

Evaluation of Climate Change Impacts on Irrigation Water Requirement (A Case Study of Metehara Sugar Estate, Ethiopia)



Gemechis Desalegn Wirtu

A Thesis Submitted to the Department of Water Resources Engineering
School of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Water Resources Engineering (Specialization in Irrigation
Engineering)

Office of Graduate Studies
Adama Science and Technology University

August, 2021
Adama, Ethiopia

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Advisor
Abdulkerim Bedewi Serur (PhD)

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APPROVAL PAGE OF THE MSC THESIS

I, the advisor of the thesis entitled **“Evaluation of Climate Change Impact on Irrigation Water Requirements: A case study of Metehara Sugar Estate, Ethiopia”** and developed by Gemechis Desalegn Wirtu, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor

Signature

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We, the undersigned, members of the Board of Examiners of the thesis by Gemechis Desalegn Wirtu have read and evaluated the thesis entitled **“Evaluation of Climate Change Impact on Irrigation Water Requirements: A case study of Metehara Sugar Estate, Ethiopia”** and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Masters of Science in Water Resources Engineering (Specialization in Irrigation Engineering)

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I hereby declare that this MSc Thesis entitled “**Evaluation of Climate Change Impact on Irrigation Water Requirements: A case study of Metehara Sugar Estate, Ethiopia**” is my original work and has not been submitted for the award of any academic degree, diploma or certificate in any other university, and all sources of material used for this thesis have been duly acknowledged through citations.

Gemechis Desalegn Wirtu

Name of the Student

Signature

Date

RECOMMENDATION OF THE ADVISOR

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled **“Evaluation of Climate Change Impact on Irrigation Water Requirements: A case study of Metehara Sugar Estate, Ethiopia”** prepared under my guidance by Gemechis Desalegn Wirtu submitted in partial fulfillment of the requirements for the degree of Masters of Science in Water Resources Engineering (Specialization in Irrigation Engineering). Therefore, I recommend the submission of the thesis to the department for further evaluation.

Abdulkerim Bedewi Serur (PhD)

Name of the Advisor

Signature

Date

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ACRONOMS AND ABBREVIATIONS

AR	Assessment Report
ARB	Awash River Basin
CanESM2	Canadian Earth System Model
CMIP	Coupled Model Inter Comparison Project
CORDEX	Coordinated Regional Downscaling Experiment
CO ₂	Carbon Dioxide
CROPSYST	Cropping System
CV	Coefficient of Variation
CWR	Crop Water Requirement
ENMA	Ethiopian National Meteorological agency
ESGF	Earth System Grid Federation
ET	Evapotranspiration
FAO	Food and Agricultural Organization
FC	Field Capacity
GCM	General Circulation Model
GHM	Global Hydrological Model
HVA	Hangler Vander Amsterdam
IFPRI	International Food Policy Research Institute
IPCC	Intergovernmental Panel on Climate Change
ITCZ	Inter Tropical Convergence Zone
IWR	Irrigation Water Requirement
MCMC	Monte Carlo Markov Chain
MI	Multiple Imputation
MK	Man Kendall
MSE	Metehara Sugar Estate
NCEP	National Centers for Environmental Prediction
PCP	Precipitation
PET	Potential Evapotranspiration
PWP	Permanent Wilting Point
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
SDSM	Statistical Downscaling Model
SRES	Special Report on Emission and Scenario
TAM	Total available Moisture
Tmax	Maximum Temperature
Tmin	Minimum Temperature
USDA SCS	United States Department of Agriculture Soil Conservation Service

ABSTRACT

Climate change is the main source of fluctuation in global food production, particularly in the tropical countries of the developing world. Water resources are under pressure, with an increasing deficit between available supplies and water demand and climate change is further exacerbating the water scarcity through rising temperatures which likely increase the quantity of evaporation combined with unevenly distribution of rainfall are adversely affecting irrigation water availability in the Metehara Sugarcane Estate. In this study, therefore, climate change which triggers changes in temperature and precipitation and its effect on current and future sugarcane irrigation water requirement have been studied considering Metehara Sugar Estate in Ethiopia as a case study. The climate change impacts on temperature and precipitation characteristics within the watershed have been studied using CanESM2 climate model for RCP8.5, RCP4.5, and RCP2.6 scenarios from coupled model inter-comparison project 5 (CMIP5) experiments which have been downscaled by statistical downscaling model (SDSM). Long term climate change and its effects on sugarcane irrigation water requirement for current and future time period under three RCP scenarios with three thirty year time slices (2020s, 2050s, and 2080s) were estimated by FAO CROPWAT software program. The change in mean annual maximum temperature from the base period has indicated increment by 0.32, 0.33, and 0.2 °C in the RCP2.6, 0.33, 0.41, and 0.44 °C in the RCP4.5, and 0.37, 0.42, and 0.5 °C in the RCP8.5 for the 2020s, 2050s, and 2080s, respectively while in case of mean annual minimum temperature an increment by 0.05, 0.025, and 0.074 °C in the RCP2.6, 0.064, 0.067, and 0.09 °C in the RCP4.5, and 0.1, 0.12 and 0.2 °C in the RCP8.5 for the 2020s, 2050s and 2080s, respectively. In case of precipitation, increment of mean annual percentage change from the base period was detected by 1, 4.4, and 2.97% in the RCP2.6, 3, 4.94, and 6.74 in the RCP4.5, and 3.1, 5.05, and 8.7% in the RCP8.5 for the 2020s, 2050s, and 2080s, respectively. The result of annual future sugarcane irrigation water requirement showed an increase by 5.15 mm (0.8%) and 1.9 mm (0.3%) in 2020s and 2080s respectively; however it decreased by 9 mm (1.36%) in 2050s under RCP2.6. The future sugarcane irrigation water requirement was increased by 1.73mm (0.26%) in the 2020s while it was decreased by 2.78 mm (0.4%) and 7.8 mm (1.2%) in the 2050s and 2080s respectively under RCP4.5. Under RCP8.5, the future sugarcane irrigation water requirement was increased by 0.6 mm (0.08%) and 5.2 mm (0.78%) in 2020s and 2050s respectively; however in the 2080s, it showed decline by 3.33 mm (0.5%) in relative to baseline scenario. It's clearly observed from the results that there is considerable temporal variations of sugarcane irrigation water requirement under three RCP scenarios in all the future time periods which implied that climate change is putting significant impact on irrigation water requirement.

Keywords: Climate Variability and Change, Mann–Kendall Trend, CMIP5-CanESM2-RCPs Scenarios, SDSM-CROPWAT Software Programs, IWR, Metehara Sugarcane Estate in Ethiopia

1. INTRODUCTION

1.1. Background

Climate is dynamic and thus making it one in every of the foremost catching problems round the world (Kassie et al., 2014). This dynamism nature of global climate will be known by changes in the mean or the variability of its properties which lasts for an extended period, usually decade or more. The most contributors in the significant changes in global climatic patterns are the increasing concentration of atmospheric greenhouse gases that afterwards end up in global warming.

Studying the impacts of climate change require knowledge of general circulation models. The General Circulation Models (GCMs) are one of the most suitable tools for quantifying impact of climate change and they work on the fundamental conservation laws for the simulation of atmospheric variables for changing greenhouse gas concentration (Rummukainen, 2010). But, to study impacts of climate change on irrigation water requirement or any other hydrological processes in general, direct use of GCMs outputs is difficult and need to be downscaled in to local scale variables of interest because of scale mismatch between what GCM outputs supply and what hydrological models require to simulate local scale hydrological variables of interest (Brown et al., 2008). Therefore, statistical downscaling of climate variables at point location scale using statistical downscaling model (SDSM) was applied for this study, and it is paramount to bridge the scale gap between GCMs output supplied and hydrological models required.

The recent studies on emission scenarios are summarized in coupled model inter-comparison project 5 (CMIP5) representative concentration pathways (RCPs) scenarios which contains a wide range of parameters used to assess future climate scenarios and their impact on various atmospheric variables (Taylor et al., 2012). The CMIP5 datasets are the results of the advance phase of Coupled Model Inter-comparison Projects (CMIPs) and generated from the RCP concentration scenarios. RCPs include mitigation policies and methods to be adopted to realize permissible emission target together with the population projection technological and social growth (Taylor et al., 2012). The suffix of RCPs represents the approximate dominating

radiative forcing (W/m^2) at the end of the century. In present CMIP5-GCMs-RCP datasets, four radiative forcing scenarios have been formulated from low (RCP2.6) to high (RCP8.5) with two moderate scenarios of RCP4.5 and RCP6.0.

Ethiopia is prone to climate change for the reason that the country's economy principally depends on agriculture, which could be very sensitive to climate change and variations (Tekle, 2015). Average annual temperatures nationwide are expected to increase 3.1°C by 2060, and 5.1°C by 2090 (Rovin et al., 2013). In the Awash River basin, the average maximum and minimum temperatures are expected to increase by 1.9 and 2.3°C under RCP 4.5 and RCP 8.5 respectively while rainfall is expected to increase by 18 and 26% under RCP 4.5 and RCP 8.5 respectively (Bekele et al., 2019). These changes in temperature and precipitation will lead to increasing water scarcity which in turn affects crop and irrigation water requirement.

Various researchers reported that irrigation water requirement is highly dependent on the local climate of the surrounding environment. Therefore, this study was emphasized to assess the sugarcane irrigation water requirement under climate change scenarios using combination of SDSM-a tool for the assessment of climate change impacts at point location scale from CMIP5-GCM experiment under low emission scenario (RCP2.6), intermediate emission scenario (RCP4.5) and high emission scenario (RCP8.5), and agronomic (CROPWAT) models, which such information would allow managers, stakeholders, and producers to select appropriate crop management systems that ensure efficient use of water resources and results in adequate crop product and productivity.

Therefore, in this study, the statistically downscaled CMIP5-GCM (CanESM2) model for the RCP2.6, RCP4.5 and RCP8.5 scenarios were used to generate future daily precipitation, both temperatures series for averaged weather stations found inside and around study area, CWR, and IWR for the study area of Metehara Sugarcane Estate in Ethiopia. The analysis of future maximum and minimum temperature, precipitation, CWR, and IWR were carried out on an annual, seasonal and monthly basis for three-time slices (the 2020s; represents 2011-2040 time series data, 2050s; represents 2041-2070 time series data and 2080s; represents 2071-2100 time series data) in the upcoming periods.

1.2. Statement of the Problem

Global factors such as climate change that are; increasing temperatures, fluctuations in precipitation and increasing concentrations of atmospheric carbon dioxide (CO₂) are placing increasing stress on agricultural systems and drive variations in the irrigation water requirement (Wang and Chen, 2014). There is a total increase of 0.78°C in global temperature from the second half of the 19 century to the 1st decade of 20th century while the number of cold days and cold nights have decreased, the number of warm days and nights have increased globally (IPCC, 2019). Due to these changes in temperature and precipitation, glaciers have continued to shrink globally, and arctic sea ice and spring snow cover have decreased remarkably in Northern Hemisphere (IPCC, 2019).

Climate change is also posing alteration in temperature and precipitation in Sub-Saharan African countries such as Ethiopia. Average annual temperatures nationwide are expected to increase 3.1°C by 2060, and 5.1° C by 2090 (Rovin et al., 2013). The country is facing numerous development challenges that exacerbate its vulnerability to climate change, including high levels of food insecurity and ongoing conflicts over natural resources. Ethiopia is rich in water resources with 12 river basins, but they are unevenly distributed. Projected rises in the frequency of droughts, increased evaporation and evapotranspiration and possible changes in precipitation patterns and runoff further reduce irrigation water availability. Climate changes increase irrigation demand within the majority of world regions due to a mix of decreased precipitation and increased evaporation arising from increased temperatures (Niang et al., 2015).

In Ethiopia, the Awash River Basin is presently facing with a scarcity of water because of irrigation expansion, urbanization, growing needs and variability of climates. The excessive abstraction of water resources in the basin without proper assessment of the available water resources resulted in water scarcity (Gedefaw et al., 2019). Rising temperatures, a likely increase in the quantity of evaporation combined with rainfall uncertainty are adversely affecting irrigation water availability in the study area (Metehara Sugarcane Estate).

1.3. Objectives

1.3.1. General objective

The overall objective of the research was to assess the impacts of climate change on irrigation water requirements for the study area of Metehara Sugarcane Estate in Ethiopia.

1.3.2. Specific objectives

In order to meet the general objective of the study, the following specific objectives are set to:

- i. Analyze historical rainfall and temperature variability and trend in the study area.
- ii. Evaluate the performance of SDSM in simulating historical climate variables in the study area.
- iii. Develop spatiotemporal variations of climate variables (maximum temperature, minimum temperature and precipitation) under changing climate.
- iv. Investigate the responses of sugarcane irrigation water requirements under changing climate.

1.4. Research Questions

The study was directed by the following research questions:

- i. How climate change and variability is expected to trigger changes in rainfall and temperature series that would affect the irrigation water availability in the study area?
- ii. How well SDSM perform in simulating historical climate variables in the study area?
- iii. How alarming is the future rainfall and temperatures change of the study area can be? (Is there a warming trend in the Metehara Sugar Estate?)
- iv. How will the future changes in climate variables (rainfall and temperatures) affect the sugarcane irrigation water requirement in the study area?

1.5. Significance of the Study

Studying climate change impacts on irrigation water requirement and crop water requirement has a huge role in creating conducive environment for crops. Understanding the changes in water requirement is vital for preparedness and planning adaptation to climate change effects on water resources, irrigation water requirement and to achieve sustainability in agriculture. It is also a key factor for proper water management to investigate and solve danger related to water resources available for irrigation water based on future variability in climatic and meteorological variables.

In general, this study will help water managers, decision makers and producers to understand climate impact and plan appropriate adaptation measures that must be taken ahead of time. It will also help to enhance the scientific community's and other stakeholder's awareness and knowledge of climate change impacts on water use for irrigation at local level.

1.6. Scope and Limitation of the Study

The study only focused on Metehara sugar estate which has a latitude and longitude of 8°21' to 8°29' N and 39°12' to 39°18' E with an elevation of 947 meters above sea level and the study aimed to assess impacts of climate change on irrigation water requirements for crop in the study area (specifically sugarcane) by integrating both climate and agronomic models.

Representative concentration pathways of high emission (RCP 8.5), medium emission (RCP 4.5) and low emission (RCP 2.6) were used in this study to provide necessary inputs to climate models. RCP 6.0 is also another emission scenario which is not used in this study, since it provides medium emission scenario like that of RCP 4.5.

In this study, Statistical Downscaling Model (SDSM) was used for downscaling global large scale climate variables into local scale rainfall, maximum and minimum temperatures. The future downscaled rainfall and temperatures series data up to year 2100 were then used to investigate future sugarcane irrigation water requirement using CROPWAT model. In this study, climate change impacts on sugarcane irrigation water requirement considering only future rainfall, maximum temperature, and minimum temperature was assessed keeping other physical factor such as land use land cover change and watershed management practices constant due to time and budget constraint.

1.7. Thesis Organization

Chapter 1 is the introduction and it discusses the background information, problem statement, general and specific objectives, scope and limitations of the study. It brings to focus the problems experienced in this region in light of the changing climate.

Chapter 2 is the Literature review which summarizes literature regarding the climate scenarios and GCMs, effects of climate change on temperature, precipitation, irrigation water availability, crop water requirement, irrigation water requirement, and evapotranspiration in terms of global, continental and regional aspect.

Chapter 3 is the materials and methodology and it describes the location of the study area, various data used in the study, their sources, the methods adopted to fulfill objectives of the study.

Chapter 4 is the result and discussion which presents the output of model application to assess the impact of climate change. It gives detailed results of variability and trend analysis, performance evaluation statistical downscaling model, climate projection and finally determination of climate change effect on irrigation water requirement.

Chapter 5 is the conclusion and recommendation that summarizes important findings that contribute to the objectives and questions of the research.

2. LITERATURE REVIEW

2.1. Global climate change and variability

Sub-Saharan Africa is among the most vulnerable regions to climate changes and variability (Solomon, 2007). Even though the impact of climate change is vast, the changing pattern of precipitation deserves urgent and systematic attention as it affects food security in this part of the world (Dore, 2005). It is also noted that precipitation and temperature changes are not globally uniform. Regional variations can be much larger, and considerable spatial and temporal variations may exist between climatically different regions (Yue and Hashino, 2003).

There is also an emerging consensus that Eastern Africa, particularly Ethiopia, is one of the most susceptible regions regarding the impacts of climate variability and change (Slingo et al., 2005). Different studies were conducted to assess the variability and trend of rainfall in different parts of Ethiopia. Bekele et al. (2017) used standard statistical descriptors such as coefficient of variation (CV) to characterize rainfall variability for agricultural water management in Awash River Basin, Ethiopia. According to the authors, the mean annual rainfall distribution across the 12 stations in Awash River Basin varies from 209.7 mm in Dubti to 1,186.8 mm in Addis Ababa. The authors also revealed that the annual weighted average rainfall of the stations is 853.1 mm with 22.7% CV and most of the stations show moderate variation in annual rainfall ($CV\% < 30$).

Eshetu (2020) assessed variability and trend of hydro-climatic variables of five different representative stations at Upper Awash River Basin, Modjo River watershed using M-K trend test and Coefficient of variation (CV) and revealed that most of the stations showed low variation in annual rainfall ($CV\% < 20$) while the main (Kiremt) and short (Belg) season rainfall exhibited CV ranging from low to high. The author also reported that both annual and seasonal rainfall showed a non-significant trend at all stations for the past 30 years.

2.1.1. Causes and effects of climate change and variability

Climate change can be caused by natural processes such as volcanic activity, solar variability, plate tectonics, or shifts in the Earth's orbit, ozone layer depletion. It can also be caused by human activity such as increased greenhouse gas emissions, deforestation. The latest (fifth) Assessment report from the Intergovernmental Panel on Climate Change (Wu et al., 2013) for example found that on average global temperatures increased about 0.85°C from 1880 to 2012, and concluded that more than half of the observed increase in global average temperatures was caused by elevated emissions of carbon dioxide and other greenhouse gases.

Climate variability can occur due to internal or external processes. Internal processes include changes in the distribution of energy in the ocean and atmosphere while external processes involve changes in solar output and volcanism and this will result in abrupt disruptions, such as floods, droughts, or tropical storms (Sodangi et al., 2011).

2.2. General Circulation Model (GCM)

The General Circulation Model (GCM) is one of the most suitable tools for measuring impact of climate change and its variability and they work on the fundamental conservation laws for the simulation of atmospheric variables for changing greenhouse gas concentration. General Circulation Models (GCMs) implies that increasing concentrations of greenhouse gases will have significant implications for climate at global and regional scales (Wilby and Dawson, 2007).

Although GCMs have ability to simulate the atmospheric general circulation at the continental scale, they are not essentially capable of capturing the detailed processes related with regional local climate variability and changes that are needed for regional and national climate change assessments (Rummukainen, 2010). Unfortunately, GCMs are restricted in their utility for local impact studies by their coarse spatial resolution (typically of the order 50,000 km²) and inability to resolve significant sub-grid scale features such as clouds and topography scales (Wilby and Dawson, 2007). Therefore it is needed to downscale these global variables to regional variables for the study of climate change impacts.

2.2.1. Climate Scenarios

Climate scenarios are a reasonable description of the future climate based on various climate relationships and assumptions about radiative forcing. It can be visualized using global climate models (GCMs) and regional climate models (RCMs), which are complicated three dimensional mathematical representations used to show the processes of interactions among the atmosphere, oceans, land surface, sea and ice which resulted from climate change (Kang and Ma, 2009).

In climate change research, climate scenarios have become an important element as they enable researchers to understand the long-term consequences and describe plausible pathways of climatic condition (Moss et al., 2010). Over time, various scenarios have been used in climate research from SA92 used in IPCCs first assessment report to Special Report on Emissions and Scenarios (SRES) used in third and fourth assessment report. Recently, the new scenarios called Representative Concentration Pathways were developed and used for preparing fifth assessment report (AR5) of IPCC released in 2015.

2.2.2. Representative concentration pathways (RCPs)

RCPs are the latest generation of scenarios that provide necessary inputs to climate models in climate research. The RCPs were developed by combined efforts of the researchers from different disciplines involved in climate research (Van Vuuren et al., 2011). RCPs are time and space dependent trajectories of concentrations and emission of greenhouse gases and pollutants which arises from human activities, including changes in land use.

According to IPCC the fifth assessment report of (Pachauri et al., 2014), four representative concentration pathways are developed for impact assessment studies. RCP2.6, RCP4.5, RCP6.0, and RCP8.5 are termed after probable variety values of radiative forcing +2.6, +4.5, +6.0, and +8.5 W/m² correspondingly, relation to pre-industrial values in the year 2100. The four pathways (Sahilu, 2015) are explained as:

RCP 2.6 (Low Emissions): This type of scenario is evolved through Netherlands Environmental Assessment Agency. Here Radiative forcing equals 3.1 W/m² earlier than it returns to 2.6 W/m² by 2100. In order to attain such forcing levels, formidable greenhouse gas emissions reductions would be required over time. This future could require a reduction in oil

consumption, low energy intensity, a world population of nine billion by year 2100, use of croplands rising due to bio-energy production, more intensive animal husbandry, methane emissions reduced by 40% and CO₂ emissions stay at today's level until 2020, then decline and become negative in 2100.

RCP 4.5 (Intermediate Emissions): RCP 4.5 is a medium emission and is developed via the Pacific Northwest National Laboratory in the US. Here radiative forcing is stabilized shortly after year 2100 and its features are comparable with SRES scenario B1. This scenario is consistent with lower energy intensity, strong reforestation programs, decreasing use of croplands and grasslands because of rise in yield and changes in dietary, stringent climate policies, stable methane emissions and CO₂ emissions rise only slightly before decline commences around 2040.

RCP 6.0 (Intermediate Emissions): This scenario is developed by the effort of National Institute for Environmental Studies in Japan. Radiative forcing is stabilized quickly after year 2100, which is consistent with utility of various technologies and strategies for lowering greenhouse gas emissions. It is related to the SRES scenario, B2. The feature of this moderate to high emission scenario is consistent with heavy reliance on fossil fuels, intermediate energy intensity, increasing use of croplands and declining use of grasslands, stable methane emissions and CO₂ emissions peak in 2060 at 75 percent above the current levels, then decline to 25 percent above today.

RCP 8.5 (High Emissions): This scenario is consistent with a feature with no policy changes to minimize emissions. It was first developed by the International Institute for Applied System Analysis in Austria and is characterized by increasing greenhouse gas emissions that lead to high greenhouse gas feature of this high emission scenario is consistent with rapid increase in methane emissions, three times today's CO₂ emissions by 2100, heavy reliance on fossil fuels, lower rate of technology development, high population growth, increased use of croplands and grassland which is driven by an increase in population and no implementation of climate policies.

Table 2.1. Description of the four representative concentration pathways (RCPs) (Van Vuuren et al., 2011)

RCPs	Description	Greenhouse gas emissions	Publication-IA Model
RCP8.5	Rising radiative forcing pathway leading to 8.5 W/m ² (~1370ppm CO ₂) by 2100	High baseline	(Riahi et al. 2011)-MESSAGE
RCP6.0	Stabilization without overshoot pathway to 6 W/m ² (~850ppm CO ₂ eq) at stabilization after 2100	Medium baseline; high mitigation	(Fujino et al. 2006; Hijioka et al. 2008)-AIM
RCP4.5	Stabilization without overshoot pathway to 4.5 W/m ² (~650ppm CO ₂ eq) at stabilization after 2100	Medium-Low mitigation; Very low baseline	(Clarke et al. 2007; Smith and Wigley 2006)-GCAM
RCP2.6	Peak in radiative forcing at ~3W/m ² (~490ppm CO ₂) before 2100 and the decline (the selected pathway declines to 2.6 W/m ² by 2100)	Very low	(Van Vuuren et al., 2007a; Van Vuuren et al. 2006)-IMAGE

2.3. Trend Analysis of Climatic Data

Trend is a unidirectional gradual increasing or decreasing in the average value of a variable (Karamouz et al., 2003). This is observable in hydrologic system because natural and human factors cause variation in systems causing non stationary time series. In water resources planning and management it is necessary to quantify these trends.

The Mann–Kendall (MK) trend test is a commonly used non-parametric test to detect trends in hydro meteorological time series. The test compares the relative magnitudes of sample data rather than the data value themselves. The advantages of this test are that the data does not need to conform to any particular distribution and it is less sensitive to sudden breaks due to inhomogeneous time series (Jaagus, 2006).

Trend analysis and variability in precipitation series have been investigated by many researchers throughout the world. Different studies were also conducted in Ethiopia to assess trend of rainfall and temperature using Mann–Kendall’s test. For example, Bekele et al. (2017) used MK trend test and reported a decreased rainfall in annual, Belg (January/March to May) for eight and seven stations respectively and increasing trend in eight stations out of twelve total stations in the Kiremt (June to August) season in awash River Basin, Ethiopia. Mekasha et al. (2014) also reported increasing warm extremes in temperature and increasing precipitation in different stations across Ethiopia.

2.4. Downscaling Methods

The method used to convert GCM outputs into local meteorological variables required for reliable hydrological modeling is called downscaling. The general circulation model is commonly used tool for climate predictions. Because their insufficient spatial scale (grid-cell resolutions of approximately 100–250 km) is lacking detailed regional information, downscaling procedures are required in order to provide fine-resolution climate parameters for hydrological modeling (Pachauri and Reisinger, 2008). The output of the general circulation model (GCM) is downscaled by two approaches which are statistical and dynamic methods (Samadi et al., 2013).

2.4.1. Statistical downscaling

Statistical downscaling involves developing a quantitative relationship between large-scale atmospheric variables (predictors) and local surface variables (predictands) (Wilby et al., 2004). Studies that were undertaken using statistical downscaling for example, taking the relationship with RCMs into consideration, Maraun et al. (2009) divided statistical downscaling approaches into perfect prognosis (PP), model output statistics (MOS) and weather generators.

Advantage of statistical downscaling is that it is computationally inexpensive and efficient. This allows many different emissions scenarios and GCM pairings. The statistical downscaling methods are also simple and flexible enough to be applied for specific purposes (Wilby and Dawson, 2007).

Banze et al. (2018) assessed impact of climate change on precipitation in Zambeze River Basin in Southern Africa. The authors assessed future change projection in precipitation under RCP2.6, RCP4.5 and RCP8.5 scenarios of the CanESM2 outputs using the Statistical Downscaling Model (SDSM) for 50 stations in Zambeze River basin during the two future periods which were near future (2031-2060) and far future (2071-2100). For assessment of climate change, the authors partitioned baseline period (1979-2013) into two periods for SDSM calibration (1979-1996) and validation (1997-2013). They concluded that SDSM was not a very robust method for the simulation of precipitation for this study area, the model could not replicate observed precipitation very well, which occurred due to its conditional nature and high variability in space.

2.4.2. Dynamical downscaling

Dynamic downscaling is a method of extracting local-scale or nearby information by developing limited area models or regional climate models (RCM) with the coarse GCM data used as boundary condition. Instead of the traditionally used statistical downscaling, the ‘nested’ RCM approach allows a dynamic downscaling to capture climate processes at local scale (Teutschbein and Seibert, 2010).

Many studies have found that the skill improvement of RCM depends not only on the RCM resolution but also on the region and the season (Rauscher et al., 2010). Although RCMs may give feedback to their driving GCMs, many dynamic downscaling approaches are based on a one way nesting approach and have no feedback from the RCM to the driving GCM (Maraun et al., 2009).

Advantages of dynamic downscaling are that it is based on consistent physical mechanisms and the fact that it resolves atmospheric and surface processes occurring at sub-GCM grid scale but it is computationally expensive and requires significant computing resources (Wilby and Dawson, 2007).

2.5. Agricultural (Crop) Models and Its Classification

Crop models are computer-aided representations of crop growth, development, and yield, that are simulated using mathematical equations as a function of soil conditions, weather, and

management options (Basso et al., 2013). Crop models have been developed to simulate risks related with crop management options in the face of climatic change and variability. They simulate plant growth, development, and yield in response to water, temperature, solar radiation and nutrient inputs.

Some of the frequently applied agricultural models include CROPWAT, AQUACROP and CROPSYST. The two models that are specifically strong on the relationship between water availability, crop growth and climate change are CROPWAT and AQUACROP (Kasampalis et al., 2018).

2.5.1. CROPWAT model and its application

CROPWAT is software developed by the Land and Water Development Division of Food and Agriculture Organization (FAO) for planning and management of irrigation (Allen et al., 1998). It is a practical tool to carry out standard calculations for reference evapotranspiration, CWR, IWR, and more specifically the design and management of irrigation schemes. CWR and irrigation timing are particularly important in water resources management.

Arku et al. (2012) used the CROPWAT model version 8.0 to determine water requirement and irrigation timing for *Amaranthus Hybridus* in Maiduguri Metropolis, North-Eastern Nigeria. Based on the authors result the theoretical values of water requirements and irrigation timing were computed using the Penman Montieth equation in CROPWAT 8.0 for dry season drip irrigation system as water saving measure and optimum yield.

Tibebe and Birhanu (2015) applied CROPWAT model after analyzing water demand and irrigation requirement for major Crops at Holetta Catchment, Awash Sub basin, Ethiopia. In the study, reference evapotranspiration, effective rainfall, crop pattern, and soil data were used for analysis. The major crops were identified from the survey analysis and used in the calculation of CWR.

2.5.2. Effective Rainfall and Crop Coefficient

In figuring out and determining irrigation water requirement effective rainfall is essential parameter. Agriculturists believe a portion of rainfall effective that directly satisfies crop water requirements. Monthly rainfall data are required to calculate the effective rainfall (on monthly basis) P_e , which can be calculated depending on USDA Soil Conservation Service method provided in the CROPWAT model (Allen et al., 1998).

Adnan and Khan (2009) used USDA SCS method to estimate effective rainfall using data from 58 meteorological stations covering irrigated plains of Pakistan. The effective rainfall have been estimated for two crop growing seasons, that is Rabi (October to April) and Kharif (May to September) and concluded that the highest value of effective rainfall in Rabi season is 100% at southern parts of Pakistan when net depth of irrigation of water application of 100mm and the lowest is 54.40% at southern Balochistan; when net depth of irrigation of water application of 25mm. The highest value of effective rainfall during Kharif season is 100% at southern Balochistan and central Sindh regions; when net depth of irrigation of water application of 100mm and lowest value is 60% at southwestern Balochistan when net depth of irrigation of water application of 25mm.

Determining the crop water requirement and crop coefficient at various growth stages is needed for planning, designing and implementing crop water management practices (Win et al., 2014). In order to estimate water consumption by the crop, the most widely used method which derives evapotranspiration (ET_c) for crops growing with adequate water, nutrition and free of pests and diseases, from a reference evapotranspiration (ET_o) which is carried out with Penman-Monteith equation and crop coefficient (K_c) to convert ET_o to ET_c for a given stage of development (Allen et al., 1998). This is not only important for determining IWR and irrigation scheduling, but also for increased water-use efficiency. Allen et al. (1998) reported that values of K_c for sugarcane range from 0.4 to 1.25 for the initial (low canopy) and mid (full canopy) periods of crop development to 0.7 for the end (harvest) of development.

Development of crop coefficient (K_c) can enhance crop evapotranspiration (ET_c) estimates in specific crop growth stages. Locally pre-determined values of K_c are available in Ethiopia for some of major crops. However, locally quantified K_c data is not available for other important

crops in Ethiopia such as sorghum. For instance, Shenkut et al. (2013) conducted a study to determine growth stage specific K_c and crop water use for sorghum at the Melkassa Agricultural Research Center which is located in a semi-arid climate zone in Ethiopia. Drainage type lysimeter was used to measure crop water consumption under water balance system on a clay loam soil and local weather data were used to determine the reference evapotranspiration (ET_o) and the authors develop crop coefficient from measured ET_c and ET_o calculated using weather data.

2.6. Climate Change Impact on Temperature and Precipitation Characteristics

2.6.1. Climate change impact on temperature and precipitation in global perspective

Almost the entire globe has been experiencing surface warming and the evidence for this warming comes from multiple climate system indicators from atmosphere to the oceans (Harmsen et al., 2009). There is a total increase of 0.78°C in global temperature from the second half of the 19 century to the 1st decade of 20th century. While the number of cold days and cold nights have decreased, the number of warm days and nights have increased globally (IPCC, 2019). Due to these changes in temperature and precipitation, glaciers have continued to shrink globally, and arctic sea ice and spring snow cover have decreased remarkably in Northern Hemisphere (IPCC, 2019).

One of the studies done in California, explore the implications of the highest and lowest Intergovernmental Panel on Climate Change emissions pathways for climate change and associated impacts (Hayhoe et al., 2004). The authors used two global climate models, parallel climate model (PCM) and Hadley center climate model version 3 (HadCM3) to calculate climate change resulting from the SRES (B1 and A1 emission scenarios) and found that annual temperature increases nearly double from the lower B1 to the higher A1 emissions scenario before 2100. Three of four simulations also show greater increases in summer temperatures as compared with winter.

2.6.2. Climate change impact on temperature and precipitation on Africa

The African continent is expected to be the foremost stricken by climate change, land degradation, and desertification (Hummel, 2016). Africa has been identified as one of the parts of the world most vulnerable to the impacts of climate change (IPCC, 2019). There will likely be an increase in annual mean rainfall in tropical and East Africa Sub-Saharan Africa is considered to be the most vulnerable to the impacts of climate change because of its high dependence on agriculture and natural resources, warmer baseline climates, fluctuation in rainfall, and limited adaptability. Several studies have proven that surface water and groundwater evolutions over the past ten years in Sub-Saharan Africa have been consistently affected by rainfall variations (Hassan and Nhemachena, 2008).

In Africa, Malawi, the study was undertaken to evaluate the ability of existing general circulation models (GCMs) and Regional Climate Models (RCMs) to hind cast climatic variables at a resolution appropriate for climate change impact assessment and adaptation planning (Warnatzsch and Reay, 2019). The authors focused on monthly precipitation rate, and mean, maximum and minimum surface air temperature and used RCMs produced by many different groups within the Coordinated Regional Climate Downscaling Experiment (CORDEX) initiative and provided projections for representative concentration pathways (RCPs) 4.5 and 8.5 were selected as these are deemed the most useful for further research on future climate change vulnerability and responses and concluded that none of the individual or ensemble RCMs or GCMs correlate well with the observed datasets for any of the assessed climatic variables. While, they simulate the trending change in temperature variables sufficiently, the simulated outputs for rainfall are highly divergent.

2.6.3. Climate change impact on temperature and precipitation on Ethiopia and Awash River Basin

Ethiopia is highly vulnerable to the impacts of climate change due to social, economic and ecological factors. In particular, due to high levels of poverty, speedy population growth, a high level of dependence on rain-fed agriculture, high levels of environmental degradation, chronic food insecurity and frequent cycles of natural drought increase vulnerability of climate

change in this country. Climate change will have a huge impact on Ethiopia's climate variables such as temperature and precipitation; average annual temperatures nationwide are expected to increase 3.1°C by 2060, and 5.1° C by 2090 (Rovin et al., 2013).

Gebre and Ludwig (2015) used five bias-corrected 50 km × 50 km spatial resolution GCMs for RCP4.5 and RCP8.5 scenarios to downscale and assess future climate change of four watersheds (Gilgel Abay, Gumara, Ribb and Megech) located in Tana sub basin for the time period of 2030s and 2050s respectively. The result noted that the selected five GCMs disagree on the direction of future prediction of rainfall, but multimodal average monthly and seasonal rainfall may generally increase over the watershed.

