Climate Change and Optimal Watershed Management Scenarios in the Jemma Sub-basin of Upper Blue Nile Basin, Ethiopia

Gebrekidan Worku Tefera

A Dissertation Submitted to the Center for Environment and Development Studies

College of Development Studies

Presented in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

in Development Studies (Environment and Development)

Addis Ababa University

Addis Ababa, Ethiopia

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Declaration

I, the undersigned, declare that this is my original work, has never been submitted and presented in this or any other University, and that all the resources and materials used for the dissertation, have been fully acknowledged.

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Date: - 30/12/2019

Place: - Addis Ababa

Date of submission 15/03/2020

This dissertation has been submitted for examination with my approval as supervisor.

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Dissertation Approval

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This is to certify that the dissertation prepared by Gebrekidan Worku Tefera entitled "**Climate Change and Optimal Watershed Management Scenarios in the Jemma Sub-basin of Upper Blue Nile Basin, Ethiopia**" and submitted in the fulfillment of the requirement for Degree of Doctor of Philosophy (Environment and Development) complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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General Abstract

This dissertation develops climate scenarios, climate impact scenarios and prioritize watershed management alternatives which can provide optimal benefits of adaptation under different climate scenarios. First, it characterizes the historical (baseline) climate that was a frontier for future climate scenarios. The baseline climate (1981-2014) unfolds an increase in the annual and main rainy season (June-September) rainfall and annual maximum temperature (TMAX) and minimum temperature (TMIN). Different rainfall and temperature extreme indices corroborate a steady increase of rainfall and temperature extreme events in the baseline climate. To develop future climate scenarios, first it was essential to identify Regional Climate Models (RCMs) which can simulate the historical climate of the study area. Accordingly, this study has identified that Global Climate Models (GCMs) dynamically downscaled through CCLM4 and REMO modeling schemes were better in simulating the historical (1981-2005) mean rainfall and the distribution of rainfall events. However, the RCM simulations overestimated and underestimated rainfall in high elevation (>2800m.a.s.l) and lower elevation (<2300m.a.s.l) areas, respectively.

Thus, it was worthwhile to adjust such biases through robust statistical bias correction method before using RCM simulations to develop climate scenarios and climate impact scenarios. The intercomparison of different statistical bias correction methods under different metrics revealed comparable performance in adjusting mean rainfall, TMAX and TMIN simulations of RCM. Nonetheless, most bias correction methods struggle to adjust the frequency and intensity of RCM simulations. Distribution mapping bias correction method was superior in adjusting the frequency and intensity of RCM simulations such as the wet day probabilities and the 90th percentiles of rainfall and temperature. Subsequently, RCM simulations bias adjusted using distribution mapping method were used to develop future climate scenarios. Future climate scenarios developed from the ensemble mean of statistically bias corrected RCM outputs designate a likely decrease of rainfall whilst steady increase of TMAX and TMIN under all future climate scenarios. The future climate will be also characterized by temperature and rainfall extreme events. Along with climate scenarios, climate impact scenarios were developed using the multi-model ensemble mean and multi-gauge calibrated and validated hydrological model. All climate impact scenarios describe a steady decline of surface runoff, water yield and an increase in loss of water through evapotranspiration.

As a response, multi-criteria decision analysis system which straddles climate scenarios, climate impact scenarios, the stakeholders' perspectives and other biophysical settings was used to identify watershed management alternatives for optimal climate adaptation. The multi-criteria analysis establishes water harvesting structures as the most prioritized watershed management alternatives for climate adaptation under the scrutiny of different criteria. The potential of water harvesting structures in reducing climate change impacts was evaluated using GIS and hydrological model. Water harvesting, particularly, in-situ water harvesting structures will significantly ($\leq$0.05) reduce surface runoff and thereby significantly increase soil water under baseline and future climate scenarios. There will be an insignificant change on the streamflow due to the realization of water harvesting structures under all climate scenarios. Therefore, effecting water harvesting structures at highly and optimally suitable watersheds will increase water availability and strengthen watershed-based climate adaptations under different climate change scenarios.

Key words: climate change, climate models, downscaling, statistical bias correction, RCPs, extremes, SWAT model, watershed management, water harvesting, optimal scenarios, Jemma sub-basin, Blue Nile Basin, Ethiopia

The work of this dissertation is based on the following articles.

I. Worku, G., Teferi, E., Bantider, A. and Dile, Y. 2018. Observed changes in extremes of daily rainfall and temperature in the Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia. ***Theoretical and Applied Climatology, 135, 839–854.*** **https://doi.org/10.1007/s00704-018-2412-x**

II. Worku, G., Teferi, E., Bantider, A., Dile, Y. and Taye, M.T. 2018. Evaluation of performance of Regional climate models in simulating rainfall climatology of the Jemma sub-basin, Upper Blue Nile Basin. ***Dynamics of Atmospheres and Oceans 83, 53–63.*** https://doi.org/10.1016/j.dynatmoce.2018.06.002

III. Worku, G., Teferi, E., Bantider, A. and Dile, Y. 2019. Statistical Bias Correction and Climate Change Projection using Regional Climate Models Simulation; Application to the Jemma Sub-basin, Blue Nile Basin, Ethiopia. ***Theoretical and Applied Climatology 139:1569–1588, https://doi.org/10.1007/s00704-019-03053-x***

IV. Worku, G., Teferi, E., Bantider, A. and Dile, Y. 2020. Hydrological processes under climate change scenarios in the Jemma Basin, upper Blue Nile Basin of Ethiopia. **Journal of Climate Risk Management, Under review.**

V. Worku, G., Teferi, E., Bantider, A. and Dile, Y. 2020. Prioritization of Watershed Management Scenarios under Climate Change in the Jemma sub-basin, Upper Blue Nile Basin. **Journal of Hydrology: Regional Studies, Accepted.**

VI. Worku, G., Teferi, E., Bantider, A. and Dile, Y. 2020. Watershed management technologies under climate change scenarios in selected watersheds of the Jemma sub-basin – a case study. **Under preparation**.

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Abbreviation and Acronyms

CCLM4	Consortium for Small-scale Modeling (COSMO) Climate Limited-Area Model
CDF	Cumulative Distribution Function
CMhyd	Climate Model data for Hydrologic Modeling
CMIP	Climate Model Intercomparison Project
CNRM-CM5	ESM developed at Météo- France and CERFACS
CN	Curve number
CORDEX	Coordinated Regional Downscaling Experiment
CSA	Central Statistics Agency
DSST	Differential Split-Sample Testing
EC-EARTH	European Community Earth-System Model
EEA	European Environment Agency
ECMWF	European Centre for Medium-Range Weather Forecasts
ENSO	El Niño-Southern Oscillation
EPA	Environmental protection authority
EPCC	Ethiopian Panel For Climate Change
ERA	ECMWF Re-Analysis
ETCCDI	Expert Team on Climate Change Detection and Indices
FAO	Food and Agricultural Organization of the United Nations
FDRE	Federal Democratic Republic of Ethiopia
GCMs	Global climate models
HadGEM2-ES	Hadley Global Environment Model 2 - Earth System
IGBP	International geosphere biosphere program
IOD	Indian Ocean Dipole
IPCC	Intergovernmental panel on climate change
ITCZ	Intertropical Convergence Zone
m.a.s.l	Meter above sea level
MEA	Millennium Ecosystem Assessment
MICE	Multivariate Imputation by Chained Equations
MoWIE	FDRE, Ministry of Water, Irrigation And Electricity
MPI-ESM-LR	ESM of the Max-Planck-Institut für Meteorologie ESM
ND	No Date
NAPA	FDRE, National Adaptation Program of Action
NMA	National meteorological Agency
NPC	FDRE, National Planning Commission
NARCCAP	North American Regional Climate Change Assessment Program
NSE	Nash Sutcliffe efficiency
PBIAS	Percent Bias
PCC	Population Census Commission
PRUDENCE	Prediction of Regional scenarios and Uncertainties for Defining European Climate change risks and Effects'
RCA	Rossby Center Regional Atmospheric Model
RCMs	Regional climate models
RCP	Representative concentration pathways
REMO	Max Planck Institute Regional Model

SCRP	Soil Conservation Research Program
SST	Sea Surface Temperature
SWAT	Soil and water assessment tool
TGICA	Task Group on Data and Scenario Support for Impact and Climate Assessment
UNFCCC	United Nations Framework Conventions to Climate Change
TMAX	Maximum temperature
TMAX	Minimum temperature
UNECA	United Nations Economic Commission for Africa
WCRP	World Climate Research Program
WMO	World meteorological organization

PART I: GENERAL INTRODUCTION OF THE STUDY

Chapter 1

Introduction

1.1 Background of the Study

The concentration of carbon dioxide (CO_2) in the atmosphere, changes in natural ecosystems and changes in the biogeochemistry of the global nitrogen cycle are among the three best documented global changes (IGBP, 2001; MEA, 2005). The major factor for these global changes is ever-increasing human activities. For instance, humans have altered natural ecosystems more rapidly and extensively since the 1950s than any other human history (MEA, 2005). Whilst, the industrial revolution since 18thC has triggered a tremendous concentration of CO_2 and other greenhouse gases (water vapour, nitrous oxide and methane) in the atmosphere. The concentration of CO_2 in the atmosphere is growing from 280ppm (parts per million) in the year 1750, 365 ppm in the year 1998, 391 ppm in the year 2011 and it is also projected to reach well above 500ppm by the year 2100 (IPCC, 2013). These global changes together further resulted in greenhouse gas emissions to the atmosphere and contribute to global climate changes that affect all humanity and the earth system.

Climate change is unequivocal, and there is a plethora of evidence which show climate change. From 1880 to 2012, an increase of global land and ocean surface temperature by 0.85°C was observed (IPCC, 2013). Besides, an increase of atmospheric moisture, changes on the spatial and seasonal pattern of rainfall, an increase of rainfall and temperature extremes and a rise of global sea level by 19cm to 21cm were observed (IPCC, 2007a; IPCC, 2013). Different from the far past, the last three decades (1980-2010) were successively warmer and almost the entire globe has experienced surface warming (IPCC, 2013). Another problem of climate change is the dissimilarity of climate change among different regions of the world. For instance, in the 20th century, an increase of rainfall by 0.5-1% and a decrease of rainfall by 0.2-0.3% per decade was observed over most mid-high latitudes of the Northern Hemisphere and the tropical areas of the world, respectively (IPCC, 2013). Similarly, an increase of annual rainfall in the Sahel and Southern Africa regions, but a decrease of rainfall in East Africa region was observed from the year 1983-2010 (Maidment et al., 2015). This accentuates the need to study climate change at regional and local spatial scales using climate model simulations.

Climate models are instrumental to study the response of the climate system to the change in the composition of the atmosphere due to greenhouse gases concentration (IPCC, 2013). However, due to low spatial resolution, Global Climate Models (GCMs) simulation of climate variables, for instance, cloud cover and rainfall remains challenging at the national and regional scales and in mountainous and coastal regions (Fowler et al., 2007; Randall et al., 2007; Flato et al., 2013; Woldemeskel et al., 2015). Another limitation is that GCMs struggle to realistically capture climatic extreme events. There is an underestimation, overestimation, incorrect estimation of extreme events and values and occurrence of too many wet days or dry days in climate models (Ines & Hansen, 2006). Thus, downscaling of GCMs' simulation at the regional and lower spatial scale is worthwhile to get reliable climate information for local climate impact studies (Fowler et al. 2007; Flato et al., 2013).

Statistical and dynamical downscaling are the main downscaling techniques that produce regional and local-scale climate data from GCMs (Wilby et al., 2002). There are evidence which accentuate dynamical downscaling is superior to statistical downscaling techniques to simulate rainfall of regions with diverse topography (Schmidli et al., 2007). Similar to statistical downscaling, the dynamical downscaling method is dependent on the GCM boundary forcing. However, dynamical downscaling is better in simulating physically consistent atmospheric processes on a smaller scale and does not assume the stationary relationship between predictor and predictand (Fowler et al., 2007). Equivalent to GCMs, dynamical downscaling also uses mathematical representations of the physical processes that create the climate system, but it has higher spatial resolution and able to capture the effect of mountains, coastlines and local climate drivers (Evans, 2011).

Using the dynamical downscaling approach, there are crucial regional and global climate modelling center which produce large ensembles of RCM simulations through nesting of RCMs to third and fifth phases of Climate Model Intercomparison Project GCMs (CMIP3 and CMIP5) (Christensen and Carter, 2007; Giorgi et al., 2009; Evans, 2011; Mearns et al., 2013; Gutowski et al., 2016). For instance, under the auspice of the World Climate Research Program (WCRP), the Coordinated Regional Climate Downscaling Experiment (CORDEX) is an international program to avail downscaled climate dataset, to blend model evaluation frameworks and to use climate models data for climate change impact studies (Giorgi et al., 2009). The outputs of CORDEX were evaluated and used for climate change impact studies in different regions of Africa and showed reasonable performance (Nikulin et al., 2012; Dosio et al., 2015; Haile and Rientjes, 2015). But, as yet the output of downscaled RCMs revealed steady biases (Piani et al., 2010; Gudmundsson et al., 2012). As a result, climate model simulations without bias corrections provides less reliable climate information, particularly in producing extreme climate events (Maraun, 2016). For instance, runoff simulated using the simulation of RCMs is less reliable compared to runoff simulated using bias-corrected climate data (Hagemann et al., 2011). Therefore, it is necessary to use bias corrected RCM simulations before using for climate change impact assessment.

Climate change affects the hydrological cycle that further influence the availability of freshwater resources through changes in evaporation, soil water and runoff (Bates et al., 2008; IPCC, 2014). An increase of surface runoff and flood events were observed on a plethora of land regions of the world after the 1950s (IPCC, 2007b; IPCC, 2014). In contrast, nearly 1.4 billion people lived in water-stressed watersheds of the world as of 1995 (Arnell, 2004). Immense impacts of climate change on the natural ecosystem and humanity is also projected for years to come. For instance, it was projected that the number of people under water stress will increase in the order of 12 - 81 million in the 2020s and 79 - 178 million in the 2050s (Arnell, 2004) under different emission scenarios. A decrease of soil moisture that could trigger an increase in agricultural drought is also projected at regional and global scales by the end of the 21^{st}C (IPCC, 2013). Such climate change driven hydrologic changes trigger repercussions on every aspect of human well-being such as water supply and agricultural productivity.

In Ethiopia, voluminous literature exists which show an increasing trend of TMAX and TMIN and inconsistent trend of historical rainfall in different regions of Ethiopia (Bewket and Conway, 2007; NMA, 2007; Cheung et al., 2008; Mengistu et al., 2013; EPCC, 2015a). Aside to the historical climate, an increase of temperature, inconsistent change of rainfall and higher frequency of flooding and drought are also projected for the future (NMA, 2007; EPCC, 2015a). The change in climate also further triggers rampant impacts on natural ecosystems of the country. In Ethiopia, climate change and climate variability caused drought, floods, heavy rains and frosts. Among these impacts, drought is the most severe which affects the country frequently (World Bank, 2006; NMA, 2007; Awass, 2009). Subsidence of rainfall in the Awash River Basin (Hailemariam, 1999; Taye et al., 2018) and Blue Nile Basin (Elshamy et al., 2009) was projected to the future period. In contention, there are studies project an increase (Worqlul et al., 2018; Liersch et al., 2016) and non-linear (Setegn et al., 2011) trend of rainfall in Blue Nile Basin. However, in both regions where there will be an increase or decrease of rainfall, a decrease in water availibility is imminent due to an increase in evapotranspiration and consumptive losses following population and economic growth. High dependence of the growth and transformation strategies of the country on agriculture and water sectors will also further intensify the repercussion of climate change.

As a response to these multifaceted impacts of climate change, robust climate change adaptation strategies which could provide optimal benefits under a wide range of climate conditions are to be developed at landscapes and watersheds level (Groves et al., 2008; IPCC, 2014). However, existing climate change adaptation strategies are not capable of thwarting the anticipated climate change and will provide narrow margin to buffer future climate change impacts since the strategies are designed based on historical hydro-climatic data (Snover et al., 2003; Bates et al, 2008; WMO, 2009). Therefore, elegant climate adaptation strategies that consider future climate scenarios and climate impact scenarios are essential to defy future climate change and climate extreme impacts (IPCC, 2007b; IPCC, 2012). Furthermore, designing adaptation strategies is challenging due to the uncertainties in climate information stem from emission scenarios, the conceptualization of GCMs and downscaling methods (Yang et al., 2012; Kundzewicz et al., 2018). This emphasizes the need to develop and integrate robust climate scenarios with climate adaptation decision analysis at regional, landscapes and watersheds scales.

Integrating climate change information with watershed-based climate adaptation can help to optimize the benefits of watershed management structures in reducing climate change impacts. Climate change affects the potential of current watershed management structures which will not be robust enough to buffer the impacts of anticipated climate change (Bates et al., 2008; EPCC, 2015b; Kundzewicz et al., 2018). For this, using climate change information underpins watershed management through identifying optimal placement of hydraulic structures, increasing effectiveness of watershed management practices and to avert mal-adaptations (Groves et al., 2008; Xie et al., 2015). On the other side, watershed management underpins climate change adaptation (Bates et al., 2008). Various field experiments (e.g Biazin et al., 2012; Mengistu et al., 2015) and models evaluation (e.g Lemann et al., 2016) show that watershed management technologies such as water harvesting, micro basins, stone bunds and vegetative measures have diverse benefits of climate change adaptation. Thus, it is essential to prudently embed climate change information into the watershed management system.

1.2 Statement of the Problem

Climate change, climate variability and extreme climatic events trigger tremendous repercussions on the agriculture and water resources sectors of Ethiopia (World Bank, 2006; NMA, 2007; EPCC, 2015b). Climate hazards particularly droughts, floods and extreme weather events resulted in manifold impacts that include food insecurity, various diseases, land degradation and damages of infrastructures (NMA, 2007). For instance, climate variability triggers more than one-third of the reduction of the growth potential of the economy of the country (World Bank, 2006). In Upper Blue Nile Basin, climate change is one of the major factors which trigger tremendous effects on the water resources base and economy of inhabitants of the basin (Baldassarre et al., 2011; Taye et al., 2015). In Ethiopia and the Jemma sub-basin in particular, the economy of the inhabitants is highly dependent on rained agriculture where climate-induced rainfall variability, drought and dry spells cause high loss of agricultural production (Awulachew et al., 2005).

Jemma sub-basin is located in the Central Highlands of Ethiopia and it is one of the sub-basins of Upper Blue Nile Basin. In this sub-basin, an increase in rainfall and temperature extremes was observed from 1981-2014 (Worku et al., 2018a). Further, climate change triggers frequent and destructive floods, landslides, soil erosion, soil fertility decline and ultimately a decline in crops productivity in large areas of the Jemma sub-basin (Bewket et al., 2015). The hydrology and rainfed agriculture based economy of the inhabitants of the Jemma sub-basin is strongly related to rainfall which could exacerbate the repercussion of climate change on the water resources of the sub-basin. For instance, in Andit Tid, Beressa and Weizer catchments of the Jemma basin, 55%, 57% and 80% of rainfall is converted into runoff, respectively (Hurni et al., 2005; Gebrehiwot and Ilstedt (2011). More inappropriately, the effect of climate change on water resources could be further intensified due to lack of strong water resources database, insufficient water resources planning and lack of hydraulic structures to retain water (World Bank, 2006; EPCC, 2015b). Consequently, robust watershed management structures which increase water storage, buffer the multifarious impacts of climate change and withstand other environmental and socio-economic challenges under different climate conditions are strongly needed.

To effectively develop watershed management structures for climate change resilience, first it is essential to develop robust climate change and climate change impact scenarios which can provide crucial information about climate change and its impacts. In the Upper Blue Nile Basin, there are no two or more studies which use similar GCMs, emission scenarios and downscaling methods (Taye et al., 2015). As a result, climate change and its impact on the water resources is not conclusive. Climate change studies which are based on multiple emission scenarios, multiple GCMs and RCMs, bias adjustment of climate model simulations and well calibrated and validated hydrological model are lacking in the Upper Blue Nile Basin (Baldassarre et al., 2011). Thus, climate scenarios which are developed based on multiple emission scenarios, multiple RCM simulations and robust bias correction techniques at lower spatial scale are needed. In parallel, watershed management alternatives which can provide optimal benefits of reducing climate change impacts on the physical environment and the communities are also essential.

In the Jemma sub-basin, watersheds based soil and water management activities were implemented since the 1980s (Hurni, 1985; Desta et al., 2005). In parts of the Jemma sub-basin, soil and water management technologies for instance graded and level *Fanya Juu,* stone and soil bunds and grass strips were introduced through a Food-for-Work campaign (SCRP, 2000). The main objective of these technologies was to reduce runoff velocity and soil loss. While, the 1990s watershed development programs and the Participatory Watershed Development Program which was initiated in 2005 were planned for soil and water conservation, rural development and to improve the livelihood of the rural community (Desta et al., 2005). In contrast to such programs of watershed management, watershed management structures were implemented on only about 40% of the area up until 2016 (Google Earth, 2016), whilst huge soil and water management investment is essential.

Besides to the low spatial coverage, there is an insufficient link between climate information and watershed management structures designed to reduce climate change impacts (World Bank, 2006; Conway and Schipper, 2011; EPCC, 2015b). The existing watershed management technologies are designed exclusively based on the historical hydro-climate condition. Consequently, existing watershed management structures could not have a buffer to effectively withstand future climate impacts. It is concluded that success of existing watershed management structures is not comparable and outweigh by environmental and socio-economic challenges (Amdihun et al., 2014; EPCC, 2015b). Thus, vigorous watershed management planning which can guarantee communities and the physical environment to have better resilience to the negative impacts of climate change under different climate conditions are to be devised. For this, it is fundamental to develop robust climate scenarios, climate impact scenarios and to incorporate the perspectives of the stakeholders. Particularly, it is worthwhile to develop and prioritize optimal watershed management scenarios which can increase water availability and reduce climate extreme impacts under different climate change scenarios.

1.3 Objectives of the study

The overall objective of this study was to develop different climate and climate impact scenarios and watershed management alternatives which can provide optimal benefits of climate adaptation in the Jemma sub-basin of the upper Blue Nile Basin.

The specific objectives were to:

1. Examine the trend of mean and extremes of rainfall and temperature of baseline climate
2. Identify Regional Climate Models which better simulate the rainfall climatology of the Jemma sub-basin,
3. Evaluate the skill of different statistical bias correction methods in adjusting rainfall and temperature simulations of RCM,
4. Explore multiple future climate change scenarios using different climate models and emission scenarios,
5. Assess the response of hydrological processes to different climate scenarios in the Jemma sub-basin,
6. Prioritize watershed management alternatives which can provide optimal benefits of adaptation under different climate change scenarios.

1.4 Significance of the Study

This study will develop a framework which integrates climate change scenarios with different watershed-based climate adaptation decisions. First, this research establishes a robust baseline and future climate and climate impact scenarios for the Jemma sub-basin. Such scenarios underpin to develop watershed management planning which can provide optimal benefits of climate adaptation. Subsequently, this study is also essential to defy the impact of both drought and flood events under existing and future climate conditions. Climate change impact may go beyond and threaten the potential of the existing watershed management practices. Thus, this research develops watershed management decisions which can maximize water storage and water yield under different climate conditions. This study can be a foundation to review existing policy and programs of watershed-based water management in the perspectives of climate change.

1.5 Scope and Limitation of the Study

There are various environmental and socio-economic problems in the Jemma sub-basin which can be an active area of research. However, this study takes only current and future climate change conditions as an environmental problem. From various biophysical and socio-economic impacts of climate change, this study focuses on the impact of different climate change scenarios on hydrological processes. Furthermore, there are an array of natural and socio-economic response strategies to defy climate change impacts. This study intercompares physical and biological watershed management technologies. Watershed management technologies may also provide socio-economic and environmental benefits. However, in this study, the implication of watershed management scenarios to water availability under climate change scenarios was evaluated.

1.6 Structure of the Thesis

This dissertation is structured into nine chapters.

Chapter one commences with the general introduction and also includes problem statement, objectives, significance and scope and limitation of the dissertation.

Chapter two is on description of the study area. This chapter embraces description on climate, hydrology, land uses, socio-economics and natural resources management conditions of the Jemma sub-basin.

Chapter three contains the theoretical and empirical literature review and the conceptual and analytical framework of the study.

Chapter four presents the baseline climate scenario which was a frontier of future climate scenarios. This chapter also embraces data quality control and a study of the changes in the trend of mean and extreme rainfall and temperature events in the baseline climate.

Chapter five is on evaluation of different RCMs' performance in simulating the historical rainfall climatology of the Jemma sub-basin.

Chapter six deals evaluation of statistical bias correction methods in adjusting the rainfall and temperature simulations of RCM and identifies robust bias correction method. This chapter also develops different near-term and long-term future climate scenarios using RCM simulations adjusted through robust statistical bias correction method.

Chapter seven discusses climate impact scenarios. To develop climate impact scenarios, hydrological climate change impact assessment was performed using the multi-model ensemble mean of climate models and multi-gauge calibrated and validated hydrological model.

Chapter eight straddles climate scenarios, climate impact scenarios, stakeholders view and biophysical features of the sub-basin to develop watershed management scenarios which can provide optimal adaptation benefits under different climate scenarios.

Chapter nine comprises synthesis, conclusions and recommendations of the dissertation.

Chapter 2

Literature Review

2.1 Climate Modelling

Climate modelling is a numerical representation of the climate system of the earth based on the physical, chemical and biological properties of its systems, their interactions and feedback processes and that accounts for all or some of its known properties (Houghton, 2002; Randall et al., 2007; Flato, 2011). The science of climate modelling starts with the first law of thermodynamics, energy balance, radiative transfer and laws of motion for a fluid and hydrological cycle (Houghton, 2002). Since the 1960s, the principal tools of climate science have been the Global Circulation Models (Flato, 2011; Edwards, 2011). Global Circulation Models/Global Climate Models hereafter GCMs are the primary tools to investigate the response of the climate system to various radiative forcing, for making climate predictions on seasonal to decadal time scales and for making projections of future climate (IPCC, 2013). Further, climate models are instrumental to develop climate change scenarios that can be used for climate change impact assessment and climate adaptation decision (Taylor et al., 2012).

There are non-trivial improvements in climate modeling and increasingly becoming comprehensive. The Geophysical Fluid Dynamics Laboratory of United States, the University of California, the Los Angeles Department of Meteorology (UCLA) and the National Center for Atmospheric Research (NCAR) of US were the leading centers for GCMs research since the 1950s (Edwards, 2010). Moreover, different GCMs were developed by these centers, for instance, NCAR has developed the Community Climate Model (CCM) series and the Community Climate System Model (CCSM) (Blackmon et al., 2001). Britain's Hadley Centre, Germany's Max Planck Institute, Japan's Earth Simulator Centre and the Goddard Institute for Space Studies in the United States are other most active climate modelling centers since the1980s and 1990s (Edwards, 2010).

Another proliferation in the evolution of GCMs is the establishment of frameworks where climate models were developed by more than one modelling center. Combining an ocean model from one lab with a sea ice model from another and an atmospheric model from a third was started (Hill et al., 2004). In 2002 NCAR, NOAA, NASA, and Department of Defence developed an Earth System Modeling Framework (ESMF) (Edwards, 2010). Earth system models (ESMs) which couple atmosphere–ocean GCMs with the land surface, the cryosphere, hydrology, and vegetation processes are an important advancement in the evolution of climate modeling. Earth System models also include the biogeochemical cycle, aerosols and anthropogenic sulphur dioxide emissions (Flato, 2011). Application of earth system models is widespread since IPCC's fourth assessment report (IPCC, 2007a). The initiation of Coupled Model Intercomparison Project (CMIP) in the mid1990s is another improvement in climate modelling which aims to archive climate simulations at the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and to perform climate analysis based on the multi-model dataset (Meehl et al., 2005). There are successive CMIP phases, for instance, the fourth and fifth IPCC assessment reports were based on CMIP3 and CMIP5, respectively (Taylor et al., 2012). In advance than other CMIP phases, CMIP5 provides a framework which better coordinate climate change experimentation, better documentation of models (Taylor et al., 2012). CMIP5 framework also provides GCMs simulation with better horizontal resolution and GCMs driven by emission scenarios called Representative Concentration Pathways (RCPs) (Taylor et al., 2012; Woldemeskel et al., 2015).

2.2 Climate Change Scenarios

In climate change research, scenarios are not solely forecast rather, scenarios are an internally consistent, coherent and plausible description of how the future can unfold through exploring various trajectories of change (Moss et al., 2010; IPCC, 2013). Scenarios include socio-economic scenarios, emission scenarios, climate scenarios and climate change impact scenarios. The socio-economic scenarios represent population growth, socio-economic development, energy production and use, technology, agriculture, forestry and land use (Moss et al., 2010; van Vuuren et al., 2011). The socio-economic scenarios further lead to develop emission scenarios which show the possible emission and concertation of greenhouses gases in the atmosphere. IPCC has used several sets of emission scenarios. In 1990, SA90 scenario was developed and updated into a more complete study of emissions scenarios i.e IS92 which encompass assumptions on how greenhouse gases emission involve in the absence of climate policies (IPCC, 1992).

The Third and Fourth Assessment Reports of IPCC were based on new methods of emission scenarios called Special Report on Emission Scenarios (SRES) which is developed in 2000. Wider than IS92, SRES scenarios represent demographic, economic and technological driving emissions and are a representative of the then literature (IPCC, 2000). In the SRES, there are scenarios which represent a future world of very rapid economic growth (A1), heterogeneous, market-led world with less rapid economic growth (A2), development with clean and efficient environmental technologies (B1) and B2 scenario which represent development with environmentally, economically and socially sustainable locally-oriented pathways (IPCC, 2000).

The fifth IPCC assessment report introduces a new method of emission scenario called Representative Concentration Pathways (RCPs). In comparison with other scenarios, RCPs provide detail information on a range of emission and concentrations including land use and air pollution (IPCC, 2013; van Vuuren et al., 2011). There are four pathways; one high pathway (RCP8.5) for which radiative forcing reaches >8.5 W/m^2 by 2100 and continues to rise, two intermediate "stabilization pathways" (RCP6 and RCP4.5) where radiative forcing is stabilized at approximately 6 W/m^2 and 4.5 W/m^2 after 2100 (Moss et al., 2010; van Vuuren et al., 2011). There is a pathway (RCP2.6) which represent radiative forcing of $3W/m^2$ peaks at approximately and then declines before 2100 (Moss et al., 2010; van Vuuren et al., 2011). The RCPs are compatible with the full range of stabilization, mitigation and baseline emissions scenarios of the current scientific literature and used to drive GCMs to develop climate scenarios (Moss et al., 2010).

Climate scenarios are consistent and plausible representations of future climate conditions (for instance temperature and rainfall) through blending physical representation of climate systems by climate models and emission scenarios (IPCC-TGICA, 2007; Moss et al., 2010). Climate scenarios are instrumental to investigate the potential consequences of anthropogenic changes in the climate system of the earth (IPCC, 22013). Climate models, for instance, GCMs are used to develop climate scenarios. However, application of GCMs for climate scenarios development is challenging due to steady uncertainty in GCM simulations, low spatial resolution of GCMs and limitations of GCMs in simulating rainfall and cloud cover in the mountain and coastal regions (Fowler et al., 2007; Randall et al., 2007). The best spatial resolution of climate models during the first to third IPCC report was in the order of 1° in the horizontal direction and up to 40 layers in the vertical direction in both the ocean and atmospheric components (Houghton, 2002). About half of the CMIP3 models had a horizontal resolution of coarser than 1°, while only 2 out of 30 models of the CMIP5 have a resolution of 1° coarse (Taylor et al., 2012). Even though the resolution of current climate models is improving, many phenomena which have non-trivial influences on the climate system cannot be resolved explicitly (Randall et al., 2007; Fowler et al., 2007).

There are different approaches recommended to reduce the limitations of GCMs and the uncertainties in climate models. Using multiple greenhouse gas emissions scenarios, a multi-model ensemble mean and multiple downscaling methods are among the primary strategies to reduce uncertainty (Randall et al., 2007; Flato et al., 2013). Considering the ability of climate models to capture the inter-annual variability associated with natural climate processes like El Niño-Southern Oscillation (ENSO) is another criteria that could reduce uncertainty. Downscaling of GCMs is also another technique to improve the horizontal resolution of climate models and to capture the climate of regions with diverse topography at regional and lower spatial scales (Wilby et al., 2002; Fowler et al., 2007; Flato et al., 2013).

2.3 State of the art in Climate Models Downscaling

Downscaling is the methodology of linking large scale climatic variables and much smaller scale climatic variables to drive information from large scale models, GCMs (Wilby et al., 2002; Fowler et al., 2007). Climate models downscaling narrows the gap form coarse-grid GCMs to fine grid that can be suitable for impact study, for instance, hydrological processes (Wilby et al., 2002). As a result downscaling bridges the gap between what GCMs can deliver and what climate society requires and ultimately avail climate models data for impact assessment and decision-making (Wilby et al., 2002; Fowler et al., 2007). Broadly, there are two categories of downscaling methodologies; statistical and dynamical downscaling. Statistical downscaling method involves developing empirical relationships between local-scale predictands and large-scale predictors (Wilby et al., 2002; Fowler et al., 2007). Statistical downscaling needs calibration and validation of empirical relationships between historical and/or current large-scale atmospheric and local climate variables (Giorgi, 2008; Flato et al., 2013). After a relationship is determined and validated, future atmospheric variables that GCMs project are used to project future local climate variables. In statistical downscaling, the reliability of projections strongly depends on the quality of calibration data (observation data) that is used as a predictand, the choice of predictor and the selected statistical downscaling scheme (Wilby et al., 2002; Giorgi, 2008).

Dynamical downscaling is the nesting of Regional Climate Models (RCMs) which have a higher resolution with a coarser resolution GCMs (Giorgi, 2008; Feser et al., 2011). Similar to GCMs, dynamical downscaling uses mathematical representations of the physical processes that create the climate system, but it has higher spatial resolution and able to capture the effect of mountains and coastlines (Fowler et al., 2007). In dynamical downscaling, the RCM uses the GCM to define time-varying atmospheric boundary conditions within which the physical dynamics of the atmosphere are modelled using better horizontal grid spacing (Fowler et al., 2007; Feser et al., 2011).

Dynamical and statistical methods have comparable skill at simulating surface climate variables under present climate conditions (Fowler et al., 2007; Feser et al., 2011). But, to assess future climate change scenarios, statistical downscaling methods are problematic since there are inter-variable biases in host GCMs. Statistical downscaling method assumes as there is always a linear relationship between large scale predictors and local pridictand which is the major drawback of this downscaling approach (Wilby et al., 2002; Fowler et al., 2007; Flato et al., 2013). Conversely, dynamical downscaling can resolve atmospheric processes, guarantees consistency with the driving GCM and generates internally consistent output variables (Wilby et al., 2002; Fowler et al., 2007; Giorgi, 2008). The dynamical downscaling approach is better in simulating physically consistent atmospheric processes on a smaller spatial scales (Fowler et al., 2007). And equivalent to GCMs, but with higher spatial resolution, dynamical downscaling uses mathematical representations of the physical processes that create the climate system (Evans, 2011). This helps dynamical downscaling approach to capture the effect of mountains, coastlines and local climate drivers (Giorgi, 2008; Feser et al., 2011).

