395, 199-215.
- Pohlert, T. 2018. Non-parametric trend tests and change-point detection. The r project for statistical computing. Recuperado em.
- Raju, K. S. & Kumar, D. N. 2020. Review of approaches for selection and ensembling of gcms. *Journal of Water and Climate Change*, 11, 577-599.
- Ranasinghe, G. & Piyadasa, R. U. 2017. Forecasting temporal and spatial climatological influence for land suitability evaluation in Bentota Sri Lanka. *International Journal of Built Environment and Sustainability*, 4.
- Randall, D. A., Wood, R. A., Bony, S., Colman, R., Fichefet, T., Fyfe, J., Kattsov, V., Pitman, A., Shukla, J. & Srinivasan, J. 2007. Climate models and their evaluation. *Climate change 2007: The physical science basis. Contribution of Working Group I to the Fourth Assessment Report of the ipcc (far)*. Cambridge University Press.

- Rathjens, H., Bieger, K., Srinivasan, R., Chaubey, I. & Arnold, J. G. 2016. Cmhyd user manual. *Doc. Prep. Simulated Clim. Change Data Hydrol. Impact Study*, 1413.
- Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Da Silva, L. A., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Strefler, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J. C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-Campen, H., Obersteiner, M., Tabeau, A. & Tavoni, M. 2017. The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, 42, 153-168.
- Rivera, J. A. & Arnould, G. 2020. Evaluation of the ability of cmip6 models to simulate precipitation over southwestern South America: Climatic features and long-term trends (1901–2014). *Atmospheric Research*, 241, 104953.
- Rogelj, J., Popp, A., Calvin, K. V., Luderer, G., Emmerling, J., Gernaat, D., Fujimori, S., Strefler, J., Hasegawa, T., Marangoni, G., Krey, V., Kriegler, E., Riahi, K., van Vuuren, D. P., Doelman, J., Drouet, L., Edmonds, J., Fricko, O., Harmsen, M., Havlík, P., Humpenöder, F., Stehfest, E. & Tavoni, M. 2018. Scenarios towards limiting global mean temperature increase below 1.5 °c. *Nature Climate Change*, 8, 325-332.
- Rowell, D. P., Booth, B. B., Nicholson, S. E. & Good, P. J. J. o. C. 2015. Reconciling past and future rainfall trends over East Africa. 28, 9768-9788.
- Salehie, O., Hamed, M. M., Ismail, T. b., Tam, T. H. & Shahid, S. 2023. Selection of cmip6 gcm with the projection of climate over the Amu Darya River basin. *Theoretical and Applied Climatology*, 151, 1185-1203.
- Saroar, M. M. 2016. Adaptation through climate-smart agriculture: Status and determinants in coastal Bangladesh. *Climate change adaptation, resilience and hazards*. Springer.
- Şen, Z. & Öztopal, A. 2013. Turkish Water Foundation Climate Change Downscaling Model Principles. *Causes, Impacts, and Solutions to Global Warming*, 87-101.
- Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M., Perrette, M. & Reinhardt, J. 2017. Climate change impacts in sub-Saharan