Bekele et al. (2019) used CMIP5-GCMs to study the likely impact of climate change on hydrological processes of the Keleta watershed in the Awash River Basin, Ethiopia. The authors reported that RCP 4.5 predicts an average precipitation increase of 15.2 and 17.2% for mid and end-of-century data, respectively, while RCP 8.5 predicts an average precipitation increase of 19.9 and 34.4% for mid and end-of-century data, respectively. The authors also revealed that mid-century minimum and maximum temperature increases range from 1.8 to 1.6 °C (RCP 4.5) to 2.6 to 2.1 °C (RCP 8.5), respectively, while end-of-century increases vary from 2.4 to 2.0 °C (RCP 4.5) and 4.6 to 3.7 °C (RCP 8.5), respectively.

Roba et al. (2021) analyzed rainfall and temperature changes in middle Awash River Basin and showed that there was an increment in rainfall and temperature in the district. According to the authors, rainfall showed the likely increase within the range of 5.7 to 9.51% and 3.45 to 6.43% for both RCP 4.5 and RCP 8.5 scenarios respectively. The authors also reported that minimum temperature was projected to increase by 1.04 °C to 3.02 °C and 0.03 °C to 5.13 °C under both scenarios for the 2020s and 2050s and the maximum temperature was expected to increase in the range of 0.95 °C to 1.98 °C and 1.38 °C to 2.83 °C for the 2020s and 2050s of both scenarios.

2.7. Climate Change Impact on Irrigation Water Availability

A lack of available water for agricultural production, energy projects, other types of anthropogenic water consumption, and ecological use is already a serious issue in many parts of the world and is expected to grow all of the more severe with rising population, higher food (especially meat) demand, increasing temperatures, and changing rainfall patterns (Elliott et al., 2014).

Irrigation is of predominant importance to increasing productivity on existing agricultural lands, and projected per-hectare irrigation consumption is therefore crucial output of global gridded crop models (GGCMs). Irrigation is additionally out and away the biggest element of anthropogenic demand for fresh water and as such constitutes a vital part of the global hydrological cycle and thus of global hydrological model (GHM) simulations (Haddeland et al., 2014).

In Ethiopia, the Awash River Basin is presently facing with a scarcity of water because of irrigation expansion, urbanization, growing needs and variability of climates. The excessive abstraction of water resources in the basin without proper assessment of the available water resources resulted in water scarcity. Gedefaw et al. (2019) aimed to develop a water evaluation and planning (WEAP) model for Awash basin to allocate the supplies of water supplies to demanding sectors based on an economic parameter to boost the economic benefits. Three different scenarios were developed to analyze water demands, water shortages, and supply alternatives, namely reference (1981–2016), medium-term development (2017–2030), and long-term development (2031–2050) future scenarios with the baseline period (1980). The results of the study showed that the total quantity of water needed to meet the irrigation demands of all the stations was 306.96 MCM from 1980 to 2016.

Taye et al. (2018) assessed the potential impact of climate change on water availability of the Awash Basin, Ethiopia in different seasons using three climate models from Coupled Models Inter-comparison Project phase 5 (CMIP5) and for three future periods (2006–2030, 2031–2055, and 2056–2080). The authors estimated the future water availability as the difference between precipitation and potential evapotranspiration projections using the representative concentration pathway (RCP8.5) emission scenarios and concluded that projections for the

future three periods show an increase in water deficiency in all seasons and for parts of the basin, due to a projected increase in temperature and decrease in precipitation.

2.8. Climate Change Impact on CWR and Evapotranspiration

With respect to the relations between the water cycle and the climate system, every climate change could affect all meteorological parameters and this result in changing crop water requirement in agriculture. Studies were done regarding climate change effects on crop water requirement; for instance, Parekh et al. (2007) showed the clear influence of climate change on crop water requirement of Rabi and Hot Weather crops. The results show that crop water requirement of all Hot Weather crops (Millet, Ground nut, Maize, Small vegetables and Tomato) in all future periods is rising compared to base period 2003-2009. Crop water requirement of Rabi crops (Wheat, Sorghum, Maize, Small Vegetables, Tomato, Gram and Cowpeas) shows insignificant decrease in crop water requirement in the period 2011-2020 but all plants shows a significant increase in water requirement in the period of 2021-2030 including the periods between 2046-2065 and 2080-2099 as compared to base period 2003-2009.

Climate change also affects evapotranspiration which are important in studying about crop water requirement. Crop water requirement can be expressed as the difference between potential and actual evapotranspiration. Potential evapotranspiration is a measure of the ability of the atmosphere to remove water from the surface through the processes of evaporation and transpiration whereas; Actual evapotranspiration is the quantity of water that is actually removed from a surface due to the processes of evaporation and transpiration.

In Ethiopia numerous research are performed to assess the variability of potential evapotranspiration (PET) and water availability within the Awash River Basin (ARB). For instance, Tadese et al. (2020) investigated The PET and water availability of the ARB during the period of 1995–2009 and two future scenarios (2050s and 2070s) under the representative concentration pathways (RCP4.5 and RCP8.5) and the result noted a rise in the monthly mean PET from March to August in the 2050s, and all the months in the 2070s. The study also implies a shortage of net water availability in the majority of the months investigated and the

occurrence of mild to extreme drought in about 40–50% of the analysed years at the three study locations (Holetta, Koka Dam, and Metehara).

2.9. Climate Change Impact on Irrigation Water Requirement

The irrigation water requirement (IWR) is the quantity of water that need to be provided to a crop via irrigation to attain optimum crop growth, considering the losses incurred during the transport and application of the irrigation water. Global factors such as climate change that are; increasing temperatures, fluctuations in precipitation and increasing concentrations of atmospheric carbon dioxide (CO₂) are placing increasing stress on agricultural systems and drive variations in the IWR (Wang and Chen, 2014).

A number of studies over the past few years have quantified the effect of future climate change on irrigation at regional and global scales. Significant increases had been estimated for the long-term period IWR due to warming climate and increased evaporative demand (Fischer et al., 2007; Konzmann et al., 2013; Pfister et al., 2011).

Ding et al. (2017) examined the spatial and temporal responses of rice irrigation water needs to climate change in the central and lower Yangtze River in China and found that over the past 50 years, irrigation requirement significantly decreased by 1.58 and 2.10 mm/year for late rice and single cropping rice respectively. Projected future irrigation water requirement will increase for all types of rice in the whole region under RCP4.5 and RCP8.5 scenarios (up to 100 mm), but decrease for single cropping and late rice in the southeast region (up to 40 mm).

Roba et al. (2021) studied climate change impacts on crop water requirement and irrigation water requirement of maize in middle Awash River Basin, Ethiopia using combination of CROPWAT model and seventeen GCMs from the MarkSim-GCM for RCP 4.5 and 8.5 scenarios for two-time slices of the future period 2020 (2014–2043) and 2050 (2044–2073), and found that CWR of maize will increase by 8.16 and 10.39% for RCP4.5 and by 9.45 and 10.94% for RCP 8.5 of the 2020 and 2050s respectively. The study also investigated that irrigation water requirement of maize crop will increase by 5.1 and 9.5% for RCP 4.5 and by 6.55 and 10.3% for RCP 8.5 of the 2020s and 2050s from the base period.

Table 2.2. Summary of important reviewed literatures

No	Author/s and Year	Topic/title name	Methodology Applied	Major Findings
1	(Eshetu, 2020)	Hydro-Climatic Variability and Trend Analysis of Modjo River Watershed, Awash River Basin Ethiopia.	CV, PCI and SAI For variation estimation Mann-Kendall trend test and Sen's slope.	Low variation in annual rainfall (CV<20%) and low to high variation (CV between 20 and 40%) in seasonal rainfall. Increasing or decreasing trend for both annual and seasonal rainfall at all stations for the past 30 years.
2	(Banze et al., 2018)	Impact of Climate Change on Precipitation in Zambeze River Basin, South Africa.	SDSM was used to project future change in precipitation under CanESM2 scenario (RCP2.6, 4.5 and 8.5).	Monthly precipitation decreased during wet period (October-March) and increased during dry period (April-September) SDSM didn't replicate observed precipitation very well during validation period.
3	(Bekele et al., 2019)	Modeling Climate Change Impact on the Hydrology of Keleta Watershed in the Awash River Basin, Ethiopia.	SDSM was used to downscale 20 CMIP5-GCMs under RCP 4.5 and 8.5 for time slices of 2050s and 2080s.	Average precipitation was increased by 15.2 and 17.2% (RCP 4.5) and 19.9 and 34.4% (RCP 8.5) for mid and end of century data respectively, which led to an average increase in runoff by 70%.
4	(Taye et al., 2018)	Climate Change Impact on Water Resources in the Awash Basin, Ethiopia	Three CMIP5 were used for future time slices (2006-2030, 2031-2055, and 2056-2080) under RCP8.5.	Water deficiency was increased in all of the three future time slices due to projected increase in temperature and decrease in precipitation.

5	(Tadese et al., 2020)	Long-term Variability in Potential evapotranspiration, Water Availability and Drought under Climate Change Scenarios in the Awash River Basin, Ethiopia.	GCMs and RCMs were used under RCP 4.5 and RCP 8.5 for future periods of 2050s and 2070s. Hargraves method was used for estimating evapotranspiration.	A rise in the monthly mean PET from March to August in the 2050s, and all the months in the 2070s were obtained. Shortage of net water availability was obtained in the majority of the months investigated.
6.	(Roba et al., 2021)	Modeling Climate Change Impacts on Crop Water Demand in Middle Awash River Basin: Case Study of Berehet Woreda, Ethiopia.	Seventeen GCMs for RCP 4.5 and 8.5 scenarios for two-time slices of the future period 2020s (2014–2043) and 2050s (2044–2073) were used for climate projection.	CWR of maize expected to increase by 8.16 and 10.39% (RCP4.5), 9.45 and 10.94% (RCP8.5) in 2020s and 2050s respectively. Irrigation water requirement of maize crop also expected to increase by 5.1 and 9.5% (RCP 4.5), 6.55 and 10.3% (RCP 8.5) in 2020s and 2050s respectively from the base period.

3. MATERIALS AND METHODS

3.1. Description of the Study Area

3.1.1. Location

Metahara Sugar Estate (MSE) is the second largest irrigation scheme established in 1965 in the Awash River Basin (Upper Awash sub-basin) by the Dutch company called Hangler Vonder Amsterdam (HVA). It is located in the semi-arid Upper Awash Rift Valley region of Ethiopia in Fentale Woreda at about 200km southeast of Addis Ababa (Girma and Awulachew, 2007). It is geographically located at latitude and longitude of 8°21' to 8°29' N and 39°12' to 39°18' E.

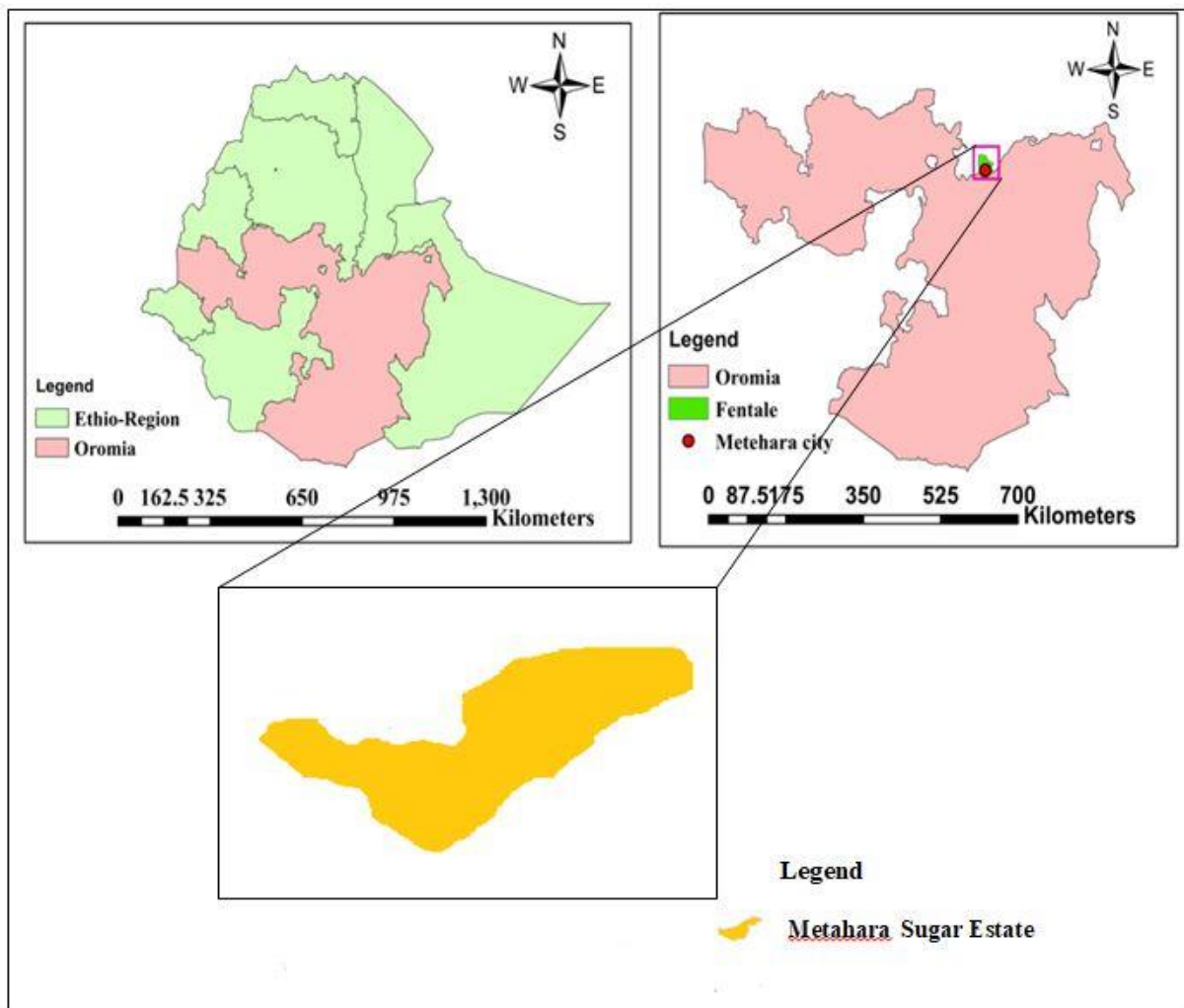


Figure 3.1. Location map of Metahara sugarcane Estate

3.1.2. Climate condition

The climate of the Awash Basin is humid to sub-humid in the highlands and semi-arid to arid in the rift valley. The climate of the Awash Basin comes under the influence of the Inter-Tropical Convergence Zone (ITCZ). This zone of low pressure marks the convergence of dry tropical easterlies and the moist equatorial westerlies. The seasonal rainfall distribution within the basin results from the annual migration of the ITCZ. The ITCZ starts its advance across the basin from south in March, bringing the small or spring rains. In June and July it reaches its most northerly location beyond the basin, which then experiences the heavy or summer rains throughout. The ITCZ returns southwards during August, September and October restoring a drier easterly air stream that prevails until the ITCZ resumes its northward migration in March. The distribution of rainfall over the highland areas tends to be modified by orographic effects.

The main season is divided in to a major rainy season (Kiremt), intermediate seasons (Tseday) and dry season (Bega and Belg). As shown in Figure 3.2, the dry season occurs between December and May; the wet season between June and August. The main rainfall season which accounts for about 70–80% of the annual rainfall occurs from July to October. The annual maximum and minimum temperature in the basin are shown in Figure 3.3.

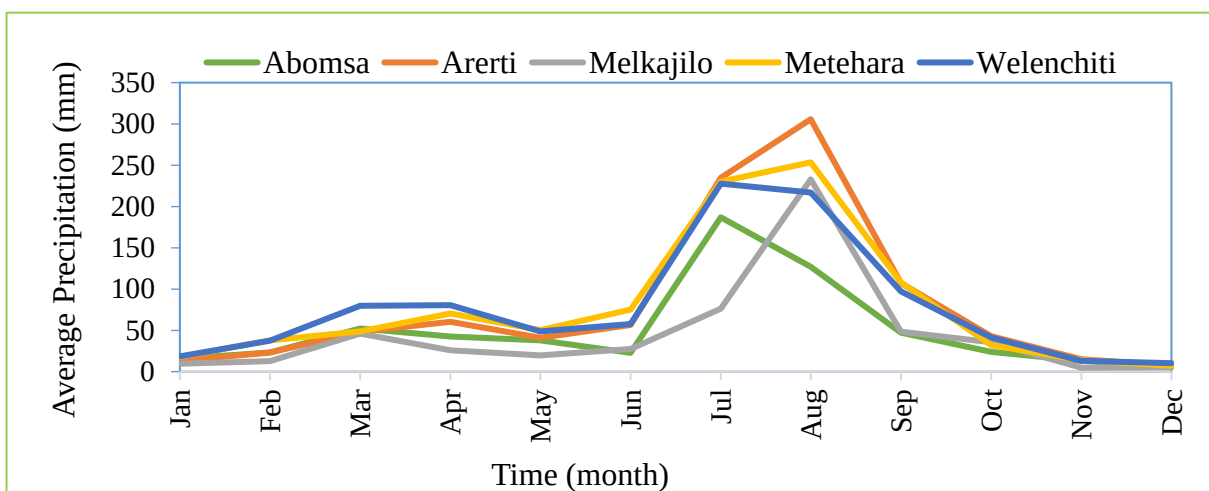


Figure 3.2. Mean annual rainfall characteristics of representative stations in upper Awash River sub-basin

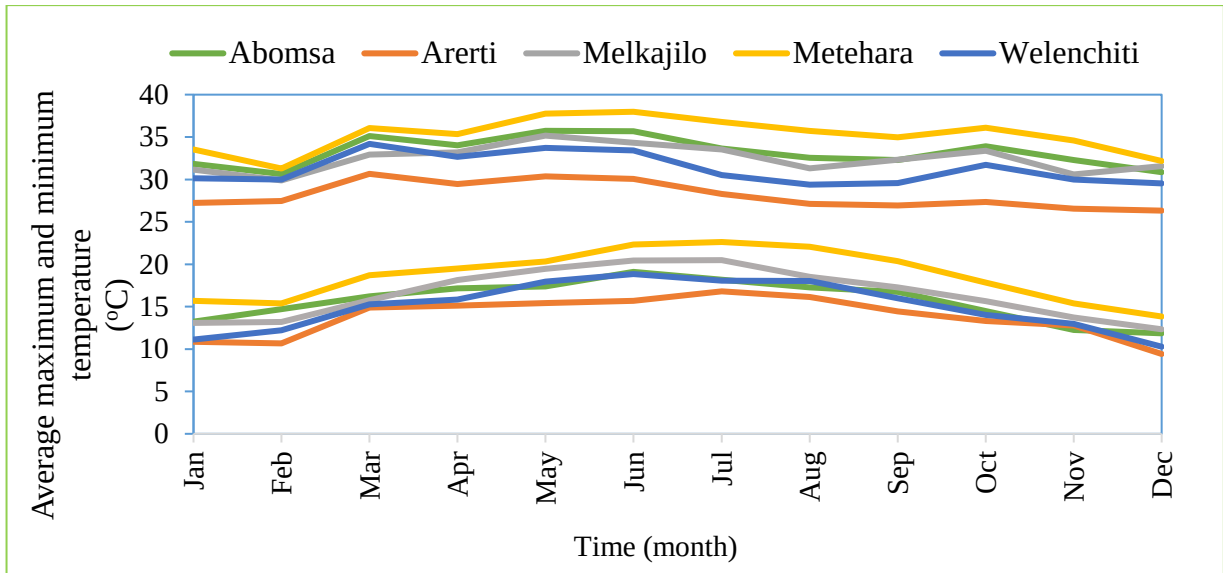


Figure 3.3. Mean annual maximum (upper series) and minimum temperature (lower series) characteristics of representative stations in upper Awash River sub-basin

3.1.3. Soil

Most soils of the experimental site at Metehara sugarcane estate are comparatively of recent alluvial origin and are classified as Cambisols. The soils have clay content (clay loam) and show shiny ped faces and thus are Hypovertic and Haplic Cambisols according to Booker Tate Limited of soil test report at Metehara research center. Most of the plains in Metahara are gentle and suitable for gravity irrigation; hence, more than 81 percent of the farm is irrigated by gravity. The Enterprise currently has a total concession area of 14,733 hectares, out of which about 10,300 hectares is covered with sugarcane plantation. The total design area of the scheme is 10,358 ha (Girma and Awulachew, 2007).

3.1.4. Irrigation water source

Irrigation water is abstracted from the Awash River through two diversion weirs and intake headworks found at Metahara and Abadir. The method of water abstraction is gravity diversion. The main intake at Metahara is made of concrete and is controlled and regulated by the state itself. However, the diversion structure at Abadir is made of gabion and is managed by the Ministry of Water Resources (Girma and Awulachew, 2007).

3.2. Methodologies

To fulfill general and specific objectives of the study, several methods that were undertaken in this research includes methods of data collection, data analysis, data consistency and homogeneity test, methods involved in downscaling GCMs and estimating CWR and IWR in the baseline period and future time slices.

3.2.1. Data collection and processing

3.2.1.1. Meteorological data

A daily observed meteorological data (rainfall, maximum and minimum temperature, relative humidity, wind speed and solar radiation) of five stations (Arerti, Abomsa, Melka Jilo, Metehara and Welenchiti) from year 1981 to 2010 was collected from Ethiopia National Meteorological Agency (ENMA). The geographical location of the representative stations is shown in Table 3.1.

Table 3.1. Geographical co-ordinates of the representative stations in the study area

Stations	Geographical co-ordinates	
	Latitude	Longitude
Arerti	8° 49'	39° 23'
Abomsa	8°35'	39°51'
Melka Jilo	8° 53'	39°37'
Metehara	8°21'	39°12'
Welenchiti	8°40'	39°26'

3.2.1.2. General circulation model outputs and future climate datasets

The most widely used Earth System Model (CanESM2) for the RCP 8.5, RCP 4.5, and RCP 2.6 scenarios from CMIP5 has been used in this study. The historical and future large-scale predictor variables, for CanESM2 climate model, have been downloaded through the official website (<https://climate-scenarios.canada.ca/?page=pred-canesm2>) of Canadian Centre for Climate Modeling and Analysis.

3.2.1.3. Soil and crop data

Soil data and sugarcane crop data which were required for as an input to CROPWAT model to find crop and irrigation water requirement were collected from FAO irrigation and drainage paper (Allen et al., 1998) and from the site (Metahara Sugar Estate Research Center). The sugar cane crop data required were dates of sowing and harvesting, growth stage duration, rooting depth (cm), crop height (m), yield response factors (K_y) and crop coefficients (K_c).

The soil data including soil type, total available of soil moisture (mm/meter), maximum rain infiltration rate (mm/day), maximum rooting depth (centimeters) and initial soil moisture depletion as percent were also collected from FAO irrigation and drainage paper to calculate total available soil moisture (TAW) as shown in Equation 3.1 (Allen et al., 1998).

$$TAM = 1000(FC - PWP) \times Z_r \quad (3.1)$$

Where TAM is total available soil moisture (mm/meter), Z_r is rooting depth (m) and FC and PWP are water content at field capacity and at wilting point respectively (m^3/m^3)

3.2.2. Filling missing data

Missing data (or missing values) is can be described as the data value that is not stored for the variable in the observation of interest. The problem of missing data is relatively common in almost all studies and can significantly affect the conclusions that can be drawn from the data. In this thesis paper meteorological data were filled with Monte Carlo Markov-Chain (MCMC) multiple imputation technique using XLSAT add-ins plug-in in Microsoft Excel. According to XLSTAT 2018 user manual different methods are there depending on the needs and data:

For quantitative data, XLSTAT allows to:

- a. Use a mean imputation method
- b. Use a nearest neighbor approach
- c. Use an MCMC multiple imputation algorithm

For qualitative data, XLSTAT allows to:

- a. Remove the observations with missing value
- b. Use a mode imputation method
- c. Use a nearest neighbor approach

An imputation method can be defined as simple or multiple. Multiple imputations (MI) are an approach for handling missing values in a data set that allows researchers to use the entirety of the observed data. Simple imputation method such as inserting a mean value or a value selected from a similar type of respondent are straight forward and interesting due to ease of concept and implementation but do not account for the variability introduced by the imputation process. They also tend to distort the variable distribution once imputation is complete. Given these limitations, multiple imputation is generally considered a preferred method for dealing with missing data (Yao and Ingelheim, 2019).

3.2.3. Data consistency and homogeneity test

Data consistency and homogeneity of recorded rainfall data for the representative stations was checked after filling missing data is performed. In this study, double mass curve method was used to check the consistency of the data by comparing data for a single station with that of a pattern composed of the data from other stations. Double mass curve was plotted using cumulative values of given stations against the cumulative average group which is shown in Appendix Figure1.

RAINBOW is a software program package for hydro-meteorological frequency analysis and evaluating the homogeneity of historical data sets. It offers a test of homogeneity which is based on the cumulative deviations from the mean. By measuring the maximum and the range of the cumulative deviations from the mean, the homogeneity of the data of a time series is tested (Raes et al., 2006). In this study the RAINBOW software program was used to check homogeneity of rainfall data at different significance levels which is determined to be generally homogeneous as shown in Appendix Figure 2-6.

3.2.4. Variability and trend analysis of rainfall and temperature

3.2.4.1. Variability analysis of rainfall and temperature

Coefficient of variation (CV) was used in this study to check rainfall and temperature variability in Microsoft Excel 2010. CV is a unit-less normalized measure of dispersion of a probability distribution. It expresses the standard deviation as a fraction of the mean and is useful when interest is in the size of variation relative to the size of the observation. In

comparing different years of rainfalls or temperatures with different means, the CV is a more useful basis of comparison than the standard deviation. It is expressed as the ratio of the standard deviation to the mean (Araya and Stroosnijder, 2011):

$$CV = \left[\frac{S}{X} \right] \times 100 \quad (3.2)$$

Where CV is the coefficient of variation; X is the average long-term rainfall (temperature) and S is the standard deviation of rainfall (temperature).

According to Hare (2003), CV is used to classify the degree of variability of rainfall (temperature) events as less ($CV < 20$), moderate ($20 < CV < 30$), high ($CV > 30$) and ($CV > 40$) indicate very high variability of rainfall (temperature).

3.2.4.2. Trend analysis of rainfall and temperature

Man-Kendall (MK) trend test is a non-parametric test that is used to identify the presence of trends within the precipitation and temperature. The null hypothesis (H_0) shows no trend in the series and the data obtained from an independent population will distribute as identical. The alternative hypothesis, H_a , indicates that the data follow a monotonous trend (negative, non-null or positive trend) (Alemu and Dioha, 2020). This test has two advantages. First, it does not need the data to be normally distributed since the test is non-parametric (distribution-free test) and second, the test has low sensitivity to abrupt breaks due to inhomogeneous time series. The data values are determined as an order time series and all subsequent data values are likened from each data value. The Man-Kendall test statistics (S) is given as (Jain and Kumar, 2016):

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^N \text{sgn}(x_j - x_i) \quad (3.3)$$

Where N is the number of data points and S is Man-Kendall test statistics.

Assuming $(x_j - x_i) = b$, the value of $\text{sgn}(b)$ is computed as:

$$\text{sgn}(b) = \begin{cases} 1 & \text{if } b > 0 \\ 0 & \text{if } b = 0 \\ -1 & \text{if } b < 0 \end{cases} \quad (3.4)$$

The value of S describes whether the trend is positive or negative. If S is positive, positive trend exists and if S is negative, negative trend exists.

For large samples ($N > 10$), the test is conducted using a normal distribution, with the mean and the variance as shown in Equation 3.5:

$$\text{Var}(S) = \frac{N(N-1)(2N+5) - \sum_{k=1}^n t_k(t_k-1)(2t_k+5)}{18} \quad (3.5)$$

Where n is the number of tied (zero difference between compared values) groups and t_k the number of data points in the k_{th} tied group. The standard normal deviate (Z -statistics) is then computed as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{var}(S)}} & \text{if } S < 0 \end{cases} \quad (3.6)$$

The positive and negative Z value generally indicates increasing trend and decreasing trend respectively. The test is said to be statistically significant if significance level (5%) is greater than p value.

The Sen's estimator is another non-parametric method used for the trend analysis of hydro climate data set. It is also used to identify the trend magnitude. Hence, this test computes the linear rate of change (slope) and the intercept. Sen's slope is considered better to detect the linear relationship as it is not affected by outliers in the data (Jain and Kumar, 2016). The positive Q_i values indicate an increasing trend, while the negative Q_i values tell that there is a negative trend in the data. The unit of Sen's slope (Q_i) is the slope magnitude per year.

$$Q_i = \frac{x_j - x_k}{j - k} \text{ for } i = 1, 2, 3 \dots N \quad (3.7)$$

Where $j > k$ and x_j and x_k are data values at time j and k respectively.

Trend analysis for rainfall and temperature (maximum and minimum) of representative stations in upper Awash sub-basin has been done for five stations at annual and monthly time series using M-K test in XLSTAT 2018 software. XLSTAT 2018 is a software tool which is used for data analysis and statistical computations that works as an add-on to Microsoft Excel.

3.2.5. Statistical downscaling model (SDSM)

The SDSM model is an auxiliary computer software program for assessment of the effects of local climate change, which is developed by (Wilby et al., 2002). This model uses the independent observational data to assess the relationship between local downscaled variables and atmospheric up-scaled variables (Wilby and Dawson, 2007).

The SDSM version 4.2 was used since it is simple, inexpensive and flexible enough to be applied for downscaling approach. This software reduces the task of statistically downscaling daily weather series into seven discrete steps (Wilby and Dawson, 2007):

- 1) Quality Control and Data Transformation: Simple quality control check-ins in SDSM enable the identification of gross data errors, specification of missing data codes and outliers prior to model calibration. Since many of the meteorological stations are incomplete handling of missing and imperfect data is necessary.
- 2) Screening of Predictor Variables: The main purpose of the screen variables operation is to assist the user in the selection of proper and good downscaling predictor variables.
- 3) Model Calibration: The calibrate model operation takes a user-specified predictand along with a set of predictor variables, and computes the parameters of multiple regression equations via an optimization algorithm (either dual simplex or ordinary least squares).
- 4) Weather Generation (using observed predictors): The Weather generator operation generates ensembles of synthetic daily weather series given observed atmospheric predictor variables. The procedure enables the verification of calibrated models and the synthesis of artificial time series for present climate conditions.
- 5) Statistical Analyses: SDSM provides means of interrogating both downscaled scenarios and observed climate data with the Summary Statistics and Frequency Analysis screens.

- 6) Graphing Model Output: The Frequency Analysis screen allows the User to plot extreme value statistics of the chosen data file(s). The Compare Results screen enables the User to plot monthly statistics produced by the Summary Statistics screen. The graphing option allows simultaneous comparison of two data sets and hence rapid assessment of downscaled versus observed, or present versus future climate scenarios. The Time Series Analysis screen allows the User to produce time series plots for up to a maximum of five variables.
- 7) Scenario Generation (using climate model predictors): Finally, the Scenario generator operation produces ensembles of synthetic daily weather series given atmospheric predictor variables supplied by a climate model (either for present or future climate experiments), rather than observed predictors. These steps were shown in Figure 3.4.

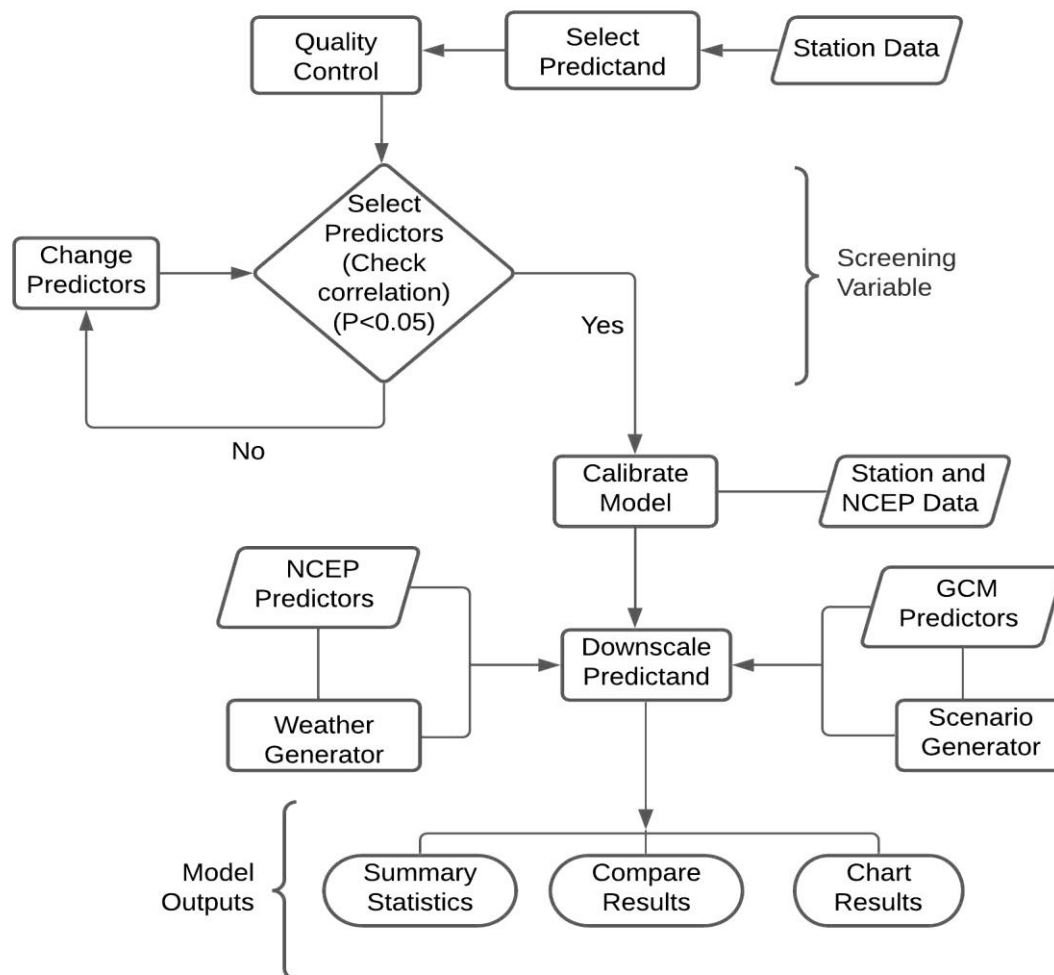


Figure 3.4. Conceptual framework showing procedures undertaken in statistical downscaling

3.2.5.1. SDSM software setup

Year length: the normal calendar year (366) which allows 29 days in February every fourth year is used whenever dealing with predictand and NCEP predictors whereas the year length of 365 days is used in the scenario generation part since CanESM2 uses model years consisting of 365 days.

Model Transformation: Specifies the transformation applied to the predictand in conditional models. The default (None) is used whenever the predictand is normally distributed as is often the case for daily temperature and fourth root transformation is applied for precipitation since the model is conditional and the data is skewed.

Variance inflation: Variance inflation controls the magnitude of variance inflation in the downscaled daily weather variables. This parameter can be adjusted during the calibration period to force the model replicate the observed data. The default value (which is 12) produces approximately normal variance inflation prior to any transformation and is applied to maximum and minimum temperature and for precipitation it can be adjusted during the calibration period.

Predictor and predictand file: Statistical downscaling involves developing quantitative relationship between the predictor and the predictand (Wilby et al., 2004). The predictand represents the local surface variables such as temperature (maximum and minimum) and precipitation. The predictors represent large scale atmospheric variables.

The predictor variables used for the SDSM model input were downloaded as zip file from Canadian climate data and scenarios website (<https://climate-scenarios.canada.ca/>?) for model output of CanESM2. When the zip file is extracted it contains CanESM2-historical-1961-2005, CanESM2-rcp26-2006-2100, CanESM2-rcp45-2006-2100, CanESM2-rcp85-2006-2100 and NCEP-NCAR-1961-2005.