Based on the dynamical downscaling approach, there are various regional and global climate programs which produce large ensembles of RCM simulations through the nesting of RCMs to third and fifth phases of CMIP5 GCMs. The PRUDENCE (Christensen et al., 2007), NARCCAP (Mearns et al., 2013) and CORDEX (Giorgi et al., 2009; Gutowski et al., 2016) are climate programs produced large ensembles of RCM simulations. For instance, CORDEX under the auspices of World Climate Research Programme is an initiative to provide high quality downscaled climate dataset, to coordinate model evaluation framework and is a setting to the applications of the climate simulations for climate change impact studies (Giorgi et al., 2009). Africa is the focus region of COREDEX and many climate modellers groups are performing simulations for this region. The outputs of CORDEX have used for climate change impact assessment in different parts of Africa and the simulations of the RCM of CORDEX have shown reasonable performance (Nikulin et al., 2012; Endris et al., 2013; Dosio et al., 2015; Haile and Rientjes, 2015). However, the RCM simulations are characterized by persistent biases thus cannot be directly used without adequate post-processing and bias correction for impact assessment.

2.4 Bias Correction of climate model simulations

Climate model biases are systematic differences between climate model simulations and observations (Teutschbein and Seibert, 2013; Maraun, 2016). Climate model biases also involve underestimation, overestimation and incorrect simulation of extreme values in climate models (Ines and Hansen, 2006). These biases can stem from the GCMs, downscaling schemes (RCMs) or internal climate variability (Teutschbein and Seibert, 2010). Thus, climate model simulations need to be bias corrected before using for climate change impact assessment. Bias correction is an adjustment of modelled values to well reflect the observed distribution and statistics (Teutschbein and Seibert, 2012; Maraun, 2016). Besides, bias correction is the process of re-scaling and post-processing of climate model output to reduce the effects of systematic errors in the climate models (Piani et al., 2010). The fundamental idea of bias correction is developing a function which adjusts the climate models simulation with observed counterparts (Piani et al., 2010; Gudmundsson et al., 2012). Bias correction of RCM simulation reduce uncertainties not only in the climate scenarios, however in the climate impact scenarios, bias correction increase reliability of results. For example, when runoff simulated by bias corrected RCMs, its more reliable than runoff simulated by non-bias corrected RCM simulations (Hagemann et al., 2011; Teutschbein and Seibert, 2012; Liersch et al., 2016). However, there are bias correction methods which trigger bias, For instance, Wang and Kotamarthi, 2015 has revealed large bias in the bias corrected (WRF) RCM model than the non-bias corrected WRF simulation. Subsequently, it is crucial to identify robust bias correction method before using its output for climate scenario development.

There are various bias correction methods ranges from some additive/multiplicative based bias correction techniques to a more advanced distribution based techniques. Linear scaling, local intensity scaling, power transformation, variance scaling, distribution mapping, the delta-change and precipitation threshold are bias correction methods (Leander and Buishand, 2007; Teutschbein and Seibert, 2012; Fang et al., 2015). Comparative analysis showed distribution mapping method has robust performance in adjusting the mean, frequency and intensity of RCM values with observed values than other bias correction methods (Teutschbein and Seibert, 2012; Gudmundsson et al., 2012). In common, all bias correction methods assume model errors and correction algorithms are stationary which implies that the biases and correction algorithm of current climate conditions are valid for future climate conditions (Maraun, 2012; Teutschbein and Seibert, 2012). However, studies (Klemeš, 1986; Teutschbein and Seibert 2013) showed the non-stationarity of biases and bias correction algorthims using the differential split sampling method (DSST) method.

2.5 Impact of Climate Change on Hydrology

Observations in the last several decades and future climate projections provide strong evidence substantiate water resources particularly freshwater resource is vulnerable and affected by climate change that further trigger repercussions on the natural and human ecosystems (Bates et al., 2008). Climate change significantly influence the hydrological processes for instance magnitude of evapotranspiration, runoff and streamflow of watersheds and river basins (IPCC, 2007; IPCC, 2013). Due to changes in hydrological components, it is projected that the number of people who will be affected by flood and drought will increase. It is projected that the number of people who will be under water stress under different SRES scenarios is estimated to range from 12 to 81 million in the 2020s and from 79 to 178 million in the 2050s (Arnell, 2004). In contrast, there will be many people in the watersheds where climate change increases the risk of flooding (IPCC, 2007b), for instance, 108 million people in Africa will be affected by flooding (UNECA, 2011). There are plethora of studies at large spatial scales (Arnell, 2004; Elshamy et al., 2009) and lower spatial scales (Beyene et al., 2010; Setegn et al., 2011; Olsson et al., 2013) which show influence of climate change on hydrological components at different regions of the world.

In Blue Nile Basin, hydrological climate change impact assessment studies provided non-conclusive impact of climate change on hydrological processes. For example, an increase in mean annual streamflow by 7.1, 9.7, and 10.1 % under A2 emission scenario and by 6.8, 7.9 and 6.4 % under B2 emission scenario for 2020s, 2050s and 2080s respectively was simulated using SWAT model and HadCM3 GCM (Adem et al., 2016). Besides, Worqlul et al., 2018 and Liersch et al., 2016 also investigated an increase in streamflow. In contrast, Elshamy et al., 2009 investigate a decrease in streamflow primarily due to an increase in temperature between 2℃ and 5°C and potential evaporation by 2–14% at the 2080s. There are also studies which confirm non-linear trend in the impact of climate change on the hydrologic components of Blue Nile Basin (e.g. Setegn et al., 2011). Thus, it is worthwhile to quantify and characterize the impacts of climate change in each sub-basin and watershed.

2.6 Climate Change and Watersheds Management

2.6.1 Watershed Management Paradigms

Watershed management is an ongoing process of formulating and carrying out a course of action on land, water and vegetation of the watersheds to achieve maximum production without adversely affecting the soil and water base (FAO, 1990). Watershed management is an old age discipline and passed through different paradigms. By 3000 BC, there were attempts to control water flow for irrigation along the rivers of Nile, Euphrates, Tigris and Yellow. During this time watershed management was viewed as water engineering and forestry and this approach remained in the period of Greeks, Romans and middle ages (FAO, 2006). In the 19th century especially in the colonial era, watershed management was an approach to reclaim degraded lands (Brooks and Eckman, 2000).

Since 20th century, population growth, land conversion, human induced soil degradation, adoption of inappropriate technologies, poor infrastructure, insufficient capital assets and other problems put watersheds into stress. As a result, watershed management was viewed as a means to ensure agricultural development and sustainable development. In the 1990s, integrated watershed management become an approach to conserve water, land and biodiversity and to enhance local livelihoods and economy of upland and downstream communities (FAO, 2006). On chapter 13 of Agenda 21, the need to promote integrated watershed development and alternative livelihood opportunities is clearly stated (UNCED, 1992). However, climate change adds another very different and strong challenge for watershed management planning.

Environmental, socio-economic and political changes trigger new watershed management approaches to emerge in the 21st century. For instance, climate change is increasingly become a strong challenge of watersheds (Drake and Hogan, 2013). As a result, new generation watershed management approaches which embrace experimentation, multi-stakeholder participation, natural resources management, upstream downstream linkages and dialogue between local and scientific community are essential (FAO, 2006). Embedded Watershed Management and Collaborative Watershed Management are new watershed management approaches which are assumed better than integrated watershed management (FAO, 2006).

In the integrated watershed management, emphasis is given to the integration of socio-economic issues within watershed management programmes while making natural resource management as part of local socio-economic development processes is the emphasis of Embedded and Collaborative Watershed Management approaches. On the other hand, integrated watershed management focuses on on-site and short-term effects. In contrast, embedded and collaborative watershed management focuses on upstream–downstream linkages and long-term impacts (FAO, 2006). In watershed management, new elements both man-made and natural occurrences may become an important course of action at any time (FAO, 1990). Climate change is increasingly become a new challenge of watersheds and a need to build watersheds which are resilient to climate change is growing.

2.6.2 Watershed management technologies for climate change adaptation

Water and soils at watersheds scale are the integral parts of agriculture and ecosystems services on which climate change has put widespread impacts. Climate change triggers reduction of soil moisture through increase in evapo-transpiration and low water storage capacity, soil erosion and decomposition of soil organic matter which could result huge carbon emission from soils (IPCC, 2013). On the other hand, soil is the global pool of 2500 Gt of carbon which is 3.3 times greater the size of the atmospheric pool (760 Gt) and 4.5 times the size of the biotic pool (560 Gt) (Lal, 2004). Watersheds can be a storage pool of water using different hydraulic structures (IPCC, 2014). Thus, it is essential to identify and adopt natural resources and watershed management technologies which could provide optimal benefits in climate change adaptation and mitigation. There are multitude of watershed management technologies which underpin climate change adaptation and mitigation through increasing water availability, agricultural production, nutrients availability, biodiversity and reducing greenhouse gases emission.

2.6.2.1 Water harvesting

Water harvesting particularly rainwater harvesting is an ancient practice which has been found in many countries around the world. For instance rainwater harvesting structures have been constructed in Jordan, Palestine, Syria, Tunisia, and Iraq over 9000 years ago(Adham et al., 2016). Similarly, in Ethiopia rainwater harvesting is also an old practice that dates back to as early as 560 BC during the Aksumite Kingdom. During Aksumite Kingdom, rainwater was collected and stored in small ponds intended for agriculture and water supply purposes(Seyoum, 1992). Since these ancient times, rainwater harvesting was defined differently. In the contemporary world, water harvesting is defined as 'the collection, storage and management of any form of water either from rainfall or runoff to increase water availability for domestic and agricultural use as well as for ecosystems sustainability (Mati et al., 2006; Biazin et al., 2012).

Water harvesting broadly categorized as in-situ and ex-situ water harvesting (Mati et al, 2006; Dile et al. 2016; Biazin et al., 2012). In-situ rainwater harvesting is a system of retaining rainwater in the root zone of the soil. The in-situ water harvesting also called micro catchments are structures that capture and store rainfall where it falls. Terraces, soil bunds, stone bunds, trenches, micro-basins, fanya juu, ridging, mulching and furrowing and hoeing are categorized as in-situ water harvesting systems (Mati et al, 2006; Biazin et al., 2012). Ex-situ is a system of collecting rainwater or surface runoff from external sources to the point of water storage. The ex-situ water harvesting structures also called macro-catchments collect water from a large area (water collection catchment) and store rainwater using storage structures. Ponds, dams, open tanks and small reservoirs are categorized as ex-situ water harvesting structures (Mati et al, 2006; Biazin et al., 2012).

The contribution of different water harvesting structures to climate change adaptation through reducing loss of surface runoff, increasing soil water and through increasing agricultural production in the wake of climate change is explored in different regions of the world. For instance, Rockstro¨m et al., 2009 has concluded that water harvesting structures are among the strategies to realize global water availability and food production through increasing green water availability under future climate change and population growth. In sub-

Saharan African countries, water harvesting structures resulted an increase of soil water (30%) (Biazin et al., 2012). In parallel, as a response to water harvesting structures, a reduction of surface runoff in the order of 13% to 60% was investigated in the semi-arid region of northern Ethiopia (Araya and Stroosnijder, 2010). In the upper Blue Nile Basin, Lemann et al., (2016) and Dile et al., (2015) also explored a reduction in surface runoff and an increase in soil water as response to different water harvesting structures. More importantly, Dile etal., (2015) has simulated that water harvesting structures have the effect to increase dry season flow (low flow) and decrease high flows in the downstream areas of the Lake Tana sub-basin of Blue Nile Basin. Water harvesting also has also contribution to increase agricultural production. Threefold increase of teff (Eragrostis tef) was simulated due to water harvesting in combination with nutrient application in the Lake Tana sub-basin, Ethiopia (Dile et al., 2016).

2.6.2.2 Physical soil and water management technologies

Physical soil and water management encompasses various technologies which include cutting and moving of soil and stones to reshape the topography. Technologies in this group of soil and water management are envisioned mainly to reduce velocity of surface runoff and soil erosion (Hurni et al., 2016). These technologies are constructed toward the direction of flow of rainwater to reduce or retain the runoff and thereby reduce the soil and water losses. In physical soil and water management technologies, increasing the concentration time of runoff, intercepting and reducing slope length and steepness and reducing damages through excessive runoff are the main principles (Desta et al., 2005). Physical soil and water management technologies include terrace, *fanya juu*, level and graded soil bunds, level and graded stone bunds, trenches and others (Desta et al., 2005).

There is a plethora of evidence which show the contribution of physical soil and water management technologies in increasing soil water, reduce soil erosion and other climate adaptation benefits. For instance, in semiarid West Africa, stone bund, *zaï* and half-moon technologies in combination with application of organic/inorganic nutrients resulted an increase in food production and increase soil ecosystem services (Zougmoré et al., 2014). In the Central Highlands of Ethiopia, physical soil and water management technologies effect a reduction of surface runoff by 28% (Adimassu et al., 2012). Similarly, physical soil and water management technologies resulted an increase of soil water (5.43%) in the watershed of the Upper Blue Nile River Basin (Mengistu et al., 2016). Herweg and Ludi, (1999), Gebrernichael et al., (2005), Hurni et al., (2005) and other studies also explore a significant reduction of loss of water through surface runoff, reduction of soil loss and an increase in soil water.

There are also evidence which reveal the contribution of physical soil and water management technologies to increase agricultural production and sequestration of greenhouse gases. In the Andit Tid Soil Conservation Research Program (SCRP) research site of Ethiopia, physical structures such as terrace and soil and stone bunds resulted higher yield than areas without such structures (SCRP, 2000). Similarly, physical soil and water management technologies resulted significant ($p < 0.05$) increase of plant height, plant biomass, seed weight and an increase of grain yield of wheat by 72.8% in southern Ethiopia (Tanto and Laekemariam, 2019). In different regions of the world, it was also explored that terraces have resulted an enhanced survival rates of plant seedlings, ecosystems restoration and eventually an increase in crop yield (Wei et al., 2016).

However, there are studies which explore insignificant contribution of physical soil and water management technologies for agricultural production and climate change adaptation. In the watersheds of the Central Highlands of Ethiopia, physical structures such as soil bunds result a reduction of cultivable area by 8.6% that further result 7% decrease of crop yield (Adimassu et al., 2012). Similarly, in the Soil Conservation Research Program (SCRP) research sites in the highlands of Ethiopia and Eritrea, Herweg and Ludi, (1999), also explore that crop yield and biomass production did not increase as a response to different soil and water management structures. On the other hand, Kato et al, (2009) has investigated that most of soil and water conservation technologies did not reduce effect of climate change in most regions of Ethiopia and conclude that the performance of these technologies is location specific. This signifies the need to augment physical soil and water management structures with other adaptation strategies and identify optimal physical structures for climate adaptation strategies.

2.6.2.3 Conservation agriculture

Conservation agriculture which embraces zero or minimum tillage, cover crops and crop residues management is an approach of agro-ecosystems management to improve and sustain productivity, increase profits and food security while preserving and enhancing the natural resource (FAO, 2013). Conservation agriculture is practiced on around 125 million hectares of land worldwide and involves minimum disturbance of soil through reducing tillage. Conservation tillage further results decrease of mineralization, increased soil cover and crop diversification (FAO, 2013). Minimum tillage, mulching with crop residue and crop rotation are the major conservation agriculture practices to increase yields through improvements in soil fertility, climate change adaptation and mitigation and sustainable agricultural intensification (Michler et al., 2019). Conservation tillage is another soil management system which aims to create a favorable soil environment for germination establishment and plant growth with minimal soil disturbance through avoiding ploughing operations that could destroy the soil structure (Hurni et al., 2016).

Conservation agriculture has multitude of benefits of climate change adaptation through increasing water availability and reducing emission of greenhouse gases. Minimum disturbance of land and soil in conservation agriculture practices reduce fossil fuel emissions, although there may be slight negative GHG impacts from application (FAO, 2013). Conservation agriculture practices reduces surface runoff, conserves water in the soil, improves the soil structure and conserves organic matter in the soil (Hurni et al., 2016). Conservation agriculture has also contribution in reducing soil erosion and stabilizing crop yields in the rainfed farming systems (Desta et al., 2005). The role of conservation agriculture in maintain biodiversity is another contribution. It promotes richness of soil microorganisms, diversification of plant species and natural biological processes above and below the ground surface. Above all, conservation agriculture has tremendous benefits in building soil's resilience to climate change (FAO, 2013).

From agricultural production perspective, conservation agriculture is agricultural production system that aims to achieve production intensification and provides high yields through planned crop rotations and integrated weed management and pest management. Particularly, conservation agriculture is suitable for areas characterized by low soil productivity and difficult climatic conditions, such as drought and rainfall irregularity to sustain and improve productivity and food security (FAO, 2013). During rainfall stress seasons, conservation agriculture has significant effect on maize and sorghum yields, however conservation agriculture has non-significant effect millet, groundnut, and cowpea yields (Michler et al., 2019). In the Sub-Saharan Africa, conservation agriculture has been widely promoted in smallholder farming systems to build resilience against climate change and climate extremes.

2.6.2.4 Precision agriculture

Precision agriculture is an approach which is intended to obtain optimal benefits through optimizing the application of water and nutrients. Precision agriculture include a more efficient use of fertilizer, nutrients and water through scheduled sprinkler irrigation or drip irrigation systems (FAO, 2013). More comprehensively, precision agriculture embraces precise seeding, fertilizer application, irrigation, and pesticide use in order to optimize crop production for the purpose of increasing grower revenue and protecting the environment (Cambouris et al., 2014). Consequently, we can assume that precision agriculture requires high level of technology and knowledge of crop requirements of soil, nutrients, terrain and climatic conditions.

Similar with other natural resources and watershed management technologies, precision agriculture has various benefits in climate change adaptation and mitigation and agricultural production. For instance, precision agriculture has an effect to lower CO2 and N2O emissions and reduce the consumption of fossil fuels through a more efficient use of fertilizer. Besides, using manure for biogas reduced methane emissions and emission of fossil fuels on farms also improve energy access (FAO, 2013). Different precision agricultural practices also trigger significant increase of the water storage capacity of the soil and such practices also found efficient way to improve tuber yields and the quality of sandy soils (Cambouris et al., 2014). Precision agriculture has paramount benefits to the environment through reducing emissions of chemicals through efficient use of nutrients, pesticides and insecticides and through more inputs (Bongiovanni and Lafayette, 2004).

A collection of precision agriculture practices such as soil survey, soil property analysis and inputs application resulted better potato productivity and profitability while reducing the environmental impacts of agricultural practices (Cambouris et al., 2014). Application of different precision agriculture such as site specific fertilization use, soils treatments, using improved seed varieties and field and laboratory tests trigger an increase in potato production (Bongiovanni and Lafayette, 2004). To satisfy the need to increase agricultural production by 60% by 2050 (FAO, 203), it is recommendable to use agricultural practices such as different precision agricultural technologies.

2.6.2.5 Climate smart agriculture

Agricultural sector is not only source of greenhouse gases emission, but also agriculture has a great potential for climate change mitigation and increase its resilience of climate change. For this, climate smart agriculture is an emerging multipurpose approach which sustainably increases agricultural production, build resilience of agroecosystems to climate change and mitigate climate change by removing and reducing emission of greenhouse gases (FAO, 2013). Climate smart agriculture focuses on contributing to economic development, resilience of natural and agricultural ecosystem functions, building natural capital and reducing trade-offs involved in meeting these goals (Freeman, 2015). Different from sustainable agriculture and climate change adaptation and mitigation approaches, climate smart agriculture is designed to identify and foster sustainable agricultural development within the explicit parameters of climate change (FAO, 2013). Climate smart technology, climate smart landscapes and others are concepts derived from climate smart agriculture with similar entry; adaptation, mitigation and food security (Freeman, 2015).

Climate smart agriculture is in practice in many parts of Africa, for instance in Zambia, Niger, Kenya and Malawi and needs qualification of its benefits. For instance, in semiarid West Africa *zaï*, half-moons and stone bunds technologies in combination with application of organic/inorganic nutrients are climate smart agricultural practices which maintain food production and increase soil ecosystem services (Zougmoré et al., 2014). In middle hill of Nepal, improved farmyard manure and compost, integrated legumes and fodder crops into cropping systems, small-scale collection of run-off water are climate smart management options which enhance soil carbon storage, improve crop resilience and food security (Shrestha et al., 2014). In Ethiopian Climate Resilient Green Economy (CRGE) strategy, different soil, water and forestry based initiatives that could lower emission of greenhouse gases and increase climate resilience and agricultural production are identified (FDRE, 2011). In these aforementioned and other countries with similar land management practices, there is a need to quantify mitigation role, multi-functionality and trade- off of land management practices in the perspective of climate smart agriculture.

2.6.3 Integrating Climate Change in Watershed Management

Water is the sector highly affected and will be affected by climate change and it is through water climate change influences earth's ecosystems and the livelihood and wellbeing of humankind (UNECA, 2011; IPCC, 2014). Therefore, water management planning at watersheds and landscapes level should prudently incorporate climate change. To incorporate climate change with watershed planning, uncertainty in climate change scenarios particularly at regional and local scales is the real challenge (Snover et al., 2003; Star et al., 2016). Different approaches were used to build climate change adaptation at the watersheds level under uncertainty. For instance, using an adaptive management approach, Lawler, (2009), prioritize water storage structures, floodplain management, restoration and streambank stabilization for freshwater ecosystems management under uncertain climate change. On the other hand, using scenario planning approach irrigation, water transfer, increase irrigation efficiency, vegetation cover and other were identified watershed management alternatives under uncertain climate and socio-economic conditions (Dong et al., 20112).

Besides the approaches and frameworks to integrate climate change with watershed planning, other water resources based climate adaptation are required to identify technologies which can be effective under different climate change scenarios. This is because climate change also erodes the effectiveness of water management structures (Bates et al., 2008; WMO, 2009; Xie et al., 2015). Existing watershed management structures such as hydraulic structures, flood protection structures and irrigation systems may not be robust enough to buffer the impacts of future climate change (Bates et al., 2008). As a result, the responsibilities of watershed management stakeholders are broadening as a response to the impact of climate change on hydrological processes and effectiveness of watershed management structures (Bates et al., 2008). Integrating climate change with watershed management planning underpins to minimize the potential negative impacts of climate change in years to come (Xie et al., 2015).

There are various studies identify watershed and water management technologies for optimal climate adaptation. Hallegatte, 2009, has investigated different water, agriculture, health and human settlements based strategies that cope different climate change conditions. Water storage and reuse, land-use planning, reduction of leakage and institutionalization of long term planning were among the water-related adaptation strategies under uncertainty (Hallegatte, 2009). In the Anyangcheon watershed of South Korea, redevelopment of existing reservoirs, construction of wastewater plants and use of groundwater were among effective watershed management alternatives under climate change and urbanization scenarios (Yang et al., 2012).

In Ethiopia, watershed-based soil and water management is among the prioritized adaptation strategies of climate change and different programs commence to incorporate watershed management in their climate change adaptation strategies (FDRE:NPC, 2016; FDRE, 2019; FDRE:MoWIE, 2015). For instance, in the consecutive Growth and Transformation Plans (GTPs) of Ethiopia, watershed management was identified to ensure climate resilient agricultural development in different watersheds of the country (FDRE:NPC, 2016). In the water sector of climate resilience, watershed management was prioritized to underpin the resilience of rainfed agricultural systems of Ethiopia and to increase water availability for small scale irrigation (FDRE: MoWIE, 2015). Rainwater management, soil moisture conservation, runoff water harvesting structures, spatial catchment planning and adaptive water governance were among the technologies identified to increase green water and climate change resilience in Ethiopia other countries (Rockstro¨m et al., 2009). At the watersheds scale, a significant reduction of surface runoff while significant increase in soil water availability was observed on areas under soil and water management structures upper Blue Nile Basin (Mengistu et al., 2015). However, an insufficient link between climate scenarios and climate adaptation strategies at water and other sectors are realized to effectively reduce climate change impacts (Conway and Schipper, 2011; FDRE, 2019).

Chapter 3

Description of the Study Area and Overall Methodology

3.1 Description of the Study Area

3.1.1 Location

Jemma sub-basin is located in the Central Highlands of Ethiopia, South-eastern part of the Upper Blue Nile (Figure 2.1) which has an area of ~15,000 km^2. Jemma sub-basin is among the sub-basins of the upper Blue Nile Basin of Ethiopia which covers ~8 % of the area and ~14 % of the total annual flow of Upper Blue Nile Basin (Yilma and Awulachew, 2009). The Jemma sub-basin entirely lies in the Blue Nile Basin, but the eastern part of the sub-basin is a water divide of the Shewa Plateau of the Blue Nile basin from Awash River Basin. Administratively, Jemma intersects the Amhara and Oromia Regional States of Ethiopia. North Shewa zone of Amhara region and North Shewa zone of Oromia region largely drained by the Jemma sub-basin.

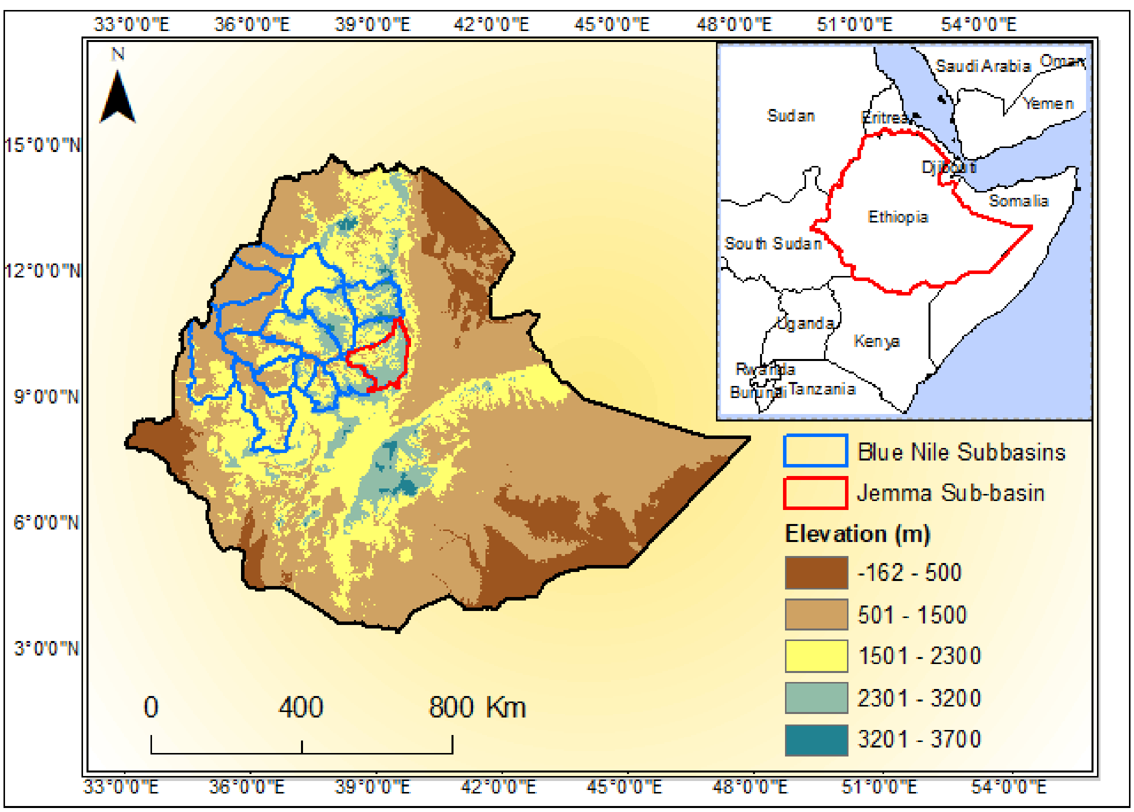

Figure 2.1 Location of Jemma sub-basin with reference to Ethiopia and Upper Blue Nile Basin**.** The elevation map is based on the DEM data of 30m resolution obtained from the Shuttle Radar Topographic Mission (SRTM) http://earthexplorer.usgs.gov

3.1.2 Topography

The topography of the Jemma sub-basin is characterized by uneven topography and dissected terrain where elevation varies with short distance. The southern part of the sub-basin is plain with even topography, however, the central areas of the sub-basin is highly dissected terrain. Elevation in the sub-basin is in the order of 1040 - 3840 m.a.s.l. The eastern part of the sub-basin is under high elevation above 3000m.a.s.l and dominantly afro-alpine and sub-afro alpine ecosystems. The high elevation in this part of the sub-basin is the water divide of the Upper Blue Nile and Awash River Basins of Ethiopia.

3.1.3 Climate

The rainfall of Central Highland of Ethiopia is driven by the moisture from the Indian Ocean, equatorial east Pacific, Gulf of Guinea, Mediterranean region and Arabian Peninsula (Seleshi and Zanke, 2004; Viste and Sorteberg, 2011). Jemma sub-basin receives annual rainfall in the order of about 700 mm to 1500 mm. The northern areas of the Jemma sub-basin are characterized by low mean annual rainfall (700 mm) whereas the high elevation areas in the eastern part of the sub-basin receive high mean annual rainfall (1500 mm) from 1981 to 2014 (Figure 2.2).

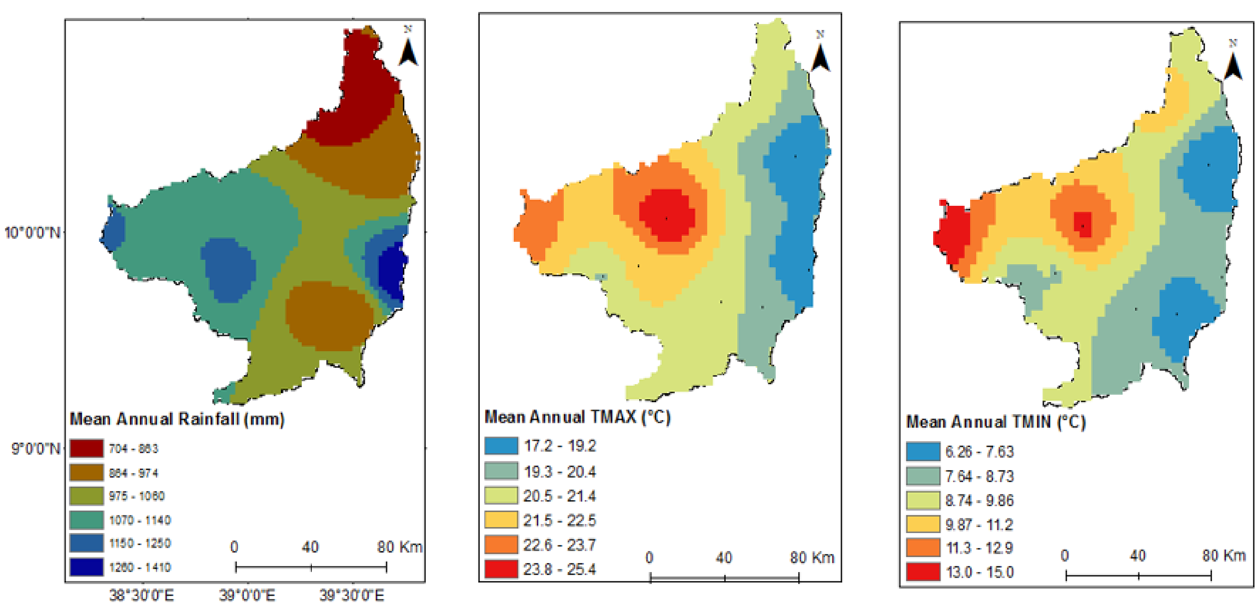

Figure 2.2 Long-term (1981-2014) mean annual rainfall, TMAX and TMIN of the Jemma sub-basin

The main rainfall season in this sub-basin occurs from June to September (summer) which is locally called *Kiremt.* Short rainfall may also happen from March to May (spring) and this season is locally called *Belg*. The rainfall of spring is important for crops and grass (forage) production particularly for Dega (>2800m) areas of the sub-basin where frost is the problem for cultivation during summer season. However, spring rainfall is characterized by high variability in which there is delay, absence, falls only for a few days or falls for months which results crops failure. Among the stations in the Jemma sub-basin, Andit Tid and Lemi stations receive higher rainfall while Wereilu and Mehalmeda stations receive lower rainfall in most months (Figure 2.3). There are areas of the sub-basin with relatively low mean annual temperature (9°C) and in contrast, there are areas with high mean annual temperature (24 °C). Lower TMAX and TMIN is on the eastern part of the sub-basin than other areas of the sub-basin (Figure 2.2).

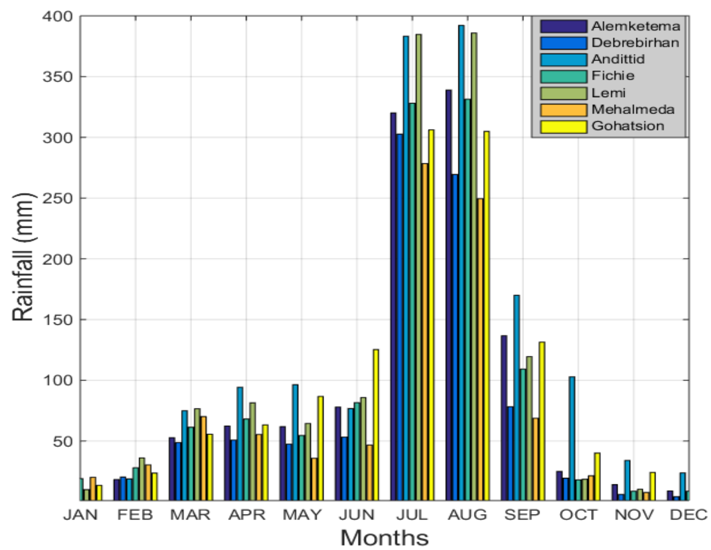

Figure 2.3 – Baseline (1981-2014) mean monthly rainfall of climatic stations of the Jemma sub-basin

3.1.4 Hydrology

Studies (Yilma and Awulachew, 2009; Ali et al, 2014) showed that Jemma sub-basin discharges significant amount of water and sediment to the Upper Blue Nile River. The Jemma River has the annual flow of 5844 MCM and 2560 MCM for the year 1996 and 1997 respectively (Figure 2.4). This sub-basin contributes about 14 % of the total annual flow of upper Blue Nile Basin (Yilma and Awulachew, 2009). There are numerous tributaries to the main Jemma river. These include Beressa, Chacha, Moferwuha, Adabay, Robit and Wonchit rivers. Beressa in the upstream, Robi-Gumero in the middle stream and Jemma at the outlet are important where they constitute hydrological gauge stations and the data from these gauge station was used for calibration and validation of the hydrological model. Beressa watershed has an area of about 220 km^2 and it is characterized by rugged topography and high elevation which ranges from 2700-3650m above sea level. In this watershed, one climatic station (Debrebirhan) and one hydrological station (Beressa) are located.

Robi-Gumero watershed drained by Robi River is also a tributary of Jemma river and located in the middle of the sub-basin. The area of this watershed is around 887km^2. Robi-Gumero watershed is also characterized by rugged topography and elevation ranges from 2300 to 3000m above sea level. In this watershed, the nearest climatic station is Lemi and the hydrological station is Robi-Gumero gauge station. Jemma gauge station is found in the outlet of the Jemma sub-basin, however, stream flow data is available only for the years 1996 to 1997 (Figure 2.4).