- Africa: From physical changes to their social repercussions. *Regional Environmental Change*, 17, 1585-1600.
- Shafeeque, M. & Luo, Y. 2021. A multi-perspective approach for selecting cmip6 scenarios to project climate change impacts on glacio-hydrology with a case study in the upper Indus river basin. *Journal of Hydrology*, 599, 126466.
- Shao, Y., Gan, Z., Epifanovsky, E., Gilbert, A. T., Wormit, M., Kussmann, J., Lange, A. W., Behn, A., Deng, J. & Feng, X. 2015. Advances in molecular quantum chemistry are contained in the q-chem 4 program package. *Molecular Physics*, 113, 184-215.
- Shawul, A. A., Chakma, S. J. T. & Climatology, A. 2020. The trend of extreme precipitation indices and analysis of long-term climate variability in the upper awash basin, Ethiopia. 140, 635-652.
- Singh, S., Ghosh, S., Sahana, A., Vittal, H. & Karmakar, S. 2017. Do dynamic regional models add value to the global model projections of the Indian monsoon? *Climate Dynamics*, 48, 1375-1397.
- Song, L., Tian, Q., Li, Z., Lv, Y. M., Gui, J., Zhang, B. & Cui, Q. 2022. Changes in characteristics of climate extremes from 1961 to 2017 in the Qilian mountain area, northwestern China. *Environmental Earth Sciences*, 81, 177.
- Stevens, L. E., Maycock, T. K., Stewart, B. C. J. J. O. t. A. & Association, W. M. 2021. Climate change in the human environment: Indicators and impacts from the fourth national climate assessment. 71, 1210-1233.
- Stouffer, R. J., Eyring, V., Meehl, G. A., Bony, S., Senior, C., Stevens, B. & Taylor, K. 2017. Cmp5 scientific gaps and recommendations for cmp6. *Bulletin of the American Meteorological Society*, 98, 95-105.
- Svoboda, M., Hayes, M. & Wood, D. 2012. Standardized precipitation index: User guide.
- Sylla, M., Giorgi, F. & Stordal, F. 2012. Large-scale origins of rainfall and temperature bias in high-resolution simulations over southern Africa. *Climate Research*, 52, 193-211.
- Tan, M. L. & Santo, H. 2018. Comparison of gpm imerg, Tampa 3b42, and Persian-cdr satellite precipitation products over Malaysia. *Atmospheric Research*, 202, 63-76.
- Tan, M. L., Yusop, Z., Chua, V. P. & Chan, N. W. 2017. Climate change impacts under cmp5 RCP scenarios on water resources of the Kelantan River basin, Malaysia. *Atmospheric Research*, 189, 1-10.

- Tasokwa, V. M. 2011. *The impact of climate variability and extreme weather events on gender and household vulnerability to food insecurity*. University of Nairobi, Kenya.
- Taye, M. T. & Willems, P. J. W. R. R. 2012. Temporal variability of hydroclimatic extremes in the blue Nile basin. 48.
- Tesso, G., Emanu, B. & Ketema, M. J. A. C. S. J. 2012. A time series analysis of climate variability and its impacts on food production in the north Shewa zone in Ethiopia. 20, 261-274.
- Thomson, K. 2009. The state of food and agriculture 2008: Biofuels: Prospects, risks and opportunities. Food and Agriculture Organization of the United Nations. Xi+ 128 pp. Rome: Fao (2008). \$65.00. Isbn 078-92-5-105980-7, issn 0081-4539. Available at: <http://www.fao.org/docrep/011/i0100e/i0100e00.htm>. *The Journal of Agricultural Science*, 147, 503-503.
- Thornton, P., Jones, P., Owiyo, T., Kruska, R., Herrero, M. & Kristjanson, P. 2006. Mapping climate vulnerability and poverty in Africa. Report to the department for international development.
- Tierney, J. E., Smerdon, J. E., Anchukaitis, K. J. & Seager, R. J. N. 2013. Multidecadal variability in East African hydroclimate controlled by the Indian Ocean. 493, 389-392.
- Timofeyeva-Livezey, M., Horsfall, F., Hollingshead, A., Meyers, J. & Dupigny-Giroux, L.-A. 2015. NOAA local climate analysis tool (lcat): Data, methods, and usability. *Bulletin of the American Meteorological Society*, 96, 537-545.
- Turrado, C. C., López, M. d. C. M., Lasheras, F. S., Gómez, B. A. R., Rollé, J. L. C. & Cos Juez, F. J. 2014. Missing data imputation of solar radiation data under different atmospheric conditions. *Sensors*, 14, 20382-20399.
- UNFCCC, F. Climate change: Impacts, vulnerabilities, and adaptation in developing countries. Bonn, Germany: United Nations Framework Convention on Climate Change, 2007.
- Van Vuuren, D. P., Kriegler, E., O'Neill, B. C., Ebi, K. L., Riahi, K., Carter, T. R., Edmonds, J., Hallegatte, S., Kram, T. & Mathur, R. 2014. A new scenario framework for climate change research: Scenario matrix architecture. *Climatic change*, 122, 373-386.
- Van Vuuren, D. P., Meinshausen, M., Plattner, G.-K., Joos, F., Strassmann, K. M., Smith, S. J., Wigley, T. M., Raper, S., Riahi, K. & De La Chesnaye, F. 2008. Temperature