3.2.5.2. Screening the predictor variables

The choice of predictor variables is one of the most crucial steps in the development of statistical downscaling procedure. Identifying empirical relationships between gridded predictors and single site predictands is central to all statistical downscaling. The screen

variable option in SDSM assists the choice of appropriate downscaling predictor variables through seasonal correlation analysis, partial correlation analysis and scatter plots (Wilby et al., 2004). The process in screening variable is set to conditional for precipitation and unconditional for temperature.

One of the approaches is to choose all predictors and run the explained variance on a group of 12 or less predictor variables at a time. The partial correlation analysis was done for selected predictors to see the level of correlation with each other. The significance level which is denoted as 'P' was used to test the significance of predictor–predictand correlations. The default is $P < 0.05$ which means significance level should be less than 5%. Therefore, out of the groups, those predictors which have high variance and lower significance P values were selected as potential predictor variables to make multiple linear regressions equation during calibration step of SDSM.

3.2.5.3. SDSM model calibration

The calibration model process performs downscaling models based on multiple regression equations, given daily weather data (the predictand) and regional-scale, atmospheric predictor variables. The model structure is set to unconditional for maximum and minimum temperature and conditional for precipitation. In unconditional models a direct link is assumed between the predictors and predictand. In conditional models, there is an intermediate process between the regional forcing and local weather. The model type determines whether individual downscaling models was calibrated for each calendar months, climatological season or entire year.

3.2.5.4. Weather generator

The weather generator operation produces ensembles of synthetic daily weather series given observed (or NCEP re–analysis) atmospheric predictor variables and regression model weights produced by the Calibrate Model operation. It enables the verification of calibrated models (assuming the availability of independent data) as well as the synthesis of artificial time series representative of present climate conditions. It can also be used to reconstruct predictands or to infill missing data.

3.2.5.5. Scenario generator

Similar to the weather generator function, the scenario generator operation also generates the ensembles of synthetic daily weather data series but for the future time period. After validation of the model, the same parameter file or regression weight that was used during weather generation operation was used to downscale the future data. But this time, instead of using potential predictor variables for ensembles of NCEP re-analysis, future GCM (CanESM2) output for the RCP8.5, RCP 4.5 and RCP 2.6) scenarios were used as large-scale atmospheric potential predictor variables.

The twenty ensembles of synthetic daily time series data were generated for the period of 2006 to 2100 for all the variables and averaged weather station and the mean of these twenty ensembles was used as final daily weather data for the specified period. According to Nigatu (2013), the mean of 20 individual ensembles outputs perform well and large number of ensembles does not improve and have chances of large deviation among ensembles. The same procedure was repeated to generate future precipitation, maximum and minimum temperature data for all the RCPs and the averaged weather station. And then the future Tmax, Tmin, and precipitation scenarios have been established by dividing the future time series into three-time slices (the 2020s, 2050s, and 2080s) for the averaged weather station.

3.2.5.6. SDSM performance evaluation

To fulfill the second specific objective of the study the coefficient of determination (R^2), the root mean square error (RMSE), and the Nash–Sutcliffe efficiency coefficient (NSE) were used to evaluate the effect of model calibration and validation in SDSM which can be expressed as follows: NSE (ranges between $-\infty$ to 1 and 0 to 1 is acceptable range) and RMSE (0 value is a perfect match) are selected to indicate correlation between observed and predicted values and R^2 (ranges between 0 to 1 and value greater than 0.5 is acceptable) is to describe the proportion of the variance in the measured data.

$$R^2 = \frac{[\sum_{i=1}^N (O_i - O')(P_i - P')]^2}{\sum_{i=1}^N (O_i - O')^2 \sum_{i=1}^N (P_i - P')^2} \quad (3.8)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (O_i - P_i)^2}{N}} \quad (3.9)$$

$$NSE = 1 - \frac{\sum_{i=1}^N (O_i - P_i)^2}{\sum_{i=1}^N (O_i - O')^2} \quad (3.10)$$

Where N is the length of time, O_i is the observed value, P_i is the simulated value, O' is the mean of the observed values, and P' is mean of the simulated values.

3.2.5.7. Precipitation and temperature scenario statistics

If percentage difference is selected in statistics:

$$\Delta 2020s = \frac{(V_{2020s} - V_{base}) \times 100}{V_{base}} \quad (3.11)$$

$$\Delta 2050s = \frac{(V_{2050s} - V_{base}) \times 100}{V_{base}} \quad (3.12)$$

$$\Delta 2080s = \frac{(V_{2080s} - V_{base}) \times 100}{V_{base}} \quad (3.13)$$

If Absolute difference is selected:

$$\Delta 2020s = V_{2020s} - V_{base} \quad (3.14)$$

$$\Delta 2050s = V_{2050s} - V_{base} \quad (3.15)$$

$$\Delta 2080s = V_{2080s} - V_{base} \quad (3.16)$$

Where: V_{base} is the mean of all ensembles (or specific ensemble) for each static for the base period. Likewise, V_{2020s} , V_{2040s} , V_{2060s} and V_{2080s} are the mean of all ensembles (or specific ensemble) for each statistic for a given period.

3.2.6. CROPWAT Model application

CROPWAT 8.0 agronomic software is a computer program for the calculation of crop water requirements and irrigation requirements from existing or new climatic and crop data. Additionally, the program supports the development of irrigation schedules for various management conditions and the calculation of scheme water supply for varying crop patterns.

CROPWAT software had been widely used in evaluating crop water requirements, irrigation scheduling and cropping patterns. A comparison of CROPWAT software with other related models showed that CROPWAT was a better tool for evaluating crop water requirements (Kang and Ma, 2009). All calculation procedures used in CROPWAT 8.0 are based on the FAO guidelines as laid down in the publication Number 56 of the Irrigation and Drainage Series of FAO "Crop Evapotranspiration -Guidelines for computing crop water requirements".

The irrigation requirement for sugarcane crop in the study area has been estimated using the irrigation demand estimation module of CROPWAT Model. The data required for irrigation demand estimation module are a) the rainfall that has occurred in the study area, b) prevailing climate variables (wind speed, relative humidity, maximum and minimum temperature, and sunshine hours), c) crop data (cropping pattern and crop name, planting date, crop coefficient (Kc), stages length, maximum rooting depth, critical depletion fraction (p), yield response factor (Ky) and maximum crop height, d) soil data (available soil moisture (field capacity, wilting point), maximum rain infiltration rate, and initial available soil moisture).

Climate variables (wind speed, relative humidity, maximum and minimum temperature, and sunshine hours) for the study area from year 1981 to 2010 were collected from Ethiopia National Meteorological Agency (ENMA). Crop data and soil data were collected from FAO and the site (Metahara Sugar Estate Research Center). For sugarcane crop, Kc values range between 0.4 and 1.25 (initial stage to mid-season), and 1.25 to 0.75 (mid-season to late season). Stage length of sugarcane crop (30 for initial stage, 60 for development stage, 180 for mid-season, and 95 for late season) was used in this study. For sugarcane crop maximum rooting depth ranges from 1.2 to 2m. In this study, maximum rooting depth of 1.5m was used as it is recommended in CROPWAT software by FAO. The critical depletion factor for all season (0.65 (65%) for sugarcane), yield response factor (0.50 for initial stage, 0.75 for

development stage, 1.2 for mid-season, and 0.1 for late season) and maximum crop height for sugarcane crop (3m) provided by FAO were used in this research.

Soil data was collected from FAO-56 depending on the type of soils in the Metehara Sugar Estate. According to Fituma and Argaw (2019), most of the soils in Metehara Sugar Estate are classified as clay loam. For clay loam, field capacity ranges between 0.3 and 0.37m³/m³ and wilting point ranges between 0.17 and 0.24m³/m³ as described by FAO. In this study, the average of the soil moistures (0.34m³/m³ for field capacity and 0.21m³/m³ for wilting point), initial available soil moisture (77mm/m), and maximum rain infiltration rate (30mm/day) that were obtained from FAO CROPWAT 8.0 model were used. Ewaid et al. (2019) also used soil parameters and crop data provided in CROPWAT 8.0 model by FAO, to calculate crop and irrigation water requirements.

The process was followed by estimation of the crop water requirement of sugarcane crop in the study area. In this research, the crop water requirement for the sugarcane crop has been estimated using CROPWAT package. CROPWAT uses FAO Penman-Monteith model (equation 3.17) for estimating reference evapo-transpiration.

3.2.6.1. Estimation of Reference Evapotranspiration

The software uses FAO Penman monteith model to estimate reference evapotranspiration (Allen et al., 1998).

$$\lambda ET = \frac{\Delta(R_n - G) + \rho_a C_p \frac{(e_s - e_a)}{r_a}}{\Delta + \gamma(1 + \frac{r_s}{r_a})} \quad (3.17)$$

Where R_n is the net radiation, G is the soil heat flux, $(e_s - e_a)$ represents the vapour pressure deficit of the air, ρ_a is the mean air density at constant pressure, C_p is the specific heat of the air, Δ represents the slope of the saturation vapour pressure and temperature relationship, γ is the psychrometric constant, and r_s and r_a are the (bulk) surface and aerodynamic resistances.

When the theoretical crop traits and the standard height for wind speed (2m) are applied to calculate the bulk surface resistance and the aerodynamic resistance, Equation 3.17 can be derived as follows:

$$ET_o = \frac{(0.408\Delta(R_n - G)) + (\gamma \frac{900}{T+273} u_2 (e_s - e_a))}{\Delta + (\gamma(1 + 0.34u_2))} \quad (3.18)$$

Where ET_o is reference evapo-transpiration (mm/day), R_n =net radiation at the crop surface (MJ/sq.m/day), G is soil heat flux density (MJ/sq.m/day), T is air temperature at 2 m height ($^{\circ}C$), u_2 is wind speed at 2m height (m/s), e_s and e_a are saturation and actual vapor pressure (KPa) respectively, Δ is slope vapor pressure curve (KPa/ $^{\circ}C$) and γ is psychometric constant (KPa/ $^{\circ}C$).

3.2.6.2. Estimation of Crop Water Requirement

After inserting all required CROPWAT 8.0 input data (ET_o , rain and crop) and by calling up successively the appropriate climate and rainfall data sets, together with the crop files and the corresponding planting dates CWR module will calculate the crop water requirement as (Allen et al., 1998):

$$Etc = Kc \times ET_o \quad (3.19)$$

Where Etc is crop evapotranspiration (mm/day), ET_o is reference crop evapo-transpiration (mm/day) and Kc is crop coefficient.

3.2.6.3. Estimation of Effective Rainfall

The CROPWAT 8.0 model uses effective rainfall method to calculate effective rain from monthly mean rainfall. The Rain module in the model require input data station and to choose one effective rainfall methods from the four. Effective rainfall methods to account for the losses due to runoff or percolation, a choice can be made of one of the four methods given in CROPWAT 8.0 (Fixed percentage, Dependable rain, Empirical formula, USDA Soil Conservation Service). In this study USDA Soil Conservation Service was used to estimate effective rainfall. USDA Soil Conservation method is the most widely used method of estimating effective rainfall (Moseki et al., 2019).

Effective rainfall is that part of the rainfall which is effectively used by the crop after rainfall losses due to surface run off and deep percolation have been accounted for. The effective rainfall is the rainfall ultimately used to determine the crop irrigation requirements.

Effective rainfall P_e was calculated by using USDA Soil Conservation Service method provided in the CROPWAT model (Allen et al., 1998).

When total rainfall (TR) is < 250 mm, effective rainfall (P_e) is given as:

$$P_e = TR \times (125 - 0.2 \times TR)/125 \quad (3.20)$$

When total rainfall is > 250 mm, effective rainfall is given as:

$$P_e = 125 + 0.1 \times TR \quad (3.21)$$

3.2.6.4. Estimation of net irrigation water requirement

After the reference evapo-transpiration, crop water requirement and effective rainfall were estimated, net irrigation water requirement was estimated as the difference between the crop evapotranspiration under standard conditions (ET_c) and the effective rainfall P_e .

$$IWR = Etc - P_e \quad (3.22)$$

Where IWR is irrigation water requirement in mm/day, P_e is effective rainfall in mm/day and Etc is crop water requirement in mm/day.

3.2.7. Investigation of climate change impact on sugarcane irrigation water requirement for Metehara Sugar Estate

After successful calibration and validation of SDSM in simulating historical climate variables (rainfall, maximum and minimum temperature), future rainfall, maximum and minimum temperature were downscaled to investigate the spatiotemporal variation of mentioned climate variables in the study area. Finally, the future downscaled rainfall, maximum and minimum temperature were used as an input to CROPWAT model to predict the future crop and irrigation water requirements under three RCP2.6, 4.5, and 8.5 with three time slices of 2020s, 2050s, and 2080s.

3.2.8. Conceptual framework of the study

The steps undertaken to meet the objectives of this research are shown here in Figure 3.5.

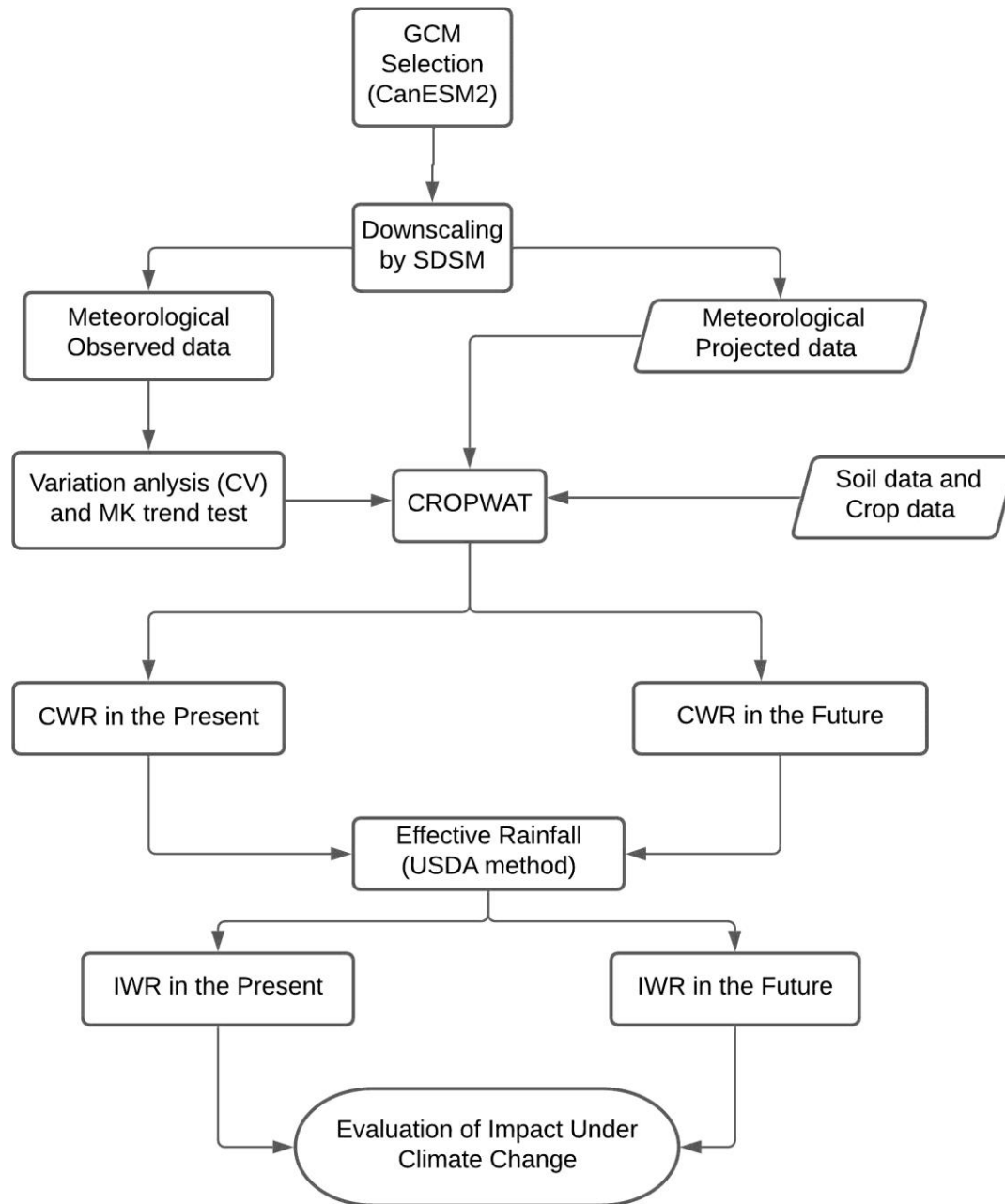


Figure 3.5. Flow chart of the study showing the overall methodology

4. RESULTS AND DISCUSSIONS

4.1. Climatic Characteristics of Metehara Sugar Estate Watershed

4.1.1. Climatic variability analysis

All of the stations showed very high variation in annual and seasonal (Kiremt and Belg) rainfall ($CV\% > 40$) as shown in Table 4.1. Hayelom et al. (2017) has also found mean coefficient of variation (CV 103.6%) for annual rainfall variation which is similar to this study. According to Hayelom et al. (2017), this high variation in rainfall indicates that the rainfall dissemination is not normal with large year to year variances and all months have homogenous character in terms of variation. Bekele et al. (2017) emphasized that the causes of annual and seasonal inter-annual variability of precipitation over Ethiopia is due to the forward and retreat pace of the African sector of the inter-tropical convergence zone (ITCZ). The high variability in Belg rainfall will cause unfavorable condition for agricultural production and the season is prone to risk for rain-fed agriculture (Kassie et al., 2014).

All of the stations showed low variation in annual and seasonal (Kiremt and Belg) maximum and minimum temperature ($CV\% < 20$) as shown in Table 4.2 and 4.3. Hayelom et al. (2017) have also found mean coefficient of variation (CV 4.7%) for annual maximum temperature variation which is similar to this study.

Table 4.1. Rainfall variability characteristics of stations within and around Metahara Sugar Estate (1981-2010)

Stations	Annual		Kiremt		Belg	
	Mean	CV%	Mean	CV%	Mean	CV%
Abomsa	537.35	40.13	320.13	52.45	164.8	45.5
Arerti	898.21	45.78	647.1	43.45	172.8	48.43
Melka Jilo	734.04	52.34	532.8	47.87	132.3	41.23
Metahara	936.03	51.87	659.7	45.32	206.0	45.78
Welenchiti	894.1	41.45	564.94	51.23	240.1	51.34

Table 4.2. Maximum temperature variability characteristics of stations within and around Metahara Sugar Estate (1981-2010)

Stations	Annual		Kiremt		Belg	
	Mean	CV%	Mean	CV%	Mean	CV%
Abomsa	33.1	6.3	33.9	5.6	34.04	5.32
Arerti	32.8	6.2	33.4	5.4	33.8	5.5
Melka Jilo	30.54	7.0	30.6	3.8	32.22	5.48
Metahara	34.36	6.7	34.87	5.0	35.01	8.31
Welenchiti	30.9	6.8	31.51	5.74	31.81	5.9

Table 4.3. Minimum temperature variability characteristics of stations within and around Metahara Sugar Estate (1981-2010)

Stations	Annual		Kiremt		Belg	
	Mean	CV%	Mean	CV%	Mean	CV%
Abomsa	17.66	16.61	20.13	5.0	18.21	10.7
Arerti	16.13	19.5	18.11	12.9	16.9	11.2
Melka Jilo	15.67	19.3	17.9	7.1	16.23	14.43
Metahara	18.3	17.12	20.77	5.1	18.47	13.84
Welenchiti	15.2	19.14	17.62	5.7	15.7	12.4

4.1.2. Trend analysis of historical climates

4.1.2.1. Trend analysis of historical rainfall

The tests were done at 5% significance level and 95% confidence interval for a period of 1981 to 2010. Trend analysis of annual, Kiremt and Belg precipitation in all of the stations indicated non-significant ($p > 0.05$) increasing or decreasing trend over the last 30 years (1981-2010) as shown in Table 4.4. The analysis however showed that increasing trend in precipitation was observed in four of the stations for annual and Kiremt season precipitation. In contrast to this, the Belg season showed a non-significant declining trend in precipitation for four of the five representative stations.

The rainfall of Abomsa station indicated a decline trend of rainfall in annual, Kiremt and Belg seasons. Similarly, rainfall of Arerti, Metahara and Welenchiti for Belg season showed declining trend over the past 30 years. The analysis showed increasing trend in annual, Kiremt and Belg seasons for Melka Jilo station. In relation to this, studies conducted in Central Rift valley of Ethiopia showed, out of sixteen tested stations the trends of the annual and seasonal rainfall of most of the stations did not show statistically significant trend for period of 1977 to 2007 (Kassie et al., 2014).

Table 4.4. Trend analysis of annual and seasonal (Kiremt and Belg) precipitation for the stations in the study area

Stations	Annual			Kiremt			Belg		
	Z	Q	P-value	Z	Q	P-value	Z	Q	P-value
Abomsa	-0.53	-2.89	0.59	-1.84	-1.01	0.45	-0.16	-2.5	0.23
Arerti	0.77	4.42	0.44	0.07	6.8	0.89	-0.1	-2.7	0.36
Melka Jilo	0.47	17.9	0.65	0.18	14.01	0.25	0.03	2.45	0.78
Metahara	0.6	2.43	0.55	0.15	1.9	0.16	-0.11	-2.6	0.45
Welenchiti	0.86	4.01	0.34	0.19	7.51	0.22	-0.01	-5.6	0.92

4.1.2.2. Trend analysis of historical maximum and minimum temperature

Trend analysis of temperature generally showed statistically significant trend (significance level $p < 0.05$) in most of the stations for all annual and seasonal maximum and minimum temperatures in the study watershed during 1981-2010 periods as shown in Table 4.5.

Trend analysis of annual maximum and minimum temperature in all of the stations except minimum temperature trend in Welenchiti station, all have showed significant increasing trend. However, trend analysis of minimum temperature in Kiremt season for stations Arerti, Melka Jilo and Welenchiti and Belg season for stations Abomsa and Welenchiti showed non-significant increasing trend. In relation to this, studies conducted in Awash River Basin of Ethiopia (Modjo river watershed) showed, out of five tested stations the trends of the annual

and seasonal temperature (maximum and minimum) four of the stations showed statistically significant increasing trend for period of 1981 to 2010 (Eshetu, 2020).

Table 4.5. Trend analysis of annual and seasonal (Kiremt and Belg) maximum and minimum temperature for the stations in the study area

Stations	Variables	Annual			Kiremt			Belg		
		Z	Q	P-value	Z	Q	P-value	Z	Q	P-value
Abomsa	Tmax	0.65	0.08	0.01	0.48	0.055	0.01	0.48	0.11	0.01
	Tmin	0.5	0.025	0.04	0.36	0.02	0.02	0.28	0.025	0.34
Arerti	Tmax	0.9	0.19	0.00	0.74	0.23	0.00	0.63	0.34	0.00
	Tmin	0.3	0.08	0.03	0.21	0.1	0.06	0.52	0.08	0.06
Melka Jilo	Tmax	0.15	0.086	0.00	0.12	0.095	0.00	0.01	0.02	0.00
	Tmin	0.25	0.05	0.02	0.24	0.02	0.31	0.08	0.043	0.04
Metahara	Tmax	0.84	0.06	0.00	0.69	0.045	0.02	0.43	0.083	0.01
	Tmin	0.34	0.02	0.00	0.49	0.015	0.01	0.24	0.016	0.01
Welenchiti	Tmax	0.73	0.035	0.00	0.37	0.016	0.00	0.35	0.033	0.00
	Tmin	0.24	0.025	0.82	0.61	0.021	0.43	0.33	0.025	0.21

Graphs of trend analysis of historical maximum, minimum temperature and precipitation of all representative stations in the study area for periods of 1981 to 2010 were shown in Appendix Figure 7-11.

4.2. Statistical Downscaling Model Results

4.2.1. Selection of predictor variables

The best correlated predictor variables were selected for each station's predictands. These variables were then used for calibration of the SDSM (Wilby et al., 2002). The strongest correlation between single predictand and set of predictors was identified. The list of common potential predictor variables that gave better correlation results from NCEP analysis was shown in Appendix Table1.

The correlation (partial r) for individual predictands and set of predictors were better for the case of temperature than that of precipitation; this is due to conditional behavior of precipitation whereby it is an intermediate process between the regional forcing and local weather (Wilby and Dawson, 2007). Similar results were observed by other scholars (Gulacha and Mulungu, 2017). Lists of selected predictor variables that gave better correlation results at $P < 0.05$ from CanESM2-historical model is shown in Table 4.6.

Table 4.6. List of selected common potential predictor variables that gave better correlation results at $P < 0.05$ from CanESM2-historical model for study area of Metahara Sugar Estate

Predictand	Predictor full name	Notations	Parti.cor. (r-value)	p-value
Precipitation	Mean sea level pressure	ceshmslpgl.dat	0.044	0.001
	850 hPa divergence	ceshp8zhgl.dat	0.028	0.001
	500 hPa zonal velocity	ceshp5_ugl.dat	0.002	0.010
	Specific humidity at 850 hPa	ceshs850gl.dat	0.018	0.000
	500 hPa geopotential height	ceshp500gl.dat	0.124	0.000
Maximum temperature	Mean sea level pressure	ceshmslpgl.dat	0.039	0.045
	850 hPa vorticity	ceshp8-zgl.dat	0.025	0.008
	Mean temperature at 2m	ceshtempgl.dat	0.009	0.000
	Surface specific humidity	ceshshumgl.dat	-0.178	0.000
Minimum temperature	Mean sea level pressure	ceshmslpgl.dat	0.006	0.000
	Surface specific humidity	ceshshumgl.dat	0.234	0.000
	Mean temperature at 2m	ceshtempgl.dat	0.242	0.000

4.2.2. Multi-site calibration and validation of SDSM

The calibration and validation was conducted between selected large-scale NCEP predictor variables and the observed predictands (precipitation, maximum temperature, minimum temperature) or between observed and simulated value to quantify the accuracy of data modeled. Calibration (1981-1995) and validation (1996-2010) were performed for all representative stations by dividing the 30 years baseline (observed data of 1981-2010) in to two equal period times (Klemeš, 1986).

Similar to most of the applications of SDSM reported, the model was calibrated and validated separately based on the baseline data (Mahmood and Babel, 2014). The calibration process was done by using output from NCEP reanalysis data, with the selected predictor variables. For validation process, Weather Generator in SDSM was used; that means 15 years of observed data (1996-2010) was used as an independent observed data in weather generator which was not used during calibration process. As shown in Appendix Figure 12 to 16, calibration and validation were performed for all representative stations to evaluate performance of SDSM.

R^2 , RMSE and NSE were used to evaluate the performance of SDSM during model calibration and validation that was done for each of the stations in the study area as shown in Appendix Table 2. Calibration and validation results of SDSM for Abomsa station precipitation, maximum temperature, and minimum temperature from CanESM2 GCM are shown in (Appendix Figure 12). The R^2 , RMSE, and NSE values were 0.56, 3.77 and 0.41 respectively for calibration period whereas R^2 , RMSE, and NSE values of 0.58, 1.56 and 0.23 respectively for validation period in case of precipitation (Appendix Figure 12a and b). For maximum temperature (Appendix Figure 12c and d) the R^2 , RMSE, and NSE values were 0.69, 11.4 and 0.62 respectively for calibration period whereas R^2 , RMSE, and NSE values were 0.59, 22.2 and 0.67 for validation period. Calibration and validation results for Abomsa station minimum temperature is shown in (Appendix Figure 12e and f). The R^2 , RMSE, and NSE values were 0.73, 28.4 and 0.48 respectively for calibration period whereas R^2 , RMSE, and NSE values of 0.70, 24.67 and 0.70 respectively for validation period.

Calibration and validation results of SDSM for Arerti station precipitation, maximum temperature, and minimum temperature from CanESM2 GCM are shown in (Appendix Figure 13). The R^2 , RMSE, and NSE values were 0.42, 13.46 and 0.13 for calibration period and 0.53, 12.45 and 0.21 respectively for validation period in case of precipitation (Appendix Figure 13a and b). For maximum temperature (Appendix Figure 13c and d) the R^2 , RMSE, and NSE values were 0.74, 0.45, 0.37 and 0.72, 12.34, 0.64 for calibration and validation period respectively. For Arerti station minimum temperature as shown in (Appendix Figure 13e and f), the R^2 , RMSE, and NSE values were 0.69, 14.5 and 0.38 for calibration period; whereas for validation period, values of 0.68, 23.3 and 0.48 were obtained from the statistical indices.

The results of statistical downscaling model in simulating historical precipitation, maximum and minimum temperature for Melka Jilo station were shown in Appendix Figure 14. The R^2 , RMSE, and NSE values were 0.38, 17.91 and 0.49 respectively for calibration period and 0.59, 24.62 and 0.18 respectively for validation period in case of precipitation (Appendix Figure 14a and b). For maximum temperature (Appendix Figure 14c and d) the R^2 , RMSE, and NSE values were 0.71, 16.25 and 0.22 respectively for calibration period whereas R^2 , RMSE, and NSE values were 0.72, 2.07 and 0.68 for validation period. Calibration and validation results for Melka Jilo station minimum temperature is shown in (Appendix Figure 14e and f). The statistical indices of R^2 (0.67), RMSE (1.35) and NSE (0.43) for calibration while for validation, a value of R^2 (0.64), RMSE (3.27) and NSE (0.63) was obtained.

Calibration and validation results of SDSM for Metahara station precipitation, maximum temperature, and minimum temperature from CanESM2 GCM are shown in (Appendix Figure 15). The R^2 , RMSE, and NSE values were 0.47, 31.4 and 0.23 respectively for calibration period and 0.67, 17.35 and 0.15 for validation period in case of precipitation (Appendix Figure 15a and b). For maximum temperature (Appendix Figure 15c and d) the values were 0.84, 0.2 and 0.62 for calibration period and 0.92, 0.11 and 0.80 for validation period. The R^2 , RMSE, and NSE values were 0.88, 0.86 and 0.53 respectively for calibration period whereas R^2 ,

RMSE, and NSE values of 0.81, 0.98 and 0.71 respectively for validation period in Metahara station minimum temperature which is shown in (Appendix Figure 15e and f).

The results for Welenchiti station precipitation, maximum temperature, and minimum temperature from CanESM2 GCM are shown in (Appendix Figure 16). The R^2 , RMSE, and NSE values were 0.42, 12.46 and 0.12 respectively for calibration period whereas R^2 , RMSE, and NSE values of 0.64, 0.18 and 0.44 respectively for validation period in case of precipitation (Appendix Figure 16a and b). For maximum temperature (Appendix Figure 16c and d) the R^2 , RMSE, and NSE values were 0.71, 0.56 and 0.37 respectively for calibration period whereas R^2 , RMSE, and NSE values were 0.86, 0.78 and 0.34 for validation period. Calibration and validation results for Welenchiti station minimum temperature is shown in (Appendix Figure 16e and f). The R^2 , RMSE, and NSE values were 0.70, 11.5 and 0.24 respectively for calibration period whereas R^2 , RMSE, and NSE values of 0.69, 24.2 and 0.21 respectively for validation period.

Table 4.7 Summary of R^2 values in calibration of SDSM from previous studies (Nigatu, 2013)

Precipitation (%)	Minimum temperature (%)	Maximum temperature (%)	Study area	Authors
28	72	73	Toronto	(Wilby et al., 2002)
15 to 45	70 to 90	70 to 90	Mountainous regions of Japan	(Wilby et al., 1998)
6 to 10	71 to 79	71 to 79	Greater Montreal Region	(Nguyen et al., 2004)
38	55	62	Upper Blue Nile Basin Ethiopia	(Bekele, 2009)

Therefore, the calibration and validation outcomes of SDSM in this study are reasonably acceptable when it is compared with calibration and validation results of previous studies which are shown in (Table 4.7). However in this study and previous studies, calibration results for the case of precipitation showed relatively lower R^2 values than for the case of maximum and minimum temperature simulations. Lower R^2 value for precipitation is exhibited because of its complex nature and high variability (Bekele, 2009). From the statistical indices and graphical observation between simulated and observed value we can infer that SDSM has good ability to replicate historical maximum and minimum temperature for all of the stations in the study area and relatively lower ability to replicate historical precipitation of the stations in the study area.

4.2.3. Impact of climate change and variability on temperatures and precipitation characteristics for average of selected weather stations in the study area

In this study baseline period (1981-2010) climatic condition was analyzed based on the average of meteorological stations records of the study area, to determine anomaly (a deviation of future climate condition from baseline period) of future climate condition from baseline period. The anomaly of monthly precipitation is calculated as the difference from future monthly averages precipitation to the baseline period (1981-2010) monthly average precipitation value. The temperature is also calculated in the same manner precipitation is calculated. CanESM2 predictor variables in the three given climate change scenarios (RCP 2.6, 4.5, 8.5) were employed in SDSM downscaling processes to generate temperature and precipitation scenarios of the three future time slices, namely 2020s (2011-2040), 2050s (2041-2070), and 2080s (2071-2100). The seasonal scenarios also developed for temperature and precipitation as dry (December to May), intermediate (September to November) and wet (June to August) seasons.

4.2.3.1 Mean monthly maximum temperature scenarios

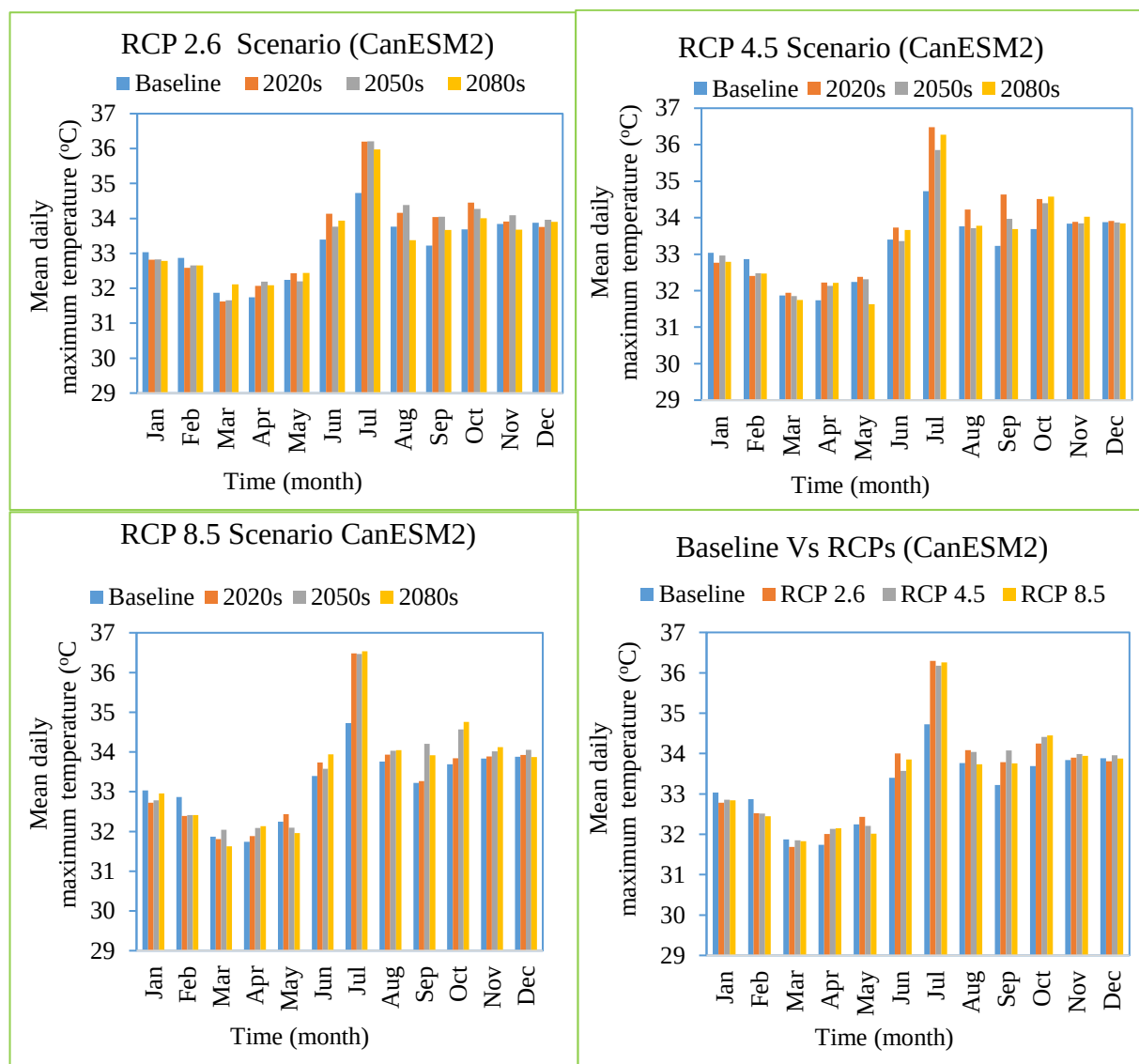


Figure 4.1. Monthly maximum temperature during baseline (1981-2010) simulation and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

A large increment in monthly maximum temperature is observed in the month of July 2020s that was 1.47, 1.75 and 1.76°C for RCP2.6, RCP4.5 and RCP8.5 scenarios respectively. The larger decrement was observed on December 2020s that were 0.28, 0.46 and 0.48°C for RCP2.6, RCP4.5 and RCP8.5 scenarios respectively as shown in Figure 4.1.