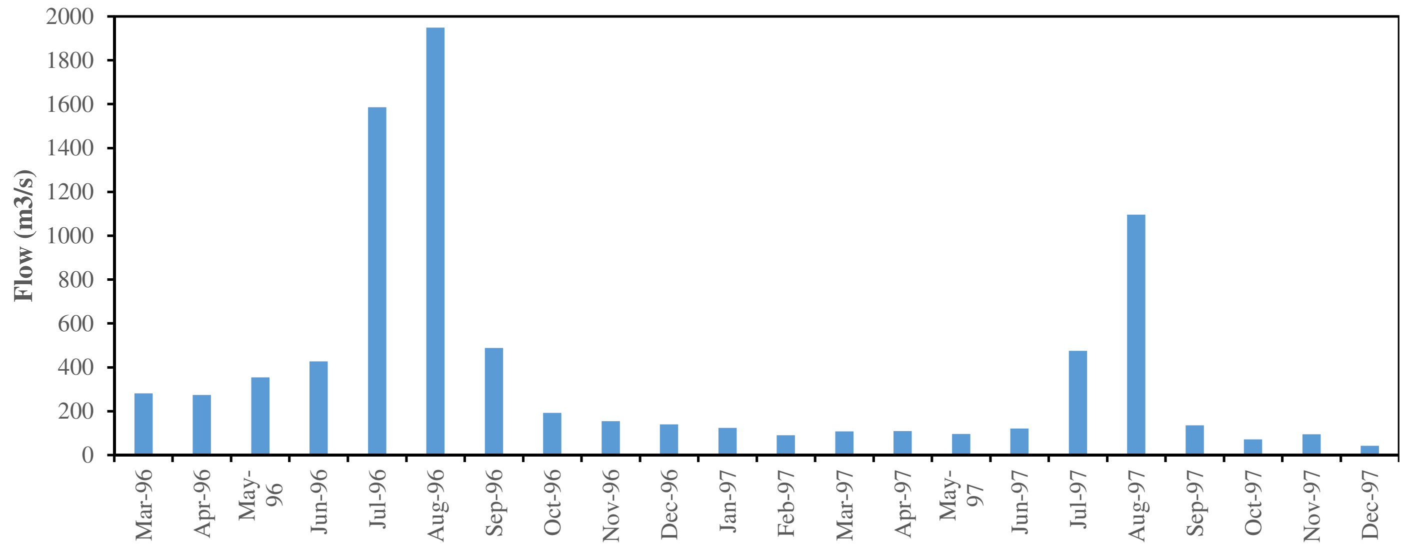

Figure 2.4 Monthly stream flow at the outlet of the Jemma sub-basin (1996-1997)

3.1.5 Land use and land cover

Based on sources from European travelers, elephants, lions and leopards were observed in natural forests before 18th C in the rivers of Chacha and Beressa (Demisie, 2015; Ayenachew, 2019). While in the 18th C, the European travellers observed and recorded that land covered by forest was restricted to some pocket areas and church compounds (Ayenachew, 2019). *Juniper* and *Podocarps* were trees which cover a large area of *Dega* and *Woyenadega* agro-ecologies of the region (Demisie, 2015). After the 18th C, absence of wood was observed and as a result, people have started to use animal dung for their domestic energy source (Ayenachew, 2019).

Land use and land cover classification of the year 2008 in the Jemma sub-basin revealed that about 57% of the sub-basin was cultivated land, which may require some form of watershed management intervention given the exposure of the land for environmental degradation. Other land use and land cover types include grazing land (14.64%), bare land (10.45%), shrubland (6.44%), woodland (6.05%), forest land (1.20%). There are also afro-alpine vegetation, eucalyptus plantations and water bodies (on the main course of the rivers) which cover small proportion of the sub-basin (Figure 2.5a). Eucalyptus plantation mainly close to the villages shows expansion in the last two decades. The rivers channel and the lower part of the sub-basin are characterized by bare-land. Wheat, barley, teff, maize and sorghum are the main crops cultivated in the Jemma sub-basin. However, due to high degree of land degradation, crop yield is low (less than 2 ton/hectare) which is among the problems of the study area (SCRP, 2000).

3.1.6 Soil

The soil types in the Jemma sub-basin include Eutric Vertisols (28.07%), Lithic Leptosols (37.44%), Chromic Lixisols (8.07%), Pellic Vertisols (6.82), Haplic Luvisols (5.79%), Haplic Acrisols (6.82%). Eutric Fluvisols, Umbric Nitisols and Alic Nitisols cover small proportion of the sub-basin (WLRC, 2016). Leptosols and Vertisols are the main soil types which cover more than 70% of the Jemma sub-basin (Figure 2.5b). This part of the Central highland of Ethiopia is among regions of Ethiopia characterized by high soil erosion (FAO, 1986). Expansion of cultivated land and grazing lands towards the steep slopes and marginal lands triggers a change in soil structure and accelerated soil erosion (FAO, 1986; SCRP, 2000). As a result, Jemma is highly prone to soil erosion; the long-term average annual sediment yield at the sub-basin outlet is 21.2 million tons/year (Ali et al., 2014).

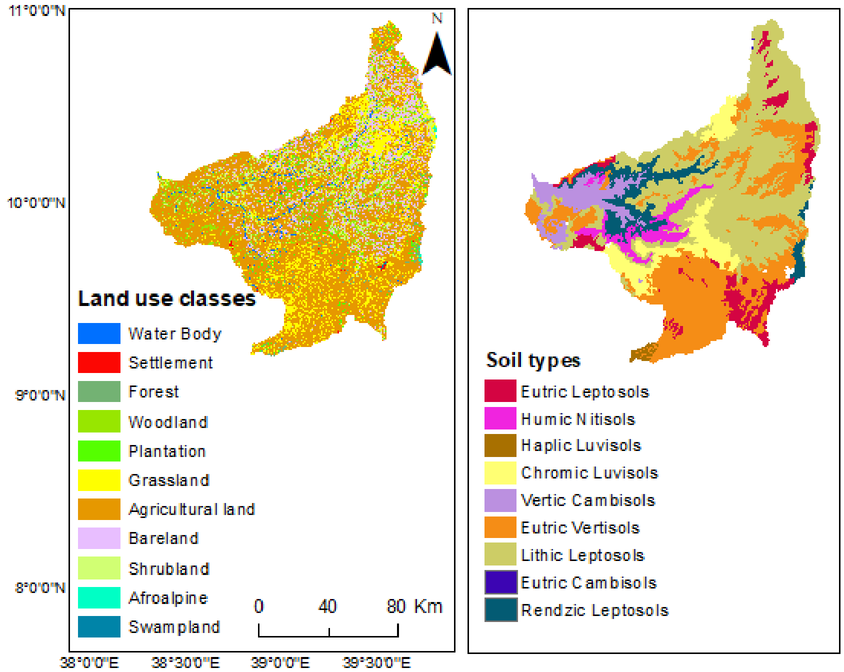

Figure 2.5 Land use/land cover classes and soil types of the Jemma sub-basin

3.1.7 Socio-economic Setting

Jemma sub-basin is located in the Shewan Plateau, intersects Amhara and Oromia regional states of Ethiopia and it covers 28 *weredas* of the regional states. The European travellers recorded that there was no intensive farming and population distribution was also very sparse before the 18thC in the Shewan Plateau. Because of suitable ecological and climatic conditions with moderate temperature and rainfall in the 18th C, agricultural settlers were successful with no challenges of agriculture (Demisie, 2015). Before 18thC, there was adequate sources of water throughout the year in the plateau and the valleys of Shewa. Consequently, there were cotton lands on both sides of the river banks of Jemma river (Demisie, 2015). In 2007, the population of the Jemma sub-basin was 2,380,371 (FDRE:PCC, 2007) and it was projected to 2,995,084 in 2017 (FDRE:CSA, 2013).

3.1.8 Natural resources management

Natural resources management practices date back to 400 years ago. In the Guassa Menz area (with elevation>3200m) of the Jemma sub-basin, indigenous natural resources management institution was practiced for over 400 years (Ashenafi, 2005). However, following the 1974 revolution, this indigenous natural resources management system was collapsed and the Guassa area has faced overexploitation and degradation of the grasslands and non-sustainable utilization of the resources in this afro-alpine ecosystem (Ashenafi, 2005). Fortunately, the Guassa Community Conservation was established to revive the indigenous management system and to sustainably manage the valuable Guassa grasses *(Festuca* *abyssinica)*, locally called Guassa since 2003. In 2012, the Guassa Conservation Council was legally established under the auspices of the council of the Amhara National Regional State under regulation No. 97/2012 (The Council of Amhara National Regional State, 2012). In addition to the grasses, Guassa area also harbours many endemic species including most endangered Ethiopian wolf (*Canis simensis*), also known as the Simien fox (Ashenafi, 2004; Ashenafi, 2005).

Following the 1970s and 1980s recurrent drought, watershed-based soil and water management was commenced. During this time, the size of watersheds as a planning unit was large comprises 30-40 thousand hectares and resulted failure due to lack of effective community participation, limited sense of responsibility over assets created, and unmanageable planning units (Desta et al., 2005). During this time, soil and water management technologies were introduced and implemented in the highlands of the Jemma sub-basin and in the Shewan plateau (FAO, 1986). In some catchments of the Jemma sub-basin, for instance in the Andit Tid catchment, *Fanya Juu* literally 'throw uphill', a new soil and water management technology which is made of soil and stone bunds was introduced from Kenya under the auspice of the then Ministry of Agriculture in collaboration with the Soil Conservation Research Programme (SCRP, 2000). However, until the 1990s the watershed management structures were implemented based on top-down approach and mainly incentive-based.

In the 1990s, there was a shift from larger watersheds to smaller watersheds for the planning of watersheds development. The achievements of planning at smaller watersheds was tested at the pilot stage through FAO technical assistance under the then Ministry of Agriculture and Rural Development of Ethiopia and showed remarkable success (Desta et al., 2005). During this time, watershed development was not limited to physical soil and water management rather rural development and poverty alleviation were also the concerns.

Since the 2000s, Ethiopia initiated Participatory Watershed Development programs in partnership with international institutions. The overall objective was to improve the livelihood of community/households in rural Ethiopia through comprehensive and integrated natural resource development (Desta et al., 2005). Community based Watershed Development Programme has became a comprehensive development concept for sustainable and efficient utilization of natural resources for the benefit of the local community with special attention to the rural poor (Desta et al., 2005). Different from the previous period, strong emphasis was given to household income generating activities and innovative approaches towards the conversion of degraded landscapes to productive lands.

Sustainable Land Management Program (SLMP) was also launched in 2008 to address a long history of soil degradation of Ethiopia under the leadership of Ministry of Agriculture and Natural Resources. In Ensaro, Basoworena, Menz mama midir, Degem, Abote, Warajarso and Kuyu woredas of the Jemma sub-basin, there are watersheds on which different soil and water management technologies are implemented under the auspice of Sustainable Land Management Program. In 2016, about 6,562 km^2 (42.71%) of the Jemma sub-basin is under different soil and water management structures which include terrace, soil bund and stone bund.

3.2 Conceptual Framework of the Study

Climate change impact is highly recognized on water sector than other sectors (UNECA, 2011; IPCC, 2014) and subsequently, water management at watersheds or regional scales requires robust adaptation decision-making. However, climate adaptation decision making is challenging due to climate change and time-variant socio-economic uncertainties. Uncertainties stem from future socio-economic development scenarios, greenhouse gases emission scenarios and climate models inefficiency to capture the complexities of nature and human activities are noticeable (Fowler et al., 2007; IPCC, 2013; Kundzewicz et al., 2018). To this effect, using approaches that underpin management of natural resources and climate adaptation in the face of uncertain future climate is worthwhile. For this, adaptive management (Williams, 2011; Prato, 2016) and scenario-based planning (MEA, 2005; ; Star et al.,2016) are approaches applicable for climate adaptation under uncertain climate.

Adaptive management is iterative management of environmental resources through planning, experimentation, monitoring and evaluation of management strategies for optimal decision making under uncertainty (Williams, 2011; Prato, 2016). Adaptive management intends to improve the performance of management alternatives and may include a transformation of adaptation (Williams, 2011). Different from other management approaches, adaptive decision making encompasses clearly stated objectives, identification of management actions (alternatives), prediction of the effectiveness of management actions using models, stakeholders involvement and monitoring of changes in natural resources system (Williams, 2011; Prato, 2016).

Particular to climate research, adaptive management embraces plausible future climate and its potential impacts, management actions to defy climate change impacts and natural resource system (Prato, 2016). Climate change and its potential impacts are considered as environmental conditions that trigger a change in the status of natural resources system. While, management actions are experiment-based decisions that could lower the impact of climate change on the natural resources system (Williams, 2011). In general, natural resources system is subject to change as a response to a magnitude of change in the environmental condition (climate change) and type and effectiveness of management actions (Figure 3.1). In the perspective of adaptive management, the scheme of the response of watershed resources (water availability) to environmental condition and management action at different time is presented on Figure 3.1.

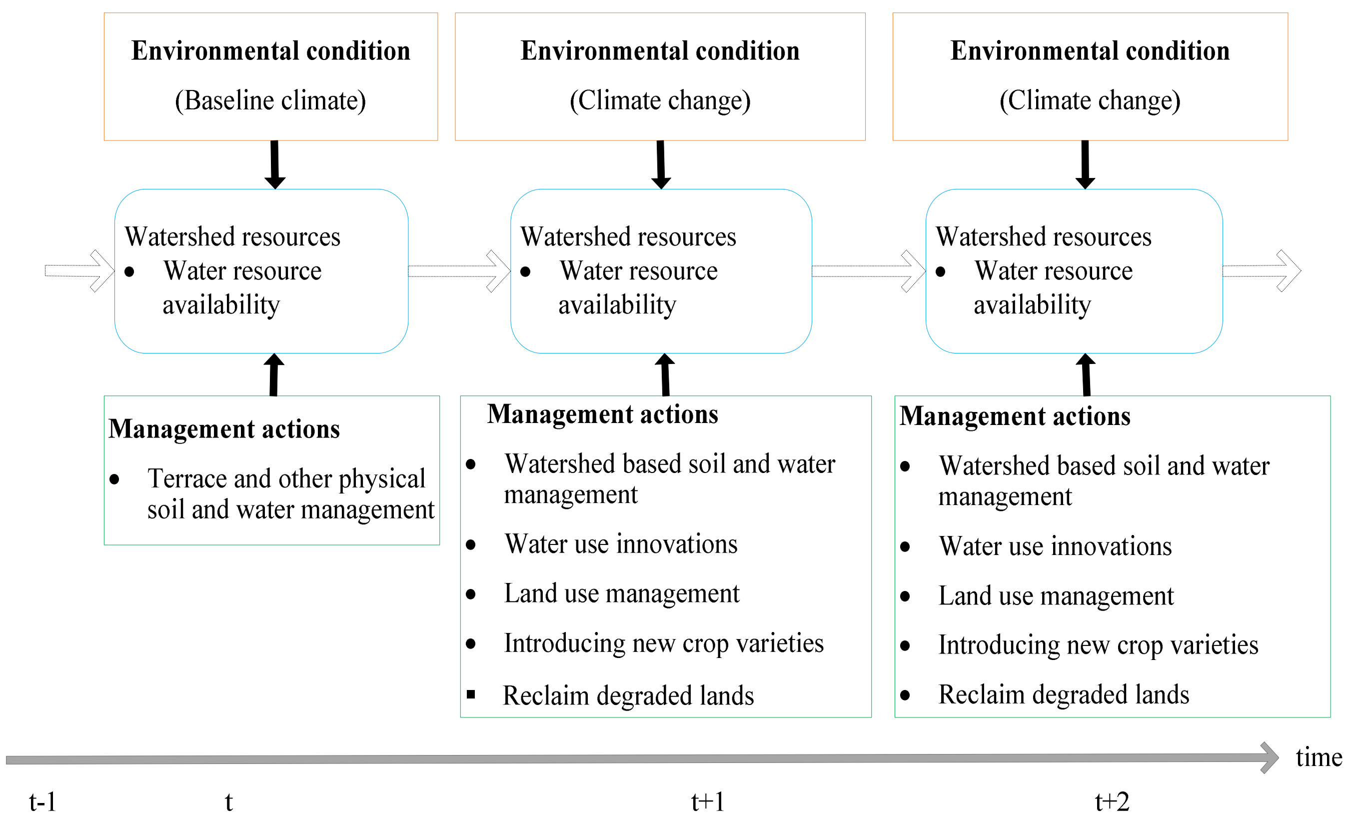

Figure 3.1 Conceptual framework of the study show the watershed resources system is a function of changes in environmental conditions and management actions over time. The solid arrows represent the effect of climate change and management actions on watershed resources, primarily water availability, while the open arrows represent changes that could happen on the status of watershed resources over time. In the time bar t-1, t, t+1 and t+2 are to show watershed resources status in past, current (baseline), near and long-term future, respectively. Adapted by the author based on adaptive management framework (Williams, 2011).

To develop plausible description of climate change and climate adaptation alternatives that perform well under various potential but uncertain climate, adaptive management is to be integrated with scenario planning (IPCC, 2013; Lawler, 2009). Scenario planning is decision-making framework to help managers understand the future climate by exploring different trajectories of change and to develop a set of plausible alternatives of climate adaptation under uncertainty (MEA, 2005; Moss et al., 2010; Dong et al., 20112; Star et al., 2016). Scenario planning is a means of viewing the future and identifying strategic decisions which can provide optimal benefits for years to come. Here, scenario planning is not to be viewed as prediction or forecast, rather scenario planning intends to develop plausible future climate (IPCC, 2013). Scenario planning is also non-trivial to examine decisions and to enhance the performance of decisions (Hallegatte, 2009; Star et al., 2016).

Scenario planning can be researcher-driven processes or participatory processes. In researcher driven scenario planning, scenarios are exclusively developed by the experts, however, in participatory scenario planning, scenarios are developed by experts with the involvement of other stakeholders (Star et al., 2016). Thus, this study is designed based on the analytical framework of participatory scenario planning to develop watershed management scenarios for optimal adaptation decision making. Subsequently, scenarios which include climate scenarios, climate impact scenarios and climate adaptation scenarios are essential to develop robust climate adaptation decisions under a wide range of possible future (Snover et al., 2003; Moss et al., 2010).

Climate scenario development commences with identifying and characterizing the historical climate that can be further used as a baseline climate scenario to compare with future climate (IPCC-TGICA, 2007; Wilby et al., 2009). Climate scenarios should also embrace multiple emission scenarios, multiple GCM simulations and downscaling schemes before using for impact assessment (Randall et al., 2007; Flato et al., 2013; Kundzewicz et al., 2018). GCMs based climate scenarios (IPCC-TGICA, 2007) are essential to assess the response of the climate system to climate forcing scenarios, to simulate regional climate change and to assess climate change impacts (IPCC-TGICA, 2007; Moss et al., 2010). Prominently, climate scenarios based on the multi-model ensemble mean is most recommended to reduce uncertainty (IPCC, 1994; IPCC, 2007a; Taylor, et al, 2012; Teuschebien and Siber, 2012).

Climate impact scenarios development involves the analysis of the change on the biophysical and socio-economic conditions with and without considering climate change (IPCC, 1994; IPCC-TGICA, 2007). In climate impact scenarios, environmental and socio-economic models which can evaluate the response of the biophysical and socio-economic environment to different climate scenarios are essential (IPCC-TGICA, 2007; Wilby et al., 2009). Thus, due caution is needed during calibration and validation of environmental models such as hydrological models (Baldassarre et al., 2011; Kundzewicz et al., 2018). Eventually, climate scenarios and climate impact scenarios are crucial to discern and develop optimal climate adaptation decisions which can provide an optimal benefit under different climate conditions (IPCC, 2007; Kuikman et al., 2009; Haque, 2016).

Participatory scenario planning and adaptive decision-making also involve prioritizing optimal climate adaptation decisions (alternatives) that reduce the anticipated impact of climate change. Concomitantly, decision analysis techniques which can straddle the environment factors and stakeholders' interest are essential. Multi-Criteria Decision Analysis tools which can integrate society's views, climate scenarios, and climate impact scenarios are important to develop adaptation decision systems (Kuikman et al., 2009; Yang et al., 2012; USAID, 2013; Haque, 2016). Particularly, GIS-based multi-criteria decision analysis is non-trivial to integrate climate scenario, climate impact scenarios, biophysical settings and communi0ty perspective to develop optimal watersheds-based adaptation decisions making.

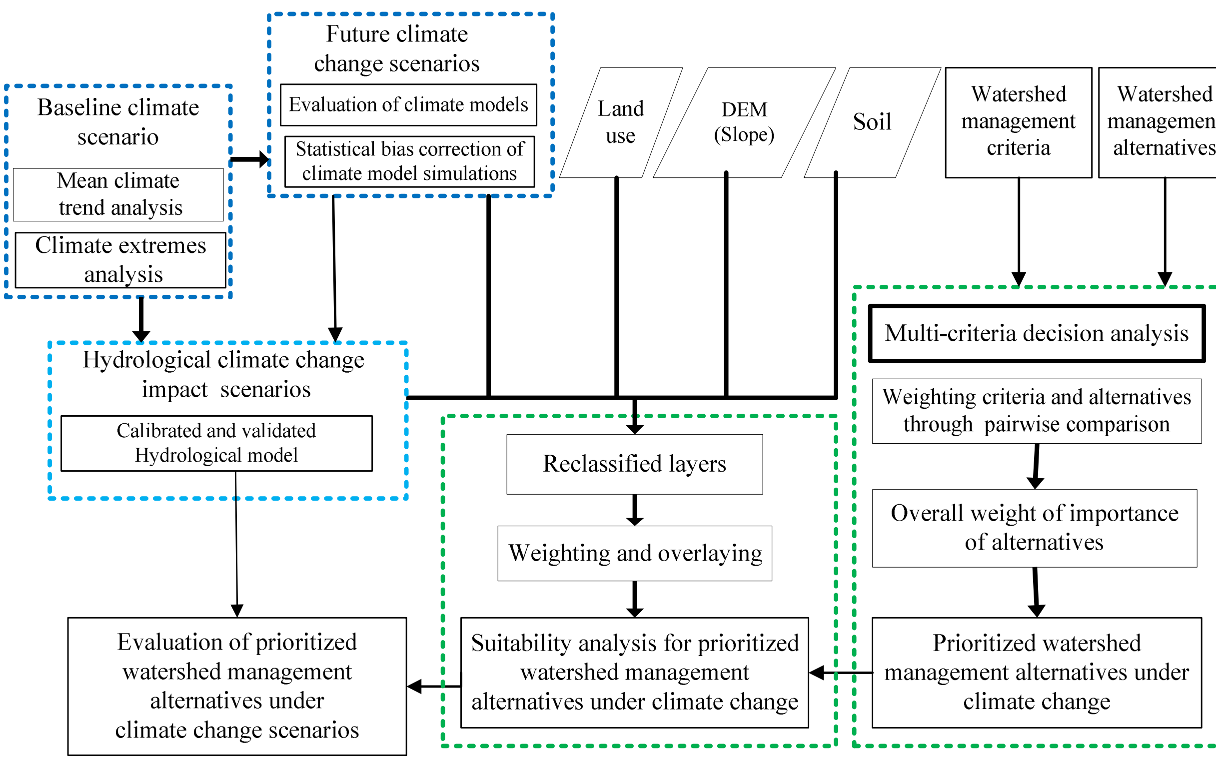

Figure 3.2 analytical framework of the study. Blue boxes represent the procedures to develop climate scenarios and climate impact scenarios while the green rectangles represent the procedures to study optimal response strategies (management actions) to climate change.

3.3 Overall Methodological Approaches

In this section, a brief of the data and the methodology of the study is presented while the details of the data and the methodology are given in the respective chapters. The data comprises observed climate and hydrological data, RCM simulations, spatial data and some qualitative data. In the methodology, brief of methodological procedures, statistical tools and models is given.

3.3.1 Observed climate and hydrological data

Observed climate data was required to establish baseline climate scenarios, future climate scenarios, hydrological climate impact scenarios and for climate adaptation decision analysis. Thus, observed (1981-2014) data of daily rainfall, TMAX, TMIN, solar radiation, sunshine, wind speed and relative humidity of nine climatic stations of the Jemma basin were obtained from the Ethiopian National Meteorological Services Agency and the Water and Land Resources Center (http://walris.wlrc-eth.org/) of Addis Ababa University. Daily streamflow data of gauge stations was obtained from Ethiopian Ministry of Water, Irrigation and Electricity. The hydrologic data was used to calibrate and validate the hydrological model and to develop baseline hydrologic balance components.

3.3.2 Regional climate models data

Historical (1981-2005) and future (2021-2100) RCM simulations driven by four CMIP5 GCMs were used in this study. The CMIP5 GCMs which were used as initial boundary conditions were CNRM-CM5, EC-EARTH, HadGEM2-ES and MPI-ESM-LR. Whilst, the RCMs which were used to regionalize these GCMs are the CCLM4 (COnsortium for Small-scale MOdeling (COSMO) Climate Limited-Area Model (CCLM) version 4.8), RCA4 (Rossby Centre Regional Climate Model) and REMO (Max Planck Institute Regional Model). These RCMs were selected for evaluation since they (especially CCLM4 and RCA4 models) were used to downscale historical and future simulations of multiple CMIP5 GCMs. RCM simulations driven through the Representative Concentration Pathways 8.5 (RCP8.5), RCP 4.5 and RCP2.6 (Moss et al., 2010) were considered. Rainfall, temperature and Sea Surface Temperature (SST) data of climate models were obtained from the publicly available Earth System Grid Federation (ESGF) web portals.

3.3.3 Spatial data

The spatial data which include Digital Elevation Model (DEM), soil data, land cover and land use data and land and water management data were acquired from different sources. The DEM data which has a 30m resolution was obtained from the Shuttle Radar Topographic Mission (SRTM). The land use/land cover data for the year 2008 was derived from Landsat satellite imagery and supervised image classification was done using maximum likelihood algorithm. The soil data was obtained from the Ministry of Water, Irrigation and Electricity of Ethiopian and the Water and Land Resources Centre of Ethiopia. Land and water management structures such as terraces and other physical soil and water structures were identified through Google Earth satellite images, field surveys and from grey literature of Zone Agricultural office. All the spatial data were projected into the projection parameters for Ethiopia, which is UTM Zone of WGS 1984, 37.

3.3.4 Qualitative data

In seven sample watersheds which cover all elevation classes of the sub-basin, interviews and focused group discussions were held with farmers and natural resources (watershed management) experts. In these sample watersheds, farmers were interviewed and focused group discussions were conducted with farmers to identify watershed management alternatives that could provide optimal benefits of climate change adaptation. Interview was also conducted with experts to list and prioritize the criteria and alternatives of watershed management for climate change adaptation.

3.3.5 Analysis of trends and extremes in the baseline climate

The missing values in the observed climatic data were imputed using Multivariate Imputation by Chained Equations (MICE) algorithm (Buuren et al., 2015) which is inbuilt on R statistical software (R Development Core Team, 2015). The quality of the climatic data of all the stations was examined using RClimDex 1.1 (Zhang and Yang, 2004). After quality control, the trend of rainfall, TMAX and TMIN under the baseline climate (1981-2014) were estimated using non-parametric Mann-Kendal test (Mann, 1945). The Seasonal-Mann-Kendall trend test (Hirsch et al., 1982) was also computed for each season separately to estimate the trend of rainfall on main rainy seasons (summer) and short rainfall season (spring) of the study area. The slope of trends in Mann-Kendal and seasonal Mann-Kendal tests was calculated using the non-parametric Theil-Sen's slope estimator (Theil, 1950; Sen, 1968). All tests in this study were estimated using the "trend" package which is inbuilt on R-statistical software (R Development Core Team, 2015). The rainfall and temperature extremes in baseline climate scenarios were measured using the Expert Team on Climate Change Detection and Indices (ETCCDI) (WMO, 2009).

3.3.6 Procedures to develop future climate scenarios

To develop future climate scenarios, RCMs which can reproduce the historical climate of the study area were identified. Three criteria were used to evaluate the performance of RCM simulations in capturing the 'historical' rainfall of the study area. The first criterion assesses the ability of the RCMs to reproduce the mean rainfall and characteristic of rainfall events. The second criteria evaluates the volumetric variations between areal rainfall of RCMs and areal rainfall of observations using statistical metrics such as BIAS, Root Mean Squared Error (RMSE) and Correlation Coefficient (Correl). The third criterion evaluates the teleconnection between SST of CMIP5 GCMs and the rainfall simulated by RCMs over the Jemma sub-basin.

RCM simulations were further adjusted using robust bias correction technique. For this, different statistical bias correction methods were intercompared using different metrics. Robust bias correction method which performs better during the historical period was used to develop climate scenarios for the near-term future (2021-2050) and long-term future (2071-2100). Commonly, all bias correction methods find a function which fits the model values with the observed values (Piani et al., 2010; Gudmundsson et al., 2012). Some of the bias correction methods (e.g linear scaling) adjust mean values while other methods (e.g distribution mapping method) adjusts the cumulative distribution (CDF) of RCM-simulated rainfall and temperature values with the CDF of observed rainfall and temperature values. To test the assumption of stationarity of biases and bias correction functions under future climate conditions, this study uses the differential split sampling method (DSST) method (Klemeš, 1986; Teutschbein and Seibert 2013). To execute different statistical bias correction techniques, this study has used the CMhyd tool (Rathjens et al., 2016) and qmap package which is built-in R statistical software (Gudmundsson, 2015).

3.3.7 Procedures to develop hydrological climate impact scenarios

To develop climate impact scenarios, hydrological model i.e the Soil and Water Assessment Tool (SWAT) model was used. Based on slope, land use and soil, the SWAT model discretizes the Jemma sub-basin into Hydrological Response Units (HRUs). The Soil Conservation Service (SCS) Curve Number method and the Penman-Monteith method were used to estimate surface runoff potential evapotranspiration (PET), respectively. The SWAT model was calibrated and validated using multi-site calibration and validation approach (Cao et al., 2006; Arnold et al., 2012) on SUFI-2 in SWAT-CUP (Abbaspour et al, 2004). The performance of the model during calibration and validation was evaluated using Nash and Sutcliffe simulation efficiency (NSE) and percent Bias (PBIAS) (Moriasi et al., 2015). The uncertainty of model simulation was also evaluated using P-factor and the r-factor on the SUFI-2 algorithm (Abbaspour et al, 2004). Eventually, the calibrated SWAT model was used to simulate hydrological processes under baseline and different future climate scenarios.

3.3.8 Procedures to develop watershed management scenarios under climate change

To identify and prioritize optimal watershed management scenarios, decision analysis tool that straddles climate scenarios, climate impact scenarios, stakeholders view and biophysical parameters was essential. Thus, multi-criteria decision analysis technique was used to integrate climate models output, hydrological models output, stakeholders perspectives and spatial and non-spatial data. A set of criteria and alternatives were selected using different literature and stakeholders' view. The criteria and the alternatives were intercompared using the Analytical Hierarchy Process (AHP) and most important criteria and alternatives for climate adaptation under different climate scenarios were selected. The spatial distribution of existing and prioritized watershed management structures was represented on the SWAT model. This was to evaluate the response of surface runoff, soil water and total water yield to different watershed management scenarios under baseline and future climate scenarios. Specifically, there were three main scenarios and subject to comparison;

Scenario-0 (Baseline): this scenario is used to show the water balance components under baseline and future climate scenarios. In this scenario, observed terrace and any anticipated watershed management scenario are not considered.

Scenario-1 (**Climate Change + Observed soil and watershed management structures**)**:** this scenario was used to evaluate the benefits of existing soil and water management structures under baseline and future climate scenarios. To evaluate changes in surface runoff, soil water and water yield, SWAT parameters which are sensitive to existing soil water management structures were modified.

Scenario-2 (Climate change + watershed management alternatives established using multi-criteria decision analysis (MCA) and Suitability Analysis (SA): this scenario was used to evaluate the effectiveness of watershed management alternatives which were identified through multi-criteiria decision analysis and suitability analysis on water resources components under baseline and future climate scenarios. Similar to scenario-1, SWAT parameters which are sensitive to prioritized watershed management structures were modified to evaluate changes in surface runoff, soil water and water yield under baseline and future climate scenarios.

PART II: RESULTS, ANALYSIS AND DISCUSSION

Chapter 4

Observed Changes in Extremes of Daily Rainfall and Temperature in the Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia

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Abstract

Climate variability has been a threat to the socio-economic development of Ethiopia. This paper examined the changes in mean and extreme rainfall, TMAX and TMIN at the Jemma sub-basin of the Upper Blue Nile Basin for the period 1981 to 2014. The nonparametric Mann-Kendall test, seasonal Mann-Kendall test and Sen's slope estimator were used to estimate annual trends. Ten rainfall and twelve temperature extreme indices were used to study changes in rainfall and temperature extremes. The results accentuate an increasing trend of annual and summer rainfall in more than 78% of the stations and a decreasing trend of spring rainfall in most of the stations. An increase in rainfall extreme events was detected in the majority of the stations. Several rainfall extreme indices showed wetting trends in the sub-basin; whereas, limited indices indicated dryness in most of the stations. Annual TMAX and TMIN and extreme temperature indices showed a warming trend in the sub-basin. Presence of extreme rainfall and a warming trend of extreme temperature indices may suggest signs of climate change in the Jemma sub-basin. This study, therefore, recommended the need for exploring climate-induced risks and implementing appropriate climate change adaptation and mitigation strategies.

Keywords: Temperature, Rainfall, Climate Extremes, Jemma Sub-Basin, Upper Blue Nile, Ethiopia

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[*]This chapter is based on **Worku, G., Teferi, E., Bantider, A., Dile, Y.T., 2018a. Observed changes in extremes of daily rainfall and temperature in the Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia.** *Theor. Appl. Climatol. 135, 839–85,* https://doi.org/10.1007/s00704-018-2412-x.

4.1 Introduction

Compelling evidence exists that climate change is occurring globally and concerns have arisen about its impact. Global land and ocean surface temperature has increased by 0.85 °C for the period 1880-2012 (IPCC, 2013). Analogously, the last three successive decades were warmer globally compared to any other decades since 1850 (IPCC, 2013). Temperature has been showing an increasing trend in almost all regions of the world. However, the trend and magnitude of change of rainfall are not conclusive; it may vary by regions and seasons (Alexander et al., 2006; IPCC, 2013; Maidment et al., 2015). An increase in rainfall by 0.5-1% per decade over most mid and high latitudes of the Northern Hemisphere and by 0.2-0.3% per decade over the tropical land areas was estimated in the 20th century (IPCC, 2001; IPCC, 2013). Likewise, an increase in annual rainfall in the Sahel and Southern Africa regions and a decrease in March-May rainfall in East Africa region was observed over the period from 1983 to 2010 (Maidment et al., 2015). While the focus of most long-term climate change studies has been on changes on an average climate. Extreme climate events are more sensitive to climate changes (Alexander and Arblaster, 2009; WMO, 2009) and warrant adequate focus of studies.

Change in the extremes of rainfall and temperature was observed in various regions of the world. For example, a decrease of the number of cold days and nights, an increase in the number of warm days and nights, frequency of extreme high temperatures and frequency of heavy rainfall were discerned on the second half of the 20th century (IPCC, 2012; IPCC, 2013). Changes in extreme climate have profound impacts on society by causing property damage, injury, poverty, loss of life and biodiversity (IPCC, 2012). Moreover, extreme events speed up changes in the ecosystem structure and function more than the average climate (Peterson and Manton, 2008). Such extreme events demand rigorous risk management and adaptation measures, which further require a detailed understanding of the trend of climate extremes.