- increase of 21st century mitigation scenarios. *Proceedings of the National Academy of Sciences*, 105, 15258-15262.
- Van Vuuren, D. P., Riahi, K., Calvin, K., Dellink, R., Emmerling, J., Fujimori, S., Samir, K., Kriegler, E. & O'Neill, B. 2017. The shared socio-economic pathways: Trajectories for human development and global environmental change. Elsevier.
- Vasiliades, L., Loukas, A. & Patsonas, G. 2009. Evaluation of a statistical downscaling procedure for the estimation of climate change impacts on droughts. *Natural Hazards and Earth System Sciences*, 9, 879-894.
- Viste, E., Korecha, D. & Sorteberg, A. 2013. Recent drought and precipitation tendencies in Ethiopia. *Theoretical and Applied Climatology*, 112, 535-551.
- Wagesho, N., Goel, N. K. & Jain, M. K. J. H. S. J. 2013. Temporal and spatial variability of annual and seasonal rainfall over Ethiopia. 58, 354-373.
- WB 2008. World Bank.,(2005). Managing water resources to maximize sustainable growth: A World Bank water resources assistance strategy for Ethiopia. A country water resources assistance strategy. World Bank, Washington, DC.
- WMO 2007. Wmo (world meteorological organization). 2007. The role of the World Meteorological Organization in the implementation of the Nairobi work program.
- Wodaje, G. G., Eshetu, Z., Argaw, M. J. A. J. o. E. S. & Technology 2016. Temporal and spatial variability of rainfall distribution and transpiration across an altitudinal gradient in the Bilate River watershed, southern Ethiopia. 10, 167-180.
- Worku, G., Teferi, E., Bantider, A. & Dile, Y. T. 2019. Observed changes in extremes of daily rainfall and temperature in Jemma sub-basin, upper blue Nile basin, Ethiopia. *Theoretical and Applied Climatology*, 135, 839-854.
- Worku, G., Teferi, E., Bantider, A. & Dile, Y. T. 2020. Statistical bias correction of regional climate model simulations for climate change projection in the Jemma sub-basin, upper blue Nile basin of Ethiopia. *Theoretical and Applied Climatology*, 139, 1569-1588.
- Worku, G., Teferi, E., Bantider, A., Dile, Y. T. & Taye, M. T. 2018a. Evaluation of regional climate models performance in simulating rainfall climatology of Jemma sub-basin, upper blue Nile basin, Ethiopia. *Dynamics of Atmospheres and Oceans*, 83, 53-63.
- Worku, M., De Meulenaer, B., Duchateau, L. & Boeckx, P. 2018b. The effect of altitude on the biochemical composition and quality of green arabica coffee beans can be

- affected by shade and postharvest processing methods. *Food Research International*, 105, 278-285.
- Wörner, V., Kreye, P. & Meon, G. 2019. Effects of bias-correcting climate model data on the projection of future changes in high flows. *Hydrology*, 6, 46.
- Yan, R., Li, M., Hou, Q., Yu, Z., Li, P., Ji, B., Liu, P., Yue, S. & Chang, G. 2023. Preparation and testing of a laterally graded multilayer with a double genetic algorithm and root mean square error optimization in the differential deposition. *Optics Express*, 31, 22954-22963.
- Yang, X., Zhou, B., Xu, Y. & Han, Z. 2023. Cmp6 evaluation and projection of precipitation over northern China: Further investigation. *Advances in Atmospheric Sciences*, 40, 587-600.
- Yesuf, M., Di Falco, S., Deressa, T., Ringler, C. & Kohlin, G. 2008. *The impact of climate change and adaptation on food production in low-income countries: Evidence from the Nile basin, Ethiopia*, Intl Food Policy Res Inst.
- Yue, S. & Wang, C. Y. 2002. Applicability of prewhitening to eliminate the influence of serial correlation on the Mann-Kendall test. *Water resources research*, 38, 4-1-4-7.
- Yukimoto, S., Kawai, H., Koshiro, T., Oshima, N., Yoshida, K., Urakawa, S., Tsujino, H., Deushi, M., Tanaka, T. & Hosaka, M. 2019. The Meteorological Research Institute earth system model version 2.0, mri-esm2. 0: Description and basic evaluation of the physical component. *Journal of the Meteorological Society of Japan. Ser. II*, 97, 931-965.
- Zarrin, A. & Dadashi-Roudbari, A. 2021. Projection of future extreme precipitation in Iran based on cmip6 multi-model ensemble. *Theoretical and Applied Climatology*, 144, 643-660.
- Zenebe, G., Stage, J., Alemu, M. & Atlaw, A. J. E. f. D. D. P.-R. f. t. F. 2011. Climate change and the Ethiopian economy: A computable general equilibrium analysis.