4.2.3.2. Mean seasonal maximum temperature scenarios

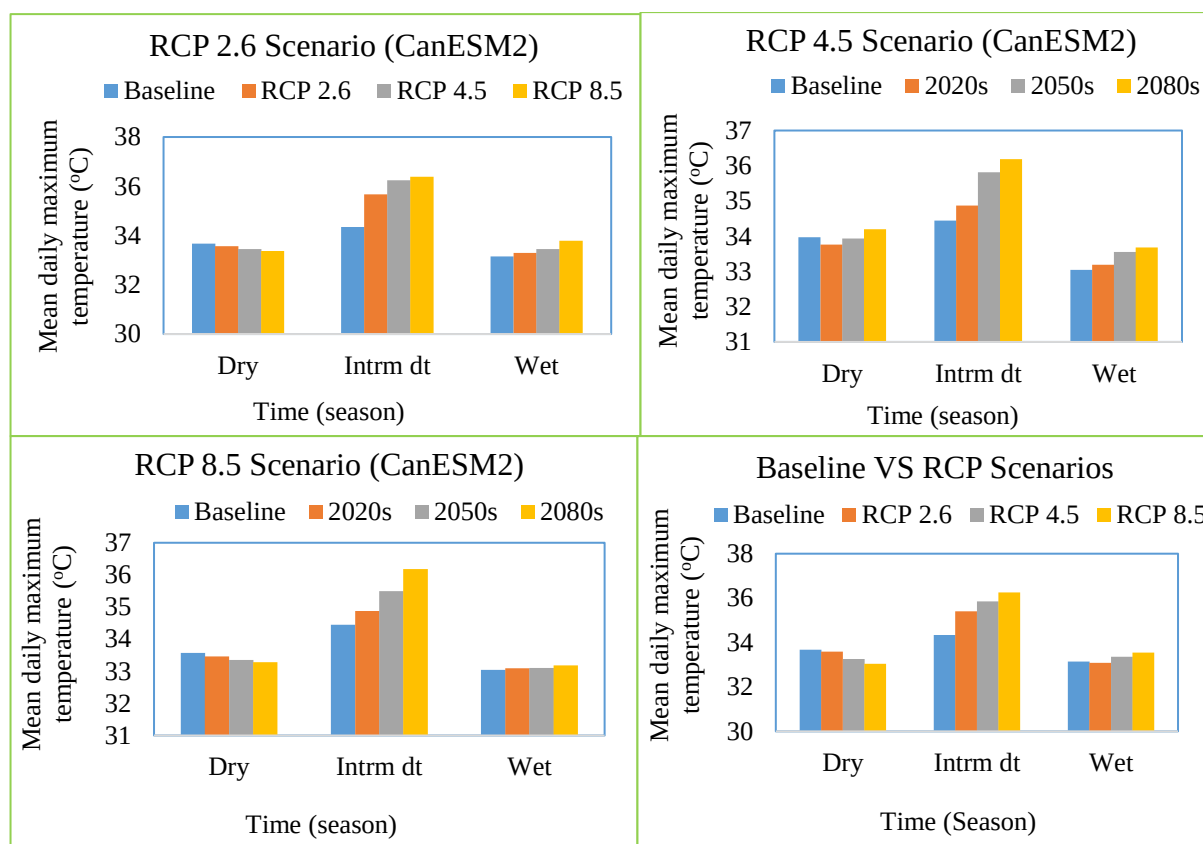


Figure 4.2. Seasonal maximum temperature during baseline (1981-2010) simulation and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

As shown in Figure 4.2, the projected seasonal maximum temperature shows an increasing trend in the wet and intermediate seasons for all of the RCPs (RCP 2.6, 4.5 and 8.5) in all of the future time slices. In contrast to this, it showed decreasing trend in the dry season in all of the three future time slices for RCP2.6, RCP4.5 (except for 2050s and 2080s which showed increasing trend), and RCP8.5 scenarios.

4.2.3.3. Mean annual maximum temperature scenarios

Figure 4.3 shows the change anomalies in mean annual maximum temperature of future time slices (2020s, 2050s and 2080s) from baseline period under CanESM2-RCP 2.6, CanESM2-RCP 4.5 and CanESM2-RCP 8.5 scenarios. The CanESM2-RCP 2.6 scenario simulation

indicated an increasing pattern by 0.32°C (0.98%) at 2020s, 0.33°C (1%) at 2050s and 0.2°C (0.6%) at 2080s. The CanESM2-RCP 4.5 scenario simulation showed an increasing pattern of maximum temperature by 0.33°C (1%) at 2020s, 0.41°C (1.22%) at 2050s and 0.44°C (1.31%) at 2080s. The CanESM2-RCP 8.5 scenario simulation showed an overall increasing pattern of maximum temperature by 0.37°C (1.11%) at 2020s, 0.54°C (1.26%) at 2050s and 0.5°C (1.46%) at 2080s.

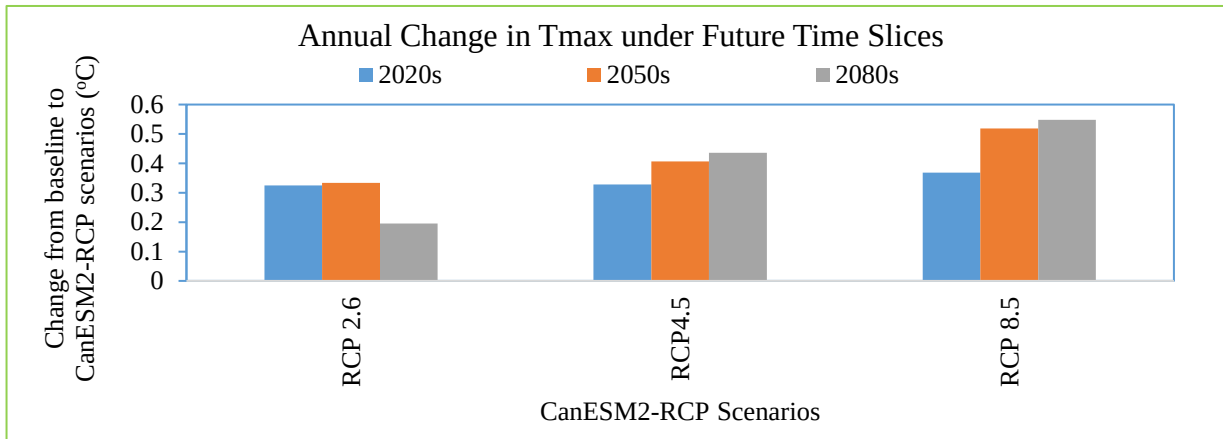


Figure 4.3. Absolute change from baseline simulation of annual maximum temperature in CanESM2-RCP scenario in the 2020s, 2050s and 2080s time slices

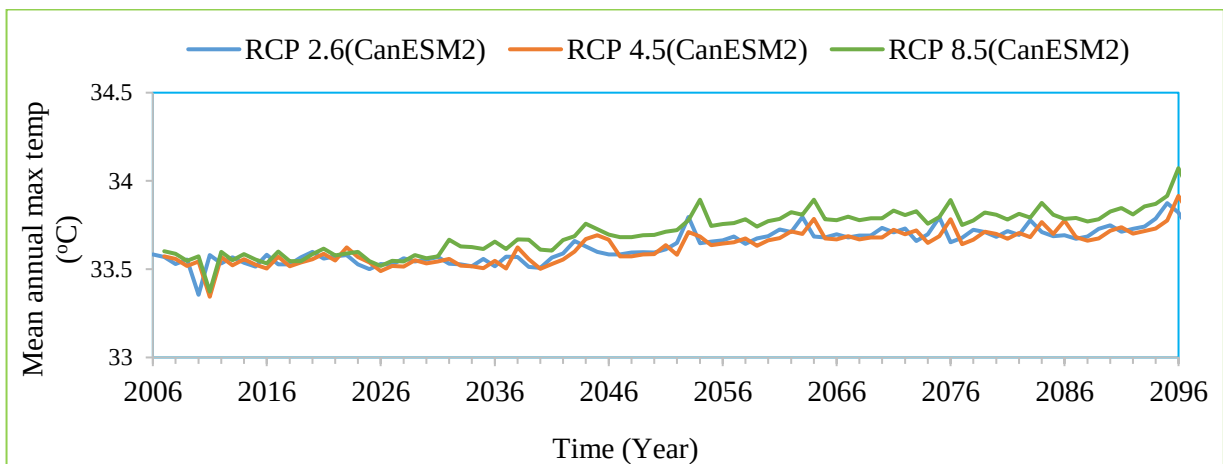


Figure 4.4. Future trend of mean annual maximum temperature (°C) in the CanESM2-RCP

As shown in Figure 4.4, increasing trend of mean annual maximum temperature was observed for all of the CanESM2-RCP scenarios (RCP 2.6, 4.5 and 8.5) until the end of the century, and

the variability of maximum temperature is higher in CanESM2-RCP 8.5 than CanESM2-RCP 2.6 and CanESM2-RCP 4.5.

4.2.3.4. Mean monthly minimum temperature scenarios

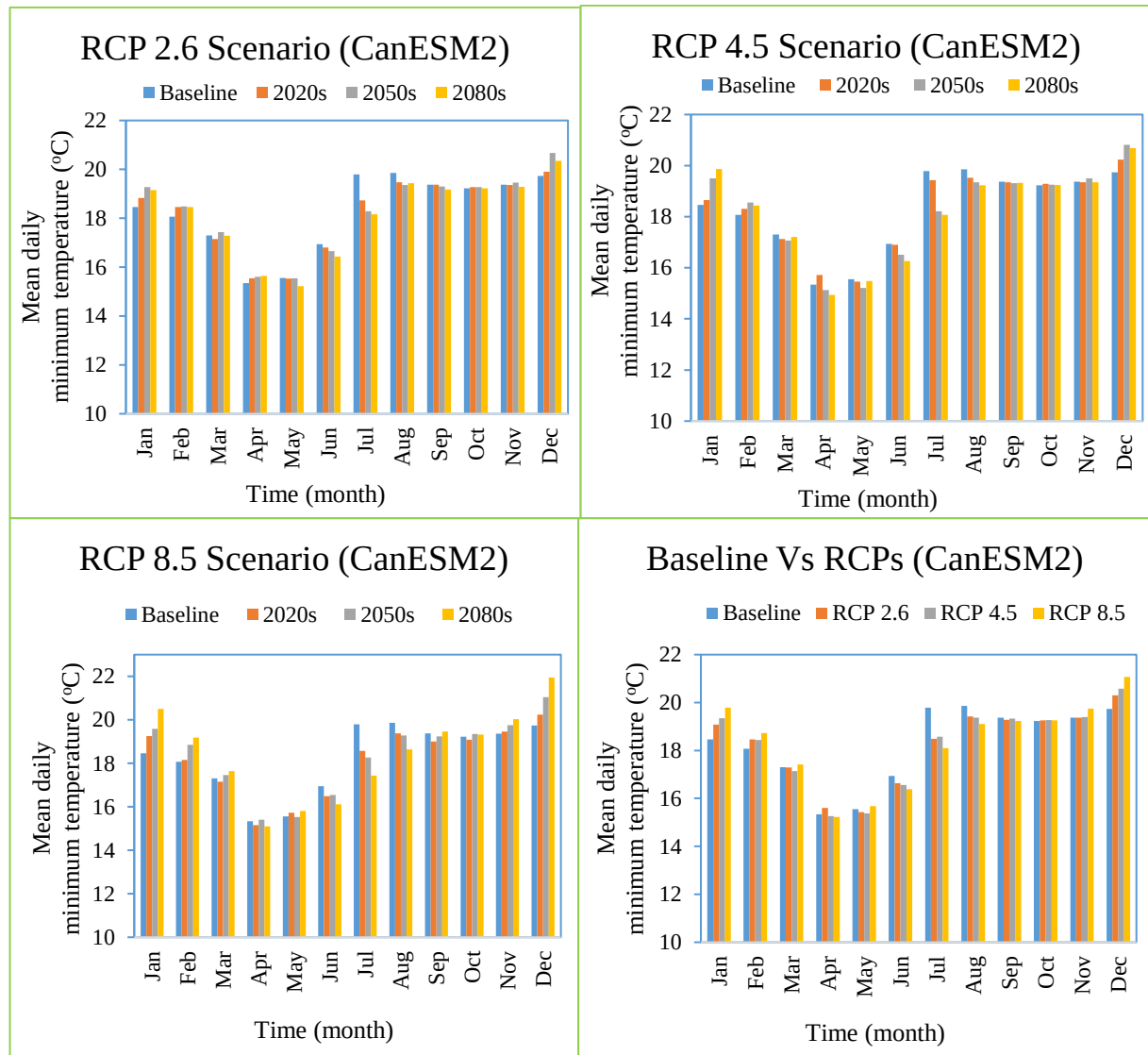


Figure 4.5. Monthly minimum temperature during baseline (1981-2010) simulation and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

A large increment in monthly minimum temperature is observed in the month of January 2080s that was 0.69, 1.41 and 2.04°C for RCP2.6, RCP4.5 and RCP8.5 scenarios respectively.

The larger decrement was observed on July 2080s that was 1.62, 1.71 and 2.35°C for RCP2.6, RCP4.5 and RCP8.5 scenarios respectively as shown in Figure 4.5.

4.2.3.5. Mean seasonal minimum temperature scenarios

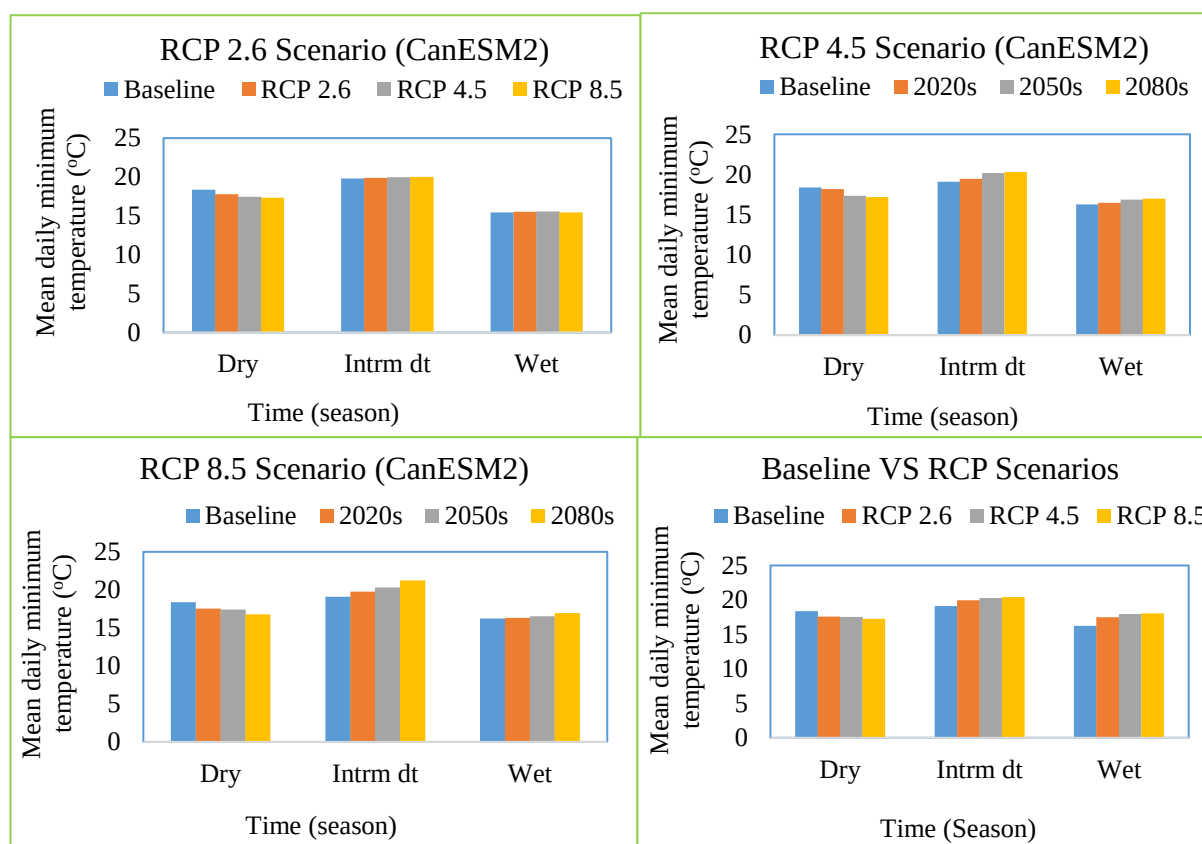


Figure 4.6. Seasonal minimum temperature during baseline (1981-2010) simulation and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

As shown in Figure 4.6, the projected seasonal minimum temperature shows an increasing trend in the intermediate and wet seasons for all of the RCPs (RCP 2.6, 4.5 and 8.5) in all of the future time slices. In contrast to this, it showed decreasing trend in the dry season in all of the three future time slices for RCP2.6, RCP4.5, and RCP8.5 scenarios.

4.2.3.6. Mean annual minimum temperature scenarios

Figure 4.7 shows the change anomalies in mean annual minimum temperature of future time slices (2020s, 2050s and 2080s) from baseline period under CanESM2-RCP 2.6, CanESM2-

RCP 4.5 and CanESM2-RCP 8.5 scenarios. The CanESM2-RCP 2.6 scenario simulation indicated increasing trend of minimum temperature by 0.048°C (0.15%) at 2020s, 0.025°C (0.14%) at 2050s and 0.074°C (0.4%) at 2080s. The CanESM2-RCP 4.5 scenario simulation showed an increasing trend of minimum temperature by 0.064°C (0.27%) at 2020s, 0.067°C (0.27%) at 2050s and 0.09°C (0.41%) at 2080s. The CanESM2-RCP 8.5 scenario simulation showed increasing pattern of minimum temperature by 0.1°C (0.6%) at 2020s, 0.12°C (0.63%) at 2050s and 0.2°C (1%) at 2080s.

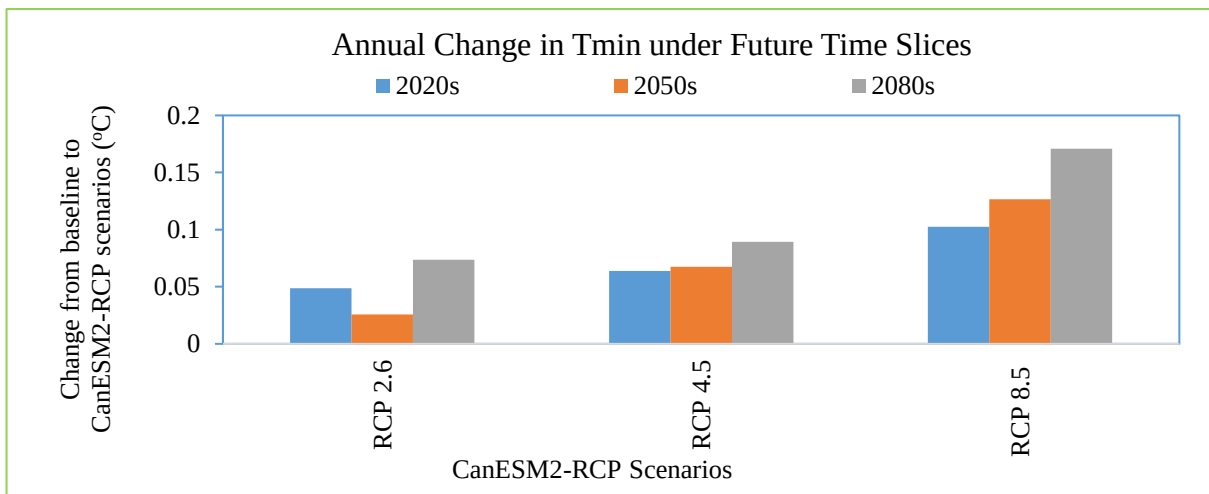


Figure 4.7. Absolute changes from baseline simulation of annual minimum temperature in CanESM2-RCP scenario in the 2020s, 2050s and 2080s time slices

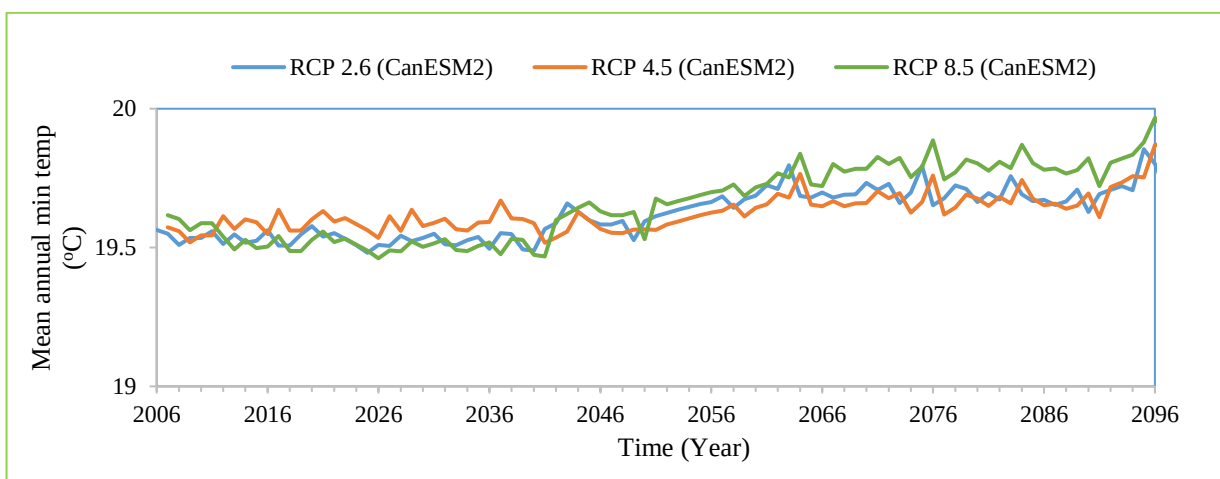


Figure 4.8. Future trend of mean annual minimum temperature (°C) in the CanESM2-RCP scenarios

As shown in Figure 4.8, increasing trend of mean annual minimum temperature was observed for all of the CanESM2-RCP scenarios (RCP 2.6, 4.5 and 8.5) starting from half of the century to the end of the century, and the variability of minimum temperature is higher in CanESM2-RCP 8.5 than CanESM2-RCP 2.6 and CanESM2-RCP 4.5 for time slices of 2050s and 2080s; that means a year from 2041-2096. However, from 2006 to 2050 the variability of minimum temperature is higher in CanESM2-RCP 4.5 than CanESM2-RCP 2.6 and CanESM2-RCP 8.5.

4.2.3.7. Mean monthly precipitation scenarios

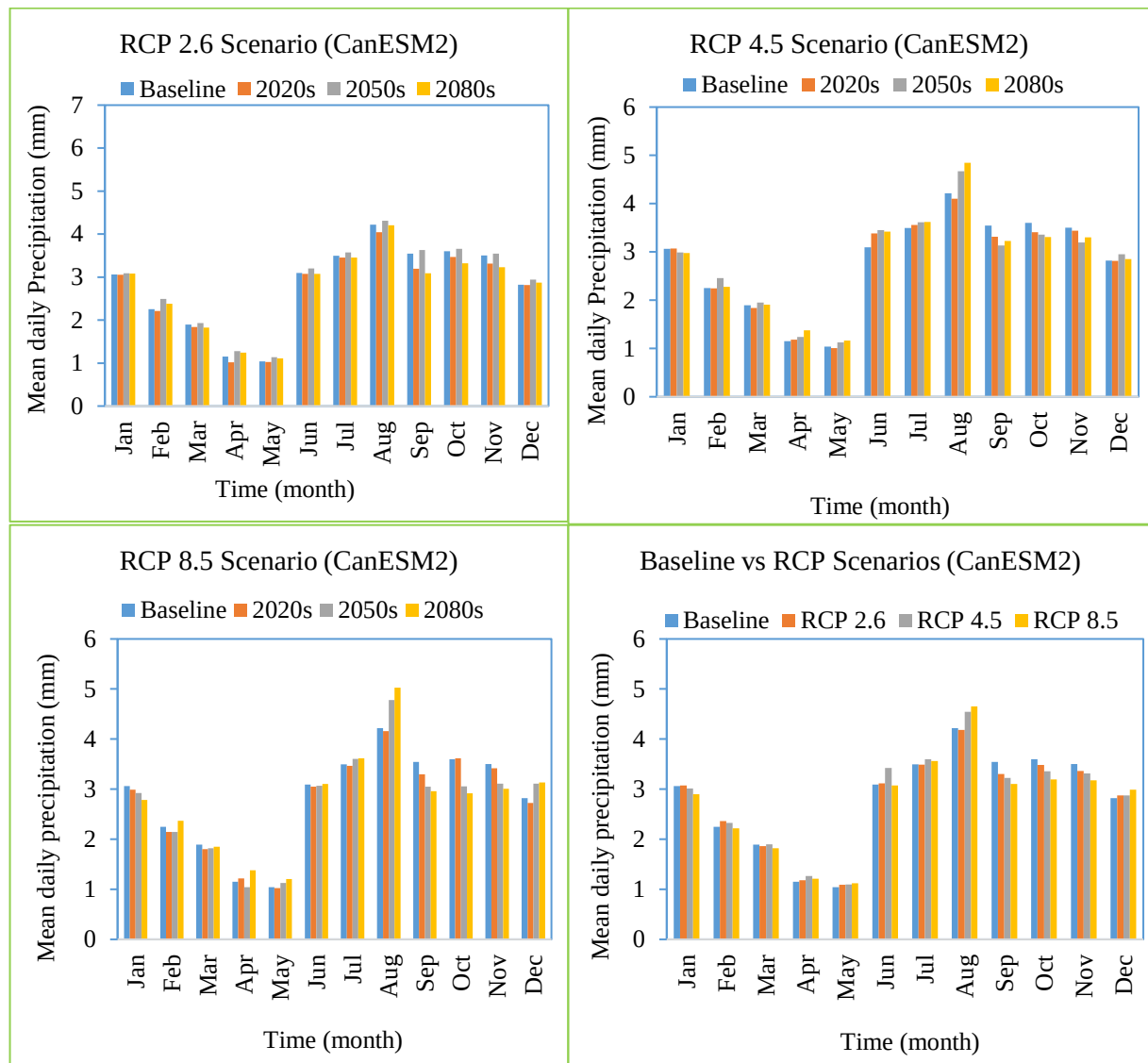


Figure 4.9. Monthly precipitation during baseline (1981-2010) simulation and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

A large increment in monthly precipitation was observed in the month of August 2080s that were 0.63 and 0.81 mm for RCP4.5 and RCP8.5 scenarios respectively and for RCP 2.6, it was observed in the month of February 2050s which was 0.24 mm. The larger decrement was observed on September 2080s that were 0.46, 0.32 and 0.58 mm for RCP2.6, RCP4.5 and RCP8.5 scenarios respectively as shown in Figure 4.9.

4.2.3.8. Mean seasonal precipitation scenarios

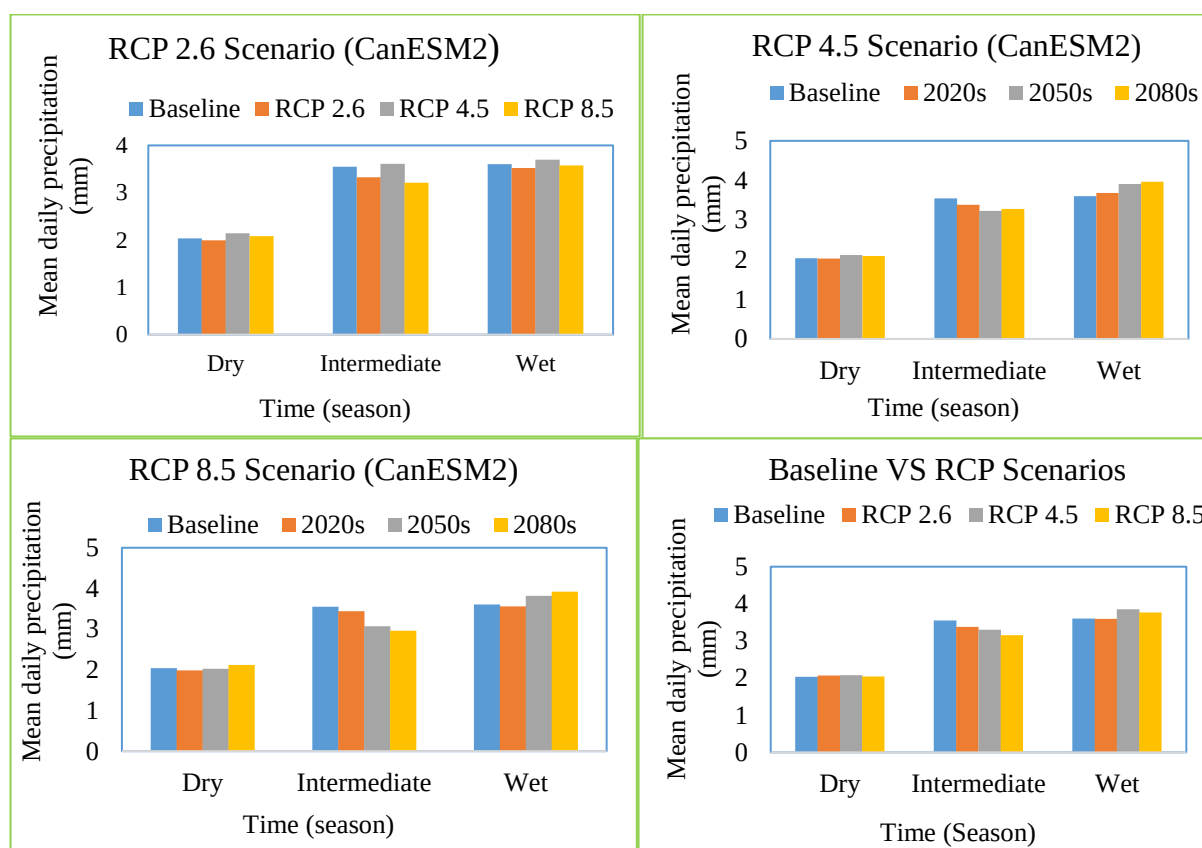


Figure 4.10. Seasonal precipitation during baseline (1981-2010) simulation and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

As shown in Figure 4.10, the projected seasonal precipitation shows decreasing trend in the dry season for all of the RCPs (RCP 2.6, 4.5 and 8.5) in the future time slices of 2020s; while it shows increasing trend in the time slices of 2050s and 2080s. Similarly, the projected seasonal precipitation shows decreasing trend in the intermediate season for all of the RCPs (RCP 2.6, 4.5 and 8.5) in the future time slices of 2020s, 2050s (except RCP 2.6 which

showed increasing trend in this time slice) and 2080s. In contrast to this, the projected seasonal precipitation shows increasing trend in the wet season for all of the RCPs (RCP 2.6, 4.5 and 8.5) in the future time slices of 2020s (except RCP2.6 and 8.5 which showed decreasing trend in this time slice), 2050s and 2080s.

4.2.3.9. Mean annual precipitation scenarios

Figure 4.11 shows the change anomalies in mean annual precipitation of future time slices (2020s, 2050s and 2080s) from baseline period under CanESM2-RCP 2.6, CanESM2-RCP 4.5 and CanESM2-RCP 8.5 scenarios. The CanESM2-RCP 2.6 scenario simulation indicated an increasing pattern by 0.3 mm (1%) at 2020s, 1.3 mm (4.4%) at 2050s and 0.88 mm (2.97%) at 2080s. The CanESM2-RCP 4.5 scenario simulation showed an increasing pattern of precipitation by 0.9 mm (3%) at 2020s, 1.46 mm (4.94%) at 2050s and 2 mm (6.74%) at 2080s. The CanESM2-RCP 8.5 scenario simulation showed an overall increasing pattern of precipitation by 0.913 mm (3.1%) at 2020s, 1.5 mm (5.05%) at 2050s and 2.6 mm (8.7%) at 2080s.

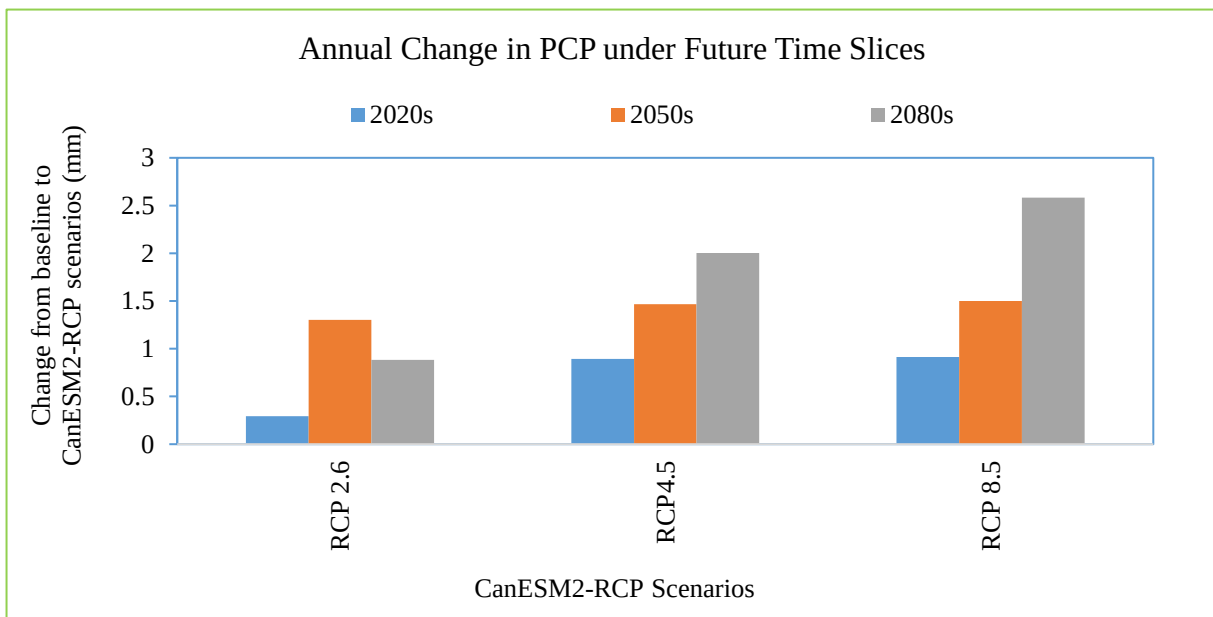


Figure 4.11. Absolute change from baseline simulation of annual precipitation in CanESM2-RCP scenario in the 2020s, 2050s and 2080s time slices

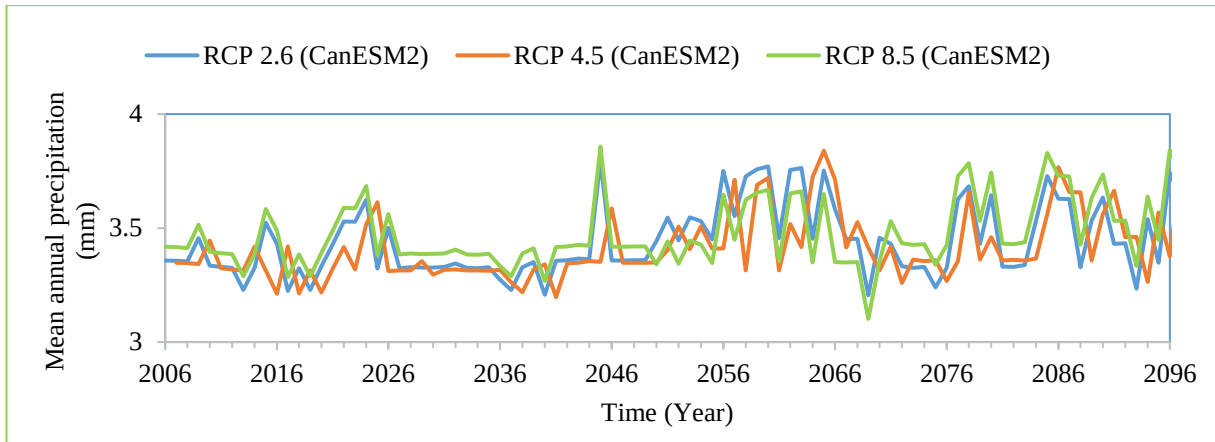


Figure 4.12. Future trend of mean annual precipitation (mm) in the CanESM2-RCP scenarios

As shown in Figure 4.12, inconsiderable (slight) increasing trend of precipitation was observed for all of the CanESM2-RCP scenarios (RCP 2.6, 4.5 and 8.5) until the end of the century, and the variability of precipitation in CanESM2-RCP 8.5 is higher than the variability in CanESM2-RCP 4.5 and CanESM2-RCP 2.6 in the time slices of 2050s and 2080s; that means a year from 2041-2096.