Climate extremes are affecting most of the rural poor where their economy is fully dependent on climate. For example, the Ethiopian economy is characterized by high dependency on rain-fed agriculture which has low adaptive capacity to adverse impacts of climate change (World Bank, 2006; Conway and Schipper, 2011). There are polarized rainfall trends across different agroecological zones of Ethiopia (Cheung et al., 2008; Mekasha; et al., 2013) which intricate rainfall-runoff modelling and drought risk assessment. For instance, a significant decline of summer (June to September) rainfall is recorded in the Baro-Akobo, Omo-Ghibe, Rift Valley, and Southern Blue Nile areas of Ethiopia (Cheung et al., 2008).

High variability and non-significant trend of rainfall is reported in pastoral, agro-pastoral and highlands of Rift Valley, southern range-lands and eastern highlands of Ethiopia (Mekasha et al., 2013). On the other hand, Seleshi and Zanke, 2004 found a decline of annual and summer rainfall in eastern, southern and southwestern parts of Ethiopia since 1982. Such a difference in the findings related to rainfall variability may stems from differences in spatial and temporal scale of studies and topography of the study areas.

Few studies explore the extreme climatic trends in the Upper Blue Nile Basin, which is one of the major food-producing basins in Ethiopia. The basin has also significant international importance since it contributes more than 60% of the flow to Nile River at Aswan, Egypt (Conway and Hulme, 1996). In this basin, some studies (Baldassarre et al., 2011; Mengistu et al., 2013) showed increasing trends in both annual TMAX and TMIN. Mengistu et al., 2013, using linear trend analysis, showed a statistically non-significant increasing trend of rainfall by 35 mm per decade. On the other hand, (Taye and Willems, 2012) observed a significant decrease in the 1980s and non-significant increase in the 1960s &1970s as well as in the 1990s & 2000s on the trend of rainfall extremes for the entire Upper Blue Nile Basin. Most of the studies in the Upper Blue Nile Basin are conducted for the entire Upper Blue Nile Basin which has diverse climate and topography. It is, therefore important to study the spatio-temporal variability of mean and extremes of rainfall and temperature at sub-basins level to implement appropriate local adaptation and mitigation strategies.

This study is focused on one of the sub-basins of the Upper Blue Nile basin called Jemma, which is vulnerable to frequent drought and extreme cold temperature events (Tesso et al., 2012). The Jemma sub-basin is characterized by high soil erosion and sedimentation more than any other sub-basins of the Upper Blue Nile Basin (Betrie et al., 2011). Frequent climate variability and climate extremes affect agricultural production (Tesso et al., 2012) and can also aggravate land degradation unless appropriate watershed management practices are implemented. This paper, therefore, aims to study the mean annual and seasonal trends of rainfall and temperature and extremes of rainfall and temperature in the climatic stations of the Jemma sub-basin which aid for planning appropriate adaptation and mitigation strategies. Findings from this study could be applied to areas which have similar agroecology to the Jemma sub-basin in Ethiopia or other regions of Africa.

4.2 Data and Methodology

4.2.1 Data Pre-Processing and Quality Control

Daily observed climate data (i.e. rainfall, maximum and minimum temperature) for the period from 1960 to 2014 were collected from the Ethiopian National Meteorological Services Agency and the water and Land Resources Center (http://walris.wlrc-eth.org/) of Addis Ababa University for the climatic stations located in the Jemma sub-basin. Climatic stations that have better quality data were considered for this study. Climate stations that are characterized by several missing values and having a length of less than 30 years of rainfall data were excluded from the analysis. However, some stations (Anditid and Mendida) which have 29 and 27 years observation, respectively are include due to lower missing records and to maintain the spatial homogeneity of the stations. Totally, nine climatic stations (Table 4.1) were found to have minimal missing data which range from 2% to 17% from 1981-2014. The data from these stations were used for trend and extremes analysis of the baseline climate (1981-2014). The studied climatic stations are evenly distributed and represent the diverse agro-ecological zones range from cold moist sub-afro alpine to warm sub-moist lowlands (Figure 4.1).

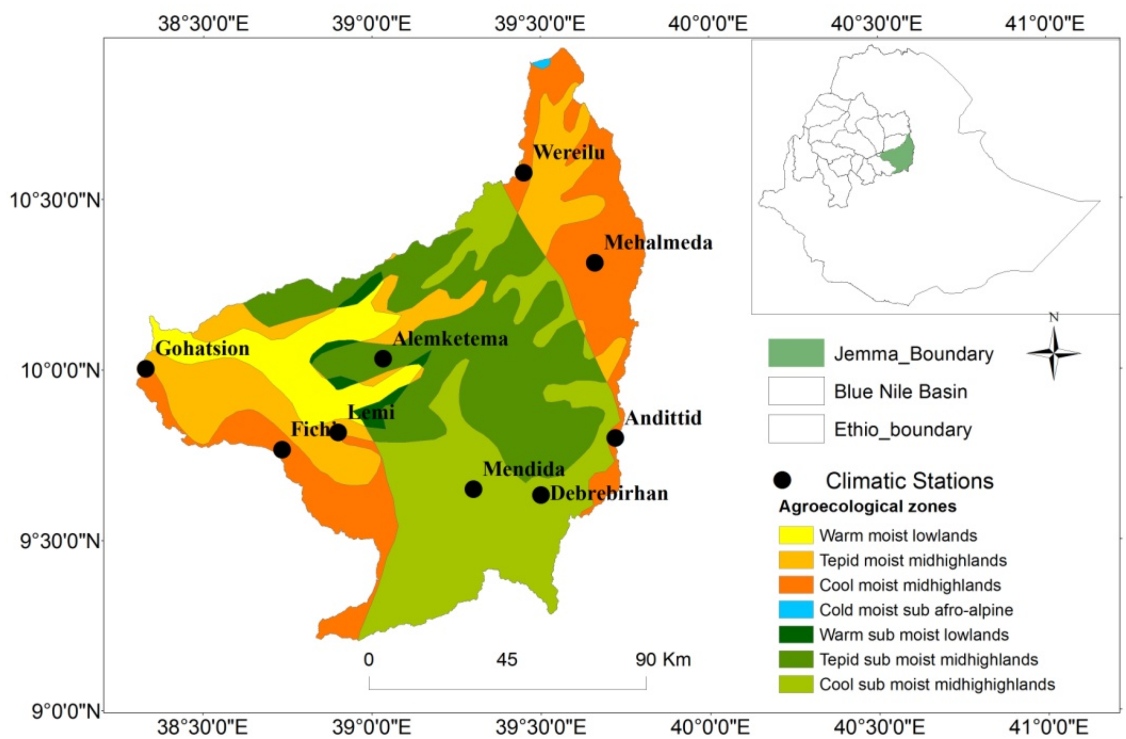


Figure 4.1 Agroecological zones and climatic stations in the Jemma sub-basin

The missing data was completed using Multivariate Imputation by Chained Equations (MICE) algorithm (Buuren et al., 2015) which is inbuilt on R statistical software (R Development Core Team, 2015). The MICE algorithm calculates missing values at a single station using the recorded observed values of all stations under study as predictors. The MICE creates multiple predictions for each missing value and considers uncertainty in the calculations and provides standard errors (Buuren et al., 2015). As such the MICE algorithm is better than other methods such as Inverse Distance Weighting (IDW) and Multiple Linear Regression (MLR) in imputing missing data.

The quality of the data of all the stations was examined using RClimDex 1.1 (Zhang and Yang, 2004). The quality control involves errors such as TMIN greater than TMAX and negative rainfall values were corrected using the nearby stations. Outliers, which are values plus or minus four times standard deviation (WMO, 2009) were replaced by average values of days before and after the outlier's day. The data after the quality control was used for trend and extremes analysis.

Table 4.1 Description of studied climatic station

Stations	**Geographical coordinates**		**Elevation (m)**	**Mean Annual Rainfall (mm)**	**Mean TMAX (°C)**	**Mean TMIN (°C)**	**Period of Observation**	**Rainfall missing records in (%)**
	Longitude (º)	**Latitude (º)**						
Alemketema	39.03	10.03	2280	1123	25.44	13.32	1981-2014	5.52
Debrebirhan	39.50	9.63	2750	908	19.87	6.26	1981-2014	1.97
Fichie	38.73	9.77	2784	1106	20.33	8.11	1981-2014	2.27
Lemi	38.90	9.82	2500	1278	21.64	8.66	1981-2014	8.20
Mehalmeda	39.66	10.32	3084	884	18.14	6.25	1981-2014	8.02
Gohatsion	38.24	10.00	2507	1187	23.519	15.03	1981-2014	11.37
Wereilu	39.44	10.58	2708	697	20.96	10.46	1981-2014	16.73
Andit Tid	39.72	9.80	3248	1475	17.18	7.90	1986-2014	5.69
Mendida	39.30	9.65	2800	956	20.94	8.47	1988-2014	2.57

4.2.2 Rainfall and Temperature Trend Analysis

The trend of annual rainfall, annual TMAX and annual TMIN were estimated using non-parametric Mann-Kendal test (Kendall, 1975; Mann, 1945). The test is considered statistically significant when the level of significance is less than or equal to 5%. The Mann-Kendall test statistic is calculated as;

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \mathrm{sgn}(X_j - X_i) \quad \ldots\ldots 1$$

$$sgn(x) = \begin{cases} 1\ if\ x > 0 \\ 0\ if\ x = 0 \\ -1\ if\ x < 0 \end{cases} \quad \ldots\ldots 2$$

where X_j and X_i are the annual values in years j and i, respectively but, j > i. A positive and negative value of *S* indicates an increasing and decreasing trend, respectively.

The Seasonal-Mann-Kendall trend test (Hirsch et al., 1982) was computed for each season separately to estimate the trend of rainfall on main rainy seasons (summer) and short rainfall season (spring) of the study area. The Seasonal-Kendall tests monotonic trend in a time series with seasonal variations such as hydro-meteorological data (Hirsch et al., 1982). Seasonal rainfall was computed using the monthly rainfall for the period 1981-2014.

Unlike Ordinary Least Square (OLS) methods, Mann-Kendall and Seasonal-Mann-Kendall tests were used for trend detection since they are non-parametric (distribution-free) and not sensitive to single outliers and skewed distributions. Therefore, for rainfall and temperature data which are not normally distributed, it is commendable to use Mann-Kendall and seasonal Mann-Kendal tests for trend detection.

The slope of trends was calculated using the non-parametric Theil-Sen's slope estimator (Theil, 1950; Sen, 1968). The Theil-Sen's slope estimator is a robust non-parametric estimator which uses the median slope to assess the trend over time (Theil, 1950; Sen, 1968). The Theil–Sen's approach is not sensitive to outliers and extreme values which are common in climatological data. It also provides consistent performance in statistical metrics of standard deviation, Root Mean Square Error (RMSE) and Bias of the slope estimator than parametric slope estimators. Theil-Sen test estimates the median of the slopes (β) using the equation:

$$b_{Sen} = \mathrm{median}\left(\frac{y_j - y_i}{x_j - x_i}\right) \ldots\ldots 3$$

where $i<j$ and i= 1, 2, …, n-1 and j = 2, 3,…, n.

All tests in this study were estimated using the ‘trend’ package which is inbuilt on R-statistical software (R Development Core Team, 2015).

4.2.3 Rainfall and Temperature Extreme Indices Analysis

Expert Team on Climate Change Detection and Indices (ETCCDI) (WMO, 2009) has defined 27 extreme indices for temperature and rainfall. The indices unfold the frequency, amplitude and persistence of extremes. Based on ETCCDI, 10 rainfall and 12 temperature extreme indices found relevant and selected for this study area. Table 4.2 presents the selected indices with their description and units. The indices were calculated at each climatic station using RClimDex 1.1 (Zhang and Yang, 2004). Daily observed rainfall, TMAX and TMIN data after quality control were used to calculate these indices. The areal average value of the index of meteorological stations was used to estimate the sub-basin wide trend of indices. The standardized anomaly of each index at the sub-basin level was calculated as;

$$SA_{x,t} = \frac{(X_t - X_{mean})}{\sigma} \quad \text{.......................................} 4$$

Where $SA_{x,t}$ is a standardized anomaly of index x at year t, x_t is annual index value in year t, X_{mean} is a long-term mean annual index throughout observation and σ is the standard deviation of the annual index for observation. The 5-year moving average was also used to show the annual variation of extremes within the scrutiny period.

Table 4.2 Selected ETCCDI rainfall and temperature extreme indices for the study area. Detailed discussion of the indices is available at WMO, 2009

Index	Index name	Definition of the Index	Units
PRECPTOT	Annual total wet-day rainfall	Annual total PRCP in wet days (RR>=1mm)	mm
R95p	Very wet days	Annual total PRCP when RR>95th percentile	mm
R99p	Extremely wet days	Annual total PRCP when RR>99th percentile	mm
CDD	Consecutive dry days	Maximum number of consecutive days with RR<1mm	Days
CWD	Consecutive wet days	Maximum number of consecutive days with RR>=1mm	Days
R10mm	Number of heavy rainfall days	Annual count of days when PRCP>=10mm	Days
R20mm	Number of very heavy rainfall days	Annual count of days when PRCP>=20mm	Days

Rx1day	Max 1-day rainfall amount	Monthly maximum 1-day rainfall	mm
Rx5day	Max 5-day rainfall amount	Monthly maximum consecutive 5-day rainfall	mm
SDII	Simple daily intensity index	The ratio of annual total rainfall to the number of wet days (≥ 1 mm)	mm/day
TXx	Max Tmax	Monthly maximum value of daily maximum temp	ºC
TNx	Max Tmin	Monthly maximum value of daily minimum temp	ºC
TXn	Min Tmax	Monthly minimum value of daily maximum temp	ºC
TNn	Min Tmin	Monthly minimum value of daily minimum temp	ºC
TN10p	Cool nights	Percentage of days when TN<10th percentile	%
TX10p	Cool days	Percentage of days when TX<10th percentile	%
TN90p	Warm nights	Percentage of days when TN>90th percentile	%
TX90p	Warm days	Percentage of days when TX>90th percentile	%
WSDI	Warm spell duration indicator	Annual count of days with at least 6 consecutive days TX>90th percentile	Days
CSDI	Cold spell duration indicator	Annual count of days with at least 6 consecutive days when TN<10th percentile	Days
SU25	Summer days	Annual count when TX(daily maximum)>25ºC	Days
FD0	Frost days	Annual number of days when Tmin<0 ◦C	Days

4.3 Result and Discussion

4.3.1 Trends in Annual and Seasonal Rainfall and Temperature

The annual and seasonal rainfall trend analysis exhibited different trends in the studied climatic stations for the period 1981-2014. In most (78%) of the climatic stations, positive trend of annual rainfall was observed. Exceptionally, a decreasing trend of annual rainfall was found in Alemketema and Mehalmeda climatic stations. The annual rainfall trend showed a statistically significant increase in Debrebirhan and Fichie stations. For the summer rainfall, a decreasing trend was observed only in Alemketema climatic station (Table 4.3). Corresponding to the annual rainfall trend, a significant increase in summer rainfall was found in Debrebirhan and Fichie stations. In contrast, a decreasing trend in spring season rainfall was detected in Fichie, Debrebirhan, Mehalmeda, Mendida and Alemketema climatic stations (Table 4.3 and Figure 4.2). This highlights a shift of bimodal pattern of the rainfall to a unimodal pattern of rainfall in the Jemma sub-basin.

Table 4.3 Trend of annual, summer and spring seasons rainfall in the baseline climate. S and b_{sen} are Mann-Kendal test and Sen Slope values respectively. The symbol "*" represents significance trends at the 5% level.

Stations	**Annual**			**Summer**		**Spring**	
	S	**b_{sen}**	**p-value**	**S**	**b_{sen}**	**S**	**b_{sen}**
Alemketema	-1.50	-6.54	0.15	-0.20	-0.48	***-2.00****	-2.43
Debrebirhan	***2.00****	3.45	0.05	***2.40****	5.02	-0.60	-0.79
Fichie	***2.80****	5.88	0.05	***3.70****	8.70	-1.60	-1.72
Lemi	1.30	6.70	0.19	1.30	5.40	1.00	1.80
Mehalmeda	-0.30	-0.76	0.76	0.80	2.06	-0.60	-1.00
Gohatsion	1.40	4.70	0.16	1.20	2.58	0.20	0.53
Wereilu	0.40	1.00	0.63	1.20	2.12	0.00	-0.07
Andit Tid	1.30	9.67	0.14	1.30	6.10	0.10	0.41
Mendida	1.10	6.02	0.17	1.60	5.64	-0.60	-0.39

Concomitantly, there are studies which investigate an increase in annual and main rainy season rainfall and negative trend of spring season rainfall. For instance, in the Andit Tid climatic station of the Jemma sub-basin, Hurni et al., 2005 has investigated an increase and decrease of summer and spring seasons rainfall, respectively from 1981-2002. Bewket and Conway, 2007 has also reported a positive but non-significant trend of rainfall in Debrebirhan climatic station for the period 1975-2003. On the other hand, Cheung et al., 2008 has estimated a decrease of summer rainfall by 2.6 mm/year and an increase of spring rainfall by 0.6 mm/year for the period 1960-2002 in Fichie station. The difference with these findings may be related to the difference in the study period.

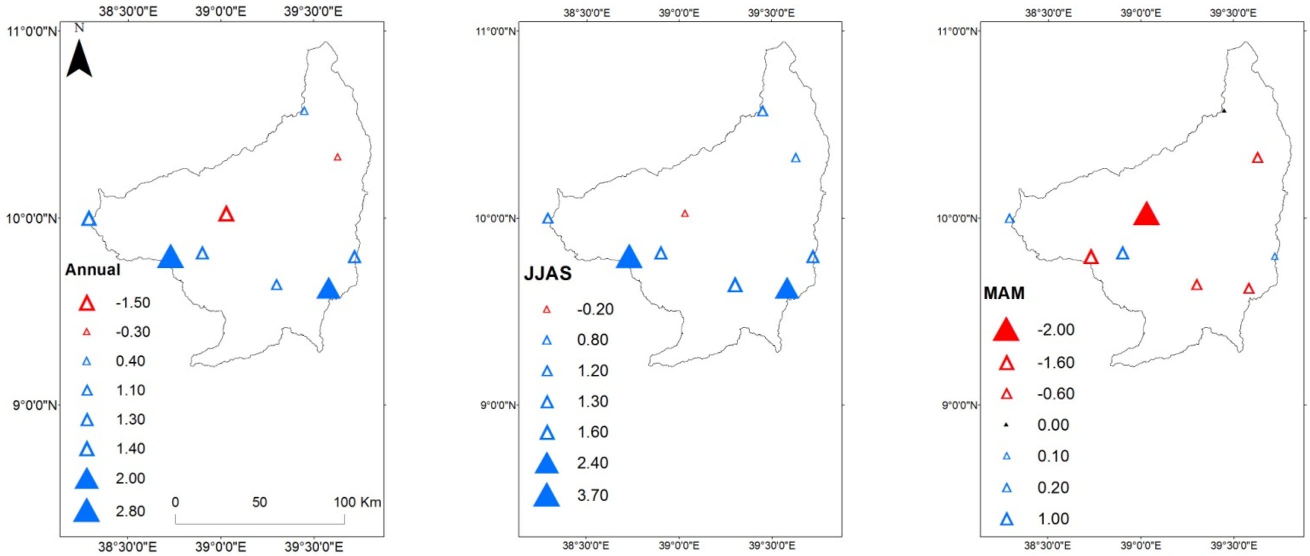


Figure 4.2 Spatial variations of annual, summer (JJAS) and spring (MAM) rainfall trends in the baseline climate (1981-2014). Blue and Red triangles represent increasing and decreasing trends, respectively. Solid triangles represent significant trends at the 5% significance level based on the Mann–Kendall test. While the open triangles show non-significant trends. The size of the triangles is proportional to the magnitude of the trend.

An increasing trend but differ in the magnitude was observed for TMAX and TMIN in all the climatic stations of the Jemma sub-basin (Table 4.4). Statistically significant increase in TMAX was observed in 88% of the stations. This may suggest that climate change is behind the increase in temperature in the Jemma sub-basin. An increasing trend was also divulged in TMIN in all of the stations except Andit Tid and Gohatsion. The increase in TMIN is insignificant in Debrebirhan and Mehalmeda stations. However, increasing trend of TMIN in stations located in higher altitude and cool sub-moist, cool moist and sub-afro-alpine agro-ecologies is statistically insignificant. The trend of TMIN in Andit Tid station which is located in cold sub-afro-alpine agroecology is significantly negative. Perhaps, the presence few extreme cold days (sec 3.3.3) may attribute a negative trend of TMIN. However, such an assertion requires detailed investigation. Mengistu et al., 2013 has corroborated the findings of this study which reports an increasing trend in mean TMAX and TMIN in moist and sub-moist agro-ecologies of the Upper Blue Nile Basin.

Table 4.4 Trends of annual TMAX and TMIN in the baseline climate. S and b_{sen} are Mann-Kendal test and Sen Slope values, respectively. The symbol ‘‘*” represents trends significance at the 5% level.

Stations			**TMAX**			**TMIN**		
	Longitude(º)	**Latitude(º)**	**S**	**b_{sen}**	**p-value**	**S**	**b_{sen}**	**p-value**
Alemketema	39.03	10.03	**0.05 ***	4.20	0.00	**0.05***	3.90	0.00
Lemi	38.90	9.82	0.03	1.50	0.13	**0.09***	3.80	0.00
Fichie	38.73	9.77	**0.03 ***	2.30	0.02	**0.02***	2.30	0.02
Gohatsion	38.24	10.00	**0.05 ***	3.90	0.00	0.00	0.1	0.22
Debrebirhan	39.50	9.63	**0.03 ***	3.40	0.00	0.02	1.70	0.09
Mehalmeda	39.66	10.31	**0.03 ***	4.10	0.00	0.01	1.10	0.28
Wereilu	39.44	10.58	**0.02 ***	4.90	0.00	**0.01***	4.2	0.00
Andit Tid	39.72	9.80	**0.09 ***	3.20	0.00	**-0.06***	-4.4	0.00
Mendida	39.30	9.65	**0.03 ***	2.50	0.02	**0.03***	2.9	0.01

4.3.2 Trends in Rainfall Extremes

The trend in annual total wet-day rainfall (PRECPTOT), very wet days (R95p) and extremely wet days (R99p) showed an increase in most of the climatic stations (Figure 4.3). The trend in PRECPTOT was similar to the trend of annual rainfall and it was only in Alemketema and Mehalmeda climatic stations where the trend was negative. The increase of R95p in Fichie and Andit Tid stations and R99p in Fichie and Lemi stations were higher than other stations. Alemketema is the only climatic station where all rainfall extreme indices (e.g. Rx1DAY, Rx5DAY, R99p and R95p) showed a downward trend. An increasing trend of the intensity of extreme rainfall (e.g. R95p and R99p) in most of the climatic stations suggests growing climatic risk on human’s livelihoods and other ecosystems. The decreasing trend of rainfall indices in Alemketema may be related to the presence of sub-moist agro-ecological zone and other local topographical factors, however, this needs further study.

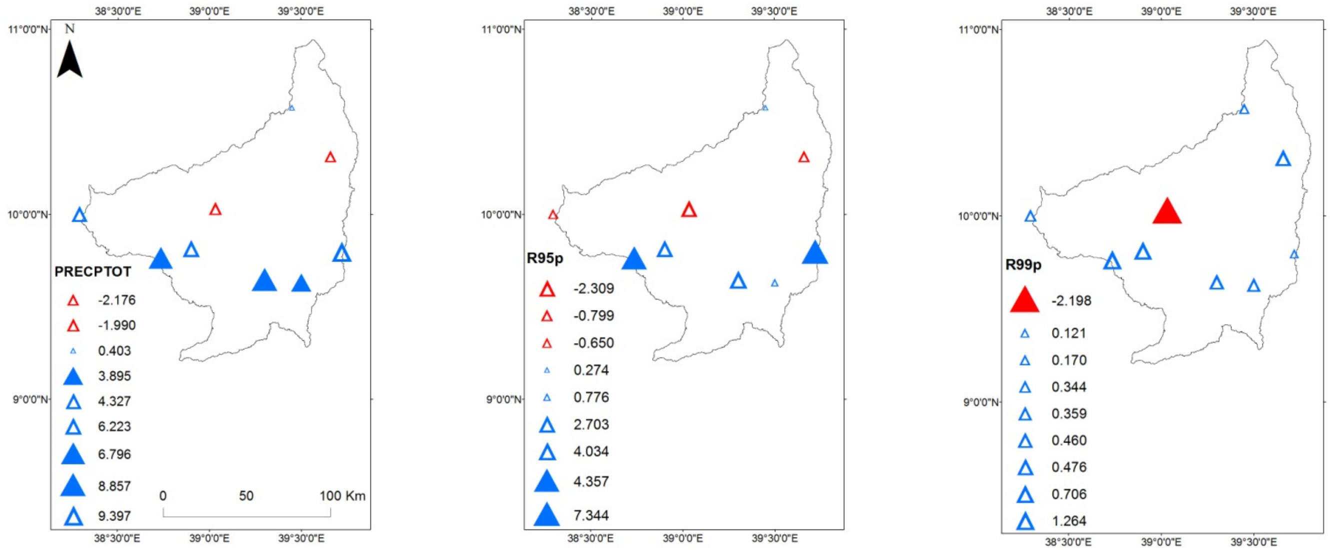


Figure 4.3 Trends (mm/year) in PRECPTOT (Annual total wet-day rainfall), R95p (very wet days) and R99p (extreme wet days) in the baseline climate. Blue and Red triangles indicate increasing and decreasing trends, respectively. Solid triangles indicate significant trends at the 5% significance level. While the open triangles show non-significant trends. The size of triangles is proportional to the magnitude of the trend.

Higher spatial coherence was found on the trend of Max 5-day rainfall amount (Rx5DAY). Of all the climatic stations, 88% of the climatic stations had a positive trend while only 12% had a negative trend (Figure 4.4). A significant increasing trend of Rx5DAY in Fichie and Mendida stations and significant decreasing trend of Rx1DAY in Alemketema station were observed. In Alemketema, Andit Tid, Mendida and Lemi stations, consistency was found between the trend in annual rainfall and Rx1DAY and Rx5DAY indices (Figure 4.4). Unlike other extreme rainfall indices, the trend in Simple Daily Intensity Index (SDII) is negative in most of the stations. This suggested that the daily rainfall amount has been declining. The negative trend of SDII also can happen due to the increase of days with small rainfall.

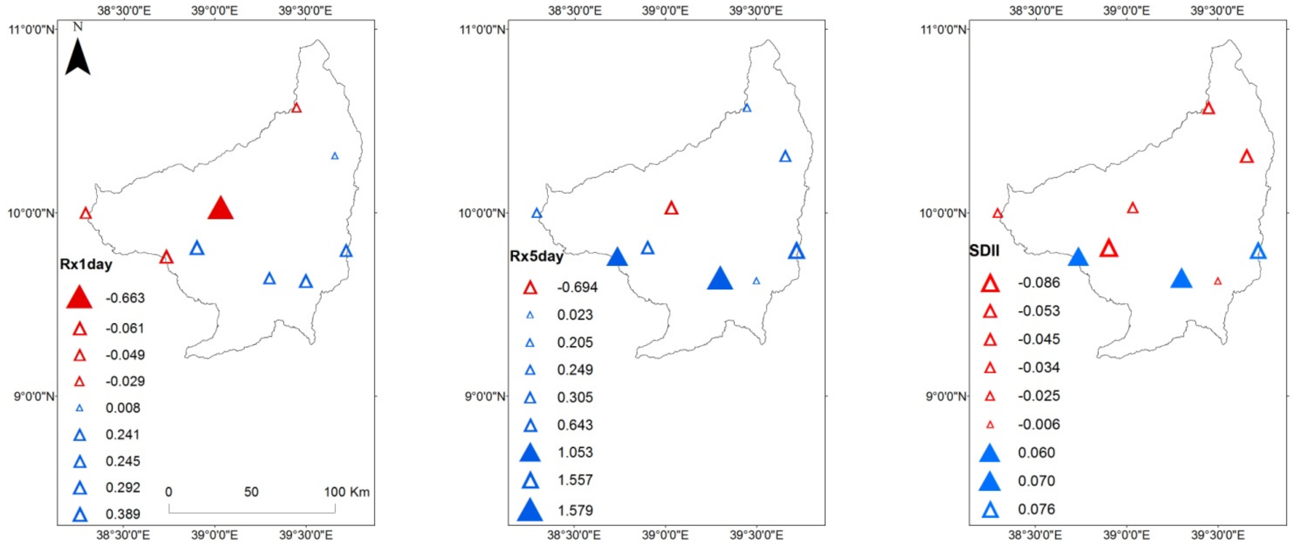


Figure 4.4 Trends (mm/year) in Rx1DAY (Max 1-day rainfall amount), Rx5DAY (Max 5-day rainfall amount) and trends (mm/day) in SDII (Simple daily intensity index) in the baseline climate. Blue and Red triangles represent increasing and decreasing trends, respectively. Solid triangles represent significant trends at the 5% level. While the open triangles show non-significant trends. The size of the triangles is proportional to the magnitude of the trend.

An increasing trend of R10mm was detected in most of the stations while divergent trends in R20mm were observed among the stations. Fichie station was characterized by a significant increase in R10mm and R20mm (Figure 4.5). An increase in these indices suggests potential risks related to flooding and soil erosion around the Fichie area. Likewise, Mekasha et al., 2013 reported a mix of significant decreasing (Negele-Borena and Asela stations) and increasing (Koka station) trends in R10mm and R25mm.

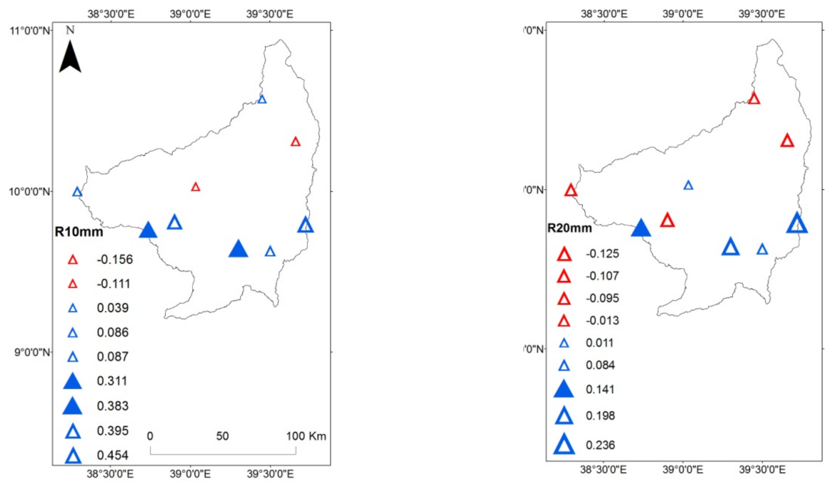


Figure 4.5 Trends (days/ year) in R10mm (number of heavy rainfall days) and R20mm (number of very heavy rainfall days) in the baseline climate. Blue and Red triangles indicate increasing and decreasing trends, respectively. Solid triangles indicate significant trends at the 5% significance level. While the open triangles show non-significant trends. The size of the triangles is proportional to the magnitude of the trend.

The presence and absence of rainfall greater than 1mm was measured using Consecutive Wet Days (CWD) and Consecutive Dry Days (CDD) respectively. Unlike other climatic stations, Alemketema station showed a decreasing trend in CWD and an increasing trend in CDD (Figure 4.6). This suggests an increase in aridity in this station. An increasing trend of CWD is significant in Debrebirhan and Mendida stations which are found in the cool sub-moist agro-ecological zone. CDD is significantly decreasing in Lemi station.

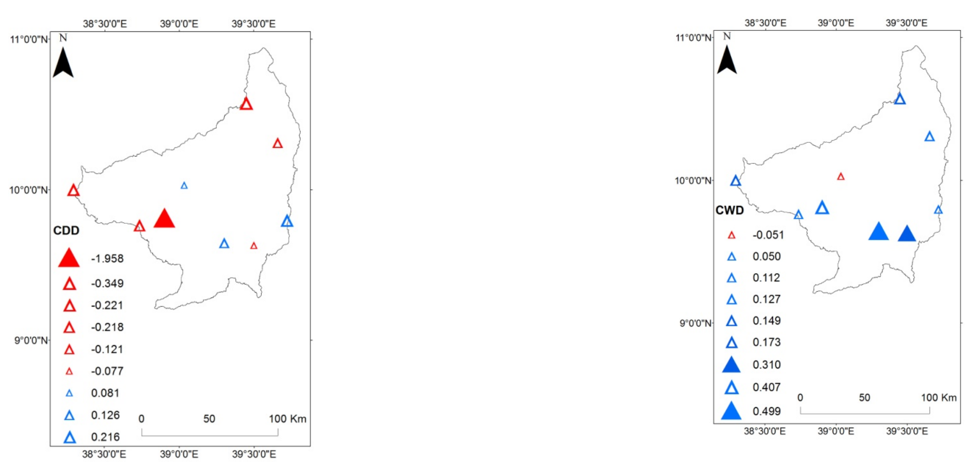
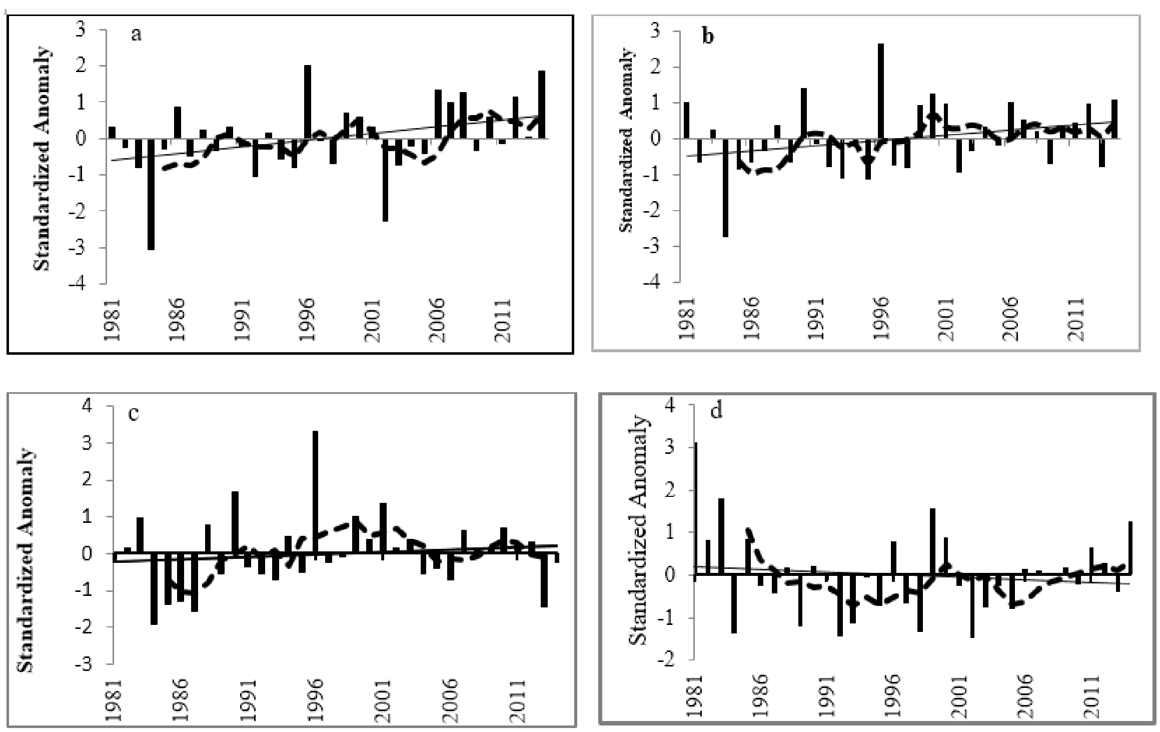


Figure 4.6 Trends (days/year) in CDD (Consecutive Dry Days) and CWD (Consecutive Wet Days). Blue and Red triangles indicate increasing and decreasing trends, respectively. Solid triangles indicate significant trends at the 5% significance level. While the open triangles show non-significant trends. The size of the triangles is proportional to the magnitude of the trend.