APPENDIX

Appendix 1: Description of studied meteorological stations over East Gojjam Zone.

No	Stations	Longitude	Latitude	Elevation	Recorded period
1	Motta	37.87	11.07	2417	1984-2014
2	Debre Work	38.17	10.66	2508	1984-2014
3	Dejen	38.24	10.22	2455	1984-2014
4	Debre Markos	37.73	10.33	2446	1984-2014

Appendix 2: Annual rainfall autocorrelation coefficient values and plots.

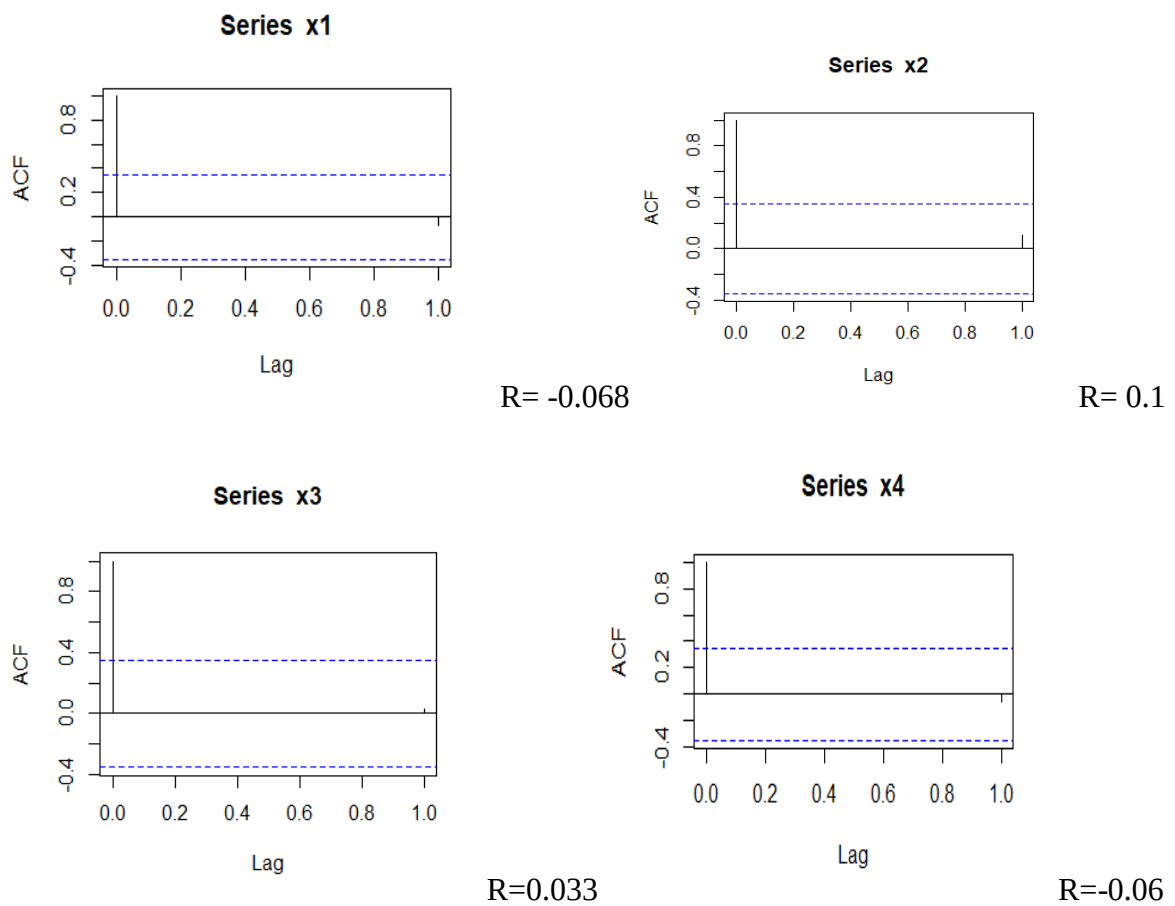