In relation to this study, Shitu and Berhanu (2020) applied SDSM for temperature and precipitation in Borkena River Catchment, Ethiopia to calculate changes in future climate and indicated an increasing trend for both annual maximum and minimum temperature in the time slices of 2020s and 2080s under CanESM2-RCP4.5 and RCP8.5. The maximum increasing value occurred in the time slices of 2020s and 2080s of RCP8.5 with a value of 1.85°C and 2.82°C for minimum and maximum temperature respectively. Similarly, in this study, maximum increasing value was observed in 2080s-RCP8.5 with a value of 0.5°C for maximum temperature scenario. Shitu and Berhanu (2020) also revealed decreasing trend of annual precipitation for both RCP4.5 and RCP8.5. In contrast to this, future precipitation in this study showed increasing trend in all of the three time slices (2020s, 2050s and 2080s) and RCP scenarios (RCP 2.6, 4.5 and 8.5). This is due to the reason that wet (Kiremt) season rainfall which is the main source of rainfall in the basin showed increasing trend for all the scenarios except RCP2.6 (2020s).

4.3. Sugarcane Crop Water Requirement and Irrigation Water Requirement under Changing Climate

4.3.1. Monthly sugarcane crop water requirement under changing climate

Sugarcane crop water requirement in the baseline period and future time slices of 2020s, 2050s and 2080s for crop growth initial stage (June), development stage (July-August), mid stage (September-February) and late stage (March-May) were shown in Figure 4.13.

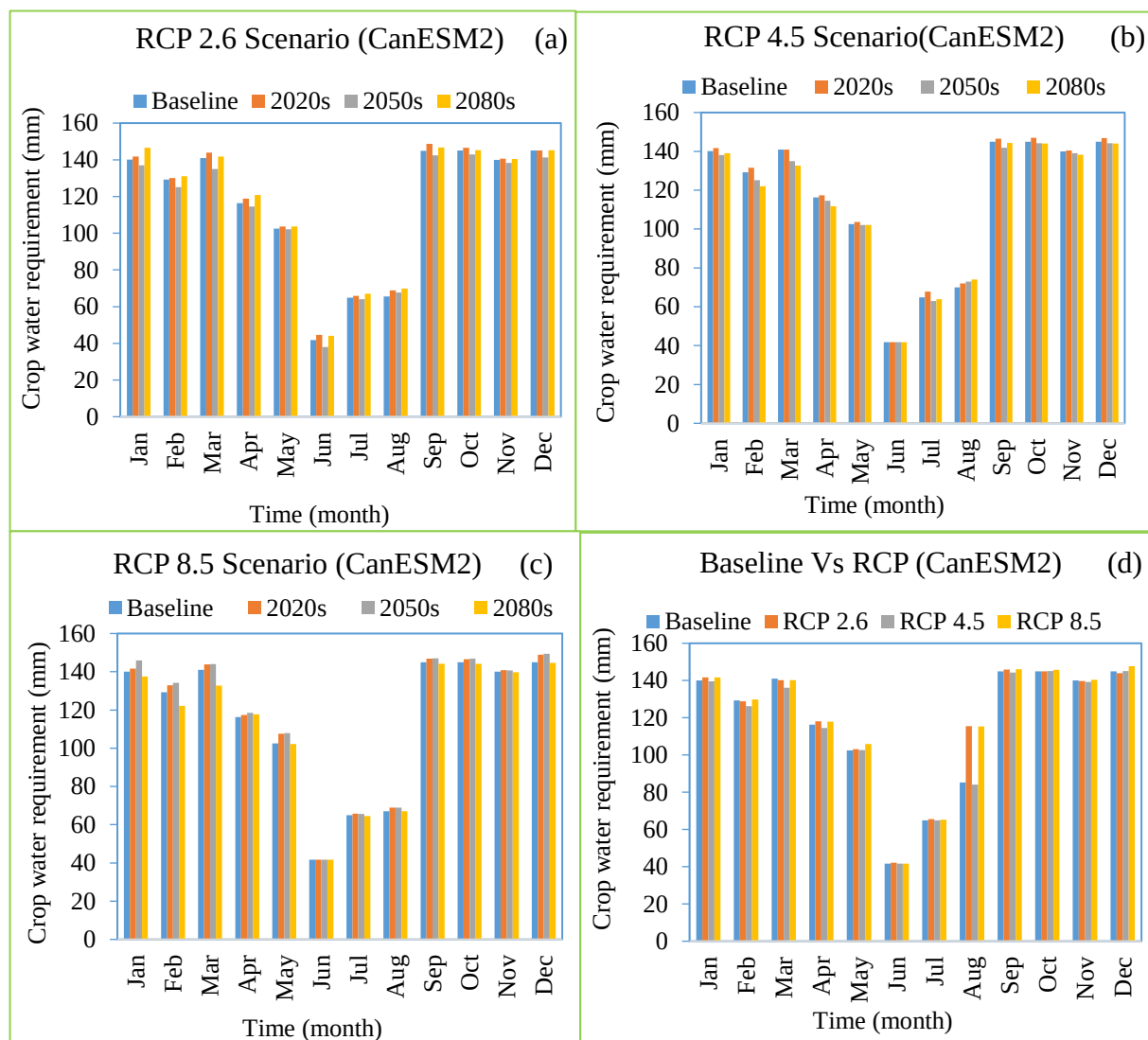


Figure 4.13. Monthly sugarcane crop water requirement during baseline (1981-2010) period and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

As shown in Figure 4.13a, large increment in monthly sugarcane crop water requirement was observed in the month of January-2080s which was 6.4 mm; while a large decrement in crop water requirement was observed in the month of March-2050s which was 5.95 mm under RCP2.6. A large increment in monthly sugarcane crop water requirement was observed in the month of July-2020s which was 2.9 mm; while a large decrement in crop water requirement was observed in the month of March-2080s which was 8.3 mm under RCP4.5 as shown in Figure 4.13b. However in Figure 4.13c, a large increment in monthly sugarcane crop water requirement was observed in the month of January-2050s which was 5.85 mm; while a large decrement in crop water requirement was observed in the month of March-2080s which was 8.3 mm under RCP8.5.

4.3.2. Seasonal sugarcane crop water requirement under changing climate

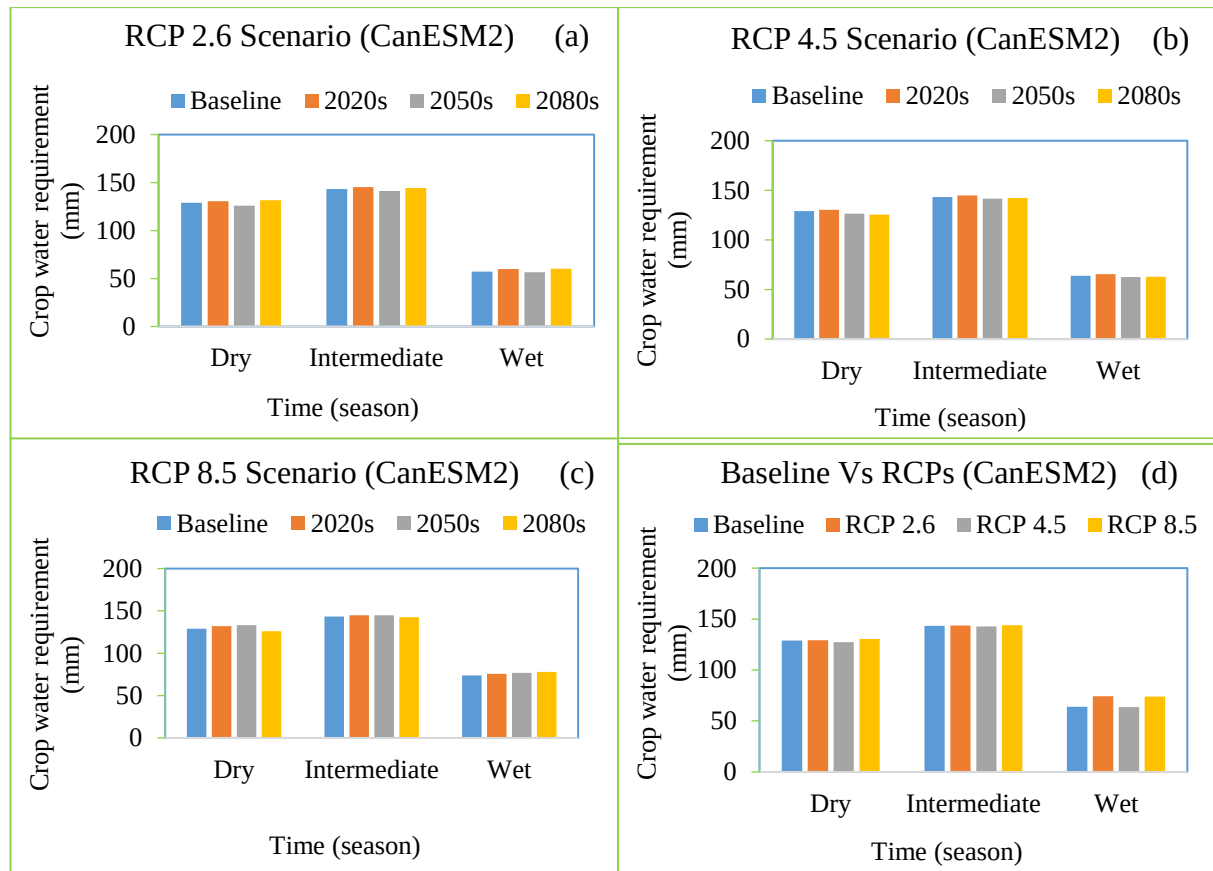


Figure 4.14. Seasonal sugarcane crop water requirement during baseline (1981-2010) period and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

The projected future crop water requirement under CanESM2-RCP 2.6 shows an increasing trend in 2020s and 2080s while it shows decreasing trend in 2050s in all seasons (dry, wet and intermediate) compared to the crop water requirement in baseline period as shown in Figure 4.14a. In dry season it showed that the future sugarcane crop water requirement will increase by 1.52 mm (1.2%), 2.5 mm (1.92%) in 2020s and 2080s respectively; however it will decrease by 3.2 mm (2.5%) in 2050s. In intermediate season, the future crop water requirement will increase by 2 mm (1.4%), 0.86 mm (0.6%), in 2020s and 2080s respectively; while it decreases by 2.1 mm (1.45%) in 2050s. In wet season, the future crop water requirement will increase by 1.78 mm (2.41%) and 1.63 mm (2.2%) in 2020s and 2080s respectively; while it decreases by 2.1 mm (2.8%) in 2050s.

Under CanESM2-RCP 4.5, the simulated future crop water requirement showed an increasing trend in 2020s while it showed decreasing trend in 2050s and 2080s in all seasons (dry, wet and intermediate) compared to the crop water requirement in baseline period which is shown in Figure 4.14b. The future sugarcane crop water requirement will decrease by 2.5 mm (1.92%) and 3.74 mm (2.9%) in 2050s and 2080s respectively in dry season; while it increase by 1.31 mm (1.01%) in 2020s. In wet season, the future crop water requirement will decrease by 1.5 mm (2.34%) and 1.2 mm (1.82%) in 2050s and 2080s respectively; while it increases by 1.5 mm (2.4%) in 2020s. However the future crop water requirement will decrease by 1.61 mm (1.13%) and 1.1 mm (0.74%) in 2050s and 2080s respectively; while it increases by 1.4 mm (0.97%) in 2020s in intermediate season.

As shown in Figure 4.14c, the projected future crop water requirement under CanESM2-RCP 8.5 shows an increasing trend in 2020s and 2050s while it shows decreasing trend in 2080s in all seasons (dry, wet and intermediate) compared to the crop water requirement in baseline period. In dry season it showed that the future sugarcane crop water requirement will increase by 3.1 mm (2.4%) and 4.3 mm (3.32%) in 2020s and 2050s respectively; however it will decrease by 2.9 mm (2.23%) in 2080s. In intermediate season, the future crop water requirement will increase by 1.43 mm (1%), 1.55 mm (1.1%), in 2020s and 2050s respectively; while it decreases by 0.67 mm (0.46%) in 2080s. In wet season, the future crop

water requirement will increase by 0.63 mm (0.85%) and 0.8 mm (1.1%) in 2020s and 2050s respectively; while it decreases by 1.1 mm (1.5%) in 2080s.

4.3.3. Monthly sugarcane irrigation water requirement under changing climate

Sugarcane irrigation water requirement in the baseline period and future time slices of 2020s, 2050s and 2080s for crop growth initial stage (June), development stage (July-August), mid stage (September-February) and late stage (March-May) were shown in Figure 4.16.

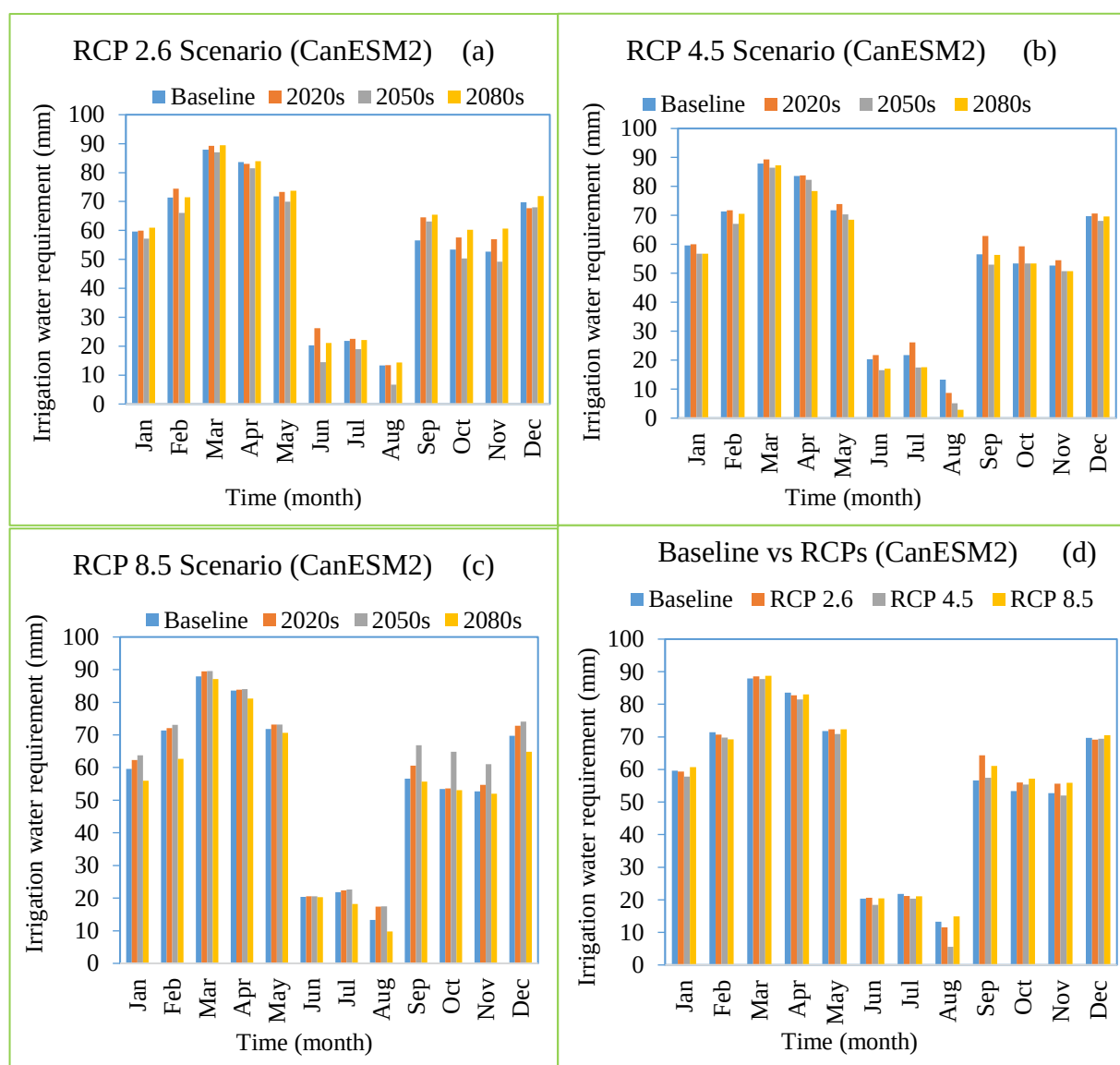


Figure 4.15. Monthly sugarcane irrigation water requirement during baseline (1981-2010) period and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

As shown in Figure 4.15a, large increment in monthly sugarcane irrigation water requirement was observed in the month of November-2080s which was 7.9 mm; while a large decrement in irrigation water requirement was observed in the month of August-2050s which was 6.6 mm under RCP2.6. However in Figure 4.15b, a large increment in monthly sugarcane irrigation water requirement was observed in the month of September-2020s which was 6.3 mm; while a large decrement in irrigation water requirement was observed in the month of August-2080s which was 10.4 mm under RCP4.5. In Figure 4.15c, a large increment in monthly sugarcane irrigation water requirement was observed in the month of October-2050s which was 11.45 mm; while a large decrement in irrigation water requirement was observed in the month of February-2080s which was 8.7 mm under RCP8.5.

4.3.4. Seasonal sugarcane irrigation water requirement under changing climate

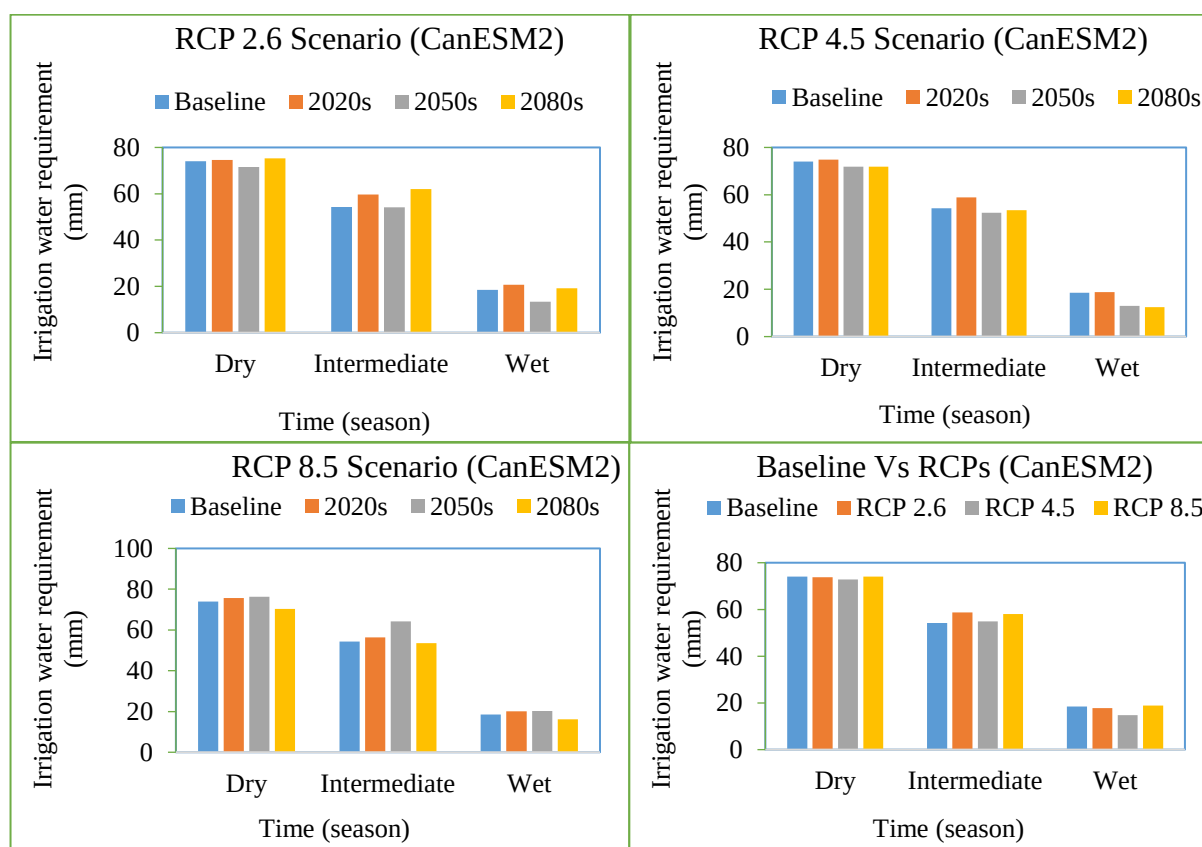


Figure 4.16. Seasonal sugarcane irrigation water requirement during baseline (1981-2010) period and three future time slice under RCP 2.6, 4.5 and 8.5 scenario for average of the stations

As shown in Figure 4.16a, the projected future sugarcane irrigation water requirement under CanESM2-RCP 2.6 showed an increasing trend in the time slices of 2020s and 2080s while it showed decreasing trend in the time slices of 2050s in all seasons (dry, intermediate and wet) compared to the irrigation water requirement in the baseline period. In dry season it showed that the future sugarcane irrigation water requirement will increase by 0.6 mm (0.8%), 3.65 mm (4.92%) in 2020s and 2080s respectively; however it will decrease by 2.41 mm (3.26%) in 2050s. In intermediate season, the future irrigation water requirement will increase by 5.5 mm (10%), 7.8 mm (14.4%), in 2020s and 2080s respectively; while it decreases by 0.02 mm (0.03%) in 2050s. In wet season, the future irrigation water requirement will increase by 2.23 mm (12.1%) and 0.74 mm (4%) in 2020s and 2080s respectively; while it decreases by 5 mm (27.4%) in 2050s.

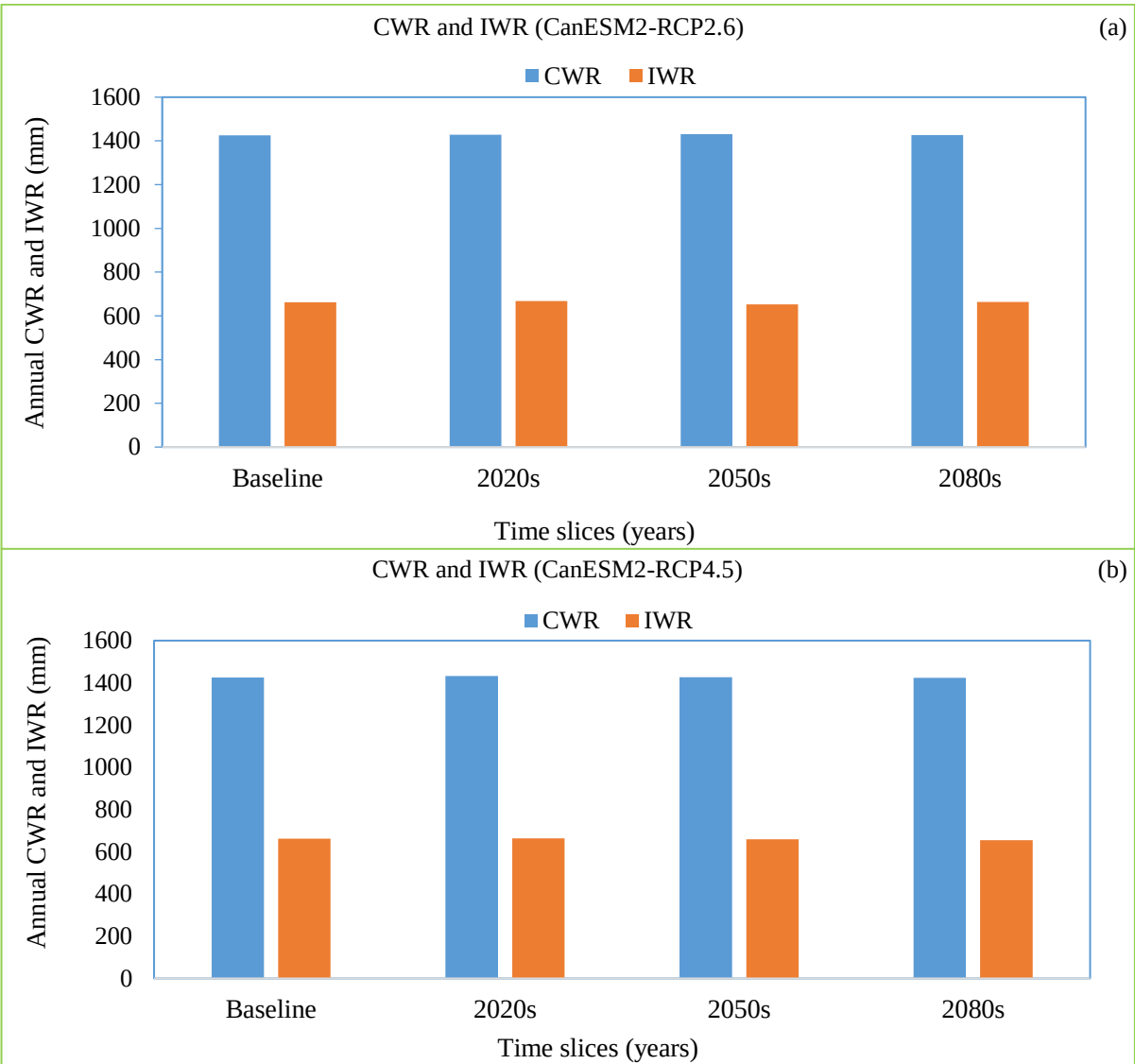
The simulated sugarcane irrigation water requirement under CanESM2-RCP 4.5 showed an increasing trend in 2020s while it showed decreasing trend in 2050s and 2080s in all seasons (dry, wet and intermediate) compared to the irrigation water requirement in baseline period as shown in Figure 4.16b. In wet season, the future irrigation water requirement will decrease by 5.43 mm (29.4%) and 5.96 mm (32.3%) in 2050s and 2080s respectively; while it increases by 0.4 mm (2.02%) in 2020s. In intermediate season, the future irrigation water requirement will decrease by 1.9 mm (3.5%) and 0.75 mm (1.4%) in 2050s and 2080s respectively; while it increases by 4.7 mm (8.6%) in 2020s. In dry season, the future sugarcane irrigation water requirement will decrease by 2.16 mm (2.9%) and 2.2 mm (2.9%) in 2050s and 2080s respectively; however it will increase by 0.9 mm (1.22%) in 2020s.

As shown in Figure 4.16c, the simulated future irrigation water requirement under CanESM2-RCP 8.5 shows an increasing trend in 2020s and 2050s while it shows decreasing trend in 2080s in all seasons compared to the irrigation water requirement in baseline period. The future sugarcane irrigation water requirement will increase by 1.62 mm (2.2%) and 2.26 mm (3.1%) in 2020s and 2050s respectively in dry season; however it will decrease by 3.6 mm (4.8%) in 2080s. In intermediate season, the future irrigation water requirement will increase by 2.1 mm (3.81%), 10 mm (18.4%), in 2020s and 2050s respectively; while it decreases by 0.65 mm (1.2%) in 2080s. In wet season, the future irrigation water requirement will increase

by 1.63 mm (8.83%) and 1.75 mm (9.5%) in 2020s and 2050s respectively; while it decreases by 2.4 mm (12.85%) in 2080s.

4.3.3. Annual sugarcane water requirement and irrigation water requirement scenarios

Graphical representation of projected sugarcane crop water requirement and irrigation water requirement under CanESM2-RCP2.6, CanESM2-RCP 4.5 and CanESM2-RCP 8.5 for different time slices (2020s, 2050s and 2080s) were shown in Figure 4.17. And the percentage difference of projected future sugarcane crop water requirement and irrigation water requirement from the baseline period were estimated and shown in Appendix Table 12.



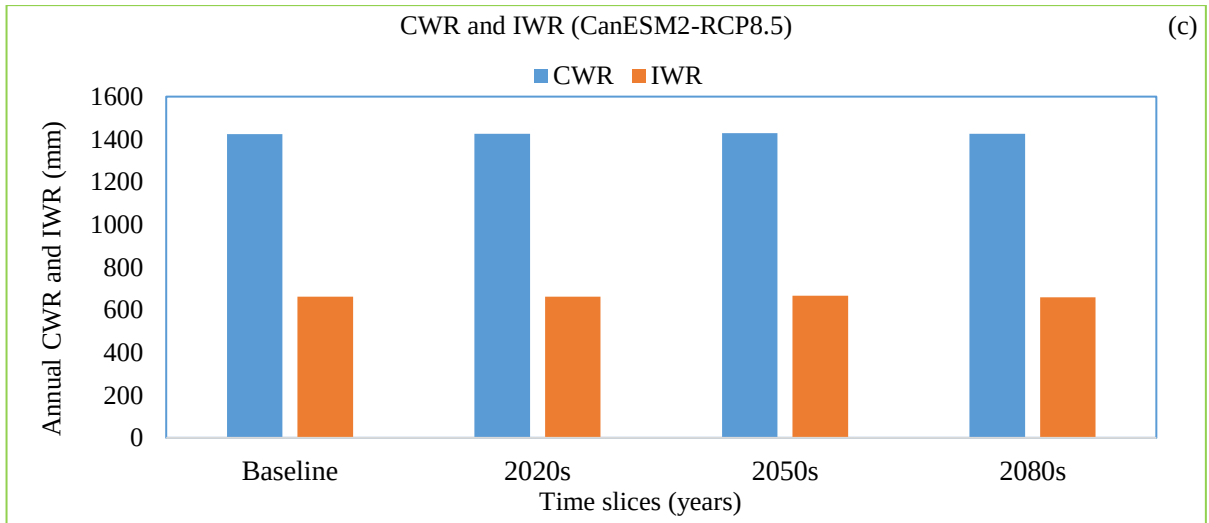


Figure 4.17. Change in CWR and IWR from baseline to future time slices under CanESM2-RCP2.6 (a), CanESM2-RCP4.5 (b) and CanESM2-RCP8.5 (c)

As shown in Figure 4.17a, the projected annual future sugarcane crop water requirement under CanESM2-RCP 2.6 showed an increasing trend in all of the time slices of 2020s, 2050s, and 2080s compared to the crop water requirement in the baseline period (1424.8 mm). The future crop water requirement will increase by 3.85 mm (0.27%), 5.56 mm (0.39%) and 2 mm (0.14%) in 2020s, 2050s and 2080s respectively under CanESM2-RCP 2.6. The future sugarcane crop water requirement will increase by 7.3 mm (0.51%) and 2.15 mm (0.15%) in 2020s and 2050s respectively, while it decreases by 0.55 mm (0.04%) in 2080s under CanESM2-RCP 4.5 as shown in Figure 4.17b. Under CanESM2-RCP 8.5, the future sugarcane crop water requirement will increase by 0.3 mm (0.02%), 4.3 mm (0.3%) and 1.45 mm (0.1%) in 2020s, 2050s and 2080s respectively (Figure 4.17c).

As shown in Figure 4.17a, the projected annual future sugarcane irrigation water requirement under CanESM2-RCP 2.6 showed an increasing trend in the time slices of 2020s and 2080s while it showed decreasing trend in the time slices of 2050s compared to the irrigation water requirement in the baseline period (662.13 mm). The future sugarcane irrigation water requirement will increase by 5.15 mm (0.8%) and 1.9 mm (0.3%) in 2020s and 2080s respectively; however it will decrease by 9 mm (1.36%) in 2050s under CanESM2-RCP 2.6. The future sugarcane irrigation water requirement will increase by 1.73 (0.26%) in 2020s while it decreases by 2.78 mm (0.4%) and 7.8 mm (1.2%) in 2050s and 2080s respectively

under CanESM2-RCP 4.5 (Figure 4.17b). Under CanESM2-RCP 8.5, the future sugarcane irrigation water requirement will increase by 0.6 mm (0.08%) and 5.2 mm (0.78%) in 2020s and 2050s respectively; however in 2080s, it showed that sugarcane irrigation water requirement will decrease by 3.33 mm (0.5%) as shown in Figure 4.17c.

In relation to this study, Haj-Amor et al. (2020) used SDSM to project future climate variables from 2019 to 2050 under RCP 4.5, 6.0 and 8.5, applied CROPWAT model to calculate net irrigation water requirement. According to the study, these three scenarios showed increasing annual maximum and minimum temperatures and decreasing trend of future rainfall. Net irrigation water requirement is expected to increase progressively from an average value of 1459 mm/year during baseline period to 1473-1950 mm/year during 2019-2050, depending on climate change scenarios.

Lee and Huang (2014) assessed impact of climate change on irrigation water requirement in Northern Taiwan. The authors compared present and future periods and revealed that climate change would lead both rainfall and temperature to rise; which caused effective rainfall and crop water requirement to increase in the future. The future irrigation requirement is 7.1% more than the first season while it is 2.1% less than the present in the second cropping season.

Bekele et al. (2019) estimated CWR of maize and IWR under RCP 2.6, 4.5 and 8.5 scenarios during periods of 2020s and 2050s. The authors revealed that monthly CWR in 2050s were lower than 2020s and future irrigation water requirement of maize under RCP scenario was increased during the Belg (March to May) season which is similar to this study.

5. CONCLUSION AND RECOMMENDATION

5.1. Conclusion

This study analyzed the impacts of climate change on irrigation water requirements based on observed and projected future climate conditions by using combination of CMIP5-GCM (CanESM2-RCPs) and CROPWAT model. The CWR and IWR in the baseline (1981-2010) period were estimated using the average of five historical weather stations in and around the study area. CanESM2 predictor variables in the three given climate change scenarios (RCP 2.6, 4.5, 8.5) were employed in SDSM downscaling processes to generate temperature and precipitation scenarios of the three future time slices, namely 2020s (2011-2040), 2050s (2041-2070), and 2080s (2071-2100) and then these future scenarios of temperature and precipitation were used to assess future sugarcane CWR and IWR under the same time slices for the study area.