In the entire Jemma sub-basin (areal mean), the trend of most extreme rainfall indices revealed an increase except SDII (Figure 4.7). These changes in rainfall extremes indices in the Jemma sub-basin is comparable with the global trend where an increase in frequency, intensity and spatial extent of rainfall extremes were reported (IPCC, 2012; IPCC, 2013). This can be attributed to global climate change and other large scale as well as local-scale drivers. For example, on 70 % of the global land area, an increase in the number of heavy rainfall days and its contribution to the total annual rainfall amount is reported (Alexander et al., 2006). Apparently, extreme weather events in Ethiopia are associated with global climate drivers such as tropical Pacific Ocean currents (EPCC, 2015a). Therefore, the changes in rainfall extremes in the Jemma sub-basin can also be attributed to changes in these large scale climate drivers. Equivalently, local scale climatic controls (e.g. diverse physiographic features) can be non-trivial drivers to the changes in rainfall extremes in the region (Bewket and Conway, 2007; EPCC, 2015a).



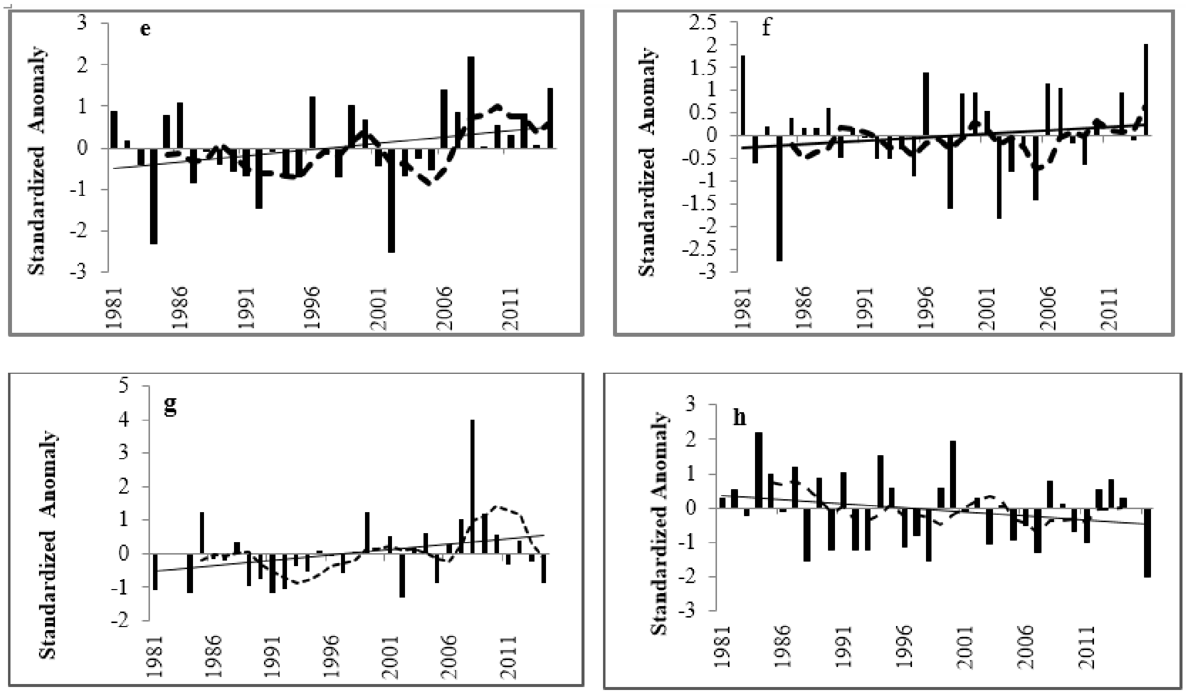


Figure 4.7 Sub-basin wide trends of rainfall extreme indices in the baseline climate. (a) Annual total wet-day rainfall(PRCPTOT), (b) Very wet days (R95p), (c) Extremely wet days (R99p), (d) Simple Daily Intensity Index (SDII), (e) Number of heavy rainfall days (R10 mm), (f) Number of very heavy rainfall days (R20 mm), (g) Consecutive Wet Days (CWD), (h) Consecutive Dry Days (CDD). The straight line is the linear trend for each extreme index whereas the dashed line is the trend for the corresponding 5-years moving average.

Similar to this study, other studies (Seleshi and Zanke, 2004; Mekasha et al., 2013) have investigated an increase in extreme rainfall events in different regions of Ethiopia. For instance, Seleshi and Zanke, 2004 reported an increase in Rx5DAY, R95p and R99p rainfall in the central highlands of Ethiopia from1965-2002. Mekasha et al., 2013 has also investigated an increasing trend of precipitation extreme indices such as Rx1DAY, Rx5DAY and R99p in stations located in the highlands of Ethiopia (e.g. Asela, Kulumsa and Kofele stations) for the period 1967 to 2008. Mekasha et al., 2013 also reported a mix of significant decreasing (Negele-Borena and Asela climatic stations) and increasing (Koka climatic stations) trends in R10mm and R25mm. In contrast, a significant decrease of Rx5DAY, R95p and R99p was detected in eastern and south-eastern (e.g. Jigjiga and Negele climatic stations) and south-western (e.g. Gore climatic station) parts of Ethiopia from 1965 to 2002 (Seleshi and Zanke, 2004).

4.3.3 Trends in Temperature Extremes

A warming trend as reflected by an increase on most of the warm extreme indices and a decrease on most of the cold extreme indices in the entire stations of the study was detected. The trend of indices of intensity of temperature extremes (TXx, TXn, TNx and TNn) emphasizes warming in the Jemma sub-basin (Figure 4.8). For instance, an upward trend of TXx and TNx is observed in 89% and 78% of the stations, respectively. TXx and TNx increase significantly in several of the climatic stations even though a large inconsistency on magnitude was observed. In magnitude, change on indices related to minimum daily temperature (TNx and TNn) is higher than indices related to daily TMAX (TXx and TXn). This is in contention with the trend of annual maximum and minimum temperature trend where higher increase is on annual TMAX than annual TMIN (sec 3.1).

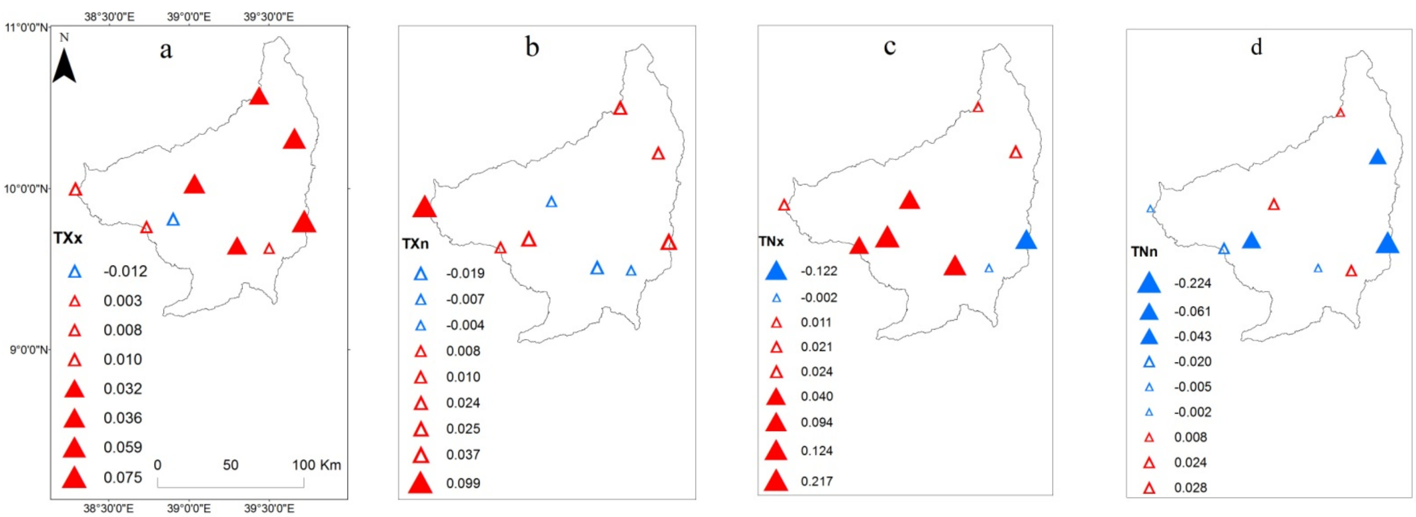


Figure 4.8 Trends (°C/year) in (a) TXx (Monthly maximum value of daily maximum temp), (b)TXn (Monthly minimum value of daily maximum temp), (c)TNx (Monthly maximum value of daily minimum temp) and (d) TNn (Monthly minimum value of daily minimum temp) in the baseline climate. Red and Blue triangles indicate increasing and decreasing trends, respectively. Solid triangles indicate significant trends at the 5% significance level. While the open triangles show non-significant trends. The size of the triangles is proportional to the magnitude of the trend.

Similar to intensity of temperature extremes indices (TXx, TXn, TNx and TNn), frequency of temperature extremes indices (TN10p, TX10p, TN90p, and TX90p) also demonstrate significant warming in most of the climatic stations (Figure 4.9). An increasing trend of warm extreme indices (TX90p and TN90p) and decreasing trend of cold extreme indices (TN10p and TX10p) were discerned. This shows that the proportion of cool days (TX10p) and cool nights (TN10p) is decreasing and the proportion of warm days

(TX90p) and warm nights (TN10p) is increasing. The significant warming trend of TX10p and TN10P at 78% of the stations was observed. Temperature of cool days and cool night was increasing in most of the stations, but the magnitude was higher on TN10p than TX10p. Such phenomenon of decreasing in the number of cold days and nights and increasing in the number of warm nights and warm days was reported as a consistent trend globally (IPCC, 2012; IPCC, 2013). However, an inconsistent trend of TX10p (cool nights) and TN90p (warm nights) was observed in the Andit Tid station. This suggests that night temperature in Andit Tid was getting cold over time and this is perhaps because of afro-alpine agroecology of Andit Tid area.

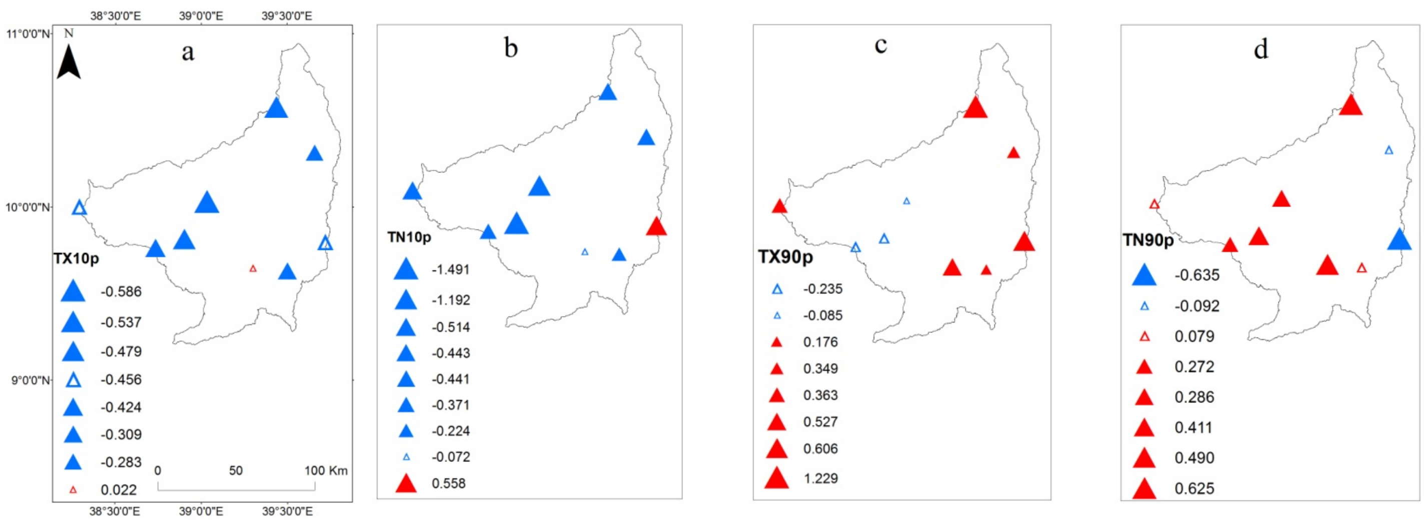


Figure 4.9 Trends (%/year) in (a) TX10p (Cool days), (b) TN10p (Cool nights), (c) TX90p (Warm days) and (d) TN90p (Warm nights) in the baseline. Red and Blue triangles indicate increasing and decreasing trends, respectively. Solid triangles indicate significant trends at the 5% significance level. While the open triangles show non-significant trends. The size of the triangles is proportional to the magnitude of the trend.

Higher inconsistency and lower spatial coherence was detected on the trend of Warm Spell Duration Indicator (WSDI) among the climatic stations of the study area (Figure 4.10). A decline on WSDI in ~44% of the stations and an increase on ~56% of the stations was detected. In regards to Cold Spell Duration Indicator (CSDI), a decrease in 78% of the stations was observed. A warming trend was substantiated by an increasing trend of summer days (SU25) in most of the stations. The trend in SU25 index exemplified that there was an increase on 78% of the stations (significant at 44% of the stations). The trend of frost days is observed only in stations located at cold moist highlands and sub-afro alpine agro-ecologies. On Debrebirhan station, frost days were significantly decreasing; while, frost events were persistent in the Andit Tid and Mehalmeda climatic stations.

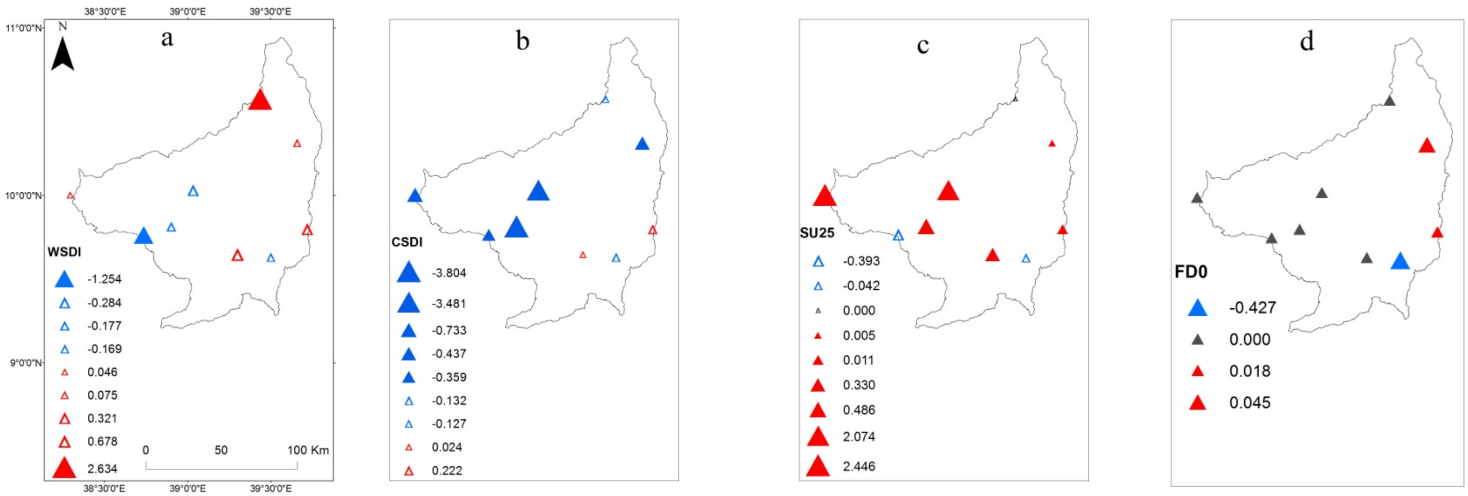


Figure 4.10 Trends (days/year) in (a) WSDI (Warm Spell Duration Indicator), (b) CSDI (Cold Spell Duration Indicator), (c) SU25 (summer days) and (d) FD0 (Frost Days). Red and Blue triangles represent increasing and decreasing trends, respectively. Black triangles represent no trend. Solid triangles indicate significant trends at the 5% significance level. While the open triangles show non-significant trends. The size of triangles is proportional to the magnitude of the trend.

In the entire sub-basin (areal values), average anomaly series of all temperature extreme indices except TNn prove warming trend. However, pronounced fluctuation on the trend and 5 years moving average of TNx, TX10p, TX90p, TN10p, TN90p and CSDI were detected (Figure 4.11). Furthermore, the magnitude of change was higher and persistent on cold extreme indices (TN10p, TX10p and CSDI) than warm extreme indices (TX90p, TN90p and WSDI). Concurrent with this, a significant decreasing trend was obtained on TX10p, TN10p and CSDI indices in Rift Valley, southern rangelands and the eastern highlands of Ethiopia (Mekasha et al., 2013). Globally, a higher rate of increase was simulated by existing climate models in TMIN extremes than TMAX extremes (IPCC, 2013). Moreover, a significant decrease in cold nights and a significant increase in warm nights is also reported (Alexander et al., 2006).

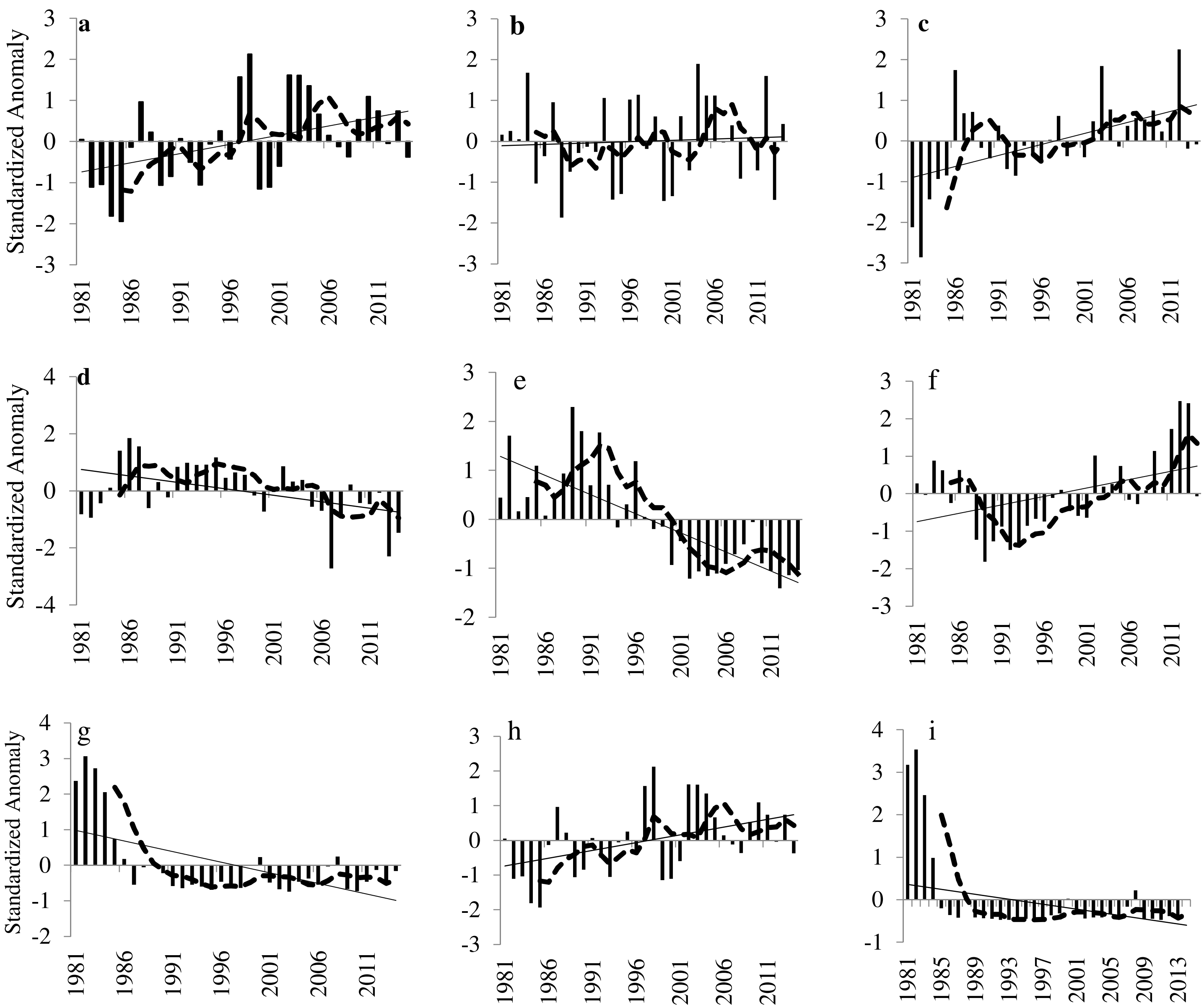


Figure 4.11 Sub-basin wide trends of temperature extreme indices in the baseline climate. (a) Monthly maximum value of daily maximum temp (TXx), (b) Monthly minimum value of daily maximum temp (TXn), (c) Monthly maximum value of daily minimum temp (TNx), (d) Monthly minimum value of daily minimum temp (TNn), (e) Cool days (TX10p), (f) Warm days (TX90p), (g) Cool nights (TN10p), (h) Warm nights (TN90p), (i) Cold spell duration indicator (CSDI). The straight line is the linear trend for the variables whereas the dashed line is the 5-years moving average.

The trend on mean annual TMAX and TMIN and most extreme temperature indices resonate higher warming trend in the Jemma sub-basin than warming trend of Ethiopia and the world. For example, in the Jemma sub-basin mean annual TMIN has increased by 0.51°C/ decade, while in Ethiopia, mean annual TMIN has increased by 0.37°C /decade for the period 1953-1999 (NMA, 2007) and there was an increase of annual mean temperature by 1.3°C from 1960 to 2006. This could be related to an increase in global temperature, multiple large scales and local scale drivers. Particularly, an increase in temperature extremes can be attributed to the change in global temperature extremes (Alexander et al., 2006). The higher elevation and the diverse physiography in the sub-basin could be other reasons which trigger a change in temperature extremes (Bewket and Conway, 2007).

4.4 Conclusion

This study analyzed the annual trend of rainfall, TMIN, TMAX and changes on rainfall and temperature extremes indices in the Jemma sub-basin of the Upper Blue Nile Basin. Annual and summer rainfall showed increasing trends in the majority of the climatic stations. However, a decreasing trend was observed on the spring season rainfall in most of the climatic stations. This implied a shift in the rainfall pattern from bimodal to mono-modal. This may strongly affect agricultural practices that take place during the spring season. In the eastern and northeastern region of the sub-basin, spring season rainfall is important, particularly for livestock pasture. Thus, a negative trend of spring season rainfall could cause strong repercussion on some areas of the sub-basin. Parallel with the mean annual and seasonal changes of rainfall, a statistically significant change on extremes of rainfall was observed. Most of rainfall extreme indices demonstrated rising of extreme rainfall events and contribution of extreme rainfall to total rainfall in the sub-basin. On the other hand, at sub-basin level average value of SDII (Simple daily intensity index) revealed the trend of subsidence on the daily rainfall. Among the stations and agro-ecologies of the study, lower spatial coherence was observed on the trend of most rainfall extreme indices than temperature extreme indices.

Almost all temperature extreme indices in almost all stations of the Jemma sub-basin showed a warming trend. Sub-basin wide analysis illustrated abrupt change on nighttime temperature extreme indices than day time temperature extreme indices. Warm extremes at nighttime were increasing while cold extremes at nighttime were decreasing more strongly than other indices. Unlike trends of rainfall extremes, trends of temperature extremes revealed consistency and spatial coherence. In stations located in higher altitude and cool sub-moist, cool moist and sub-afro-alpine agro-ecologies, the trend of annual minimum temperature and most temperature extreme indices derived from minimum temperature was different from other stations where cold extremes are persistent. In general, this study proved that the intensity and frequency of climate extremes have been increasing in the last three decades. Anticipated climate change may aggravate the situations of climate extremes. Therefore, appropriate adaptation and mitigation strategies should be planned to lessen the impacts of such climatic risks in the Jemma sub-basin.

Chapter 5

Evaluation of Regional Climate Models Performance in Simulating Rainfall Climatology of the Jemma Sub-basin, Upper Blue Nile Basin, Ethiopia

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Abstract

This study examines the performance of 10 Regional Climate Models (RCM) simulation which are dynamically downscaled from the fifth phase of Coupled Model Inter-comparison Project (CMIP5) GCMs. The RCMs are evaluated based on their ability to reproduce the magnitude and pattern of monthly and annual rainfall, frequency of rainfall events and variability related to Sea Surface Temperature (SST) for the historical period (1981-2005). The outputs of all RCMs showed dry and wet biases in the lower and higher elevation areas of the sub-basin, respectively. The wet bias of annual rainfall is in the order of 9.60% in CCLM4 (HadGEM2-ES) model to 110.9% in RCA4 (EC-EARTH) model. JJAS (June-September) rainfall is also characterized by wet bias ranges from 0.76% in REMO (MPI-ESM-LR) model to 100.7% in the RCA4 (HadGEM2-ES) model. GCMs that were dynamically downscaled through REMO (Max Planck Institute) and CCLM4 (Climate Limited-Area Modeling) performed relatively better in capturing the rainfall climatology and distribution of rainfall events. However, GCMs dynamically downscaled using RCA4 (SMHI Rossby Center Regional Atmospheric Model) were characterized by overestimation and there are more extreme rainfall events in the cumulative distribution. Most of the RCM simulations of rainfall over the sub-basin showed a teleconnection with SST of CMIP5 GCMs in the Pacific and Indian Oceans, but weak. The ensemble mean of all 10 RCM simulations

This chapter is based on **Worku, G., Teferi, E., Bantider, A., Dile, Y.T., Taye, M.T., 2018b. Evaluation of regional climate models performance in simulating rainfall climatology of Jemma sub-basin, Upper Blue Nile Basin, Ethiopia.** *Dyn. Atmos. Ocean. 83, 53–63*, https://doi.org/10.1016/j.dynatmoce.2018.06.002.

was superior in replicating the seasonal pattern of the rainfall and had better correlation with observed annual (Correl=0.6) and summer (JJAS) season rainfall (Correl=0.5) than any single model. We recommend using GCMs downscaled using REMO and CCLM4 RCMs and stations based statistical bias correction to manage elevation based biases of RCMs in the Upper Blue Nile Basin, specifically in the Jemma sub-basin.

Keywords: Regional Climate Models, Downscaling, RCM evaluation, Rainfall, Upper Blue Nile

6.1 Introduction

Global Climate Models (GCMs) are instrumental to assess relative change in the climate system due to various radiative forcing and to make climate predictions on seasonal to decadal time scales and projections of future climate (IPCC, 2013). Many GCMs were developed by different climate research centres since the 1950s (Edwards, 2011). The establishment of the Earth System Modeling Framework (ESMF) which couples atmosphere-ocean GCMs with the land surface, the cryosphere, hydrology and vegetation processes is another framework in climate modeling (Hill et al., 2009). In the CMIP5, several GCMs have been developed into Earth System Models by incorporating the representation of biogeochemical cycles (Taylor et al., 2012). Better than the earlier phases of IPCC models, the atmosphere and the ocean components of CMIP5 models have higher spatial resolution (Taylor et al., 2012; Woldemeskel et al., 2015). Consequently, CMIP5 GCMs reproduce the global scale mean surface temperature and the seasonal cycle of sea ice extent of oceans (Flato et al., 2013; Taylor et al., 2012).

Despite several improvements, CMIP5 GCMs perform less effectively in simulating cloud cover and rainfall of mountainous and coastal regions (Randal et al., 2007; Flato et al., 2013; Woldemeskel et al., 2015). Model parameterization, greenhouse gases emission scenarios, and internal climate variability are assumed the key sources of uncertainties in GCMs (IPCC, 2013). Low spatial resolution of GCMs is another source of uncertainty that hiders GCMs to replicate the local and regional scale climate especially in an uneven topography, mountain and coastal regions (Fowler et al., 2007; Salath et al., 2007). Thus, downscaling of GCMs simulation at the regional-scale is non-trivial for local climate impact studies (Flato et al., 2013). Yet again, downscaling GCMs simulation to the local scale is another vital source of uncertainty and as a result, it is essential to select a better downscaling technique. Statistical and dynamical downscaling are primary downscaling techniques that produce regional and local-scale climate data from GCMs (Wilby et al., 2002). There are evidence confirm dynamical downscaling is superior to statistical downscaling techniques to simulate rainfall of regions with diverse topography (Schmidli et al., 2007; Fowler et al., 2007).

Dynamically downscaled RCMs are developed with a higher spatial resolution to simulate climate variability at a regional scale and add value over GCMs in replicating climate of coastal and mountainous regions and in mesoscale (i.e. a spatial scale of 1-100 km) (Giorgi et al., 2009; Feser et al., 2011). There are different initiatives to produce large ensembles of RCM simulations that can be further used for climate change impact assessment at regional spatial scales. CORDEX under the support of WCRP is among the initiatives to downscale different CMIP5 GCM outputs to generate an ensemble of high-resolution historical and future climate projections (Giorgi et al, 2009; Taylor et al, 2012). CORDEX simulations add value over GCMs in Africa, particularly in representing the annual cycle of rainfall and extreme rainfall events in different regions of the continent (Nikulin et al., 2012; Dosio et al, 2015; Kim et al, 2014). However, uncertainty persists in RCMs' simulation of rainfall, temperature, wind and other variables. The other problem of RCMs is their inconsistency of performance across regions and seasons (Feser et al., 2011; Endris et al., 2013) which warrants caution in choosing RCMs to study climate of a particular region and/or seasons.

Several studies have evaluated the performance of climate models representing the climate of the Upper Blue Nile Basin using various techniques (e.g. Bhattacharjee and Zaitchik, 2015; Haile and Rientjes, 2015). Most of these studies compared observed and model outputs and evaluated the ability of climate models in capturing inter-annual variability associated with natural climate processes such as El Niño-Southern Oscillation (ENSO) (Awass, 2009; Bhattacharjee and Zaitchik, 2015; Jury, 2015; Haile and Rientjes, 2015). Little consistency was found in the performance of model outputs in simulating amount and seasonality of rainfall, and teleconnections across the Nile River headwaters region (Bhattacharjee and Zaitchik, 2015). The difference in the performance of climate models in capturing the annual cycle and inter-annual variability of rainfall and TMAX was also studied in the central highland region of Ethiopia (Jury, 2015).
Uncertainty in climate model outputs for climate change impact assessment can be reduced using multiple lateral boundary conditions (GCMs), multiple RCM outputs, and robust downscaling methods (Feser et al., 2011; Flato et al., 2013). However, only limited studies consider the diversity of methods and climate model outputs to show the range of uncertainty. For example, in the Upper Blue Nile Basin, only few studies used multiple GCM outputs and multiple RCM simulations (Haile and Rientjes, 2015; Endris et al., 2013; Bhattacharjee and Zaitchik, 2015; Nikulin et al., 2012). In fact, most of these studies used limited RCMs downscaled using few numbers of initial boundary condition (GCMs). For example, Dosio et al, 2015, has analyzed the added value of four GCMs downscaled by single RCM (COnsortium for Small-scale MOdeling, COSMO-CCLM). Haile and Rientjes (2015) also evaluated the performance of eight GCMs downscaled using single RCM (RCA4) in the Blue Nile Basin. There also other studies which used

reanalysis datasets than observational data sets to evaluate RCMs (Endris et al., 2013; Bhattacharjee and Zaitchik, 2015).

The objective of this study is to evaluate the performance of different RCMs driven by multiple GCMs in capturing the mean annual and monthly rainfall, distribution of rainfall events and large-scale climate circulation patterns (teleconnections) in the Jemma sub-basin, Upper Blue Nile Basin for the period 1981-2005. Observed data collected from the Ethiopian National Meteorological Agency was used for evaluation. The RCMs which better simulate the rainfall climatology of the Jemma sub-basin will be used for further statistical bias correction and to develop climate scenario, climate change impact scenarios and climate adaptation decision analysis in the sub-basin.

6.2 Data and Methodology

6.2.1 Observed Data

Daily observed rainfall data for the period 1981-2005 was used for regional climate models evaluation. The observed data for nine climatic stations located within the Jemma sub-basin was collected from the National Meteorological Agency of Ethiopia. The missing data were completed using MICE algorithm (Buuren et al., 2015), which is available on R statistical software (R Development Core Team, 2015). The quality of observed data of all stations was also examined using RClimDex 1.1 (Zhang and Yang, 2004). Errors such as TMIN greater than TMAX and negative rainfall values were corrected using the nearby stations. Outliers (i.e. data which are outside mean ± four times the standard deviation) (WMO, 2009) were changed into average values of days before and after the outliers' day. The observed data after the quality control was used for this study.

6.2.2 RCMs Data

Historical RCM simulations (1981-2005) driven by four CMIP5 GCMs were used in this study. The GCMs which were used as initial boundary conditions were CNRM-CM5, EC-EARTH, HadGEM2-ES and MPI-ESM-LR (Table 5.1). The historical simulations of these GCMs were initialized with the atmosphere, ocean, land and SST conditions and forced by observed natural and anthropogenic CO_2 and aerosol concentrations (Taylor et al., 2012). RCMs' rainfall values were obtained from grids fully or partially cover the Jemma sub-basin (Figure 5.1).

Table 5.1 Global Climate Models (drivers) considered in this study

GCM	Institute	Horizontal Resolution (latitude × longitude in °)	Country
CNRM-CM5	CNRM–CERFACS: Centre National de Recherches Météorologiques	1.4 × 1.4	France
EC-EARTH	ICHEC: Consortium of European research institutions and researchers	1.1 × 1.125	Europe
HadGEM2-ES	MOHC: Met Office Hadley Centre	1.875 × 1.25	United Kingdom
MPI-ESM-LR	MPI-M: Max-Planck-Institute	1.80 × 1.80	Germany

The RCMs used to regionalize GCMs are; the CCLM4 (COnsortium for Small-scale MOdeling (COSMO) Climate Limited-Area Model (CCLM) version 4.8), RCA4 (Rossby Centre Regional Climate Model) and REMO (Max Planck Institute Regional Model) (Table 5.2). These RCMs were selected for evaluation since they (especially CCLM4 and RCA4 models) were used to downscale historical and future simulations of multiple CMIP5 GCMs (e.g. CNRM-CM5, EC-EARTH, HadGEM2-ES, and MPI-ESM-LR) in the CORDEX project Africa domain. The outputs of CCLM4 and RCA4 RCMs driven by these four GCMs were frequently evaluated and showed reasonable performance over Africa (Nikulin et al., 2012; Dosio et al, 2015; Kim et al., 2014). Both rainfall and SST data of models were obtained from the publicly available Earth System Grid Federation (ESGF) web portals.