Figure 4.1. Total annual rainfall of Motta, Debre Work, Dejen, and Debre Markos stations autocorrelation coefficient values respect

Appendix 3: Mean annual maximum temperature autocorrelation coefficient values and plots.

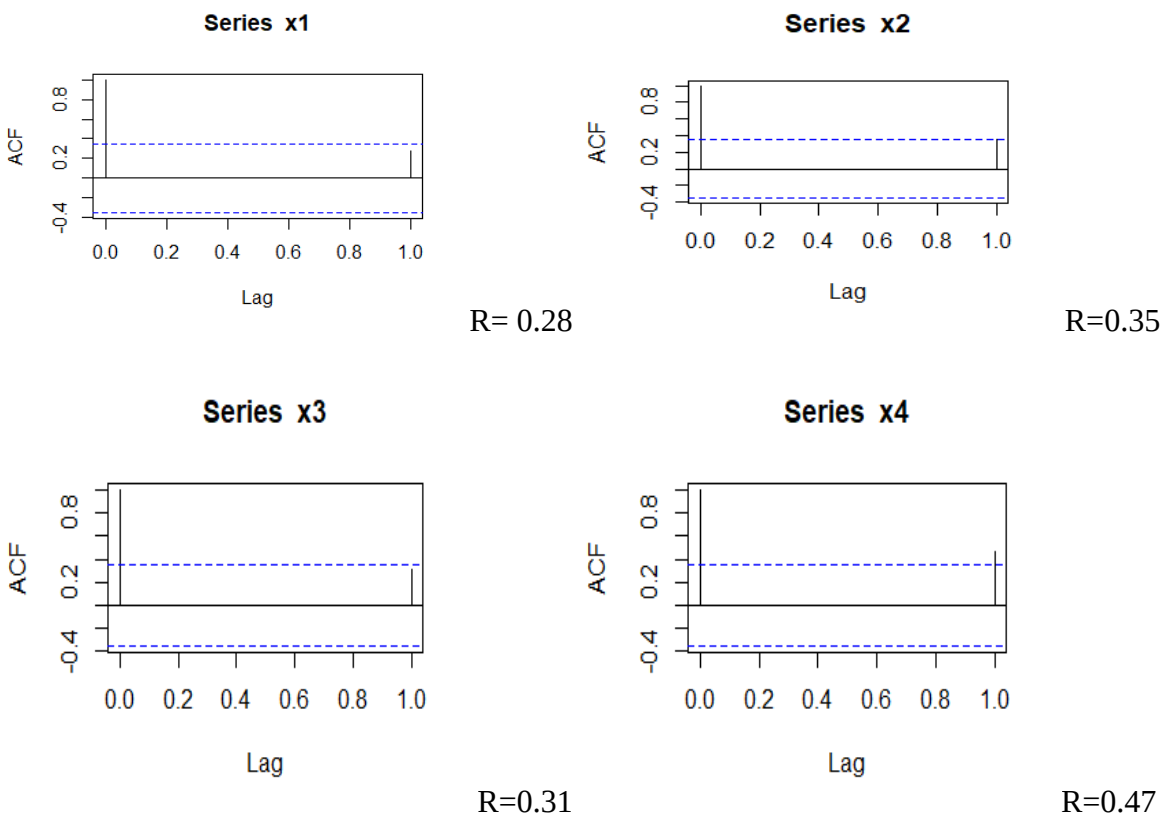


Figure 4.2. Mean annual maximum temperature of Motta, Debre Work, Dejen, and Debre Markos stations autocorrelation coefficient values respectively.