- Specifically, coefficient of variation (CV) and Man-Kendall trend test were used in the study to investigate the historical variations and trends in annual and seasonal rainfall and temperature. Results from coefficient of variation and Mann-Kendall trend test generally showed that climate change and variability is expected to trigger changes in temperature and precipitation series that would affect the irrigation water availability in the study area. The study conducted at upper Awash River sub basin revealed that all of the representative stations showed very high variation in annual and seasonal (Kiremt and Belg) rainfall ($CV\% > 40$) while it showed low variation in annual and seasonal (Kiremt and Belg) maximum and minimum temperature ($CV\% < 20$).
- The coefficient of determination (R^2), the root mean square error (RMSE), and the Nash–Sutcliffe efficiency coefficient (NSE) were used in this study, to evaluate the performance evaluation of SDSM in simulating historical climate variables (precipitation, maximum and minimum temperature). From the statistical indices and graphical observation between observed and simulated value. We can infer that SDSM has good ability to replicate historical maximum and minimum temperature for all of the stations in the study area and relatively lower ability to replicate historical precipitation for the stations in the study area.

- The analysis of annual maximum, minimum temperature and precipitation scenario revealed an increasing trend under CanESM2 (RCP2.6, RCP4.5 and RCP8.5) scenarios in the 2020s, 2050s and 2080s time slices when compared to the baseline period scenario. The projected seasonal maximum and minimum temperature shows an increasing trend in the wet and intermediate seasons for all of the CanESM2-RCPs (RCP 2.6, 4.5 and 8.5) in all of the future time slices. In contrast to this, it showed decreasing trend of maximum temperature in the dry season in all of the three future time slices in RCP2.6, RCP8.5 except time slices of 2050s and 2080s in RCP4.5; however it showed decreasing trend for minimum temperature in all of the three future time slices for RCP2.6, RCP4.5, and RCP8.5 scenarios.

The projected seasonal precipitation shows decreasing trend in the dry season for all of the RCPs (RCP 2.6, 4.5 and 8.5) in the future time slices of 2020s; while it shows increasing trend in the time slices of 2050s and 2080s. Similarly, the projected seasonal precipitation shows decreasing trend in the intermediate season for all of the RCPs (RCP 2.6, 4.5 and 8.5) in the future time slices of 2020s, 2050s (except RCP 2.6 which showed increasing trend in this time slice) and 2080s. In contrast to this, the projected seasonal precipitation shows increasing trend in the wet season for all of the RCPs (RCP 2.6, 4.5 and 8.5) in the future time slices of 2020s (except RCP2.6 and 8.5 which showed decreasing trend in this time slice), 2050s and 2080s.

- Monthly and seasonal projected future sugarcane irrigation water requirement under CanESM2-RCP 2.6 showed an increasing trend in the time slices of 2020s and 2080s while it showed decreasing trend in the time slices of 2050s in all seasons (dry, intermediate and wet); however under CanESM2-RCP 4.5, it showed an increasing trend in 2020s while it showed decreasing trend in 2050s and 2080s in all seasons (dry, wet and intermediate) in relative to the irrigation water requirement in baseline period. CanESM2-RCP 8.5 shows an increasing trend in future irrigation water requirement in 2020s and 2050s while it shows decreasing trend in 2080s in all seasons (dry, wet and intermediate).

The projection of annual future sugarcane irrigation water requirement showed that IWR increased by 5.15 mm (0.8%) and 1.9 mm (0.3%) in 2020s and 2080s respectively; however it decreased by 9mm (1.36%) in 2050s under CanESM2-RCP 2.6. The future sugarcane irrigation water requirement increased by 1.73 (0.26%) in 2020s while it decreases by 2.78 mm (0.4%) and 7.8 mm (1.2%) in 2050s and 2080s respectively under CanESM2-RCP 4.5. Under CanESM2-RCP 8.5, the future sugarcane irrigation water requirement increased by 0.6 mm (0.08%) and 5.2 mm (0.78%) in 2020s and 2050s respectively; however in 2080s, it showed that sugarcane irrigation water requirement decreased by 3.33 mm (0.5%) in relative to baseline scenario.

5.2. Recommendation

Based on results found and challenges faced while executing this piece of work, the following recommendations for further research directions are forwarded;

- 1) This study was undertaken using single Earth System Model (CanESM2) and three emission scenarios (RCP2.6, RCP4.5, and RCP8.5) to evaluate the impacts of climate change; however future studies should incorporate different Earth System Models (ESMs) in order to make comparison between different models as well as to explore a wide range of climate change scenarios that would result in different hydrological impacts. Hence this work should be extended in the future by including different ESMs.
- 2) Statistical downscaling model (SDSM) was used in this study, to downscale climate parameters (temperature and precipitation). Since downscaling models have their own limitations, others methods such as dynamical downscaling model should also be tested to allow assessments based on the result of the models.
- 3) The study assessed climate change impact on irrigation water requirement. However, In addition to fluctuations in temperature and precipitation, deforestation, population growth and industrial expansion are among current trends over the sub-basin and study area. Therefore, future studies should focus on examining the impacts of land use changes together with climate change over irrigation water requirement and crop yield of the study area.

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APPENDICES

Appendix A

Appendix Tables

Appendix Table 1. Lists of selected potential predictor variables that gave better correlation results at $P < 0.05$ from NCEP re-analysis for the study area

Predictand	Predictor full name	Notations	Partial cor. (r-val.)	P-value
Abomsa Station				
Precipitation	ncepmslpgl.dat	Mean sea level pressure	0.044	0.0001
	ncepprcpgl.dat	Unknown	0.042	0.0057
Maximum temperature	nceptempgl.dat	Mean temperature at 2m	0.310	0.000
	ncepp8thgl.dat	850hpa wind direction	0.177	0.000
Minimum temperature	ncepp5_zgl.dat	500hpa vorticity	0.104	0.000
	nceptempgl.dat	Mean temperature at 2m	0.324	0.000
Arerti station				
Precipitation	ncepp1thgl.dat	Unknown	0.04	0.01
	ncepp8zhgl.dat	850hpa divergence	0.028	0.04
Maximum temperature	ncepp8_ugl.dat	850hpa zonal velocity	0.203	0.000
	nceptempgl.dat	Mean temperature at 2m	0.195	0.000
Minimum temperature	ncepp1_ugl.dat	Unknown	0.238	0.000
	ncepp8zhgl.dat	850hpa divergence	0.217	0.000
Melka Jilo station				
Precipitation	ncepmslpgl.dat	Mean sea level pressure	0.109	0.000
	ncepp1thgl.dat	Unknown	0.123	0.000
Maximum temperature	ncepp5_zgl.dat	500hpa vorticity	0.06	0.000
Minimum temperature	ncepp1_ugl.dat	Unknown	0.275	0.000
	ncepp8zhgl.dat	850hpa divergence	0.138	0.000
Metahara station				
Precipitation	ncepshumgl.dat	Surface specific humidity	0.071	0.000
Maximum temperature	ncepshumgl.dat	Surface specific humidity	0.06	0.000
Minimum temperature	ncepp850gl.dat	850hpa potential height	0.138	0.000
Welenchiti station				
Precipitation	ncepp5_fgl.dat	500hpa airflow strength	0.02	0.043
Maximum temperature	ncepprcpgl.dat	Unknown	0.098	0.0001
Minimum Temperature	nceptempgl.dat	Mean temperature at 2m	0.11	0.000

Appendix Table 2. SDSM performance during calibration and validation

Stations	Climate parameters		Performance evaluation		
			R ²	RMSE	NSE
Abomsa	Precipitation	Calibration	0.56	3.77	0.43
		Validation	0.58	1.56	0.23
	Maximum temperature	Calibration	0.69	11.4	0.62
		Validation	0.59	22.2	0.67
	Minimum temperature	Calibration	0.73	28.4	0.48
		Validation	0.70	24.67	0.70
Arerti	Precipitation	Calibration	0.42	13.46	0.13
		Validation	0.53	12.45	0.21
	Maximum temperature	Calibration	0.74	0.45	0.37
		Validation	0.72	12.34	0.64
	Minimum temperature	Calibration	0.69	14.5	0.38
		Validation	0.68	23.3	0.48
Melka Jilo	Precipitation	Calibration	0.38	17.91	0.49
		Validation	0.59	24.62	0.18
	Maximum temperature	Calibration	0.71	16.25	0.22
		Validation	0.72	2.07	0.68
	Minimum temperature	Calibration	0.67	1.35	0.43
		Validation	0.64	3.27	0.63
Metahara	Precipitation	Calibration	0.47	31.35	0.23
		Validation	0.67	17.35	0.15
	Maximum temperature	Calibration	0.84	0.183	0.62
		Validation	0.92	0.11	0.80
	Minimum temperature	Calibration	0.88	0.86	0.53
		Validation	0.81	0.98	0.71
Welenchiti	Precipitation	Calibration	0.41	12.46	0.12
		Validation	0.64	0.18	0.44
	Maximum temperature	Calibration	0.71	0.56	0.37
		Validation	0.86	0.78	0.34
	Minimum temperature	Calibration	0.70	11.5	0.24
		Validation	0.69	24.2	0.21

CROPWAT Model results

Appendix Table 3.CROPWAT model results for CanESM2-RCP2.6-2020s

Month	Decade	Stage	Kc	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.81	1.52	15.2	2.3	12.9
Jun	2	Init	0.4	3.81	1.52	15.2	12	3.2
Jun	3	Init	0.4	3.81	1.52	15.6	12.6	3.0
Jul	1	Deve	0.4	4.05	1.6	16	11.2	4.8
Jul	2	Deve	0.5	4.05	2.01	20.1	10.9	9.3
Jul	3	Deve	0.63	4.05	2.56	25.6	19.7	8.4
Aug	1	Deve	0.77	4.03	3.11	31.1	32.8	0
Aug	2	Deve	0.9	4.03	3.63	36.3	42.3	0
Aug	3	Deve	1.04	4.03	4.23	42.5	37.2	9.3
Sep	1	Mid	1.16	4.18	4.79	47.9	29.3	18.6
Sep	2	Mid	1.18	4.18	4.93	49.3	25.2	24.1
Sep	3	Mid	1.18	4.18	4.93	49.3	26.7	21.9
Oct	1	Mid	1.18	3.99	4.71	47.1	29.2	18.6
Oct	2	Mid	1.18	3.99	4.71	47.1	30.3	16.8
Oct	3	Mid	1.18	3.99	4.7	47.0	29.5	22.2
Nov	1	Mid	1.18	3.96	4.69	46.9	28.5	18.4
Nov	2	Mid	1.18	3.96	4.68	46.8	27.9	18.9
Nov	3	Mid	1.18	3.96	4.69	46.9	27.2	19.7
Dec	1	Mid	1.18	3.99	4.7	47	26.2	20.8
Dec	2	Mid	1.18	3.99	4.71	47.1	25.3	21.8
Dec	3	Mid	1.18	3.99	4.63	46.3	25.9	25.1
Jan	1	Mid	1.18	3.8	4.56	45.6	27.4	18.3
Jan	2	Mid	1.18	3.8	4.49	44.9	28.2	16.7
Jan	3	Mid	1.18	3.8	4.51	45.1	25.4	24.2
Feb	1	Mid	1.18	3.86	4.55	45.4	21.9	23.5
Feb	2	Mid	1.18	3.86	4.55	55.6	19.3	26.3
Feb	3	Mid	1.18	3.86	4.55	45.5	18.6	18.5
Mar	1	Late	1.17	4.08	4.7	47	18.4	28.6
Mar	2	Late	1.13	4.08	4.6	46	17.6	28.4
Mar	3	Late	1.07	4.08	4.36	53.6	15.7	32.2
Apr	1	Late	1.02	4.01	4.12	41.2	13.4	27.8
Apr	2	Late	0.97	4.01	3.89	38.9	11.5	27.4
Apr	3	Late	0.92	4.01	3.73	37.3	22	15.3
May	1	Late	0.87	4.15	3.57	35.7	10.4	25.3
May	2	Late	0.82	4.15	3.4	34	20.6	13.4
May	3	Late	0.77	4.15	3.09	31	10.4	23.6
Jun	1	Late	0.72	3.81	2.75	27.5	9.1	18.4
						1428.65	761.4	667.27

Appendix Table 4.CROPWAT model results for CanESM2-RCP2.6-2050s

Month	Decade	Stage	Kc	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.79	1.52	15.2	2.5	12.7
Jun	2	Init	0.4	3.79	1.52	15.2	13.1	2.1
Jun	3	Init	0.4	3.79	1.52	15.2	13.8	1.4
Jul	1	Deve	0.4	4.03	1.61	16.1	12.1	4.0
Jul	2	Deve	0.5	4.03	2.01	20.1	11.7	8.5
Jul	3	Deve	0.63	4.03	2.54	25.4	21.3	4.1
Aug	1	Deve	0.77	4.03	3.10	31.0	35.6	0.0
Aug	2	Deve	0.9	4.03	3.63	36.3	45.9	0.0
Aug	3	Deve	1.04	4.03	4.19	41.9	39.7	2.2
Sep	1	Mid	1.16	4.18	4.84	48.4	30.3	18.1
Sep	2	Mid	1.18	4.18	4.93	49.3	25.2	24.1
Sep	3	Mid	1.18	4.18	4.93	49.3	26.5	22.8
Oct	1	Mid	1.18	3.98	4.69	46.9	28.7	18.3
Oct	2	Mid	1.18	3.98	4.69	46.9	29.3	17.6
Oct	3	Mid	1.18	3.98	4.69	46.9	28.7	18.2
Nov	1	Mid	1.18	3.97	4.68	46.8	27.9	18.9
Nov	2	Mid	1.18	3.97	4.68	46.8	27.4	19.4
Nov	3	Mid	1.18	3.97	4.68	46.8	26.9	19.9
Dec	1	Mid	1.18	4.03	4.76	47.6	26.3	21.3
Dec	2	Mid	1.18	4.03	4.76	47.6	25.7	21.9
Dec	3	Mid	1.18	4.03	4.76	47.6	26.2	21.4
Jan	1	Mid	1.18	3.84	4.53	45.3	27.4	17.9
Jan	2	Mid	1.18	3.84	4.53	45.3	23.1	22.2
Jan	3	Mid	1.18	3.84	4.53	45.3	25.6	19.7
Feb	1	Mid	1.18	3.87	4.56	45.6	22.5	23.2
Feb	2	Mid	1.18	3.87	4.56	45.6	20.2	25.4
Feb	3	Mid	1.18	3.87	4.56	45.6	19.5	26.2
Mar	1	Late	1.17	4.10	4.79	47.9	19.3	28.7
Mar	2	Late	1.13	4.10	4.63	46.3	18.5	27.8
Mar	3	Late	1.07	4.10	4.38	43.8	16.4	27.5
Apr	1	Late	1.02	4.03	4.11	41.1	13.6	27.5
Apr	2	Late	0.97	4.03	3.90	39.0	11.3	27.7
Apr	3	Late	0.92	4.03	3.70	37.0	11.3	25.8
May	1	Late	0.87	4.15	3.61	36.1	11.2	25.0
May	2	Late	0.82	4.15	3.40	34.0	10.7	23.3
May	3	Late	0.76	4.15	3.15	31.5	11.5	20.0
Jun	1	Late	0.72	3.79	2.73	27.3	17.5	9.8
Jun	1	Init	0.72	3.79	2.73	27.3	2.5	24.8
						1430.36	777.6	653.1

Appendix Table 5.CROPWAT Model results for CanESM2-RCP2.6-2080s

Month	Decade	Stage	Kc	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.79	1.52	15.2	2.4	12.8
Jun	2	Init	0.4	3.79	1.52	15.2	12.9	2.3
Jun	3	Init	0.4	3.79	1.52	15.2	13.5	2
Jul	1	Deve	0.4	4.03	1.6	16	11.8	4.1
Jul	2	Deve	0.5	4.03	2	20	11.3	8.7
Jul	3	Deve	0.63	4.03	2.54	25.4	21.3	4.1
Aug	1	Deve	0.77	3.99	3.08	30.8	36.4	0
Aug	2	Deve	0.9	3.99	3.59	35.9	47.2	0
Aug	3	Deve	1.04	3.99	4.18	42	40.3	2.3
Sep	1	Mid	1.16	4.14	4.74	47.4	29.7	17.7
Sep	2	Mid	1.18	4.14	4.81	48.8	23.8	25
Sep	3	Mid	1.18	4.14	4.81	48.1	25.4	22.7
Oct	1	Mid	1.18	3.96	4.67	46.7	28.2	19.2
Oct	2	Mid	1.18	3.96	4.67	46.7	29.2	17.5
Oct	3	Mid	1.18	3.96	4.67	46.7	28.5	22.7
Nov	1	Mid	1.18	3.93	4.64	46.4	27.7	18.7
Nov	2	Mid	1.18	3.93	4.63	46.3	27.3	19.1
Nov	3	Mid	1.18	3.93	4.64	46.6	26.7	20
Dec	1	Mid	1.18	4.01	4.69	46.9	25.8	21.2
Dec	2	Mid	1.18	4.01	4.72	47.2	25	22.2
Dec	3	Mid	1.18	4.01	4.65	46.5	25.7	25.5
Jan	1	Mid	1.18	3.82	4.58	45.8	27.3	18.5
Jan	2	Mid	1.18	3.82	4.5	45	28.2	16.9
Jan	3	Mid	1.18	3.82	4.52	45.7	25.4	24.3
Feb	1	Mid	1.18	3.86	4.54	45.4	21.8	23.5
Feb	2	Mid	1.18	3.86	4.55	45.5	19.2	26.3
Feb	3	Mid	1.18	3.86	4.65	46.5	18.5	18.7
Mar	1	Late	1.17	4.11	4.72	47.2	18.3	28.9
Mar	2	Late	1.13	4.11	4.63	46.3	27.5	18.8
Mar	3	Late	1.07	4.11	4.38	43.2	15.5	32.6
Apr	1	Late	1.02	4.03	4.14	41.4	13.1	28.3
Apr	2	Late	0.97	4.03	3.9	39	11.1	28
Apr	3	Late	0.92	4.03	3.74	37.4	11	26.4
May	1	Late	0.87	4.15	3.57	35.7	10.8	24.9
May	2	Late	0.82	4.15	3.4	34	10.4	23.6
May	3	Late	0.77	4.15	3.09	31	11.2	19.7
Jun	1	Late	0.72	3.79	2.72	27.2	9.7	17.3
						1426.8	762.8	664.05

Appendix Table 6.CROPWAT Model results for CanESM2-RCP4.5-2020s

Month	Decade	Stage	Kc	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.78	1.40	14	2.4	11.6
Jun	2	Init	0.4	3.78	1.52	15.2	13	2.2
Jun	3	Init	0.4	3.78	1.52	15.2	13.6	1.6
Jul	1	Deve	0.4	4.08	1.61	16.1	12.2	3.9
Jul	2	Deve	0.5	4.08	2.03	20.3	11.8	8.5
Jul	3	Deve	0.63	4.08	2.58	25.8	20.7	5.1
Aug	1	Deve	0.77	4.04	3.12	31.2	33.7	0
Aug	2	Deve	0.9	4.04	3.64	36.4	43.1	0
Aug	3	Deve	1.04	4.04	4.25	42.5	38.1	8.7
Sep	1	Mid	1.16	4.2	4.82	48.2	30.3	17.9
Sep	2	Mid	1.18	4.2	4.96	49.6	26.2	23.4
Sep	3	Mid	1.18	4.2	4.88	48.8	27.2	21.6
Oct	1	Mid	1.18	4	4.8	48	29	19.1
Oct	2	Mid	1.18	4	4.72	47.2	29.5	17.7
Oct	3	Mid	1.18	4	4.71	47.1	29.2	22.5
Nov	1	Mid	1.18	3.95	4.69	46.9	29.2	17.7
Nov	2	Mid	1.18	3.95	4.67	46.7	29.1	17.6
Nov	3	Mid	1.18	3.95	4.69	46.9	27.7	19.2
Dec	1	Mid	1.18	4.01	4.71	47.1	25.8	21.4
Dec	2	Mid	1.18	4.01	4.74	47.4	24.3	23.1
Dec	3	Mid	1.18	4.01	4.66	46.6	25.2	26.1
Jan	1	Mid	1.18	3.81	4.58	45.8	27	18.8
Jan	2	Mid	1.18	3.81	4.5	45	28	17
Jan	3	Mid	1.18	3.81	4.51	45.1	25.5	24.2
Feb	1	Mid	1.18	3.84	4.53	45.3	22.2	23.1
Feb	2	Mid	1.18	3.84	4.54	45.4	19.9	25.5
Feb	3	Mid	1.18	3.84	4.64	46.4	19.3	17.8
Mar	1	Late	1.17	4.09	4.7	47	19.2	27.8
Mar	2	Late	1.13	4.09	4.61	46.1	18.6	27.5
Mar	3	Late	1.07	4.09	4.37	48.1	16.4	31.7
Apr	1	Late	1.02	4.03	4.14	41.4	13.7	27.6
Apr	2	Late	0.97	4.03	3.91	39.1	11.5	27.6
Apr	3	Late	0.92	4.03	3.75	37.5	11	26.5
May	1	Late	0.87	4.15	3.58	35.8	10.1	25.6
May	2	Late	0.82	4.15	3.4	34	9.2	24.8
May	3	Late	0.77	4.15	3.09	30.9	10.4	20.5
Jun	1	Late	0.72	3.78	2.73	27.3	9.6	17.7
						1430.1	766.3	663.85

Appendix Table 7.CROPWAT Model results for CanESM2-RCP4.5-2050s

Month	Decade	Stage	Kc	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.77	1.51	15.1	2.6	12.6
Jun	2	Init	0.4	3.77	1.51	15.1	13.6	1.5
Jun	3	Init	0.4	3.77	1.51	15.1	14.2	0.9
Jul	1	Deve	0.4	4.00	1.60	16.0	12.4	3.6
Jul	2	Deve	0.5	4.00	2.00	20.0	11.8	8.2
Jul	3	Deve	0.63	4.00	2.52	25.2	22.0	3.3
Aug	1	Deve	0.77	4.00	3.08	30.8	37.2	0.0
Aug	2	Deve	0.9	4.00	3.60	36.0	48.1	0.0
Aug	3	Deve	1.04	4.00	4.15	41.5	41.0	0.6
Sep	1	Mid	1.16	4.17	4.83	48.3	30.1	18.2
Sep	2	Mid	1.18	4.17	4.91	49.1	24.1	25.0
Sep	3	Mid	1.18	4.17	4.91	49.1	25.7	23.4
Oct	1	Mid	1.18	3.99	4.70	47.0	28.6	18.5
Oct	2	Mid	1.18	3.99	4.70	47.0	29.5	17.6
Oct	3	Mid	1.18	3.99	4.70	47.0	28.7	18.3
Nov	1	Mid	1.18	3.96	4.67	46.7	27.6	19.1
Nov	2	Mid	1.18	3.96	4.67	46.7	27.0	19.8
Nov	3	Mid	1.18	3.96	4.67	46.7	26.7	20.1
Dec	1	Mid	1.18	4.04	4.76	47.6	26.2	21.4
Dec	2	Mid	1.18	4.04	4.76	47.6	25.9	21.8
Dec	3	Mid	1.18	4.04	4.76	47.6	26.0	21.7
Jan	1	Mid	1.18	3.86	4.55	45.5	26.8	18.8
Jan	2	Mid	1.18	3.86	4.55	45.5	27.2	18.4
Jan	3	Mid	1.18	3.86	4.55	45.5	24.9	20.6
Feb	1	Mid	1.18	3.87	4.57	45.7	22.1	23.6
Feb	2	Mid	1.18	3.87	4.57	45.7	19.9	25.8
Feb	3	Mid	1.18	3.87	4.57	45.7	19.3	26.4
Mar	1	Late	1.17	4.10	4.79	47.9	19.4	28.6
Mar	2	Late	1.13	4.10	4.63	46.3	18.8	27.5
Mar	3	Late	1.07	4.10	4.38	43.8	16.4	27.4
Apr	1	Late	1.02	4.01	4.09	40.9	13.3	27.6
Apr	2	Late	0.97	4.01	3.88	38.8	10.9	28.0
Apr	3	Late	0.92	4.01	3.68	36.8	10.9	25.9
May	1	Late	0.87	4.14	3.60	36.0	10.9	25.1
May	2	Late	0.82	4.14	3.39	33.9	10.6	23.4
May	3	Late	0.77	4.14	3.19	31.9	11.6	20.3
Jun	1	Late	0.72	3.77	2.71	27.1	10.2	17.0
						1426.95	767.55	659.34

Appendix Table 8.CROPWAT Model results for CanESM2-RCP4.5-2080s

Month	Decade	Stage	Kc	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.77	1.51	15.1	2.5	12.6
Jun	2	Init	0.4	3.77	1.51	15.1	13.3	1.8
Jun	3	Init	0.4	3.77	1.51	15.4	14	1.4
Jul	1	Deve	0.4	4.03	1.59	15.9	12.1	3.8
Jul	2	Deve	0.5	4.03	2	20	11.6	8.4
Jul	3	Deve	0.63	4.03	2.54	25.4	22.6	2.8
Aug	1	Deve	0.77	4	3.08	30.8	39.2	0
Aug	2	Deve	0.9	4	3.59	35.9	51.2	0
Aug	3	Deve	1.03	4	4.39	43.9	47.2	0
Sep	1	Mid	1.16	4.15	4.74	47.4	31.3	16.1
Sep	2	Mid	1.18	4.15	4.88	48.8	24.7	24.1
Sep	3	Mid	1.18	4.15	4.82	48.2	26	22.2
Oct	1	Mid	1.18	3.99	4.75	47.5	28.3	19.2
Oct	2	Mid	1.18	3.99	4.69	46.9	28.8	18.1
Oct	3	Mid	1.18	3.99	4.68	46.8	28.5	23
Nov	1	Mid	1.18	3.95	4.67	46.7	28.2	18.5
Nov	2	Mid	1.18	3.95	4.65	46.5	28	18.5
Nov	3	Mid	1.18	3.95	4.68	46.8	27.1	19.7
Dec	1	Mid	1.18	4.02	4.7	47	25.8	21.2
Dec	2	Mid	1.18	4.02	4.73	47.3	24.8	22.4
Dec	3	Mid	1.18	4.02	4.67	46.7	25.3	26
Jan	1	Mid	1.18	3.86	4.61	46.1	26.6	19.4
Jan	2	Mid	1.18	3.86	4.55	45.5	27.3	18.2
Jan	3	Mid	1.18	3.86	4.54	45.4	24.6	25.4
Feb	1	Mid	1.18	3.85	4.54	45.4	20.9	24.5
Feb	2	Mid	1.18	3.85	4.54	45.4	18.3	27.1
Feb	3	Mid	1.18	3.85	4.63	46.3	18.2	18.9
Mar	1	Late	1.17	4.09	4.69	46.9	18.6	28.3
Mar	2	Late	1.12	4.09	4.6	46	18.4	27.6
Mar	3	Late	1.07	4.09	4.35	43.5	16.5	31.4
Apr	1	Late	1.02	4.01	4.11	41.1	14.2	26.9
Apr	2	Late	0.97	4.01	3.88	38.8	12.4	26.4
Apr	3	Late	0.92	4.01	3.71	37.1	12.1	25.1
May	1	Late	0.87	4.11	3.54	35.4	11.6	23.8
May	2	Late	0.82	4.11	3.36	33.6	10.9	22.7
May	3	Late	0.77	4.11	3.06	30.6	11.7	18.9
Jun	1	Late	0.72	3.77	2.72	27.3	10.1	17.2
						1424.25	770.1	654.23

Appendix Table 9.CROPWAT Model results for CanESM2-RCP8.5-2020s

Month	Decade	Stage	Kc	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.77	1.51	15.1	2.4	12.7
Jun	2	Init	0.4	3.77	1.51	15.1	12.7	2.4
Jun	3	Init	0.4	3.77	1.55	15.5	13.4	2
Jul	1	Deve	0.4	4.04	1.6	16	12.2	3.8
Jul	2	Deve	0.5	4.04	2.01	20.1	12	8.1
Jul	3	Deve	0.63	4.04	2.56	25.6	20.7	4.9
Aug	1	Deve	0.77	4.03	3.1	31	33.5	0
Aug	2	Deve	0.9	4.03	3.62	36.2	42.9	0
Aug	3	Deve	1.04	4.03	4.2	42.2	37.8	8.4
Sep	1	Mid	1.16	4.13	4.74	47.4	30	17.5
Sep	2	Mid	1.18	4.13	4.86	48.6	25.9	22.7
Sep	3	Mid	1.18	4.13	4.79	47.9	27.5	20.4
Oct	1	Mid	1.18	3.95	4.72	47.2	30.1	17.1
Oct	2	Mid	1.18	3.95	4.65	46.5	31.3	15.2
Oct	3	Mid	1.18	3.95	4.66	46.6	30.4	20.8
Nov	1	Mid	1.18	3.97	4.66	46.6	29.4	17.2
Nov	2	Mid	1.18	3.97	4.67	46.7	28.8	17.9
Nov	3	Mid	1.18	3.97	4.69	46.9	27.3	19.6
Dec	1	Mid	1.18	4.02	4.72	47.2	25.2	22
Dec	2	Mid	1.18	4.02	4.74	47.4	23.5	23.9
Dec	3	Mid	1.18	4.02	4.67	51.4	24.4	26.9
Jan	1	Mid	1.18	3.85	4.6	46	26.4	19.5
Jan	2	Mid	1.18	3.85	4.53	45.3	27.5	17.8
Jan	3	Mid	1.18	3.85	4.53	49.9	24.9	25
Feb	1	Mid	1.18	3.86	4.54	45.4	21.4	24
Feb	2	Mid	1.18	3.86	4.54	45.4	18.9	26.5
Feb	3	Mid	1.18	3.86	4.64	46.1	18.6	18.5
Mar	1	Late	1.17	4.09	4.7	47	18.8	28.2
Mar	2	Late	1.13	4.09	4.61	46.1	18.4	27.6
Mar	3	Late	1.07	4.09	4.35	47.9	16.1	31.8
Apr	1	Late	1.02	3.99	4.1	41	13.1	27.9
Apr	2	Late	0.97	3.99	3.87	38.7	10.8	27.9
Apr	3	Late	0.92	3.99	3.72	37.2	10.6	26.6
May	1	Late	0.87	4.15	3.56	35.6	10.2	25.4
May	2	Late	0.82	4.15	3.4	34	9.5	24.5
May	3	Late	0.77	4.15	3.08	30.9	10.6	20.3
Jun	1	Late	0.72	3.77	2.71	27.1	9.4	17.7
						1425.1	762.4	662.7

Appendix Table 10.CROPWAT Model results for CanESM2-RCP8.5-2050s

Month	Decade	Stage	Kc	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.77	1.51	15.1	2.5	12.6
Jun	2	Init	0.4	3.77	1.51	15.1	13.1	2.0
Jun	3	Init	0.4	3.77	1.51	15.1	13.8	1.3
Jul	1	Deve	0.4	4.06	1.62	16.2	12.2	4.0
Jul	2	Deve	0.5	4.06	2.03	20.3	11.7	8.6
Jul	3	Deve	0.63	4.06	2.56	25.6	22	3.6
Aug	1	Deve	0.77	4.02	3.09	30.9	37.6	0.0
Aug	2	Deve	0.9	4.02	3.61	36.1	48.8	0.0
Aug	3	Deve	1.04	4.02	4.18	41.8	41.2	0.6
Sep	1	Mid	1.16	4.17	4.84	48.4	29.9	18.5
Sep	2	Mid	1.18	4.17	4.92	49.2	23.55	25.7
Sep	3	Mid	1.18	4.17	4.92	49.2	24.7	24.5
Oct	1	Mid	1.18	3.99	4.71	47.1	26.9	20.2
Oct	2	Mid	1.18	3.99	4.71	47.1	27.35	19.7
Oct	3	Mid	1.18	3.99	4.71	47.1	27	20.1
Nov	1	Mid	1.18	3.97	4.68	46.8	26.55	20.3
Nov	2	Mid	1.18	3.97	4.68	46.8	26.25	20.6
Nov	3	Mid	1.18	3.97	4.68	46.8	26.6	20.2
Dec	1	Mid	1.18	4.05	4.78	47.8	27.1	20.7
Dec	2	Mid	1.18	4.05	4.78	47.8	27.4	20.4
Dec	3	Mid	1.18	4.05	4.78	47.8	26.9	20.9
Jan	1	Mid	1.18	3.85	4.54	45.4	26.65	18.7
Jan	2	Mid	1.18	3.85	4.54	45.4	26.4	19.0
Jan	3	Mid	1.18	3.85	4.54	45.4	24.35	21.0
Feb	1	Mid	1.18	3.87	4.57	45.7	21.9	23.8
Feb	2	Mid	1.18	3.87	4.57	45.7	19.9	25.8
Feb	3	Mid	1.18	3.87	4.57	45.7	19.25	26.4
Mar	1	Late	1.17	4.12	4.81	48.1	19	29.1
Mar	2	Late	1.13	4.12	4.65	46.5	18.3	28.2
Mar	3	Late	1.07	4.12	4.40	44.0	16.4	27.6
Apr	1	Late	1.02	4.03	4.11	41.1	14	27.1
Apr	2	Late	0.97	4.03	3.90	39.0	12.05	27.0
Apr	3	Late	0.92	4.03	3.70	37.0	11.7	25.3
May	1	Late	0.87	4.14	3.60	36.0	11.2	24.8
May	2	Late	0.82	4.14	3.39	33.9	10.5	23.4
May	3	Late	0.76	4.14	3.14	31.4	11.35	20.1
Jun	1	Late	0.72	3.77	2.71	27.1	9.95	17.2
						1429.1	761.8	667.3