Table 5.2 Description of Regional Climate Models considered in this study

RCM	Full Name	Institute	Horizontal Resolution (latitude× longitude in °)	Reference
CCLM4	CLMcom COSMO-CLM (CCLM) version 4.8	Climate Limited-Area Modelling (CLM) Community (www. clm-community.eu)	0.44°	Baldauf et al., 2011
RCA4	SMHI Rossby Center Regional Atmospheric Model (RCA4)	Sveriges Meteorologiska och Hydrologiska Institut (SMHI), Sweden	0.44°	Samuelsson et al., 2011
REMO	MPI regional model (REMO)	Max Planck Institute (MPI), Germany	0.44°	Jacob et al., 2007

The RCMs have a horizontal resolution of 0.44° × 0.44° which is far better than the horizontal resolution of the GCMs (Figure 5.2). For each model, historical simulations and only the first ensemble member (r1) was used, except the EC-EARTH model from which the 12th ensemble member(r12) was used. Because, only 12th ensemble member is available for EC-EARTH model. The outputs of these simulations were obtained at a resolution of ~50 km by 50 km from the Africa domain CORDEX dataset. Overall, this study used 10 RCM outputs which were downscaled from four GCMs using three RCMs (only EC-EARTH and MPI-ESM-LR downscaled through REMO are available). The ensemble mean of these 10 RCMs was also used for the evaluation.

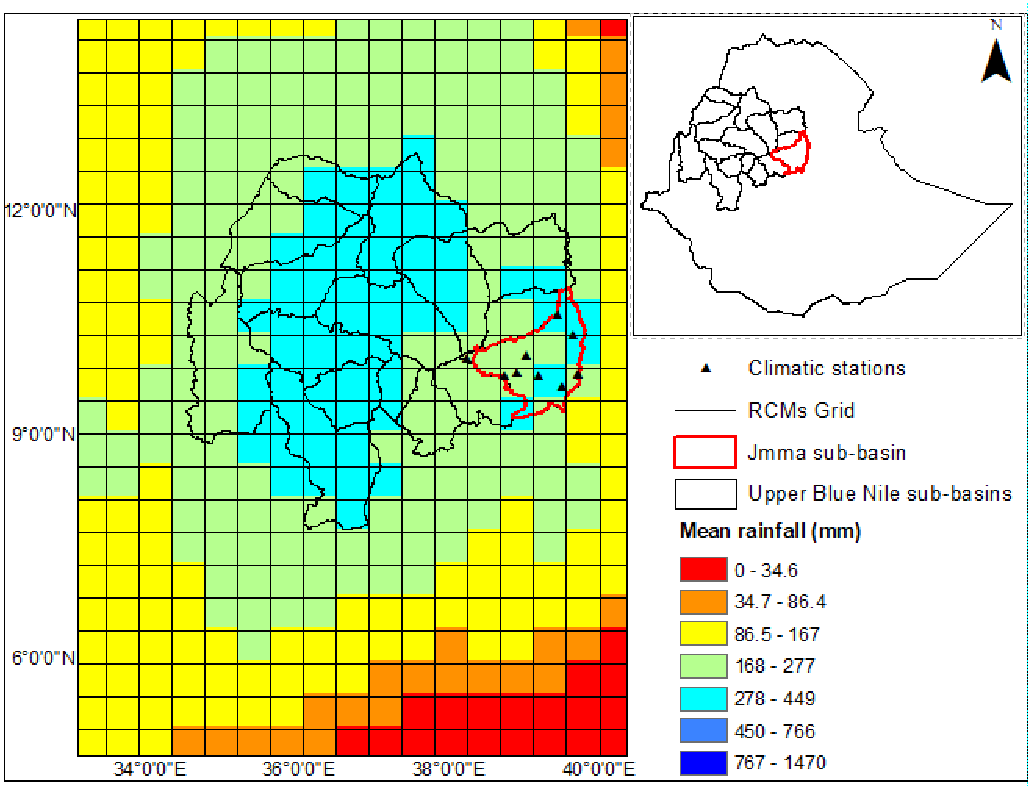


Figure 5.1 Grids of Regional Climate Models and distribution of climatic stations over the Jemma sub-basin. The grids are with a horizontal resolution of 0.44° × 0.44° which intersect the upper Blue Nile Basin and the Jemma sub-basin. The rainfall is August month long-term (1991-2000) mean rainfall simulated by CCLM4 (MPI-ESM-LR) Regional Climate Model.

The observed rainfall data (point data) which is collected from meteorological stations was converted into spatial data. This is to match with RCMs gridded data. Thiessen Polygon method (Thiessen, 1911) was used to split the sub-basin into smaller polygons based on area of influence of location of climatic stations and to calculate areal rainfall. The Thiessen Polygon method calculates areal rainfall (sub-basin wide rainfall) to each Thiessen Polygon based on the area of the polygon in proportion to the total area of the sub-basin.

Analogously, Thiessen Polygon method was used to calculate areal rainfall of each RCM in the entire sub-basin based on the area of the RCMs' grids fully or partially covering the Jemma sub-basin (Figure 5.1). After the observed and RCMs data were converted into area-average (spatial) rainfall, different metrics were used to evaluate RCMs performance in replicating the rainfall of the Jemma sub-basin.

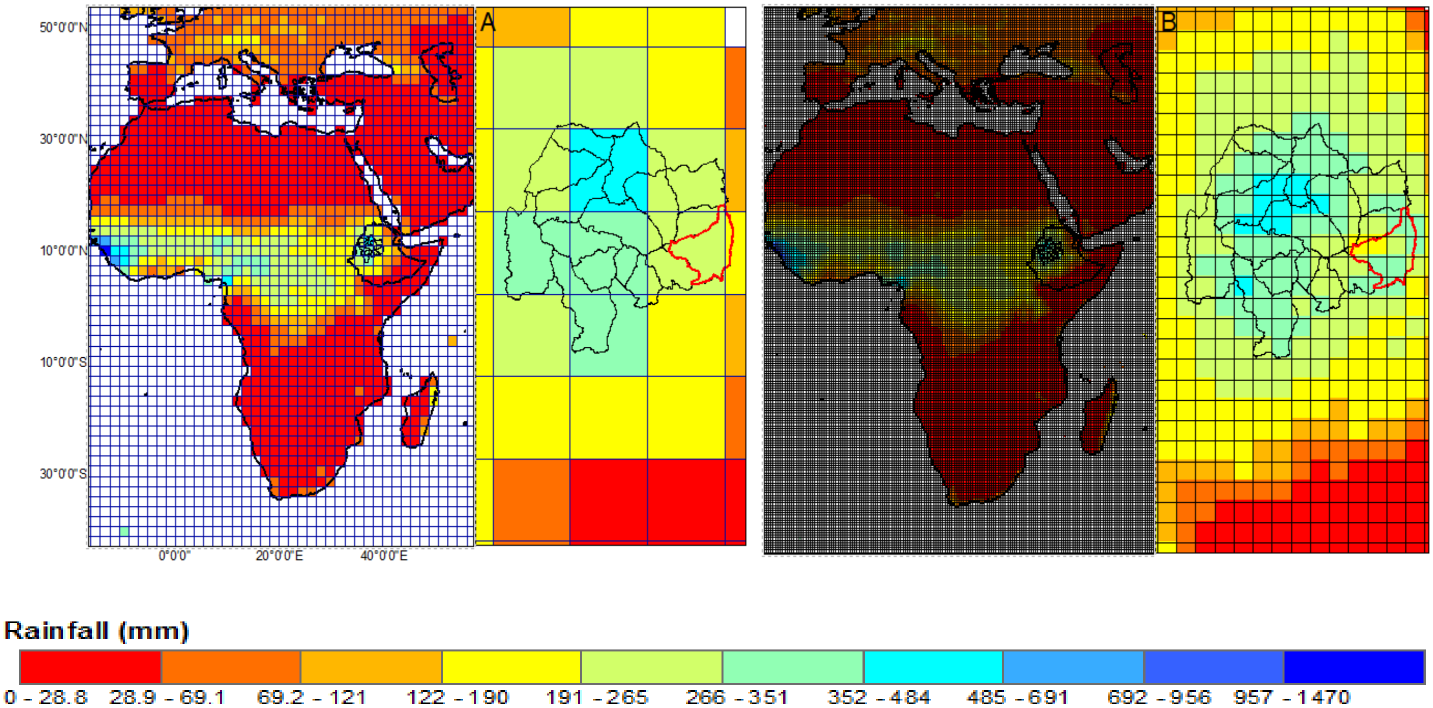


Figure 5.2 August month long term (1991-2000) mean rainfall simulated by a) MPI-ESM-LR Global Climate Model which has a resolution of 1.8° × 1.8° and b) CCLM4(MPI-ESM-LR) Regional Climate Model with a resolution of 0.44° × 0.44° over Africa, upper Blue Nile Basin and the Jemma sub-basin.

6.2.3 Data Analysis

Three criteria were used to measure the performance of climate models in capturing rainfall of the study area. The first criterion assesses the ability of the RCMs to reproduce the rainfall climatology and characteristic of rainfall events. This criterion compared the magnitude of mean annual and seasonal rainfall, mean monthly rainfall pattern, distribution and frequency of rainfall events and return period of RCM simulations compared with the observed data. The second evaluation uses statistical metrics, including BIAS, Root Mean Squared Error (RMSE) and Correlation Coefficient (Correl) between areal rainfall of RCMs and observation.

$$Correl = \frac{\sum_{t=1}^{N}\left(R_{RCM} - \overline{R_{RCM}}\right)\left(R_{Observ} - \overline{R_{Observ}}\right)}{\sqrt{\sum_{t=1}^{N}\left(R_{RCM} - \overline{R_{RCM}}\right)\sum_{t=1}^{N}\left(R_{Observ} - \overline{R_{Observ}}\right)}}$$

$$\text{BIAS}=100 * \frac{\overline{R_{RCM} - R_{Observ}}}{\overline{R_{Observ}}}$$

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(R_{RCM} - R_{Observ}\right)^2}$$

Where, R_{RCM} is a rainfall of RCMs, R_{Observ} is a rainfall of stations, the bar over the variables denotes the average over a period of 1981–2005, and N represents the analysis period (25 years).

The correlation is often used to evaluate the linear relationship between areal averaged RCMs rainfall and observed rainfall. Values close to 1.0 indicate a better linear relationship between the variables and value away from 1.0 indicates less agreement. BIAS is used to measure the volumetric difference between the RCMs rainfall and observed rainfall. A BIAS value close to 0 indicates a minor systematic difference between RCMs rainfall and observed rainfall amounts, whereas a BIAS value far from 0 suggests a deviation. RMSE measures the difference between RCMs rainfall and observed rainfall. An RMSE value close to zero unfolds better performance.

The third criterion evaluates the teleconnection between SST of CMIP5 GCMs in the Pacific and Indian Oceans and rainfall simulated by RCMs over the Jemma sub-basin. Since RCMs cover only a particular domain, we are not able to get SST data simulated by RCMs over different oceanic regions. As a result, SST of parent GCM and rainfall of RCMs is used to compute SST-rainfall teleconnection. SST of the equatorial Pacific and Indian Oceans are drivers of rainfall of the central highlands of Ethiopia and the study region (Diro et al., 2011; Rowell, 2013). NINO3.4 index is considered to analyze the GCMs simulation of SST anomaly over the Pacific Ocean. NINO3.4 index is the average SST over the region 5°S–5°N, 170°E–120°W (Rowell, 2013). While Indian Ocean Dipole (IOD) is considered to analyze GCMs simulation of SST anomaly over the Indian ocean. The IOD is the difference in the average SST of West Indian Ocean (IODW) over the region 10°S–10°N, 50°E–70°E) and East Indian Ocean (IODE) over the region 10°S–0°N, 90°E–110°E (Rowell, 2013). Location of NINO3.4, IODE and IODW is shown in Figure 5.3.

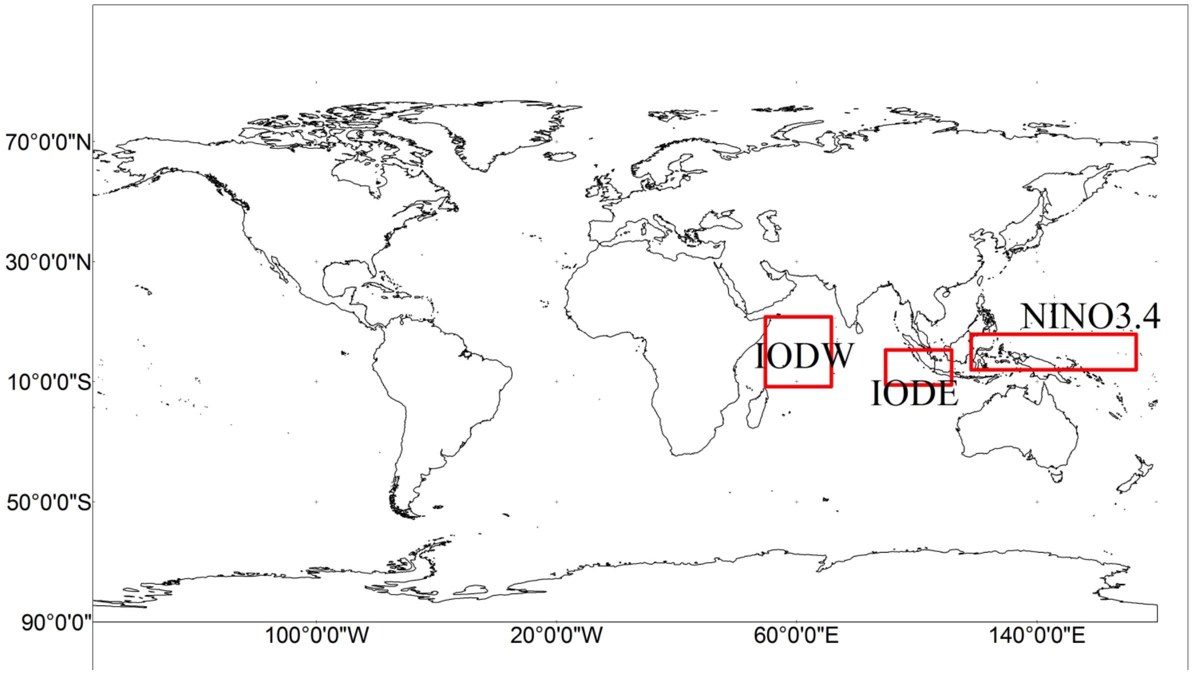


Figure 5.3 Location of SST regions used to compute indices in this study

6.3 Results and Discussion

6.3.1 Rainfall Climatology

Annual, seasonal and monthly rainfall amount and distribution of rainfall events simulated by various RCMs for the historical period corroborates a discernible difference among the RCMs (Figure 5.4). REMO model outputs were better in representing observed annual rainfall compared to other RCMs. In contention, GCMs downscaled using the RCA4 model struggle to simulate annual rainfall of the Jemma sub-basin. Outputs from the RCA4 model were characterized by underestimation in the lower altitudes and overestimation in the higher altitudes. GCMs downscaled using CCLM4 model also showed overestimation and underestimation in the higher and lower elevation areas of the Jemma sub-basin, respectively (Figure 5.4). Such biases may arise from the GCMs or RCMs parametrization of convective cloud at different elevation categories. However, there are other studies which substantiate elevation-dependent biases are stem from RCMs than GCMs. For instance, Kim et al., 2014, found that CCLM4, RCA4 and REMO models driven by ERA-Interim reanalysis overestimate rainfall in the highlands of Ethiopia. Besides, Endris et al., 2013 has also explored that RCMs driven by reanalysis datasets showed a steady overestimation of rainfall in highlands of Ethiopia. This indicates RCMs struggle to simulate rainfall which is controlled by mesoscale topographic features and large scale oceanic processes. This could be due to the noise created by the counter interaction between mesoscale and large scale drivers and RCM limitations to adequately parameterize such processes.

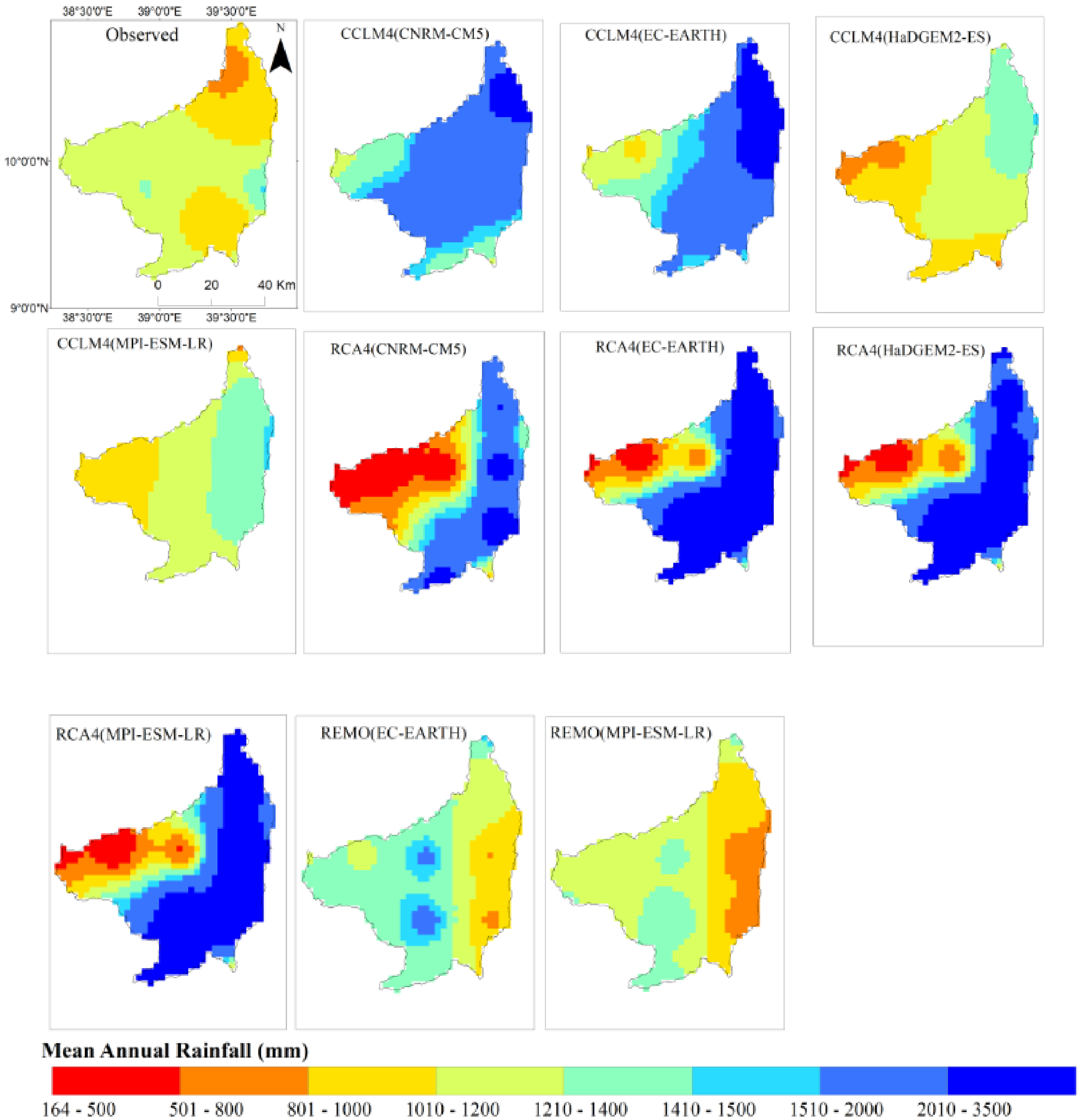
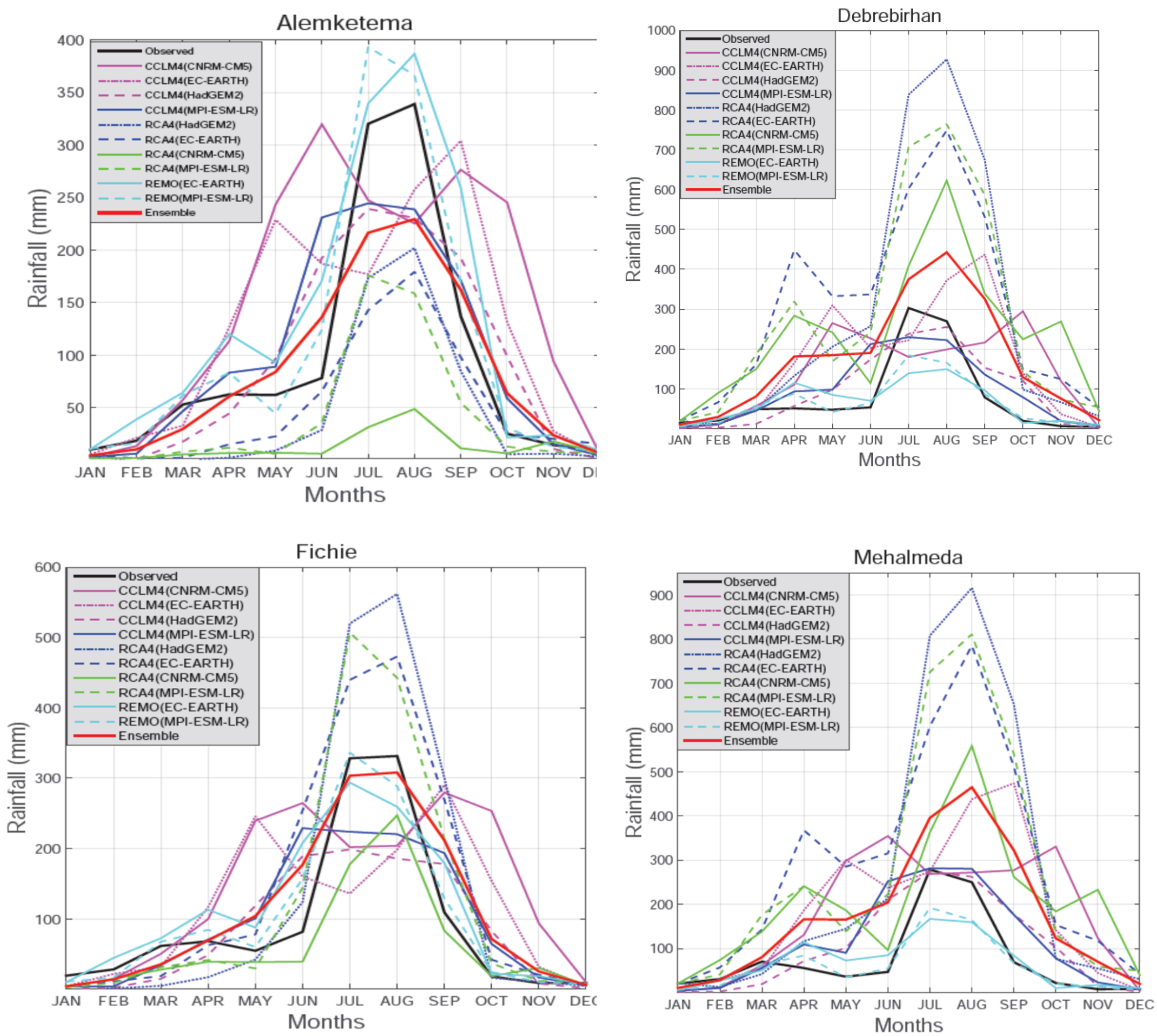


Figure 5.4 Historical (1981-2005) mean annual rainfall of observations and RCM simulations

Most of the models captured the monthly pattern of rainfall of individual stations and areal-averaged rainfall (Figure 5.5). High amount of rainfall is simulated in JJAS season, where notable inter-model differences in replicating magnitude of monthly rainfall were observed. REMO models were superior in capturing the monthly pattern of observed rainfall, while models outputs downscaled by RCA4 RCM showed the poorest performance in capturing monthly rainfall pattern. GCMs downscaled by RCA4 model is characterized by overestimated JJAS season rainfall at stations of higher altitude (e.g. Debrebirhan and Mehalmeda stations) and underestimated at stations of lower altitude (e.g. Alemketema).



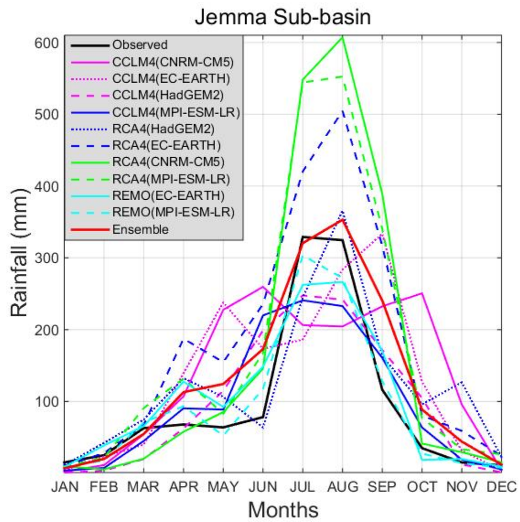


Figure 5.5 Historical (1981-2005) mean monthly rainfall of observations and RCMs simulations at different climatic stations and in the entire Jemma sub-basin. The rainfall of the entire Jemma sub-basin is areal mean annual rainfall of observation and RCMs.

6.3.2 Characteristics of Rainfall Events in Regional Climate Models

The evaluation of RCMs in capturing the distribution of extreme rainfall events is non-trivial since these extremes are responsible for flood and drought occurrences. There are a large number of dry days (0 mm/day) in the observed rainfall and RCMs' rainfall. In both observation and RCM simulations of rainfall, dry day events were discerned mainly during winter and spring seasons. More number of drizzle rainfall events (i.e. the amount of rainfall < 0.1-0.9 mm/day) were simulated in all RCMs (except RCA4 (HadGEM2-ES) compared to observed rainfall. The drizzle rainfall events in RCM simulations were detected during winter and spring seasons. Frequency of dry days is low in RCMs ensemble mean than individual RCM, because the mean of drizzle rainfall in individual RCM resulted in non-zero values in the ensemble mean. Comparable frequency of rainfall events (1mm to 6mm/day) was discerned between observed and RCMs' ensemble mean (Figure 5.6).

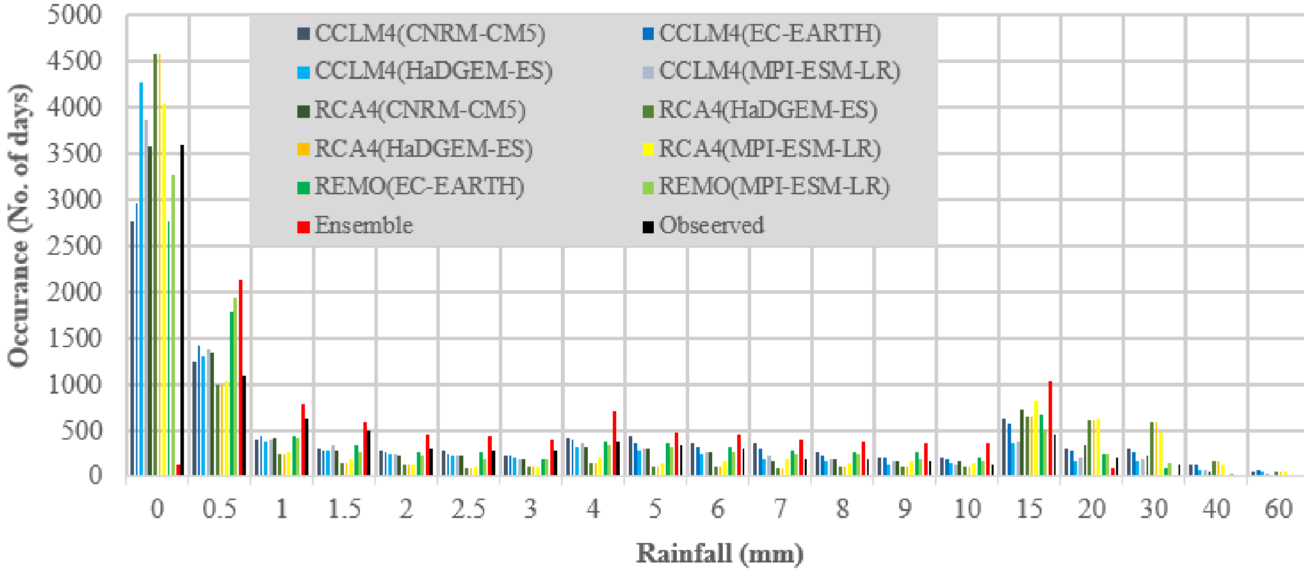


Figure 5.6 Histogram of daily rainfall of observation and RCMs in the historical period (1981-2005). The values of both observed and RCMs are areal rainfall.

Similar to the observed rainfall frequency distribution (Figure 5.6), there are more number of days with rainfall amount in the order of 0.5 to 10 mm/day in CCLM4 model family (CCLM4 (CNRM-CM5), CCLM4 (HadGEM2-ES), CCLM4 (EC-EARTH) and CCLM4 (MPI-ESM-LR) and REMO model family (REMO (EC-EARTH) and REMO (MPI-ESM-LR)). RCM simulations (especially RCA4 model family) had a higher number of heavy and very heavy rainfall events (10mm to 20mm/day respectively (WMO, 2009)) than observed rainfall. Alongside with this result, high frequency of heavy rainfall events (10mm/day) was reported using GCMs downscaled by RCA4 in the Upper Blue Nile Basin of Ethiopia (Haile and Rientjes, 2015). On the other hand, Dosio et al., 2015 evaluated outputs of four GCMs (MPI-ESM-LR, HadGEM2-ES, CNRM-CM5 and EC-EARTH) downscaled through CCLM4 and showed that these models were able to reproduce the distribution of rainfall and some extreme rainfall events over entire Africa.

Cumulative distribution of rainfall of RCMs showed a clear inter-model difference in the simulation of heavy rainfall events. The CCLM4 model family better reproduced the distribution of observed rainfall compared to other models (Figure 5.7). The proportion of heavy rainfall (rainfall more than 10 mm/day) and very heavy rainfall (rainfall more than 20 mm/day) was about 40% and 10%, respectively in most RCA4 models. In contrast, the proportion of 10 mm/day rainfall was only about 10% in most of CCLM4 and REMO models as well as in the observed rainfall. In all models except RCA4 (EC-EARTH), the proportion of drizzle and light rainfall events (0.20 to 5 mm/day) account for about 50% of the total rainfall (Figure 5.7).

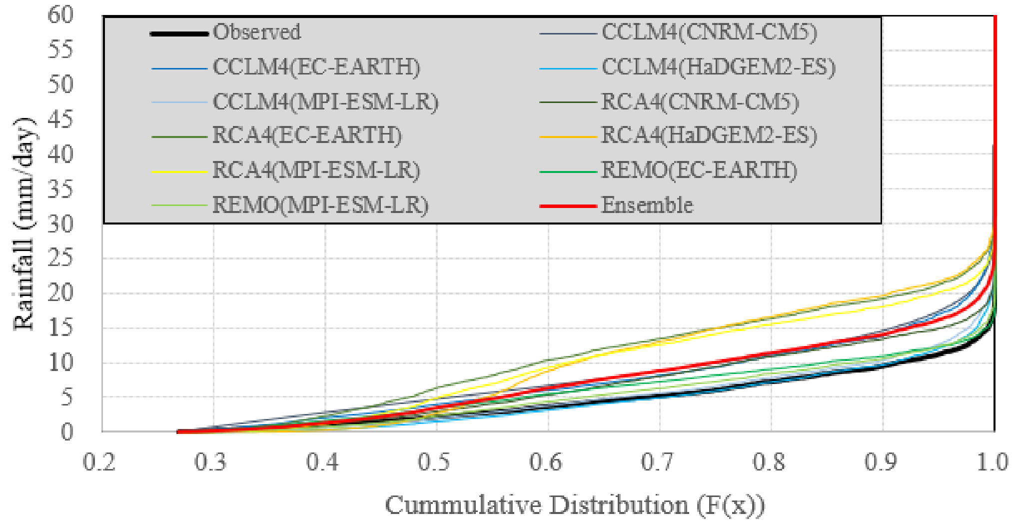


Figure 5.7 Cumulative distribution of daily rainfall of observation and RCM simulations in the historical period (1981 – 2005). The values of both observed and RCMs are areal rainfall.

Similar to the cumulative distribution of rainfall events, all models overestimated the return period, especially the RCA4 model family showed a higher overestimation of the return period. REMO model family showed good fidelity with the annual and JJAS return period of observed rainfall. Based on RCA4 models simulation, 2500mm/year rainfall, which is 150% higher than observed rainfall, can happen after every 25 years (Figure 5.8). The annual and JJAS rainfall return period analysis (Figure 5.8a and 5.8b) indicated that a large proportion of the annual rainfall (about 80%) was concentrated in the JJAS season. In few high altitude stations, RCA4 models provide more than 600 mm/month rainfall during JJAS season (Figure 5.5). However, the observed monthly rainfall is less than 300 mm/month during the JJAS season. Based on RCA4 models, there could be frequent flooding problems which may affect social and ecological systems.

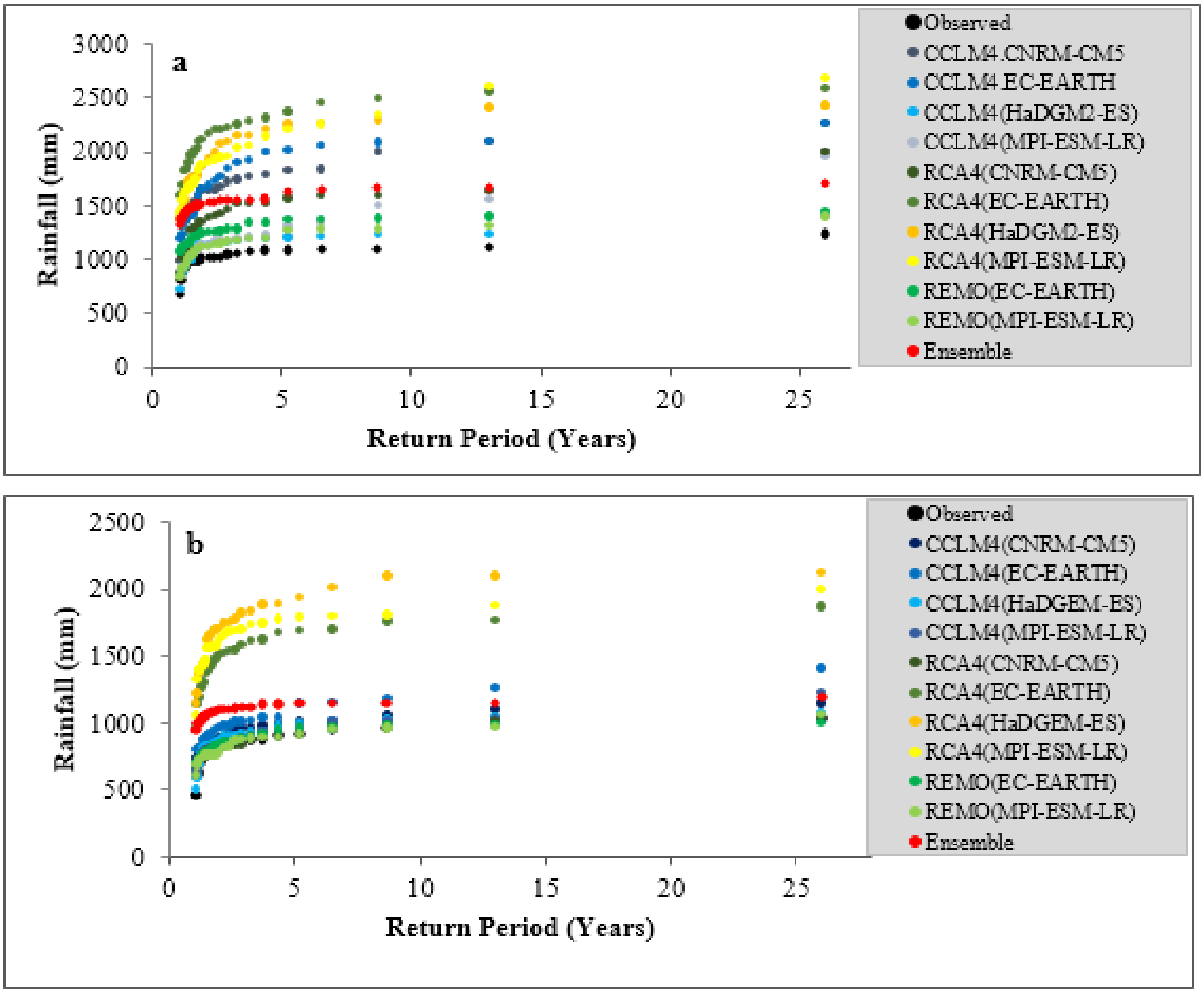


Figure 5.8 Return periods (years) of rainfall of observation and RCM simulations. (a) Annual and (b) Summer season rainfall. The values of both observed and RCMs are areal rainfall.