Appendix 4: Mean annual minimum temperature autocorrelation coefficient values and plots.

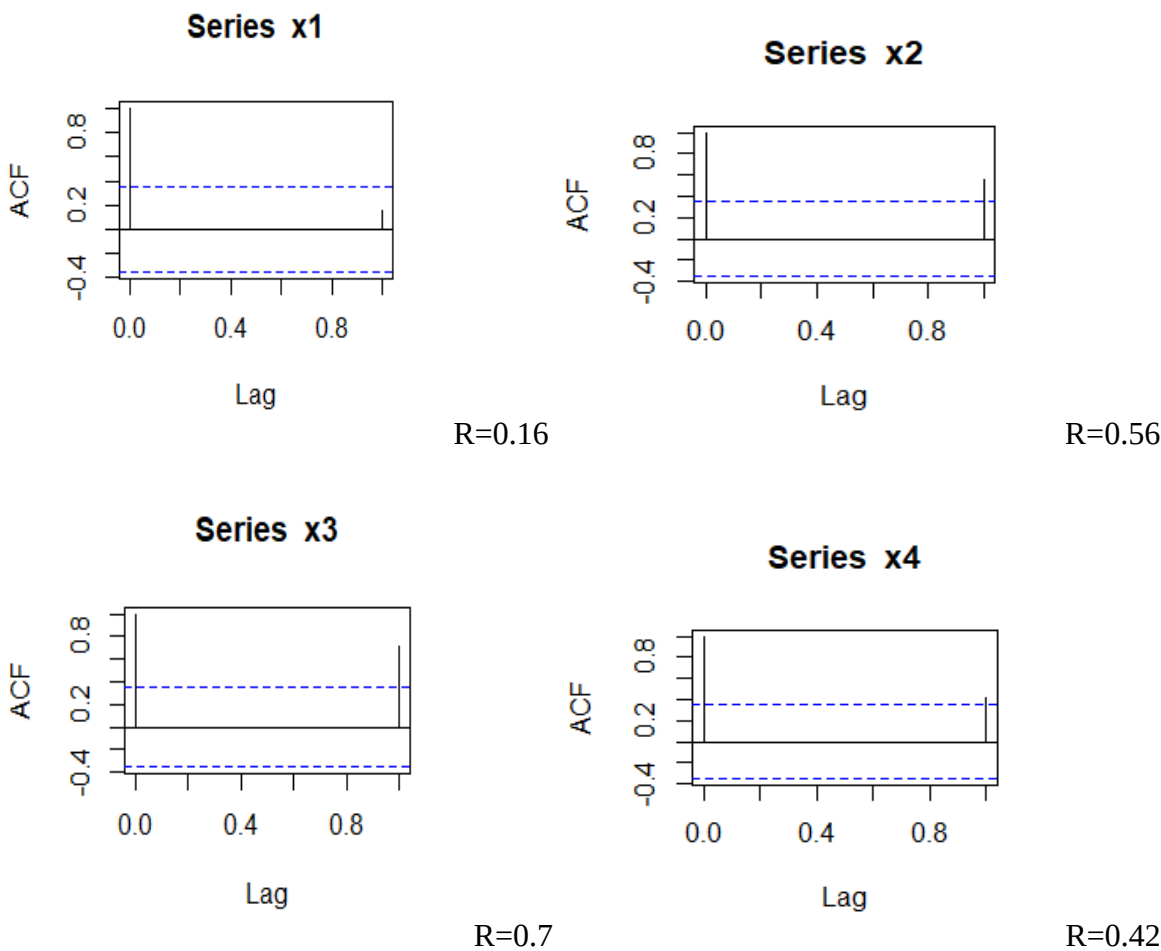


Figure 4.3. Mean annual minimum temperature of Motta, Debre Work, Dejen, and Debre Markos stations autocorrelation coefficient values respectively.