Appendix Table 11.CROPWAT Model results for CanESM2-RCP8.5-2080s

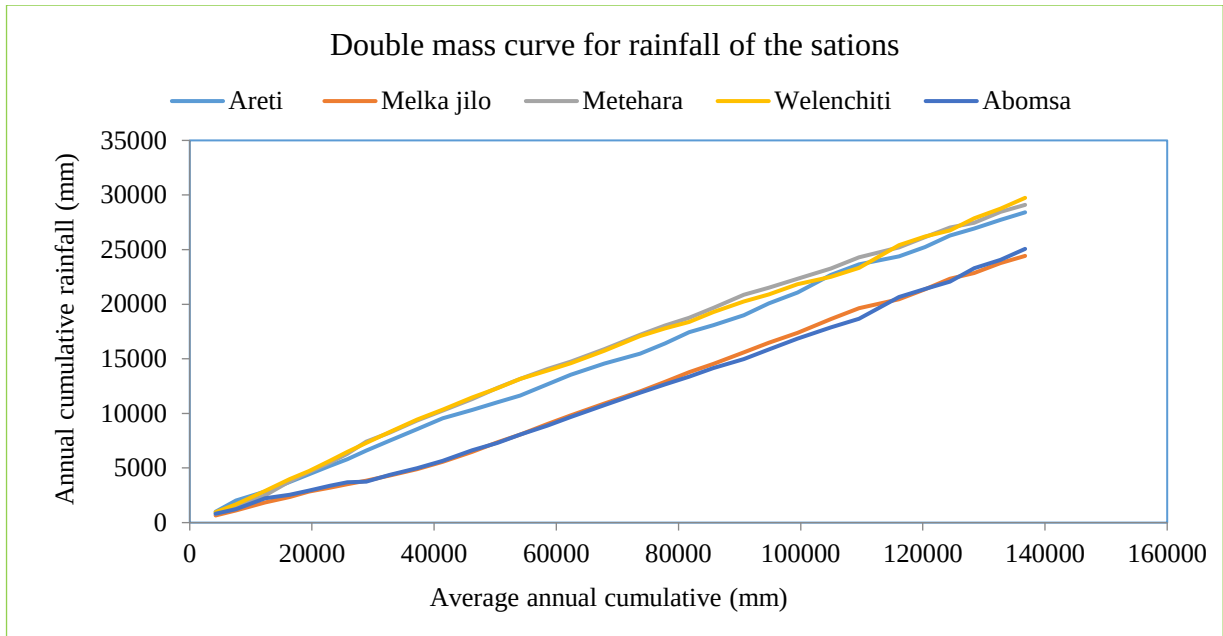
Month	Decade	Stage	Kc coeff	ETo mm/day	ETc mm/day	ETc mm/dec	Eff rain mm/dec	Irr. Req. mm/dec
Jun	1	Init	0.4	3.77	1.51	15.1	2.9	12.2
Jun	2	Init	0.4	3.77	1.51	15.1	16.2	0
Jun	3	Init	0.4	3.77	1.55	15.5	15.9	0
Jul	1	Deve	0.4	4.08	1.61	16.1	12.4	3.6
Jul	2	Deve	0.5	4.08	2.03	20.3	10.8	9.4
Jul	3	Deve	0.63	4.08	2.56	25.6	23	5.2
Aug	1	Deve	0.77	4	3.08	30.8	41.8	0
Aug	2	Deve	0.89	4	3.57	35.7	55	0
Aug	3	Deve	1.03	4	4.17	41.7	45.1	0
Sep	1	Mid	1.15	4.16	4.73	47.3	30.6	16.7
Sep	2	Mid	1.17	4.16	4.87	48.7	22.2	26.4
Sep	3	Mid	1.17	4.16	4.81	48.1	23.4	24.6
Oct	1	Mid	1.17	3.99	4.74	47.4	25.6	21.8
Oct	2	Mid	1.17	3.99	4.68	46.8	25.8	21
Oct	3	Mid	1.17	3.99	4.67	46.7	25.8	25.6
Nov	1	Mid	1.17	3.98	4.66	46.6	25.6	21
Nov	2	Mid	1.17	3.98	4.66	46.6	25.6	21
Nov	3	Mid	1.17	3.98	4.69	46.9	26.2	20.8
Dec	1	Mid	1.17	4.07	4.73	47.3	27.2	20.1
Dec	2	Mid	1.17	4.07	4.77	47.7	27.9	19.8
Dec	3	Mid	1.17	4.07	4.7	47	26.9	24.9
Jan	1	Mid	1.17	3.9	4.64	46.4	25.7	20.7
Jan	2	Mid	1.17	3.9	4.57	45.7	24.8	20.9
Jan	3	Mid	1.17	3.9	4.57	45.7	23.9	26.4
Feb	1	Mid	1.17	3.9	4.56	45.6	23	22.6
Feb	2	Mid	1.17	3.9	4.56	45.6	22.1	23.5
Feb	3	Mid	1.17	3.9	4.64	46.4	20.5	16.6
Mar	1	Late	1.16	4.11	4.7	47	18.9	28.1
Mar	2	Late	1.12	4.11	4.59	45.9	17.3	28.6
Mar	3	Late	1.07	4.11	4.35	43.8	15.9	31.9
Apr	1	Late	1.01	4.01	4.1	41	14.1	26.9
Apr	2	Late	0.96	4.01	3.87	38.7	12.5	26.1
Apr	3	Late	0.91	4.01	3.71	37.1	12.3	24.8
May	1	Late	0.86	4.14	3.54	35.4	11.7	23.8
May	2	Late	0.82	4.14	3.37	33.7	11	22.7
May	3	Late	0.76	4.14	3.06	30.7	12.6	21.1
Jun	1	Late	0.72	3.77	2.71	27.3	11.8	15.5
						1426.25	767.5	658.8

AppendixTable12. Projected annual future sugarcane CWR and IWR differences from baseline period sugarcane CWR and IWR

Parameter	Climate scenario	Time slices		
		2020s	2050s	2080s
CWR (mm)	RCP 2.6	1428.65	1430.36	1426.8
	Difference from baseline	3.85 (0.27%)	5.56 (0.39%)	2 (0.14%)
	RCP 4.5	1430.1	1426.95	1424.25
	Difference from baseline	7.3 (0.51%)	2.15 (0.15%)	-0.55 (0.04%)
	RCP 8.5	1425.1	1429.1	1426.25
	Difference from baseline	0.3 (0.02%)	4.3 (0.3%)	1.45 (0.1%)
IWR (mm)	RCP 2.6	667.27	653.1	664.05
	Difference from baseline	5.14(0.8%)	-9 (1.36%)	1.9 (0.3%)
	RCP 4.5	663.85	659.34	654.23
	Difference from baseline	1.73 (0.26%)	-2.78 (0.4%)	-7.8 (1.2%)
	RCP 8.5	662.7	667.3	658.8
	Difference from baseline	0.6 (0.08%)	5.2(0.78%)	-3.33 (0.5%)

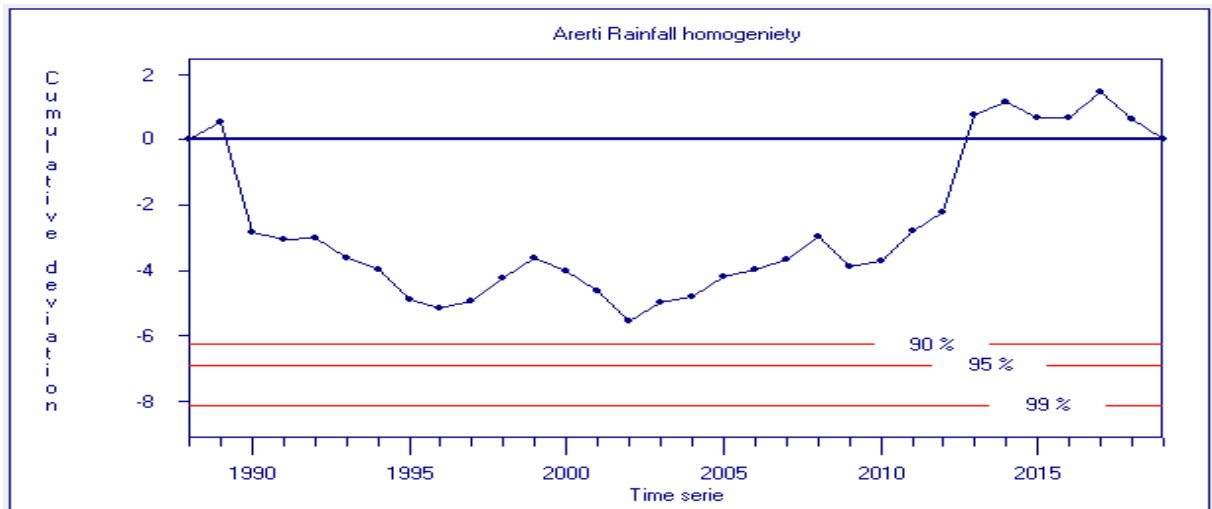
Appendix B

Appendix Figures

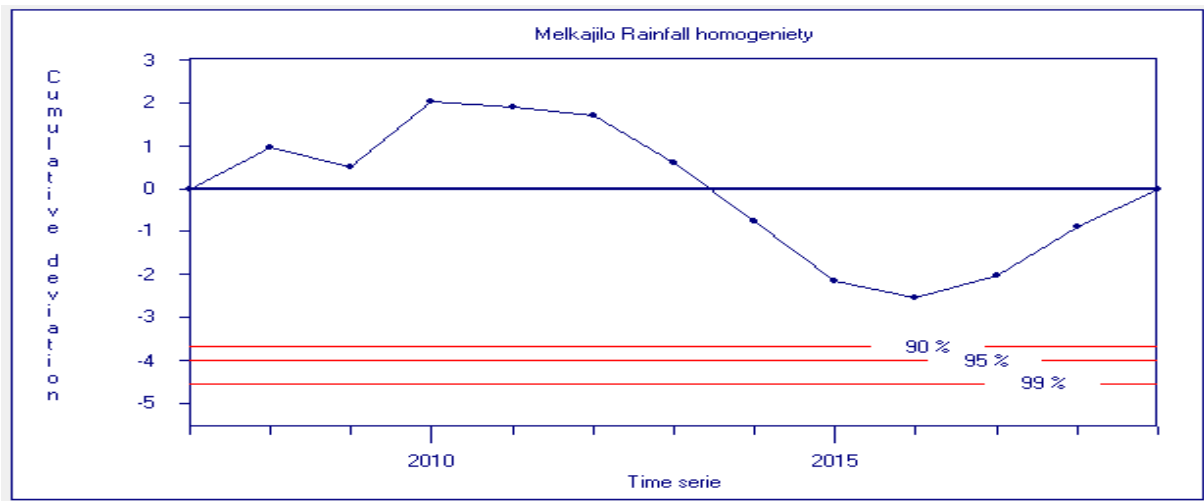


Appendix Figure 1. Double Mass Curve for stations in Upper Awash sub-basin

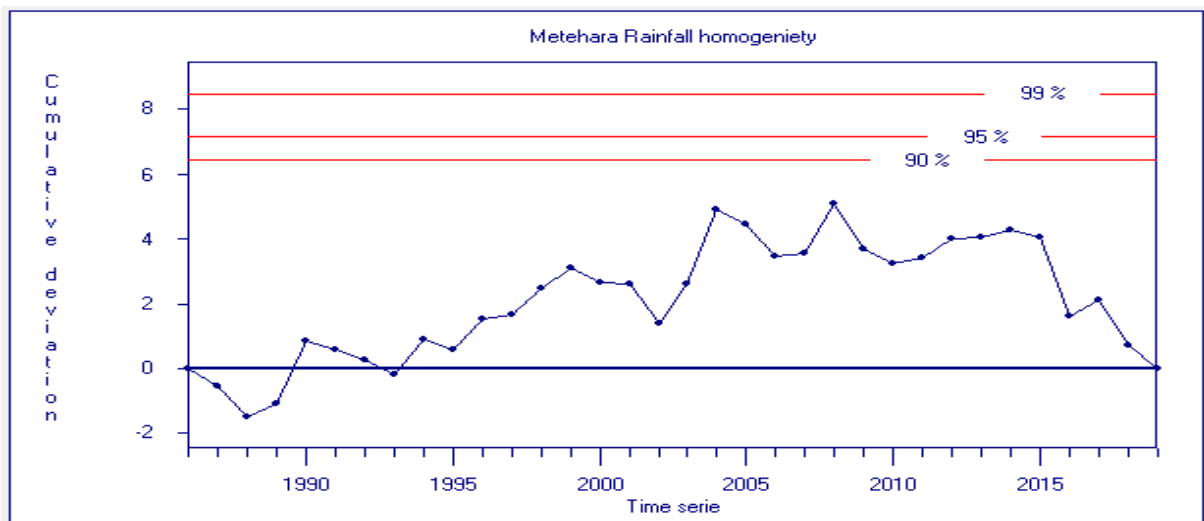
Homogeneity test graph



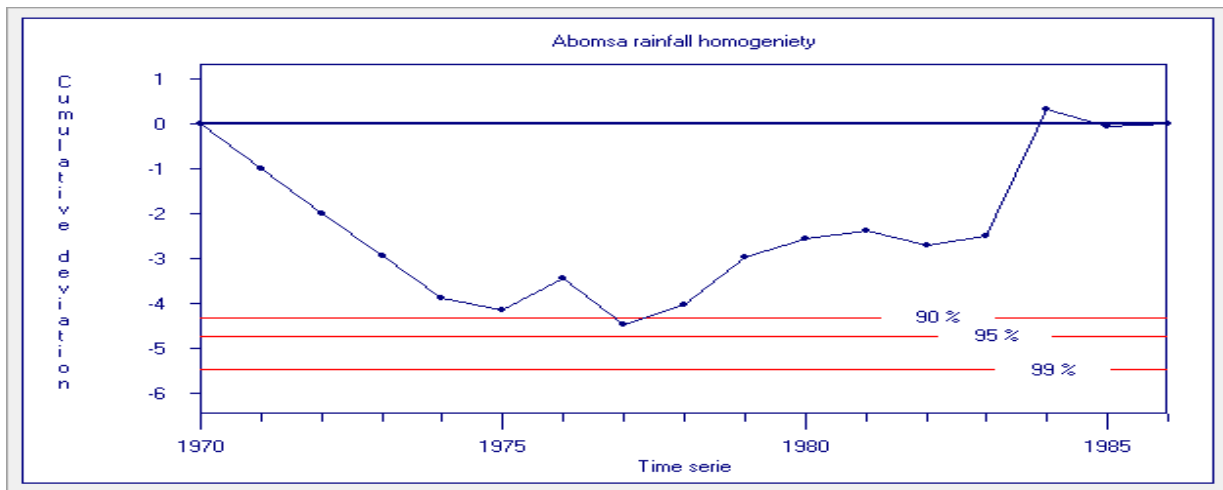
Appendix Figure 2. Homogeneity test of annual precipitation series at Arerti station (Homogeneous)



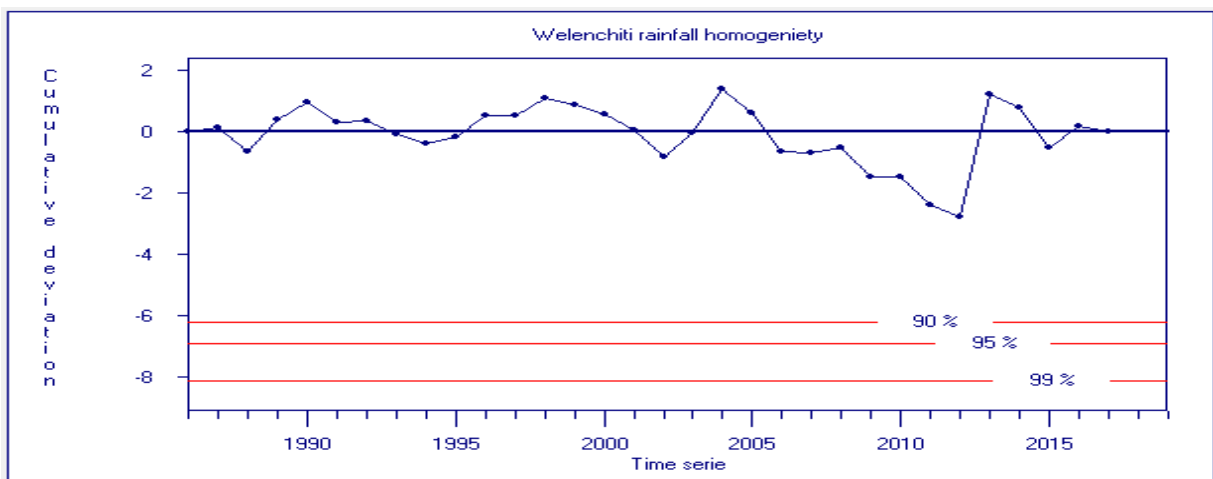
Appendix Figure 3. Homogeneity test of annual precipitation series at Melka Jilo station (Homogeneous)



Appendix Figure 4. Homogeneity test of annual precipitation series at Metahara station (Homogeneous)



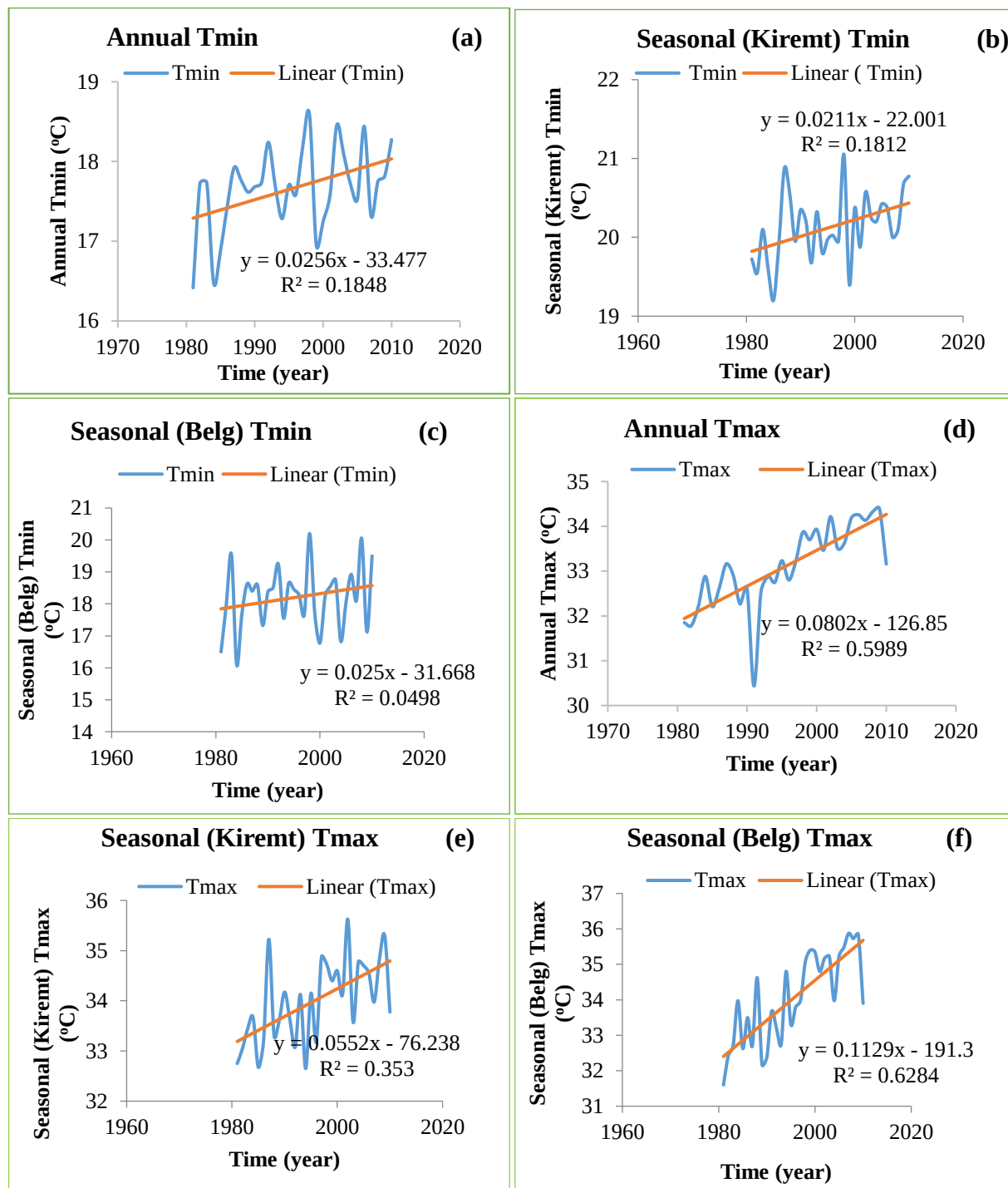
Appendix Figure 5.Homogeniety test of annual precipitation series at Abomsa station (Homogeneous)

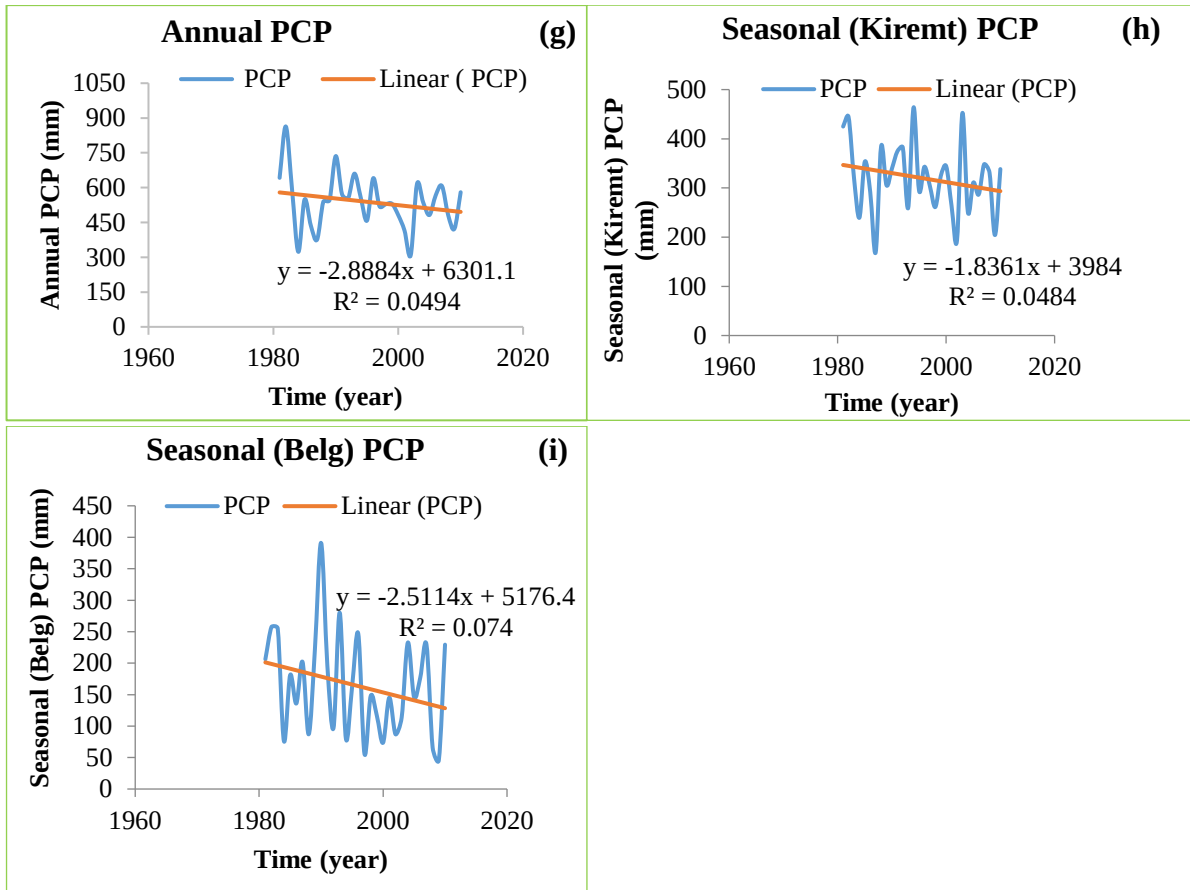


Appendix Figure 6.Homogeniety test of annual precipitation series at Welenchiti station (Homogeneous)

Graph of trend analysis of historical rainfall, maximum temperature and minimum temperature

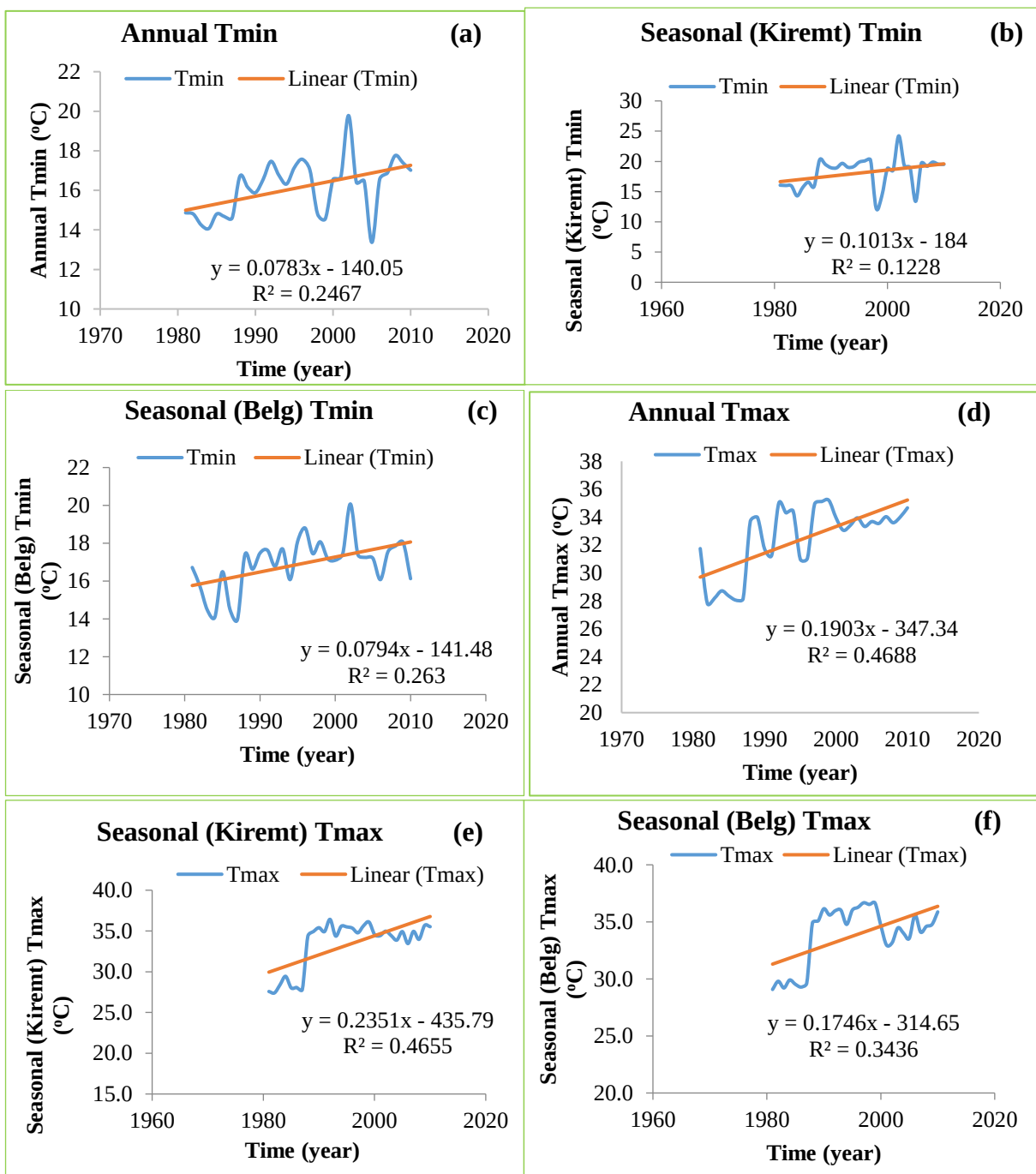
Abomsa station

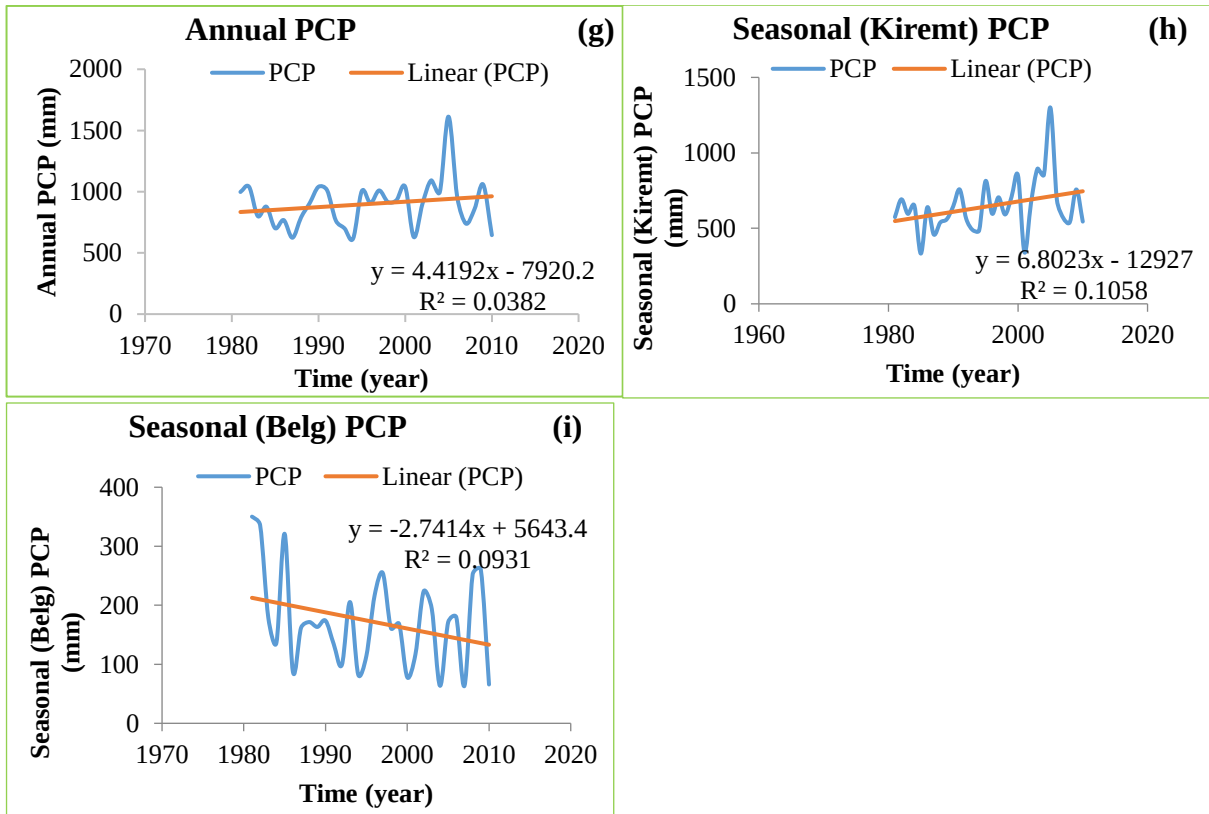




Appendix Figure 7: a, b and c: Trend analysis of annual, Kiremt and Belg (seasonal) minimum temperature respectively; d, e and f: Trend analysis of annual, Kiremt and Belg seasons maximum temperature respectively; g, h and i: trend analysis of annual, Kiremt and Belg seasons precipitation for Abomsa station of the study area.

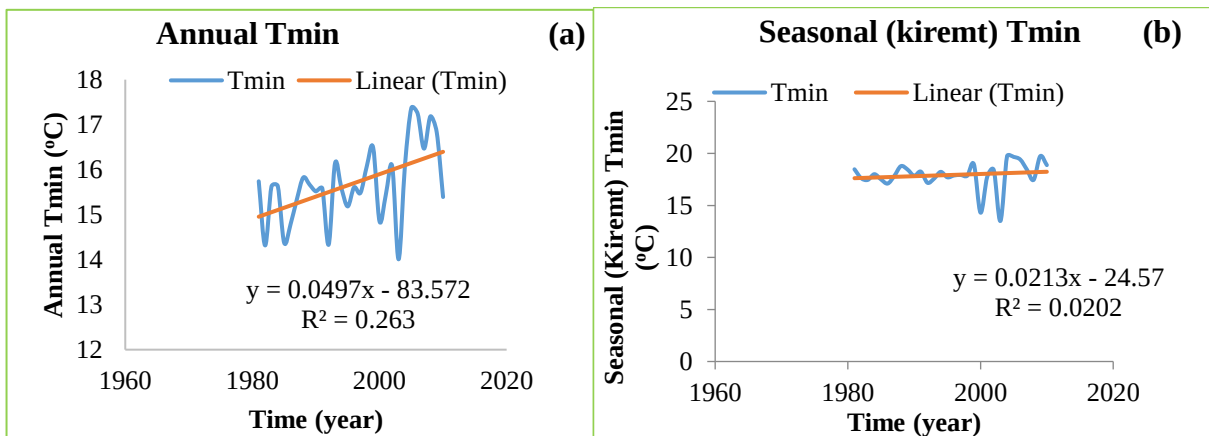
Arerti Station

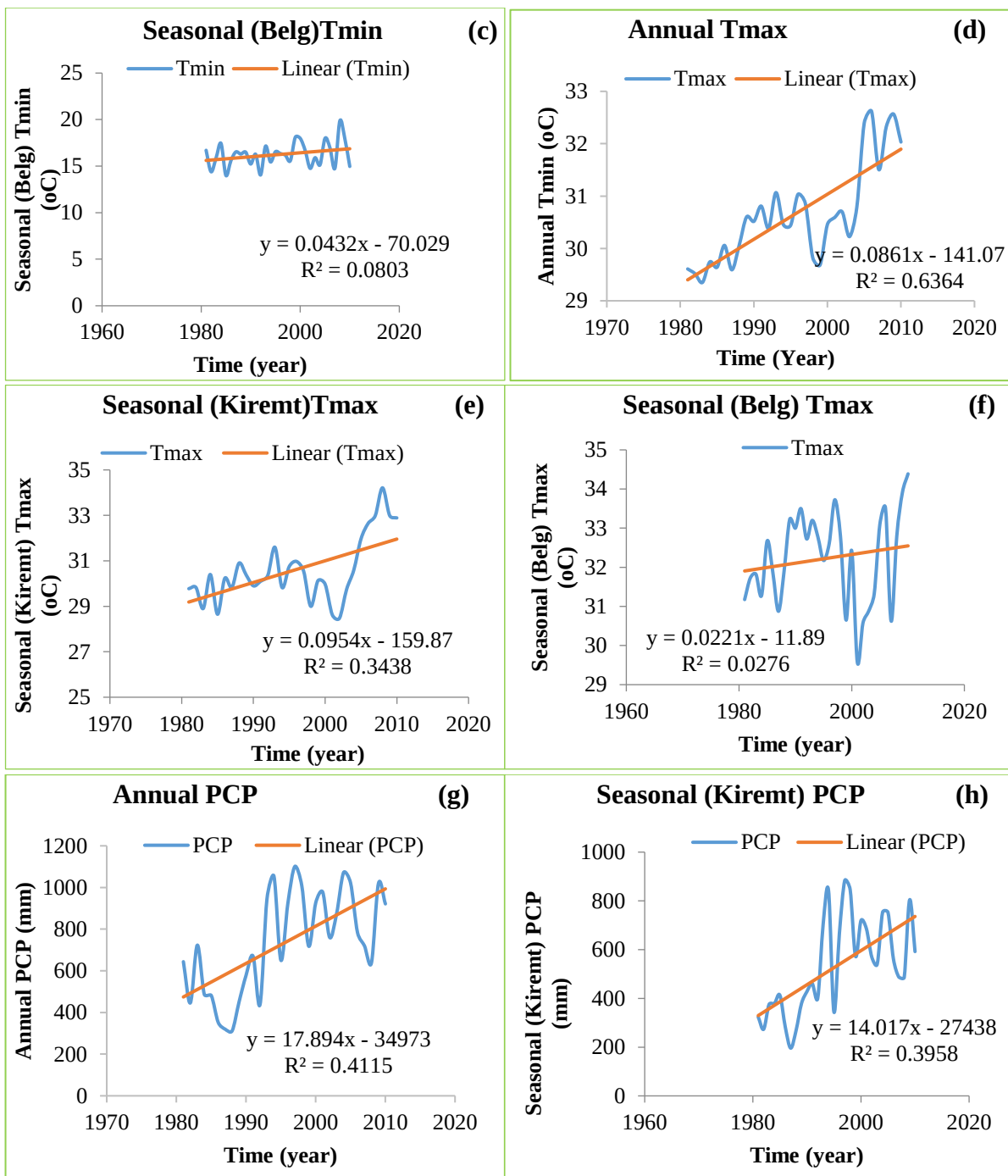


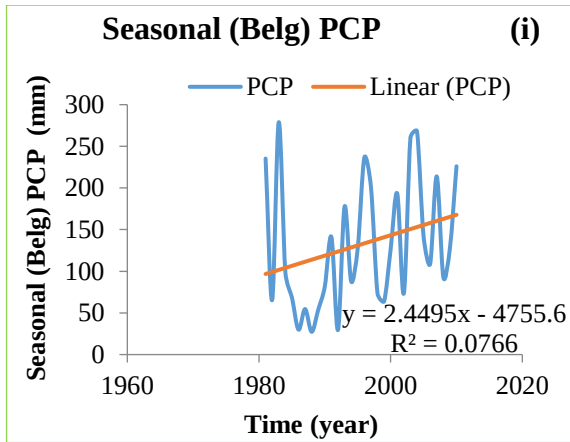


Appendix Figure 8: a, b and c: Trend analysis of annual, Kiremt and Belg (seasonal) minimum temperature respectively; d, e and f: Trend analysis of annual, Kiremt and Belg seasons maximum temperature respectively; g, h and i: trend analysis of annual, Kiremt and Belg seasons precipitation for Arerti Station of the study area.