6.3.3 Statistical Evaluation of Regional Climate Models

Statistical metrics (Correlation, BIAS and RMSE) between the areal averaged observed and RCMs simulat ed rainfall confirmed the difference in the performance of RCMs in capturing annual and JJAS rainfall of t he Jemma sub-basin. All RCM simulations overestimated the annual and JJAS rainfall, but with different magnitude. For instance, wet BIAS in annual rainfall of RCMs ranged from 9.6% in CCLM4 (HadGEM2-ES) model to 110.9% in RCA4 (EC-EARTH) model. Wet BIAS in JJAS rainfall ranged from 0.76% in RE MO (MPI-ESM-LR) model to 100.7% in RCA4 (HadGEM2-ES) model. GCMs downscaled using RCA4 RCM showed better correlation than other RCMs, but higher wet BIAS and higher RMSE compared to oth er models (Table 5.3). GCMs downscaled using CCLM4 RCM were poorly correlated with the observed r ainfall, but BIAS and RMSE in these RCMs were better than RCA4 model family. GCMs downscaled usin g REMO RCM showed better performance in BIAS, RMSE and Correlation compared to RCA4 and CCL M4 model families and the ensemble mean. At all, REMO (MPI-ESM-LR), REMO (MPI-ESM-LR), CCL M4 (HadGEM2-ES) and CCLM4 (MPI-ESM-LR) showed better performance in BIAS, RMSE, and correl ation metrics compared to other RCMs.

The ensemble mean of RCMs was superior in correlation metric which shows a higher correlation with obs erved annual and JJAS rainfall than other individual RCM (Table 5.3). The ensemble mean was also chara cterized by low coefficient of variation (CV) in relation to the observed rainfall. In CCLM4 and REMO m odel family, the BIAS and RMSE of JJAS rainfall were better than annual rainfall. While in RCA4 models , poor performance in BIAS and RMSE was observed in the JJAS due to overestimation of JJAS rainfall (Table 5.3).

Table 5.3 Correlation, BIAS and RMSE between observed and RCMs simulated rainfall of annual and summer rainfall in the Jemma sub-basin from 1981–2005.

	Average Rainfall (mm)		CV (%)		Correlation (r)		Bias (%)		RMSE (mm)	
	Annual	JJAS	Annual	JJAS	Annual	JJAS	Annual	JJAS	Annual	JJAS
Observed	1001	815	10.76	16.31	-	-	-	-	-	-
CCLM4(CNRM-CM5)	1631	903	15.95	12.81	0.12	-0.06	62.90	10.8	692	213
CCLM4(EC-EARTH)	1664	977	18.80	16.54	0.19	0.00	66.20	19.9	751	268
CCLM4(HadGEM2-ES)	1097.	860	13.54	16.22	0.23	0.04	9.60	5.50	225	191
CCLM4(MPI-ESM-LR)	1177	854	19.25	15.61	0.23	0.04	17.62	4.80	313	215
RCA4(CNRM-CM5)	1357	838	17.85	11.40	0.29	0.28	35.50	2.81	462	170
RCA4(EC-EARTH)	2108	1477	13.07	14.77	0.36	0.19	110.9	81.33	1149	730
RCA4(HadGEM2-ES)	1912	1690	15.92	15.96	0.48	0.30	91.00	100.0	969	936
RCA4(MPI-ESM-LR)	1912	1604	16.72	12.76	0.44	0.31	91.00	96.96	970	830
REMO(EC-EARTH)	1248	847	8.11	11.03	0.34	0.17	24.7	3.98	284	187
REMO(MPI-ESM-LR)	1113	821	12.51	12.74	0.37	0.20	11.1	0.76	204	173
Ensemble	1522	1087	6.15	5.50	0.60	0.50	52.0	33.44	545	315

The Taylor diagram (Taylor, 2001) graphically summarizes the deviation between different RCM simulations and observed values. Figure 5.9 showed the correlation, centered root-mean-square difference and the standard deviation of mean annual and mean summer season rainfall between each RCM, ensemble mean and observed values. Equivalent with Table 5.3, the Taylor diagram showed better correlation of RCMs and observed rainfall in annual rainfall than summer season rainfall. In both annual and summer season rainfall, simulations of RCA4 model are characterized by higher RMSE and standard deviation and better correlation than simulation of other RCMs. The ensemble mean of the RCMs showed better correlation, RMSE and standard deviation with observed annual and summer season rainfall. Except the ensemble mean of RCMs, all individual RCM simulations show a standard deviation and RMSE of greater than 5mm/day.

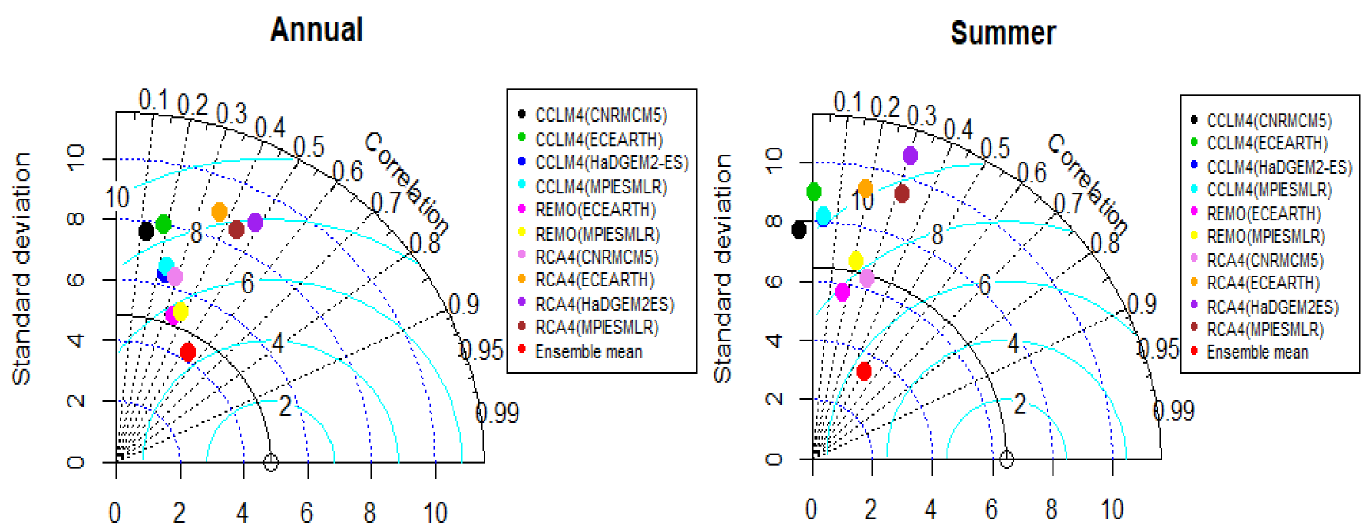


Figure 5.9 Taylor diagram displaying the statistical comparison of annual and summer seasonal mean rainfall of the 10 RCM simulations and their ensemble with observed values.

6.3.4 Associations between Sea Surface Temperature and Rainfall of Regional Climate Models

It is investigated that the increase in SST in Indian ocean and Equatorial Pacific regions triggers export of dry air from these oceanic regions toward the central highlands of Ethiopia and the Blue Nile River Basin, which further result a decrease in rainfall (Abtew et al., 2009; Taye and Willems, 2012; Endris et al., 2016). The observed rainfall of the Jemma sub-basin also showed an association with NINO 3.4 index (Table 5.4). Concurrently, this study showed the teleconnection between SST of CMIP5 GCMs and rainfall of RCMs over the Jemma sub-basin, although it is weak. Annual (90%) and JJAS (80%) rainfall of RCMs has negative correlations with GCMs' SST of Pacific Ocean (NINO3.4). The annual (60%) and JJAS (70%) rainfall of RCMs also showed a negative but weak association with GCMs' SST of Indian ocean (IOD) (Table 5.4). Simulation of SST (NINO3.4) from some CMIP5 GCMs (HadGEM2-ES and EC-EARTH) revealed a better correlation with the rainfall of RCMs. The erroneous of the RCMs to sufficiently capture the teleconnection pattern may stem from the GCMs.

Table 5.4 Correlation between SST indices and annual and seasonal RCMs rainfall of the Jemma sub-basin

	NINO3.4		**IOD**	
	Annual	**JJAS**	**Annual**	**JJAS**
Observed	**-0.48**	**-0.37**	-	-
CCLM4(CNRM-CM5)	-0.31	-0.10	-0.00	-0.23
CCLM4(EC-EARTH)	-0.20	-0.03	-0.25	-0.13
CCLM4(MPI-ESM-LR)	-0.15	-0.17	0.15	0.25
CCLM4(HadGEM2-ES)	-0.37	-0.25	0.14	0.10
CCLM4(HadGEM2-ES)	-0.37	-0.25	0.14	0.10
RCA4(CNRM-CM5)	-0.03	0.03	-0.03	-0.09
RCA4(EC-EARTH)	-0.32	-0.43	-0.04	-0.11
RCA4(HadGEM2-ES)	0.39	0.54	-0.25	-0.23
RCA4(MPI-ESM-LR)	-0.14	-0.15	-0.30	0.14
REMO(EC-EARTH)	-0.31	-0.21	0.30	-0.17
REMO(MPI-ESM-LR)	-0.12	-0.23	0.05	0.24

Other studies evaluated the performance of CMIP5 GCMs in simulating the teleconnections between the rainfall and SST in the Blue Nile River Basin, Ethiopian highlands and other different regions of Africa. RCMs (CCLM4, RCA4 and REMO) driven by Re-Analysis (ERA-Interim) reasonably simulated the teleconnection between the rainfall and ENSO indices in the Ethiopian highlands (Endris et al., 2013). In contrast, Bhattacharjee and Zaitchi, (2015) was not able to find any teleconnection between observational based ENSO indices and CMIP5 GCMs rainfall in the Upper Blue Nile Basin. The inability to represent SST by GCMs could be attributed to the fact that CMIP5 GCMs are sensitive to initial conditions, a quasi-equilibrium control run (Taylor et al., 2012). The historical run of CMIP5 GCMs is initiated from an arbitrary point rather than using observed SST data which is the case for Atmospheric models (AMIP). As a result, it is not conceivable that models simulations to occur at the same time as the observational record.

6.4 Conclusion

To develop climate scenarios, climate impact scenarios and climate adaptation decisions, it is fundamental to discern climate model outputs which can reproduce the historical climate of the region under study. However, it's based on the assumption that climate modeling schemes which perform well for the historical climate are more likely to perform well for future climate conditions (Teutschbein and Seibert, 2012). Thus, this study has inter-compared performance of different RCM simulations in capturing mean and frequency of observed rainfall of the Jemma sub-basin. This study ascertains the difference in RCMs' ability in simulating historical rainfall climatology of the Jemma sub-basin. This study showed GCMs downscaled using REMO and CCLM4 RCMs perform relatively better in representing the mean annual and monthly rainfall and distribution of rainfall events. All RCMs show bias, but the magnitude of biases and distribution of rainfall events was relatively better in REMO and CCLM4 models simulations. GCMs downscaled through RCA4 model show higher overestimation and underestimation of rainfall in the high and low elevation areas of the sub-basin, respectively.

When it comes to the areal-average rainfall across the entire sub-basin, all RCMs have shown a positive bias in annual and JJAS rainfall, but with different magnitude. The RCA4 models struggle under most of the criteria. RCA4 models revealed a higher overestimation of annual and JJAS rainfall in the higher altitudes of the sub-basin and higher underestimation in the lower elevation areas of the sub-basin. Higher BIAS, RMSE and extreme rainfall events were also estimated in the RCA4 model family. In terms of capturing the teleconnections with SST, most RCMs rainfall showed a negative association, but weak with SST of parent GCMs over the equatorial Pacific and the Indian Ocean. This is similar to other studies (Abtew et al., 2009; Taye and Willems, 2012) that found the negative teleconnection between SST and rainfall of the Blue Nile Basin and Ethiopian Highlands.

The ensemble mean of models (E-RCMs) are supposed to represent observed rainfall better than any of the individual RCMs (S-RCMs). Likewise, this study disclosed that mean ensemble output was better in capturing the monthly pattern of rainfall than any of the individual RCMs (S-RCM). Moreover, the ensemble mean rainfall output showed a better correlation with observed annual and JJAS season rainfall. It also showed low variability of rainfall compared to the S-RCM. However, higher overestimation of rainfall, particularly by RCA4 models triggers ensemble mean of RCMs to show weak performance in RMSE and BIAS metrics and in reproducing distribution of rainfall events. Due to the presence of drizzle rainfall events in individual RCM, there are lower numbers of dry days (0 mm/day) in the ensemble mean of RCMs compared to individual (S-RCM) rainfall simulation. In general, GCMs downscaled through REMO and CCLM4 regional models and the ensemble mean of RCMs showed better fidelity with the frequency of observed rainfall. The biases in REMO and CCLM4 models can be improved by using robust statistical bias correction methods and can be satisfactorily used for climate scenario, climate impact scenario development and adaptation decision support systems.

Chapter 6

Statistical Bias Correction of Regional Climate Model Simulations to develop Climate Change Scenarios: Application to Jemma Sub-basin, Blue Nile Basin

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Abstract

This study inter-compares statistical bias correction methods and develops future climate scenarios using the output of a better bias correction technique at the Jemma sub-basin. The performance of different bias correction techniques was evaluated using several statistical metrics. All bias correction methods were effective in adjusting mean values of RCM simulations of rainfall and temperature to the observed rainfall and temperature values. However, distribution mapping method was better in capturing the 90th percentile of observed rainfall and temperature and wet day probability of observed rainfall than other methods. The bias correction methods performance under climate condition different from the current climate was also evaluated using the Differential Split Sample Testing (DSST) and reveals that the distribution mapping technique is valid under climate condition different from the current climate. As a result, it is commendable to use future (2021–2100) simulation of RCMs which are bias corrected using distribution mapping technique. The output of bias adjusted RCM outputs unfold a decline of rainfall, a persistent increase of temperature and an increase of extremes of rainfall and temperature in the future climate under emission scenarios of Representative Concentration Pathways 4.5, 8.5 and 2.6 (RCP4.5, RCP8.5 and RCP2.6). Thus, climate adaptation strategies that can provide optimal benefits under different climate condition should be developed to reduce the repercussion of climate change.

Keywords: statistical bias correction, RCMs, rainfall, temperature, Blue Nile Basin, Jemma, Ethiopia

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This chapter is based on **Worku, G., Teferi, E., Bantider, A., Dile, Y.T., 2019. Statistical Bias Correction of Regional Climate Model Simulations for Climate Change Projection in the Jemma sub-basin, Blue Nile Basin of Ethiopia.** *Theor. Appl. Climatol. 139:1569–1588, http://dx.doi.org/10.1007/s00704-019-03053-x*.

6.1 Introduction

Based on the dynamical downscaling approach, climate programs across the world use the CMIP3 and CMIP5 GCMs to project the future climate and to downscale GCMs simulation (Christensen and Carter, 2007; Giorgi et al., 2009; Evans, 2011; Mearns et al., 2013; Gutowski et al., 2016). Under the auspice of the WCRP, CORDEX is an international program to avail downscaled climate dataset, to integrate model evaluation frameworks and to use climate models data for climate change impact studies (Giorgi et al., 2009). The outputs of CORDEX are evaluated and used for climate change impact studies in different parts of Africa and showed reasonable result (Nikulin et al., 2012; Dosio et al., 2015; Haile and Rientjes, 2015). But, as yet the output of downscaled RCMs showed persistent biases and can't be directly used without tailoring and bias correction for climate change impact assessment (Piani et al., 2010; Gudmundsson et al., 2012).
Bias correction is the science of scaling climate model values to reflect the statistical properties such as mean, variance or wet-day probabilities of observed climate (Maraun, 2016). There are several bias correction methods; some of these methods such as linear scaling adjust only the mean of climate models simulation, whereas other methods like distribution mapping and power transformation correct the mean and frequency of models' values with the statistical values of observations (Piani et al., 2010; Teutschbein and Seibert, 2012). Compared to other bias correction methods, distribution mapping is a better bias correction technique in adjusting the frequency of rainfall and temperature events (Teutschbein and Seibert, 2012; Fang et al., 2015).

However, bias correction techniques have some limitations and even on some instances bias correction methods trigger biases. For instance, the bias corrected Weather Research and Forecasting (WRF) RCM has presented larger wet bias than the non-bias corrected WRF simulation over Canada and Central North America (Wang and Kotamarthi, 2015). Commonly, most bias correction methods consider biases and bias correction algorithms are stationary over time (Piani et al., 2010; Maraun, 2012). Nonetheless, there are studies which investigate the non-stationarity of bias correction functions (e.g Maraun, 2012). These limitations did not curtail the application of bias correction methods since climate models are characterized by significant biases and can trigger considerable errors in impact assessment studies. Therefore, strong bias correction methods are to be identified before using bias corrected climate models output for climate scenario development and climate change impact assessment.

Several climate change impact studies in the Blue Nile Basin were based on GCMs output instead of RCMs (Beyene et al., 2010; Setegn et al., 2011). Furthermore, some studies were based on a single GCM output (e.g. Dile et al., 2013). Whilst, climate scenarios developed based on multiple GCMs, RCMs, emission scenarios and statistical bias correction methods are lacking. It had been in limited research that bias correction was applied to study the impact of climate change at the basin scale (e.g. Elshamy et al., 2009; Liersch et al., 2016). And, this is often hardly attainable to use the output of those studies at the watershed and sub-basin level, since there is dissimilar topography and climate in the upper catchments of Blue Nile Basin. For example, rainfall trend study in the Blue Nile Basin showed different trends of historical rainfall at different sub-basins (Taye et al., 2015). This suggests the need to advance climate models pre-processing that can be used for climate change impact assessment on agriculture and water resources at every area of the Upper Blue Nile Basin.

This study is therefore intended to intercompare different statistical bias correction methods and to develop climate scenarios that can be used for climate change impact assessment and climate adaptation decision analysis at water and agriculture sector of the Jemma sub-basin, Upper Blue Nile Basin. Similar to large areas of Ethiopia, the economy of the inhabitants of the Jemma sub-basin is heavily dependent on rain-fed agriculture which is affected by the adverse impacts of climate change (Conway and Schipper, 2011). In the region of Jemma, it had been studied that climate change and variability has caused drought, flooding, frost and significant loss of crops production (Tesso et al., 2012). The water resource base of the sub-basin is also highly reliant on rainfall. Rainfall contributes to 55% and 57% of runoff at the Andit Tid and Beressa catchments of the Jemma sub-basin respectively (Hurni et al., 2005; Gebrehiwot and Ilstedt, 2011). This means variation in rainfall may trigger tremendous impacts on the water resource base and agricultural production of the sub-basin. Thus, it is critical to develop strong climate change information that can be used for hydrological climate change impact assessment and to identify optimal adaptation decisions in the water resource sector of the Jemma sub-basin. This study will underpins decision making in watershed and water resource-based climate adaptation strategies in the Jemma sub-basin.

6.2 Data and Methodology

6.2.1 Observation Data

Historical (1981 - 2005) daily rainfall and temperature data of nine climatic stations was obtained from the National Meteorological Agency of Ethiopia. These nine climatic stations have data with relatively minimal missing values. Multivariate Imputation by Chained Equations (MICE) package, built in the R statistical software (R Development Core Team, 2015), was used to impute the incomplete rainfall and temperature records. RClimDex was used to examine the quality of the data and to manage outlier values of rainfall and temperature. Detail description of missing values imputation and quality control of the data is given by (Worku et al., 2018a).

6.2.2 Regional Climate Models Data

In this study, the RCMs are selected based on (Worku et al., 2018b) which has investigated that CCLM4 and REMO regional models driven by four CMIP5 GCMs were better to capture the mean values and frequency of rainfall events of the Jemma sub-basin than regional climate model (RCA4). However, differences still exist between the historical simulation of RCMs and observed data. Moreover, RCM performance in simulating the observed rainfall was different at different altitude (Worku et al., 2018b). This indicates the need for bias adjustment of RCM simulations at different locations. In this study, historical (1981 - 2005) and future (2021-2100) simulation of daily rainfall, TMAX and TMIN of CCLM4 and REMO models simulation driven by four CMIP5 GCMs (Table 6.1) were considered for statistical bias correction. Here, it must be known that one RCM i.e CCLM4(HadGEM2-ES) does not have data available for the year 2100, as a result, long term future period used for this model is 2071–2099. Totally, the simulation of six RCMs was used. The RCM data was acquired from the Earth System Grid Federation dataset.

COSMO-CLM is the coupling of COSMO (COnsortium for Small-scale MOdelling) of different European national weather services and CLM (Climate Limited-area Model) of the German Climate Research Centre (Rockel et al., 2008). CCLM4 is a non-hydrostatic model (Baldauf et al., 2011), whereas, REMO is a hydrostatic three-dimensional atmospheric model initiated at the Max Planck Institute for Meteorology (Jacob et al., 2007). The detail of physical parameterizations of CCLM4 and REMO models are given in Table 6.1.

Table 6.1 Detail description of RCMs used in this study

Model Acronym	CCLM(CNRM-CM5)	CCLM(EC-EARTH)	CCLM(HadGEM2-ES)	CCLM(MPI-ESM-LR)	REMO (EC-EARTH)	REMO(MPI-ESM-LR)
Driving GCM	CNRM-CM5	EC-EARTH	HadGEM2-ES	MPI-ESM-LR	EC-EARTH	MPI-ESM-LR
RCM	CCLM	CCLM	CCLM	CCLM	REMO	REMO
Institute	Climate Limited-Area Modelling (CLM) Community	Climate Limited-Area Modelling (CLM) Community	Climate Limited-Area Modelling (CLM) Community	Climate Limited-Area Modelling (CLM) Community	Max Planck Institute (MPI)	Max Planck Institute (MPI)
Resolution	0.44°	0.44°	0.44°	0.44°	0.44°	0.44°
Convective scheme	Tiedtke, 1989	Tiedtke, 1989	Tiedtke, 1989	Tiedtke, 1989	Tiedtke, 1989	Tiedtke, 1989
Radiation scheme	Ritter and Geleyn, 1992	Ritter and Geleyn, 1992	Ritter and Geleyn, 1992	Ritter and Geleyn, 1992	Fouquart and Bonnel, 1980	Fouquart and Bonnel, 1980
Cloud microphysics scheme	Baldauf et al., 2011	Baldauf et al., 2011	Baldauf et al., 2011	Baldauf et al., 2011	Lohmann and Roeckner, 1996	Lohmann and Roeckner, 1996
Land surface scheme	Doms et al., 2011)	Doms et al., 2011	Doms et al., 2011	Doms et al., 2011	Rechid et al., 2009	Rechid et al., 2009

After obtaining observed and historical RCM rainfall and temperature data, the observed data (point data) were interpolated to 0.44° × 0.44° grid size through the bilinear interpolation method. This is because the RCM data is gridded data (0.44° × 0.44°). To estimate sub-basin wide areal rainfall and temperature of both observation and RCM, the Thiessen Polygon method (Thiessen, 1911) was applied. Areal observed and RCMs rainfall and temperature was calculated based on the area of the polygon and the grids in proportion to the total area of the sub-basin. Some of the grids of RCMs partially extend over the study area.

In each RCM, simulation based on emission scenarios of RCP4.5, RCP8.5 and RCP2.6 were used. RCP 4.5 and RCP 8.5 were selected because these emission scenarios represent possible radiative forcing levels in the year 2100 relative to pre-industrialisation (van Vuuren et al., 2011). RCP8.5 represents high emission scenarios with increasing radiative forcing pathway resulting 8.5W/m^2 by 2100, while RCP 4.5 represents intermediate emission levels of 4.5 W/m^2 that could be reached at stabilization after 2100 (Moss et al., 2010). Between RCP4.5 and RCP8.5, there is RCP6.0 emission scenario to represent emission levels of 6 W/m^2 that could be reached at stabilization after 2100 (Moss et al., 2010). Thus, taking RCP4.5 and RCP8.5 is more representative of the spectrum of scenarios characterized by an increase in emissions in the future period. In the Paris agreement, nations were agreed to limit global warming well below 2°C (UN, 2015). Therefore, RCP2.6 was used to account for the Paris Agreement and other sustainable and substantial measures to mitigate future climate change. However, CCLM4 community have downscaled only the RCP4.5 and RCP8.5. Thus, this study has used only REMO (EC-EARTH) and REMO(MPI-ESM-LR) to develop climate scenarios under RCP2.6 emission scenario.

6.2.3 Statistical Bias Correction Procedures

Distribution mapping, linear scaling, variance scaling (for temperature) and power transformation (for rainfall) are the bias correction techniques which were evaluated and used to adjust historical simulations of rainfall and temperature of six RCMs to the values and distribution of observed (1981 - 2005) rainfall and temperature. The methods find a function *h* that fits a modelled variable V_m such that its new values equal the values of the observed values V_o (Piani et al., 2010; Gudmundsson et al., 2012). This function can be expressed as;

$$V_o = h(V_m) \qquad \text{............................1}$$

Linear scaling method (Lenderink et al., 2007) adjusts rainfall and temperature of RCM simulations using multiplicative and additive factors, respectively. The factors are developed by comparing the observed data with the corresponding historical RCM simulations. In linear scaling, the RCM rainfall and temperature output for historical (control) and future (scenario) climate period were corrected as follows;

$$R^*_{contr}(d) = R_{contr}(d)\left[\frac{\mu_m(R_{obs}(d))}{\mu_m(R_{contr}(d))}\right] \text{..................} 2$$

$$R^*_{scen}(d) = R_{scen}(d)\left[\frac{\mu_m(R_{obs}(d))}{\mu_m(R_{contr}(d))}\right] \text{....................} 3$$

$$T^*_{contr}(d) = T_{contr}(d) + \mu_m(T_{obs}(d)) - \mu_m(T_{contr}(d)) \text{..............} 4$$

$$T^*_{scen}(d) = T_{scen}(d) + \mu_m(T_{obs}(d)) - \mu_m(T_{contr}(d)) \text{................} 5$$

Where

d is day

R^* and T^* are the corrected rainfall and temperature values

$\mu_m (R_{obs})$ and $\mu_m (T_{obs})$ are average monthly observed rainfall and temperature values, respectively

$\mu_m (R_{contr})$ and $\mu_m (T_{contr})$ are average monthly simulated rainfall and temperature values for the control period, respectively

R^*_{scen} and T^*_{scen} represent the corrected RCM rainfall and temperature values for the future (2021-2100)

R_{scen} and T_{scen} are raw RCM rainfall and temperature values for the future (2021-2100)

Different from linear scaling, power transformation method reproduce the standard deviation, coefficient of variation (CV), wet-day frequencies and intensities of rainfall based on observed data (Leander and Buishand, 2007). In power transformation, daily rainfall of RCMs is changed into a corrected rainfall through fitting the CV of the corrected daily RCM rainfall with the CV of observed daily rainfall for each month. Parallel to power transformation, variance scaling was used to fit the RCM simulations of temperature (Chen et al., 2011).

In the distribution mapping method, the distribution function (CDF) of RCM-simulated rainfall and temperature values are adjusted with the CDF of observed rainfall and temperature values (Figure 6.1). Distribution mapping method adjusts the mean, standard deviation, wet day probabilities and distribution of rainfall and temperature simulations of RCM (Teutschbein and Seibert, 2012). Distribution mapping uses the Gamma distribution (Gudmundsson et al., 2012) and the Gaussian distributions (Cramér, 1999) to fit the distribution of rainfall and temperature of RCMs with observational data. Distribution mapping also uses an RCM-specific rainfall threshold (Schmidli et al., 2006) to adjust the wet day frequencies of daily rainfall. In the distribution mapping, the transformation between for instance observed rainfall and modelled rainfall is given as;

$$V_o = F_o - 1\big(F_m(V_m)\big) \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots . \ldots \ldots \ldots \ldots \ldots \ldots . . 6$$

Where

V_o is observed variable,

V_m is modelled variable,

F_m is the CDF related to V_m and

F_o^{-1} is the inverse CDF of V_o (Gudmundsson et al., 2012).

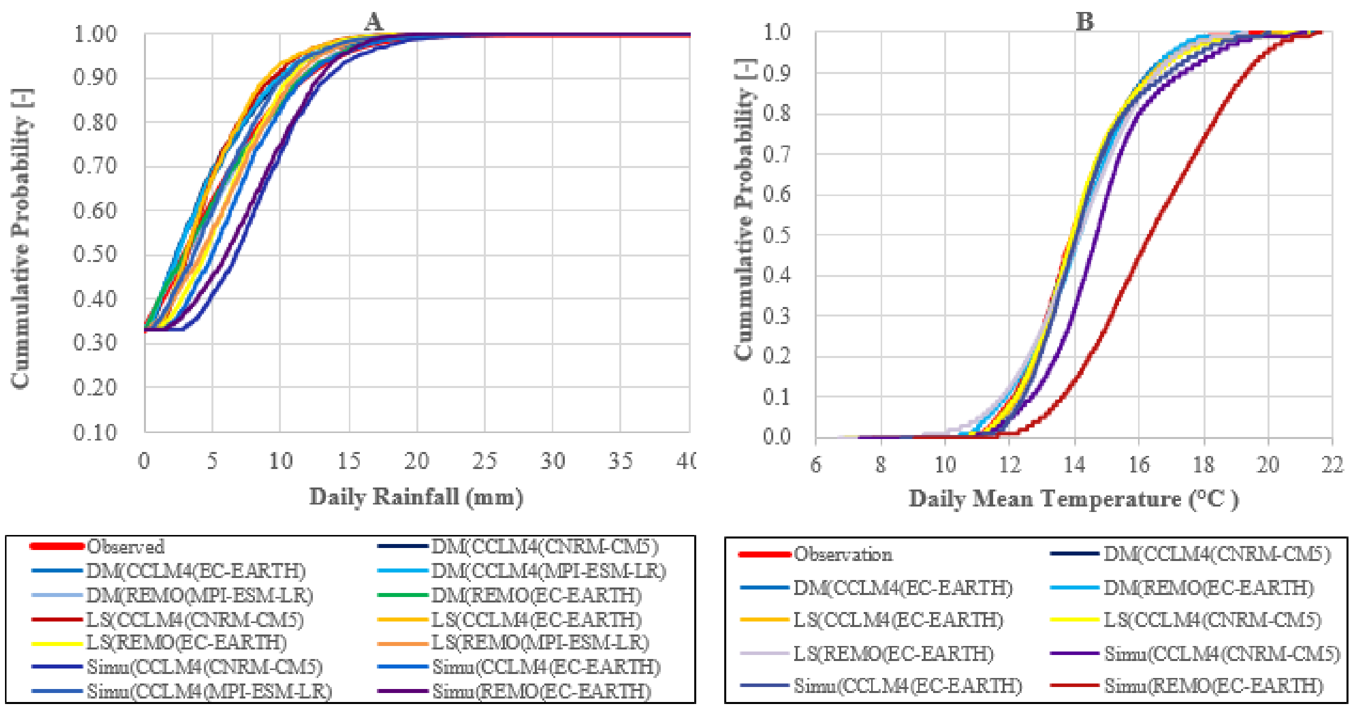


Figure 6.1 Cumulative distribution of observed, RCMs simulated (Simu) and bias corrected daily rainfall (A) and temperature (B) of the Jemma sub-basin in the historical period (1981 – 2005). DM and LS are distribution mapping and linear scaling bias correction methods respectively.

To develop monthly correction parameters (factors), distribution mapping uses the Gamma distribution and the Gaussian distributions that fit the distribution of rainfall and temperature of RCMs with observational data, respectively. The Gamma distribution uses a shape parameter (α) and scale parameter (β) to fit rainfall simulations of RCM (Figure 6.2). These shape (α) and scale (β) parameters control RCMs daily rainfall probability of occurrences (distribution) and intensities, respectively (Teutschbein and Seibert, 2012).

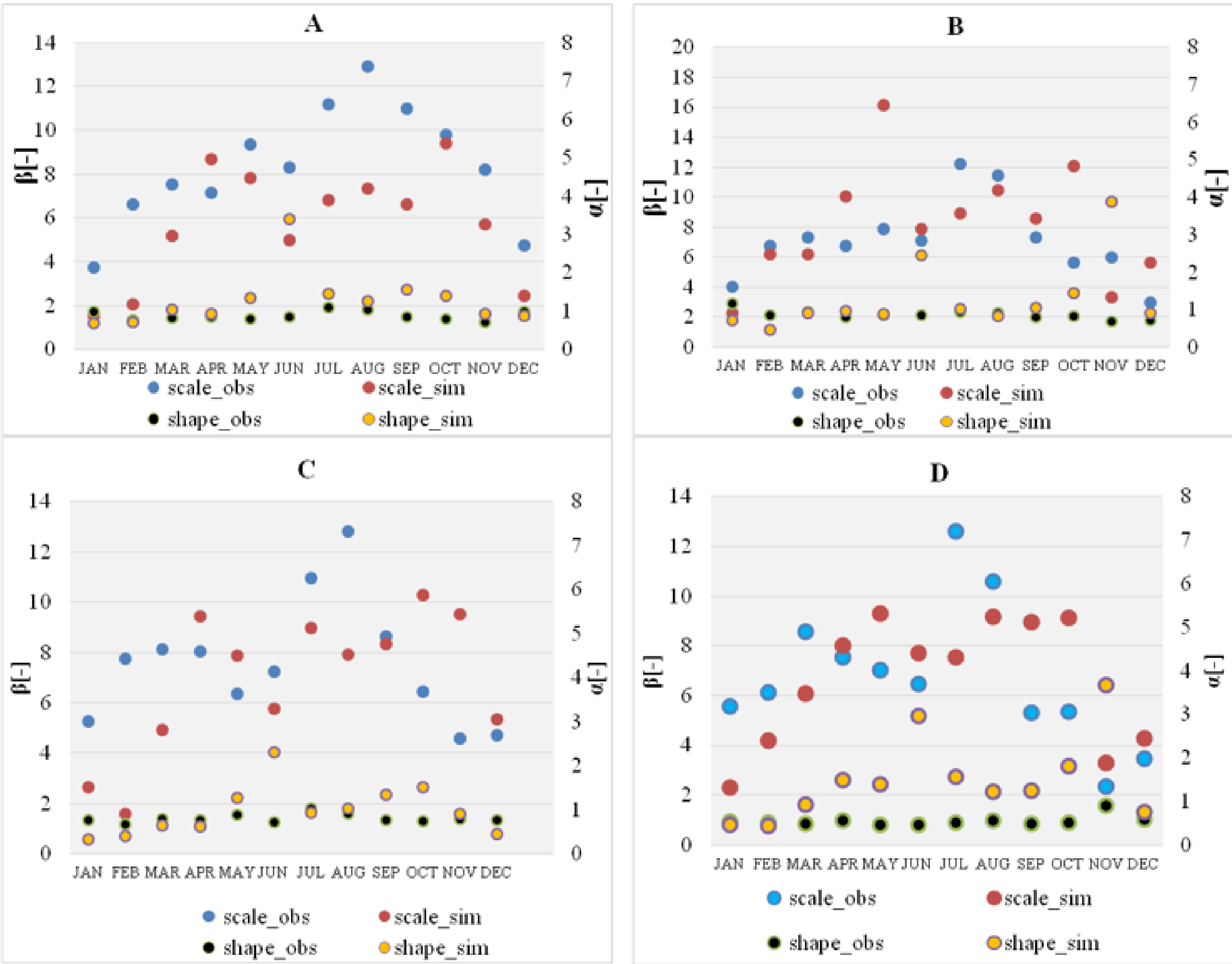


Figure 6.2 Monthly scale parameters (β) and shape parameters (α) of the Gamma distribution fitting observed and raw RCM-simulated rainfall in Central (A), Eastern (B), Western (C) and Northern (D) areas of the Jemma basin. Scale_obs, scale_sim, shape_obs and shape_sim are to indicate the scale and shape parameters of observed and RCMs simulated rainfall.