Melka Jilo Station

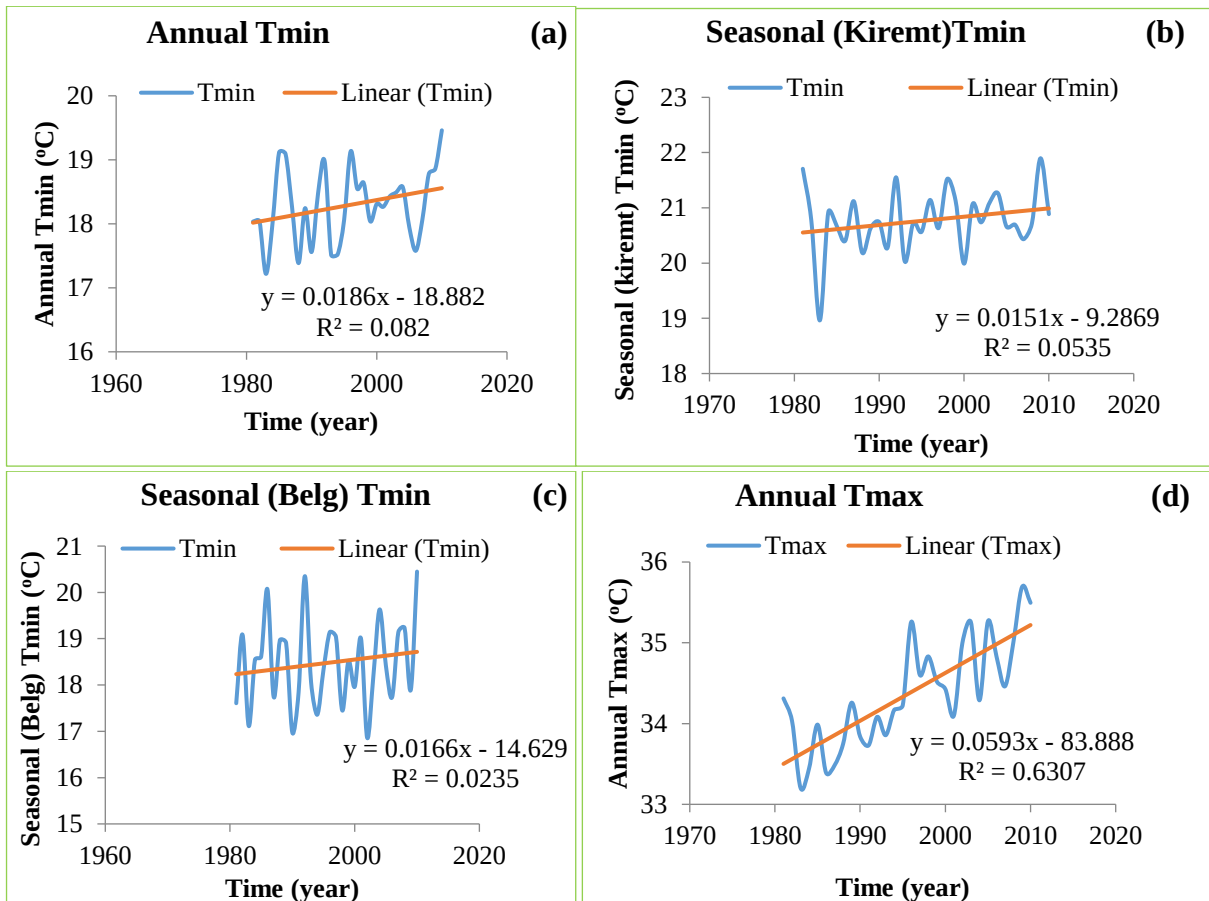


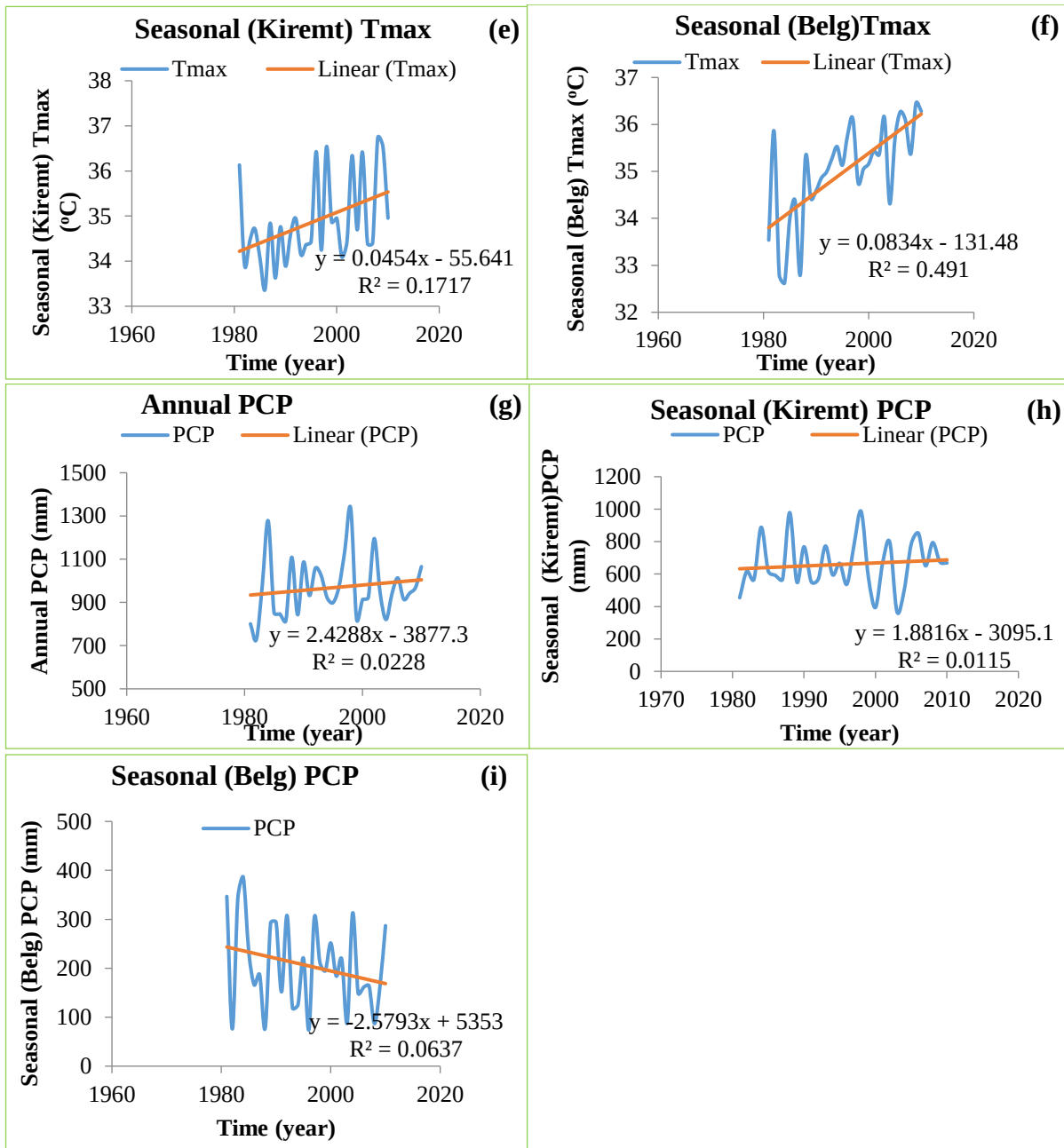




Appendix Figure 9: a, b and c: Trend analysis of annual, Kiremt and Belg (seasonal) minimum temperature respectively; d, e and f: Trend analysis of annual, Kiremt and Belg seasons maximum temperature respectively; g, h and i: trend analysis of annual, Kiremt and Belg seasons precipitation for MelkaJilo Station of the study area.

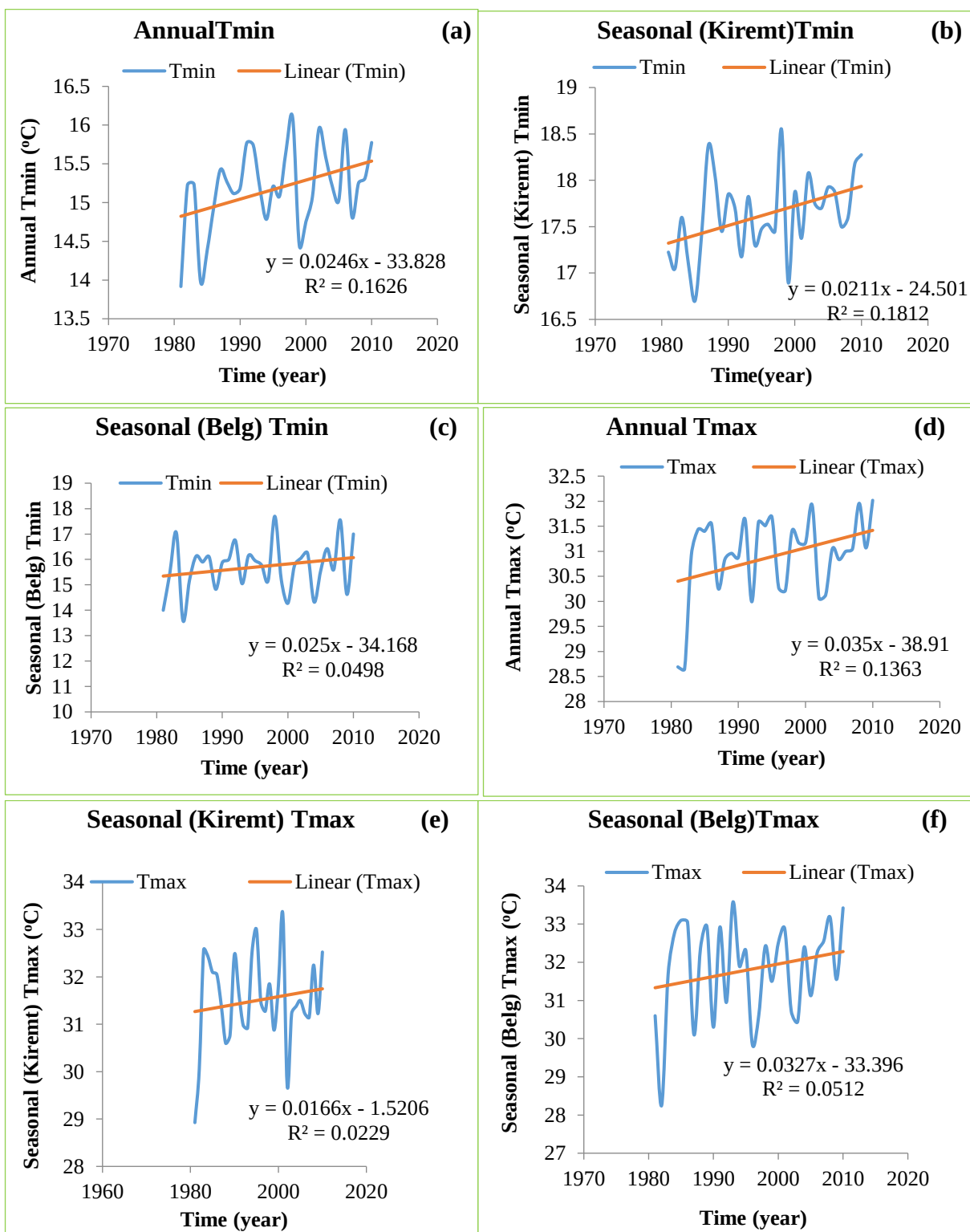
Metahara Station

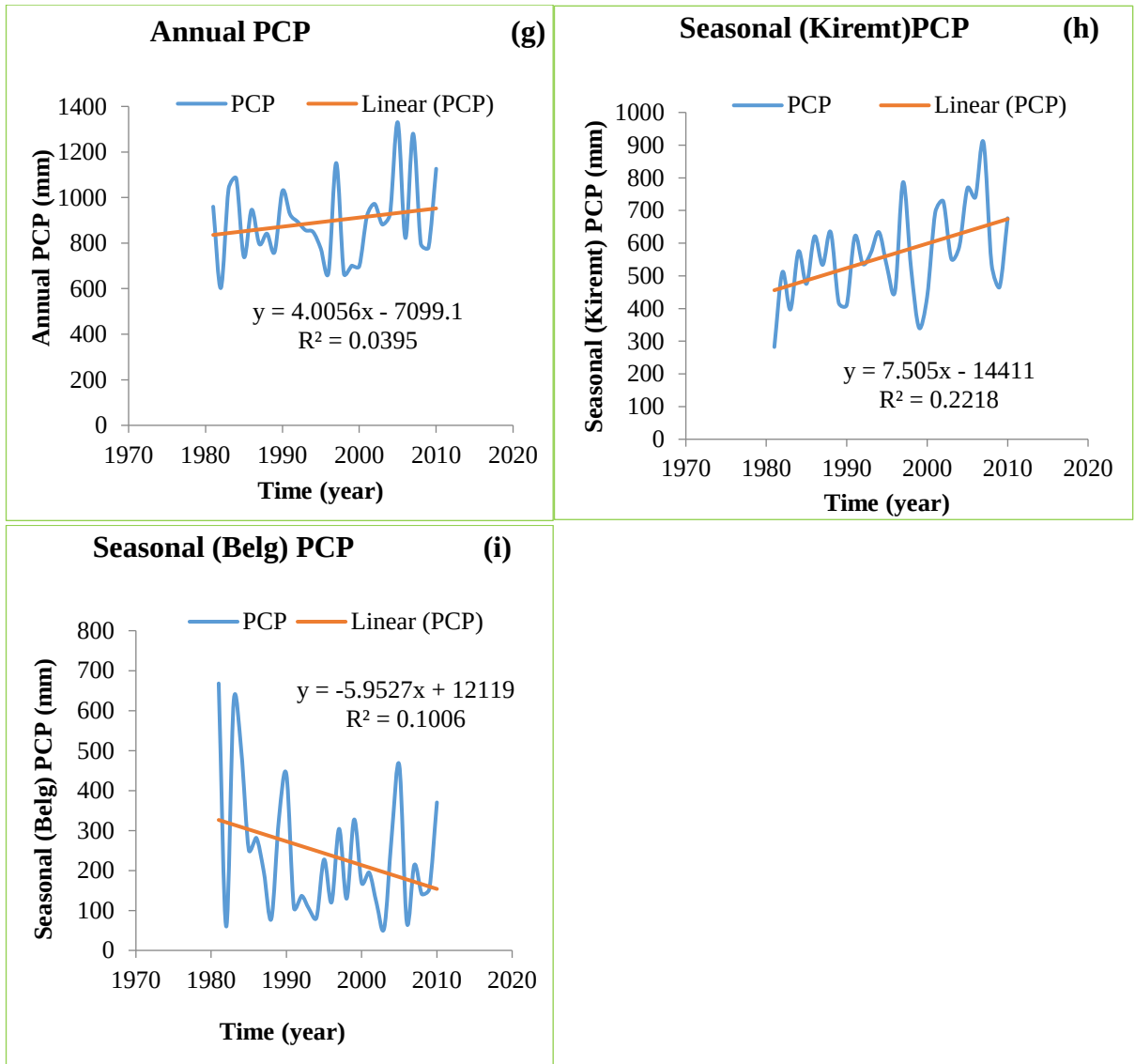




Appendix Figure 10: a, b and c: Trend analysis of annual, Kiremt and Belg (seasonal) minimum temperature respectively; d, e and f: Trend analysis of annual, Kiremt and Belg seasons maximum temperature respectively; g, h and i: trend analysis of annual, Kiremt and Belg seasons precipitation for Metahara station of the study area.

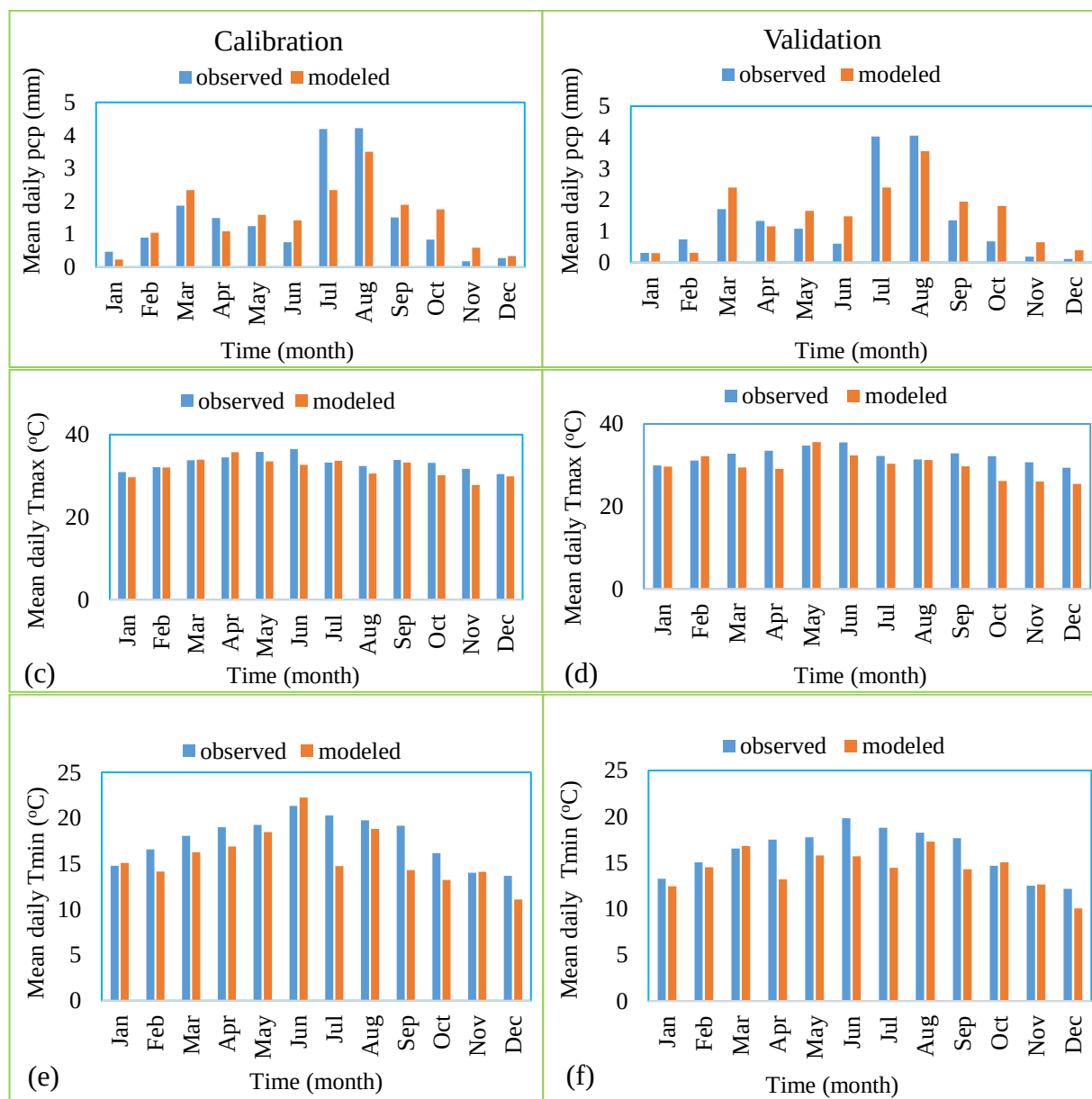
Welenchiti Station



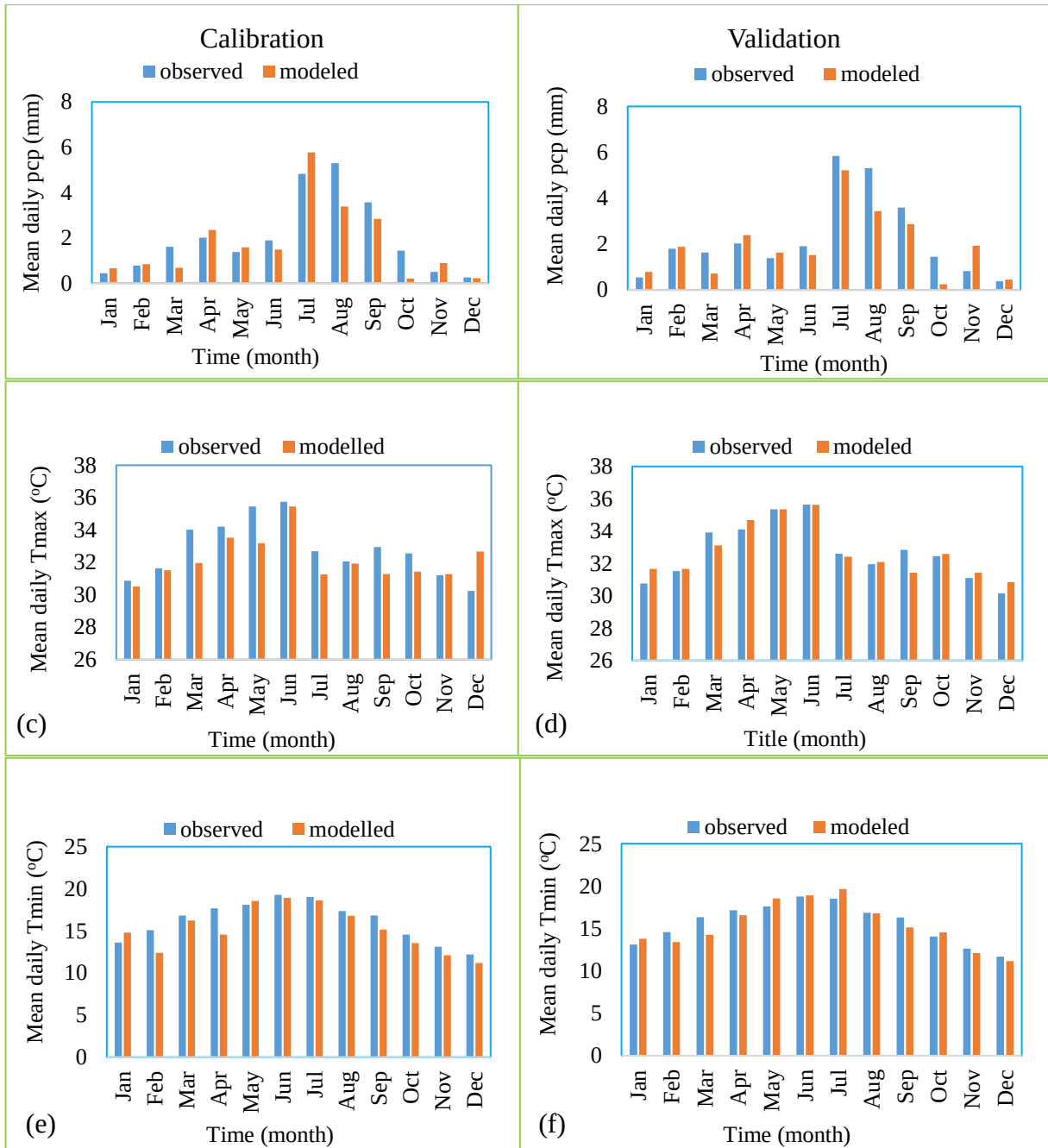


Appendix Figure 11: a, b and c: Trend analysis of annual, Kiremt and Belg (seasonal) minimum temperature respectively; d, e and f: Trend analysis of annual, Kiremt and Belg seasons maximum temperature respectively; g, h and i: trend analysis of annual, Kiremt and Belg seasons precipitation for Welenchiti station of the study area.

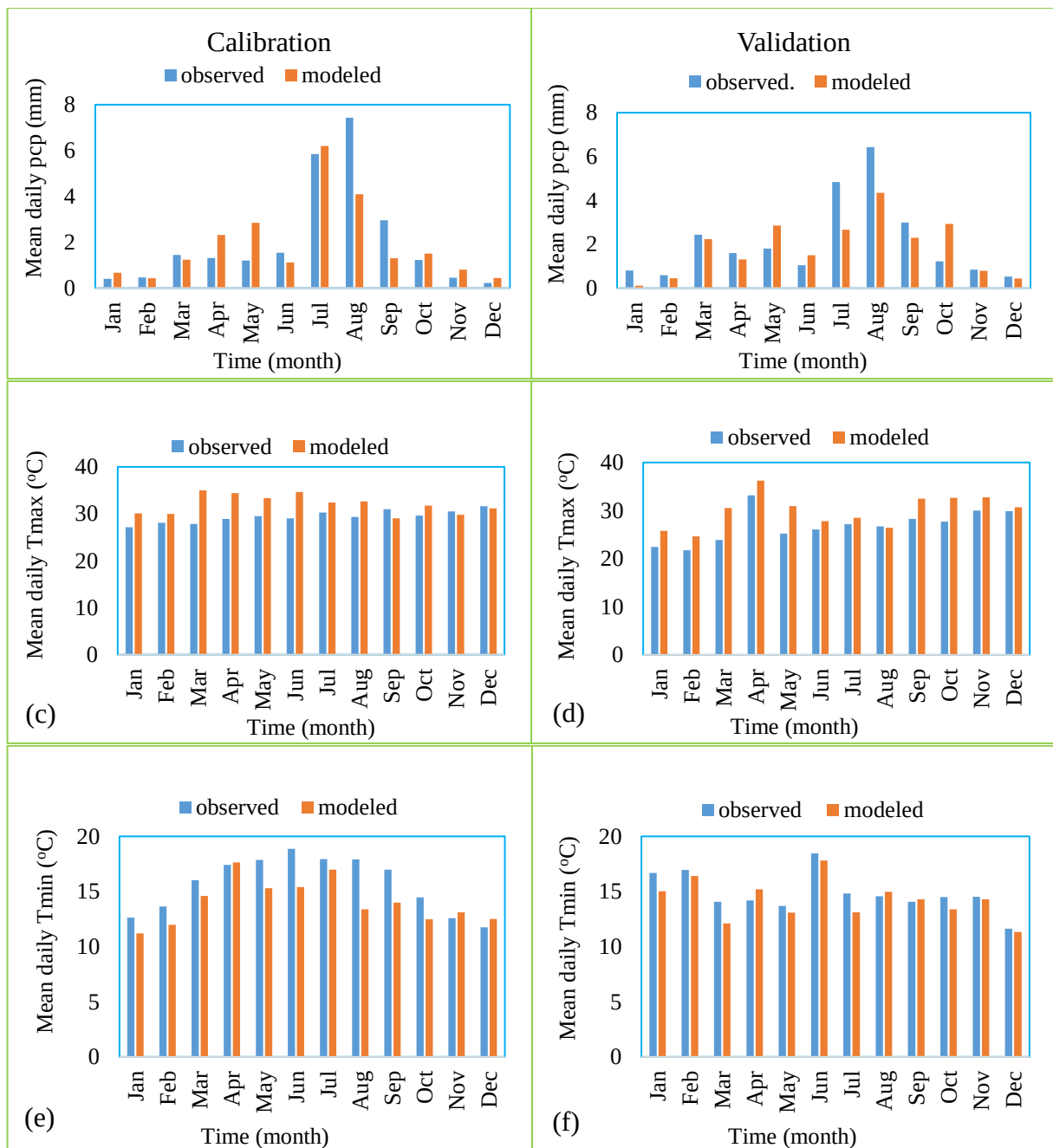
Graph of calibration and validation (SDSM) of historical rainfall, maximum temperature and minimum temperature



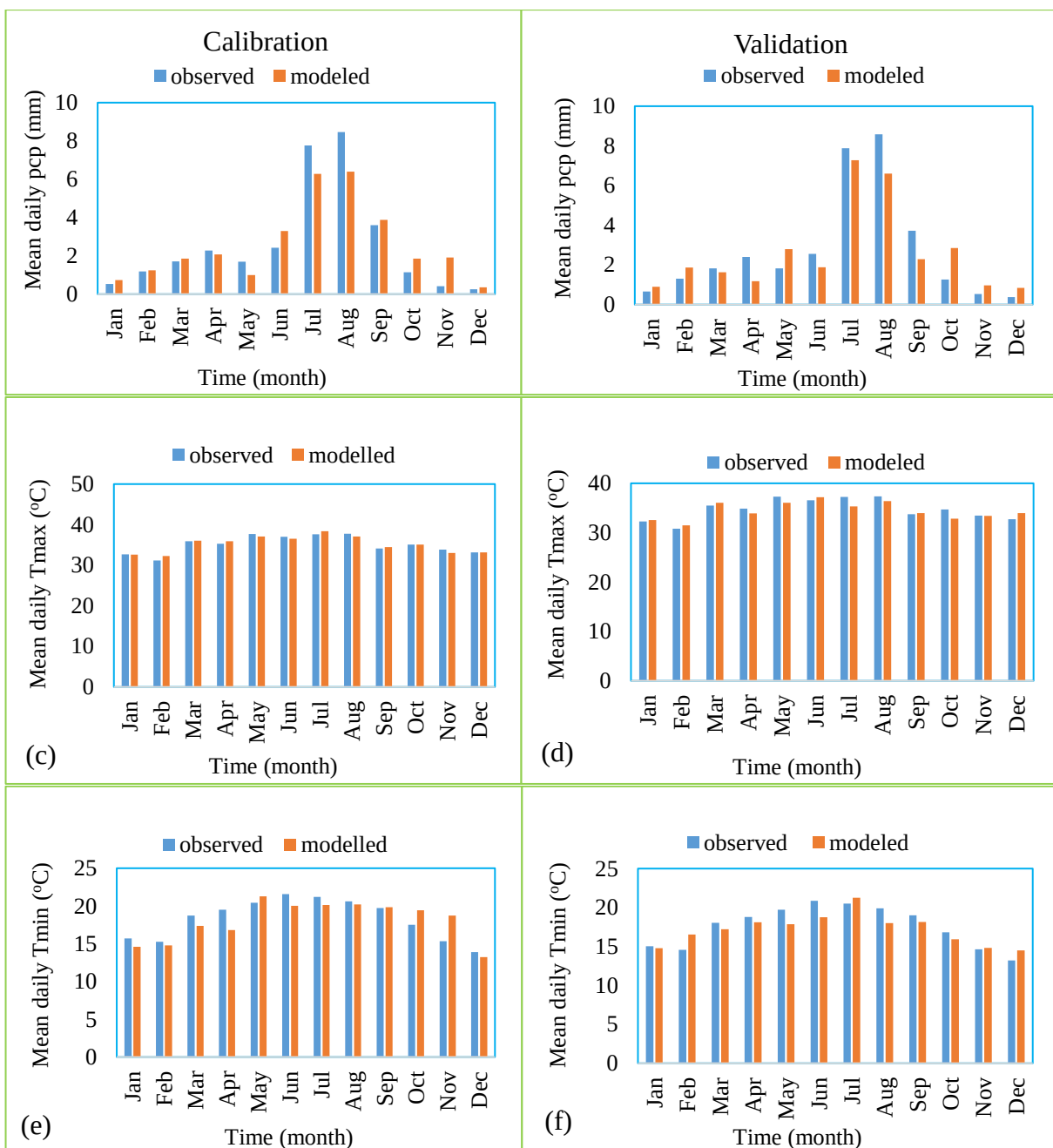
Appendix Figure 12: Calibration and validation of SDSM in simulating historical rainfall, maximum and minimum temperature at Abomsa weather station



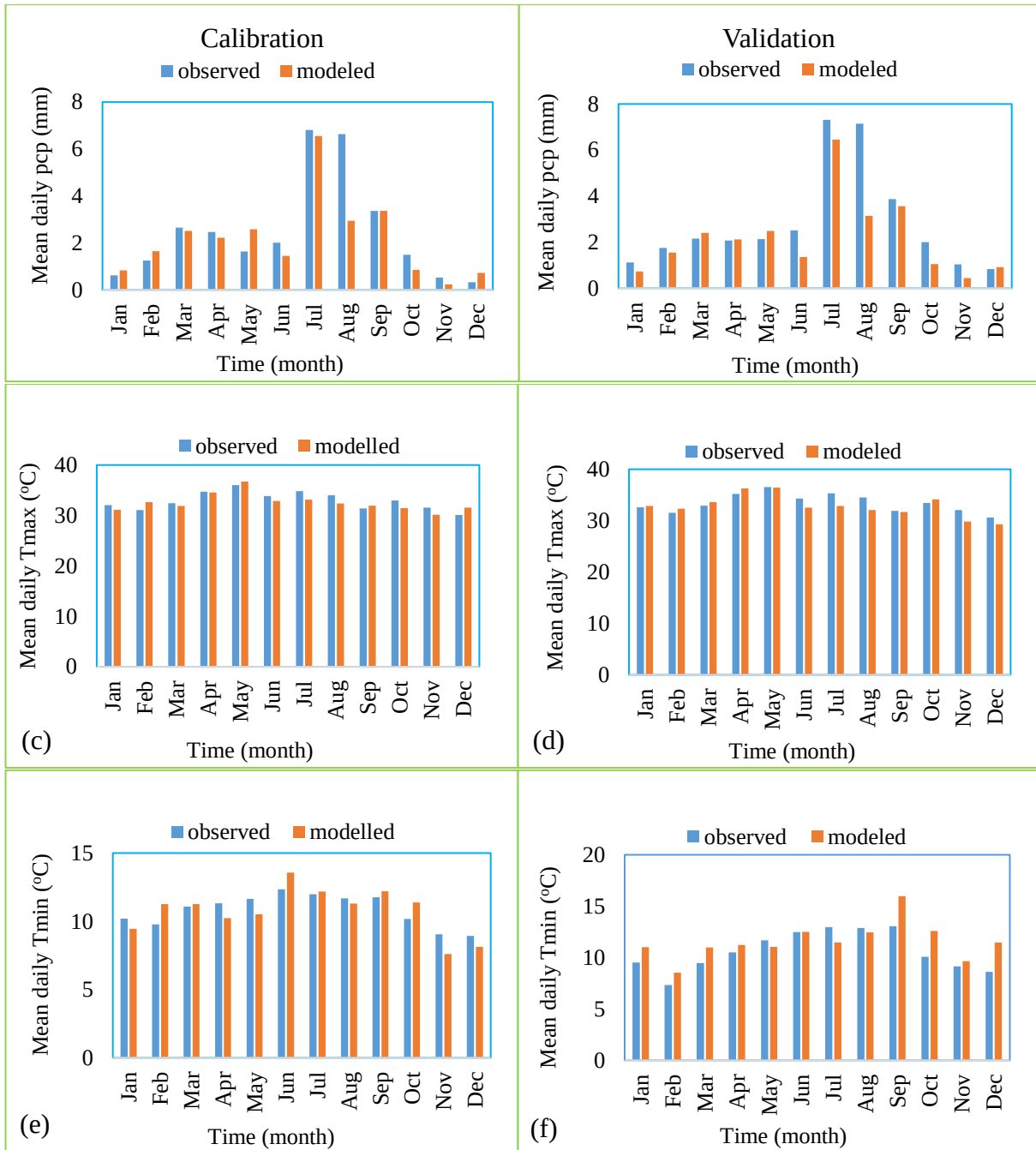
Appendix Figure 13: Calibration and validation of SDSM in simulating historical rainfall, maximum and minimum temperature at Arerti weather station



Appendix Figure 14: Calibration and validation of SDSM in simulating historical rainfall, minimum and maximum temperature at Melka Jilo weather station



Appendix Figure 15: Calibration and validation of SDSM in simulating historical rainfall, maximum and minimum temperature at Metahara weather station



Appendix Figure 16: Calibration and validation of SDSM in simulating historical rainfall, maximum and minimum temperature at Welenchiti weather station