There are different approaches to test the assumption of stationarity of biases and bias correction functions (Klemeš 1986; Teutschbein and Seibert 2013). To test how distribution mapping, power transformation, and linear scaling methods work for future climate condition, this study uses the DSST method (Klemeš, 1986). The following procedures of DSST were followed; first, based on observed mean annual rainfall, years of observation (1981-2005) were sorted by ascending order (Figure 6.3). Second, based on observed mean annual rainfall, the observed years were divided as dry years (the first 12 years) and wet years (the last 12 years) and thirdly, the RCM-simulated rainfall was sorted and rearranged to match with the annual order of the sorted observed rainfall. Subsequently, twofold cross-validation was performed. In the first case, bias correction was executed using the dry years as calibration and wet years as validation. Secondly, bias correction was executed using the wet years as calibration and dry years for validation. A similar procedure was followed to evaluate temperature bias correction methods where the mean annual TMAX and TMIN of observed data and RCM data was sorted and divided as cold years and warm years.

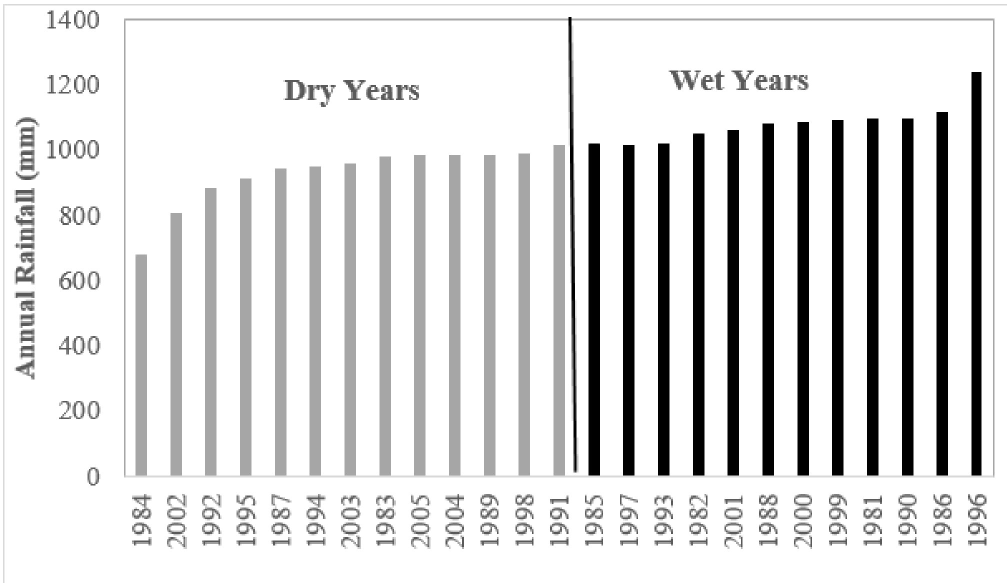


Figure 6.3 Years sorted based on historical annual rainfall (1981-2005) for Differential Split-Sample Testing (DSST).

The performance of bias correction methods at calibration and validation stages was tested using different metrics. The Nash–Sutcliffe measure of efficiency (NSE) and the Root Mean Square Error (RMSE) were used to test the volumetric variation between mean monthly and annual observation, RCM simulations and bias corrected RCM outputs. Frequency-based tests which include CV, 90th percentile (X_{90}) and the probability of wet day (Pr_{wet}) (for rainfall) were also used to evaluate the skill of bias correction methods. The bias correction method which performs better during the historical period was used to correct the RCM simulations and to develop climate scenarios for the near-term future (2021-2050) and long-term future (2071-2100).

This study has used the CMhyd tool (Rathjens et al., 2016) and qmap package which is built-in R statistical software (Gudmundsson, 2015) to execute the statistical bias correction techniques. These tools compare the raw RCM output with observed data, calculate the variation between observed and RCM simulated data and applies different bias correction methods to correct historical and future climate models output.

The bias correction algorithms derived from historical RCM simulations and observed data were applied for the bias correction of future RCM simulations.

6.2.4 Future Rainfall and Temperature Extremes Analysis

The RClimDex 1.1 (Zhang and Yang, 2004) has been applied to calculate future rainfall and temperature extremes indices. Twenty-seven rainfall and temperature extreme indices were developed by the ETCCDI (WMO, 2009). These extreme indices describe the frequency, amplitude and persistence of extreme temperature and rainfall events. In this study area, twenty two indices (ten rainfall and twelve temperature extreme indices) are relevant to study the trend of future extreme rainfall and temperature values. The indices were calculated at each grid and at sub-basin level. The result of some of the indices was presented in section (sec 6.3.3). Daily observed and bias corrected RCMs rainfall, TMAX and TMIN for the near-term and long-term future periods were used to calculate the indices.

6.3 Results and Discussion

6.3.1 Evaluation of Bias Correction Methods

Linear scaling, power transformation and distribution mapping bias correction methods are effective in adjusting mean values of RCM simulations of rainfall. A substantial difference was found between raw RCM outputs and RCM outputs after bias correction in magnitude and spatial distribution of rainfall in the Jemma sub-basin (Figure 6.4). The overestimation (CCLM4 model groups) and underestimation (REMO model groups) of annual rainfall simulations were sufficiently corrected for the entire sub-basin using linear scaling, power transformation and distribution mapping methods. These bias correction methods perform comparable performance in adjusting mean annual rainfall of RCM outputs with the observed rainfall of the sub-basin (Figure 6.4).

Another important improvement of using bias correction methods in this study is in adjusting elevation-dependent biases of RCM rainfall simulations. At relatively high elevation areas (>2800m) of the Jemma sub-basin, RCM simulations are characterized by an overestimation of mean annual rainfall (Worku et al., 2018b). Conversely, in the relatively lower elevation areas (<2300m) of the Jemma sub-basin, the RCM simulations are characterized by underestimation of mean annual rainfall. Such underestimation and overestimation of RCM simulations are effectively adjusted through all bias correction methods (Figure

6.4 - 6.5). Other studies also investigate an overestimation of rainfall through climate models simulation. The simulation of rainfall by climate models was also characterized by overestimation over the Ethiopian highlands and the Upper Blue Nile Basin (Haile and Rientjes, 2015). Probably, this could be due to the weakness of the models in the parametrization of local scale convection schemes and cloud parametrization in the high elevation areas.

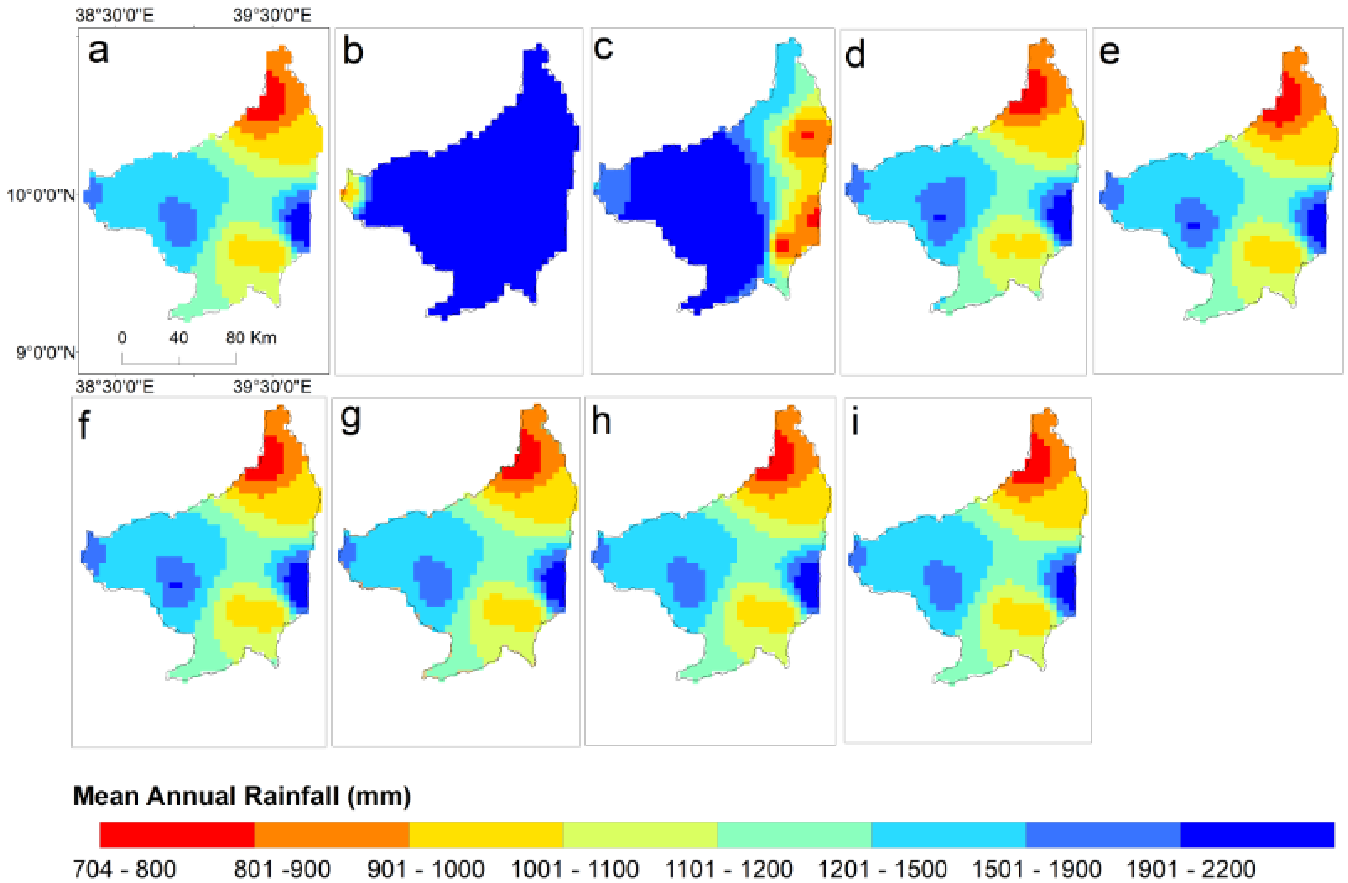


Figure 6.4 Mean annual rainfall (mm) of observed, RCM simulations and bias corrected RCM outputs for the historical period (1981-2005). a) Observation, b) raw simulation of CCLM4(CNRM-CM5), c) raw simulation of REMO(EC-EARTH), d) bias corrected output of CCLM4(CNRM-CM5) using distribution mapping, e) bias corrected output of REMO(EC-EARTH) using distribution mapping, f) bias corrected output of CCLM4(CNRM-CM5) using linear scaling, g) bias corrected output of REMO(EC-EARTH) using linear scaling, h) bias corrected output of CCLM4(CNRM-CM5) using power transformation (PT) and i) bias corrected output of REMO(EC-EARTH) using power transformation (PT).

Similar to annual rainfall simulation, the RCM simulations presented an overestimation and underestimation of mean monthly rainfall in the higher and lower elevation areas, respectively. The RCMs also provided different estimates of peak rainfall values at different locations in the sub-basin. The highest observed monthly rainfall occurred in July and August, whereas CCLM4 (CNRM-CM5) and CCLM4 (EC-EARTH) RCMs simulated higher rainfall occurred in September, October and May (Figure 6.5). Linear scaling, power transformation and distribution mapping methods were effective and showed comparable performance to correct the RCM simulations of mean monthly and seasonal rainfall biases. Sub-basin wide analysis showed that the RMSE and NSE between monthly observed rainfall and ensemble of RCM simulations of rainfall were 60 mm and 0.57, respectively. However, the RMSE and NSE between monthly observed rainfall and bias corrected ensemble of RCM outputs of rainfall were 1.82mm and 0.99, respectively.

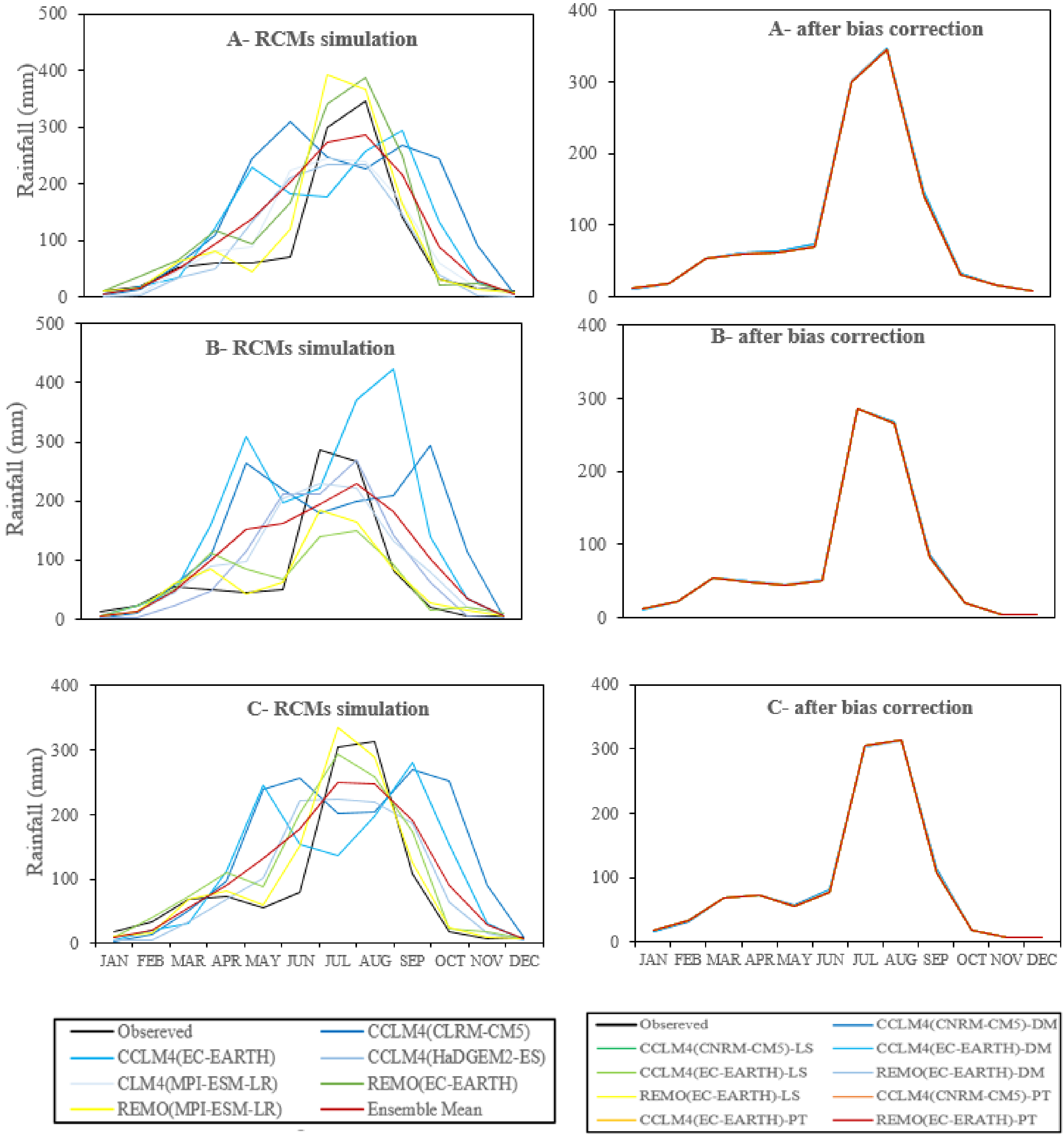


Figure 6.5 Mean monthly rainfall (mm) of observed, RCM simulations and bias corrected RCM outputs in Central (A), Eastern (B) and Western (C) areas of the Jemma sub-basin. DM, LS and PT are to indicate distribution mapping, linear scaling and power transformation bias correction methods, respectively.

Other studies (Teutschbein & Seibert, 2012; Fang et al., 2015) have also investigated comparable performance among different bias correction methods in correcting mean rainfall and temperature values. For instance, power transformation, linear scaling, variance scaling and distribution mapping methods were successfully correct the mean values (Teutschbein and Seibert (2012). In the Upper Blue Nile Basin, bias correction methods showed improved performance in reproducing monthly rainfall values of GCMs and RCM simulations (Elshamy et al., 2009; Liersch et al., 2016). Linear scaling bias correction method was also used to bias correct the Climate Forecast System Re-Analysis (CFSR) dataset and able to adjust mean daily, monthly and annual rainfall of the reanalysis dataset at different regions of Ethiopia (Berhanu et al., 2016).

The RCM simulations of temperature disclose an underestimation. For example, the RCMs provided a consistent underestimation of mean monthly TMAX and TMIN in the central and higher elevation (north-eastern) areas of the sub-basin. Linear scaling, variance scaling and distribution mapping (Figure 6.6) methods were effective and showed comparable performance in adjusting the RCM simulations of mean monthly TMAX and TMIN temperature.

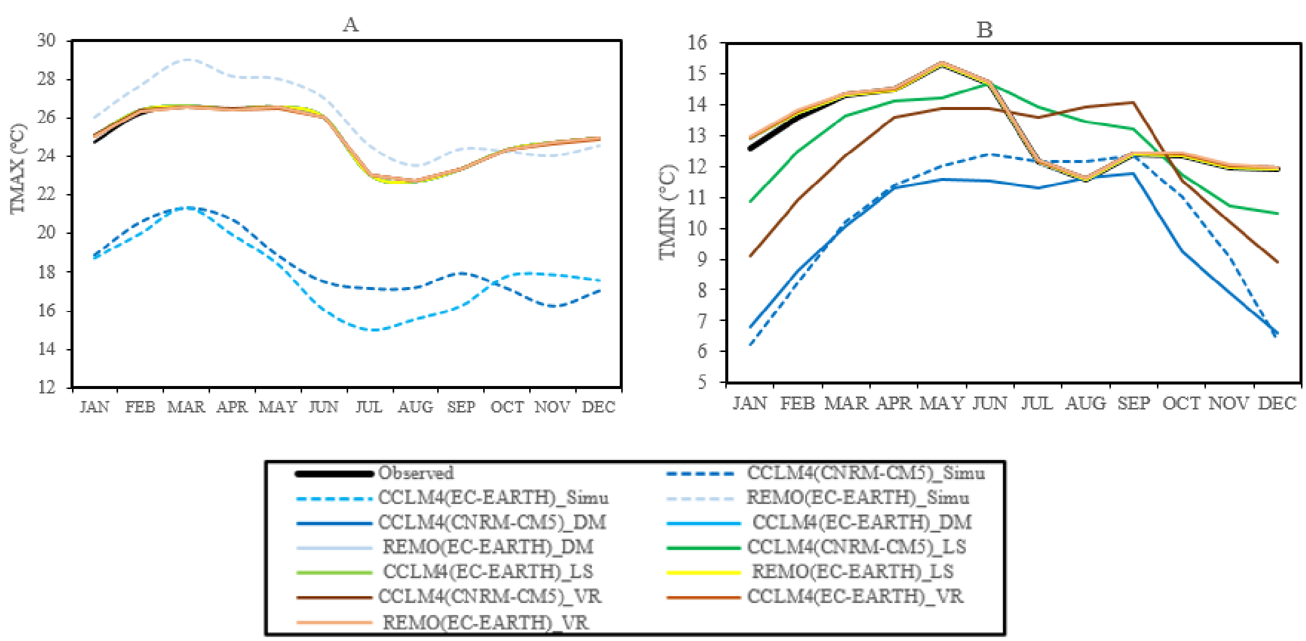


Figure 6.6- Monthly TMAX (A) and TMIN (B) outputs of RCM simulations and bias corrected RCMs in the Jemma sub-basin (areal mean). DM, LS and VR represent distribution mapping, linear scaling and Variance scaling, respectively.

The high performance of bias correction methods in adjusting mean rainfall and temperature values indicates most bias correction methods apply similar scale parameters to adjust the simulation of RCMs. The performance of bias correction methods in correcting the frequencies and intensities of rainfall and temperature events and values is to be evaluated using other robust statistical metrics. Because, these are the extreme events of rainfall and temperature which trigger a higher impact on the socio-economic and natural ecosystems (IPCC, 2012). As a result, the bias correction algorithm which can reproduce the frequencies and intensities of observed climate are to be identified to further develop climate scenarios and vigorous adaptation decisions.

Comparable skill in adjusting the CV of rainfall of the RCMs with the observed data was discerned between distribution mapping, power transformation and linear scaling methods. In all methods, there is a high CV during dry months (October – February) (Figure 6.7). There exists an apparent difference between distribution mapping, power transformation and linear scaling methods to adjust wet day probability. Distribution mapping method is better in reproducing wet day probability since it uses an RCM-specific rainfall threshold approach (Schmidli et al., 2006). There were drizzle rainfall events in all RCM simulations, which cause higher wet day probability in RCM simulations of rainfall than observational rainfall. These drizzle rainfall events were effectively corrected with distribution mapping than linear scaling and power transformation methods (Figure 6.7). Outputs from the distribution mapping were also able to capture the 90^{th} percentile of observed rainfall, particularly in the main rainy season, better than linear scaling and power transformation outputs (Figure 6.7).

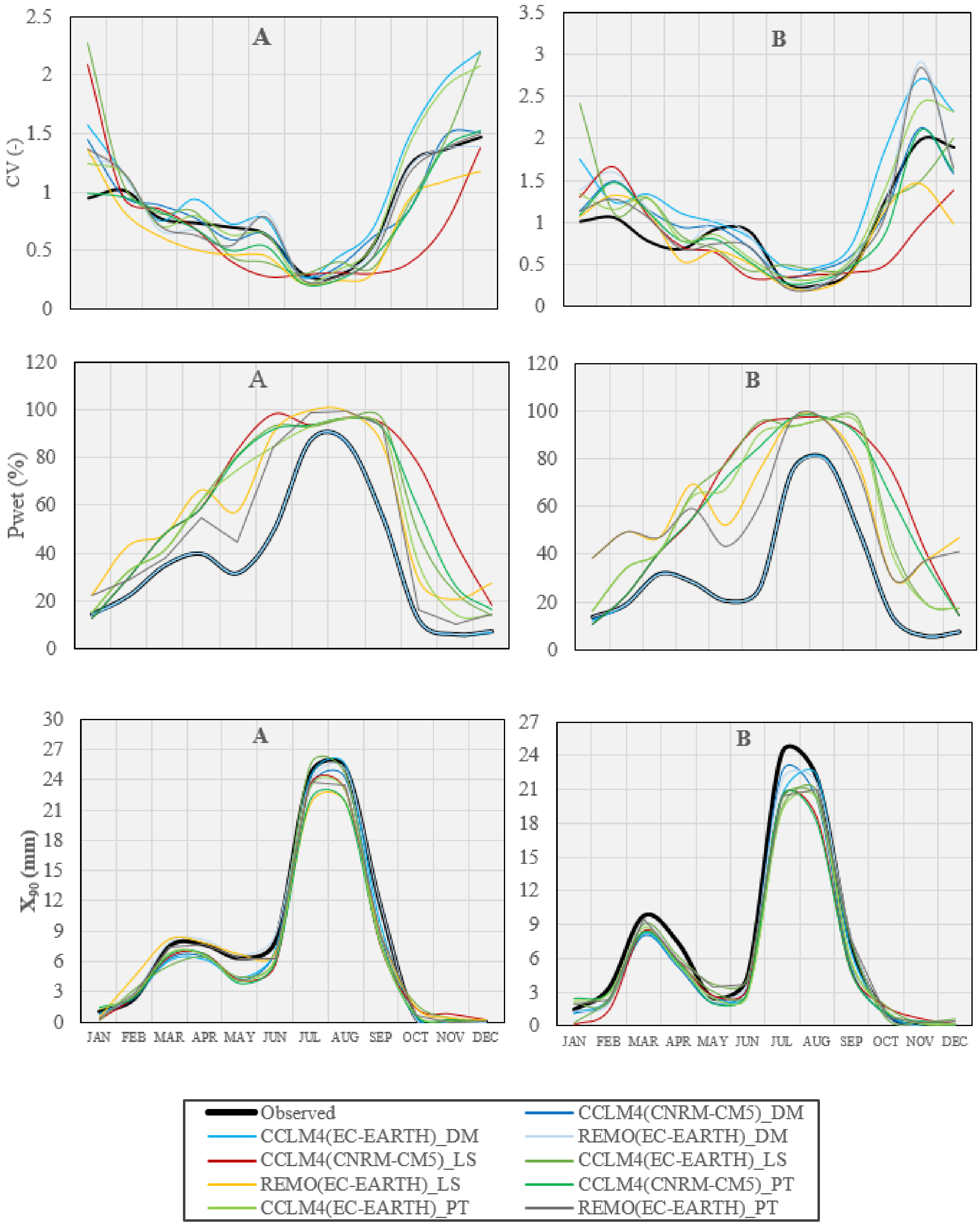


Figure 6.7 Ability of linear scaling (LS), distribution mapping (DM) and Power Transformation (PT) to adjust the daily rainfall as measured by coefficient of variation (CV), 90th percentile (X_{90}) and probability of wet days (P_{wet}) in Central (A) and Northeastern (B) areas of the Jemma sub-basin.

The 90th percentile of TMAX and TMIN were corrected well by linear scaling, variance scaling and distribution mapping methods, although distribution mapping performs better. Generally, the raw RCM simulations are characterized by underestimation of TMAX and TMIN (Figure 6.8). The distribution mapping method effectively corrected such deviations from the observational dataset. Particularly, Distribution mapping method corrected the TMAX and TMIN better in June to August compared to power transformation and linear scaling.

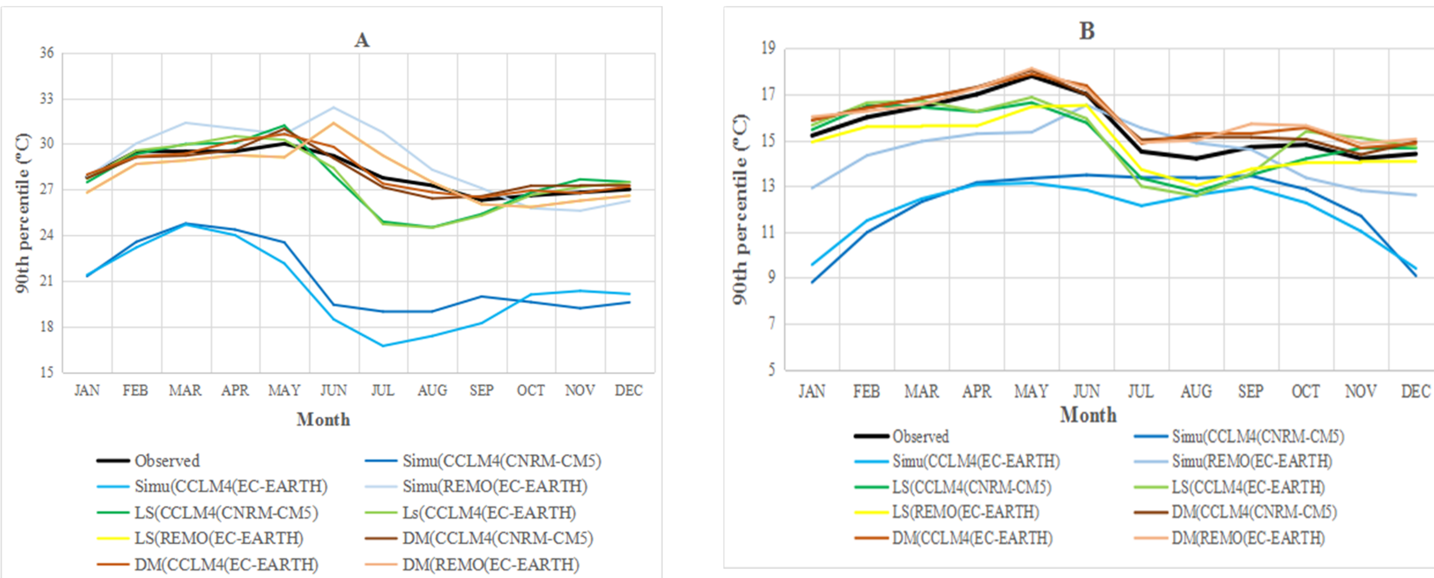


Figure 6.8 – Performance of DM (distribution mapping) and LS (linear scaling) methods to adjust the 90th percentile of TMAX (A) and TMIN (B) in the Jemma sub-basin. Simu is to indicate raw RCM simulations.

Concurrent to this study, other studies (Piani et al., 2010; Teutschbein and Seibert, 2012; Fang et al., 2015) have also investigated a difference among bias correction methods in correcting standard deviations, wet day probability, percentiles and other extreme values. Distribution mapping method generally showed better performance in adjusting wet-day probability and percentiles of rainfall and temperature (Teutschbein and Seibert, 2012; Fang et al., 2015). For instance, Teutschbein and Seibert (2012) has identified that the distribution mapping method was better in correcting standard deviation, wet-day frequencies and 90th percentile than linear scaling, power transformation, variance scaling.

Therefore, it is commendable to use distribution mapping bias corrected rainfall and temperature output of RCMs for future climate change analysis and impact assessment. Such robust RCM outputs can be useful to develop climate change adaptation and mitigation strategies, such as devising sustainable watershed management practices that help to cope with the challenges of climate change while building resilience. However, it is hardly known how these bias correction methods perform under climate condition which is different from the current climate. Consequently, the performance of bias correction methods under different climate conditions is to be evaluated before using the output of bias correction methods for further climate change impact study.

The validation of bias correction methods using Differential Split Sampling Testing shows the bias correction algorithms can work under different climate condition and this indicates the correction methods are valid for future climate condition. During validation, the skill of bias correction methods is not as high as the performance during calibration. There are overestimation and underestimation at dry and rainy months under all bias correction methods during validation using the wet years' case. Using wet and dry years, the Root Mean Square Error (RMSE) during validation showed variation than during calibration. Still, the distribution mapping method is better than power transformation and linear scaling in producing monthly rainfall pattern and the RMSE of monthly rainfall is low under the distribution mapping method during validation using wet years (Table 6.2). Concurrently, Teutschbein and Seibert, 2013 also identified that the distribution mapping method is robust under changing climate conditions.

Table 6.2 Root Mean square error (RMSE) between observation and simulation using bias correction methods during validation. In the first case, the dry years were used for calibration and wet years were used for validation and the second case vice versa. The values are area-weighted across the Jemma sub-basin.

Validation Years	Methods	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Wet years	Linear scaling	135.51	87.54	83.80	3.63	35.03	50.09	55.33	115.98	29.66	22.15	101.53	152.70
	Distribution mapping	19.16	29.11	50.55	21.61	38.71	48.96	64.17	132.46	31.47	20.11	66.68	5.74
Dry years	Linear scaling	13.80	17.86	43.37	3.30	76.33	120.51	32.00	76.12	33.55	23.51	12.32	11.77
	Distribution mapping	13.98	18.25	44.53	1.62	73.29	118.59	34.57	79.94	31.04	22.13	12.60	11.87

6.3.2 Rainfall and temperature under future climate scenarios

Future rainfall, TMAX and TMIN were projected using bias corrected outputs of RCM through distribution mapping method. Near-term (2021-2050) and long-term (2071-2100) climate scenarios' rainfall and temperature were compared with the baseline climate (1981-2014) (Table 6.3) rainfall and temperature. The near-term and long-term mean annual rainfall of the Jemma sub-basin was projected to decrease under the RCP4.5, RCP8.5 and RCP2.6 emission scenarios, but with different magnitude. The ensemble of bias corrected RCM outputs showed 19% (or more) decline of rainfall for the near-term and long-term future. The multi-model ensemble mean also revealed that the decline in rainfall was higher in the near-term (-22.68%) than long-term (-19%) under the RCP8.5 scenario. While, under the RCP4.5 scenario, a higher decline of rainfall is projected for the long-term (-21%) than the near-term future (-20%). Lower reduction of rainfall in the near and long-term future is projected under RCP2.6. When we compare the simulation of rainfall through REMO (EC-EARTH) and REMO (MPI-ESM-LR) under RCP4.5, RCP8.5 and RCP2.6, comparable reduction of rainfall under emission scenarios is projected.

Table 6.3 - Mean annual rainfall (mm) of future climate scenarios under emission scenarios of RCP4.5, RCP8.5 and RCP2.6 compared to baseline climate (1981-2014). The scenarios were developed based on the ensemble mean of six RCMs and the values are area-weighted across the Jemma sub-basin.

Scenario	**RCMs**	**Mean Annual Rainfall (mm)**	
		2021-2050	**2071-2100**
RCP4.5	Baseline (1981-2014)	1001	1001
	CCLM(CNRM-CM5)	516 (-48%)	581(-42%)
	CCLM(EC-EARTH)	788 (-21%)	740(-26%)
	CCLM(MPI-ESM-LR)	828(-18%)	782 (-22%)
	CCLM(HadGEM2-ES)	711(-29%)	659(-34%)
	REMO(EC-EARTH)	915(-9%)	997 (-1%)
	REMO(MPI-ESM-LR)	1038 (2%)	984(-2%)
	Ensemble mean	**799 (-20%)**	**791 (-21%)**
RCP8.5	CCLM(CNRM-CM5)	571 (-43%)	583(-42%)
	CCLM(EC-EARTH)	666(-34%)	703(-30%)
	CCLM(MPI-ESM-LR)	808(-20%)	804(-20%)
	CCLM(HadGEM2-3S)	647 (-36%)	650(-35%)
	REMO(EC-EARTH)	993 (-1%)	1135(12%)
	REMO(MPI-ESM-LR)	1006(0.5%)	985(-2%)
	Ensemble mean	**782(-22.68%)**	**812(-19%)**
RCP2.6	REMO(EC-EARTH)	881 (-13%)	917(-9%)
	REMO(MPI-ESM-LR)	954(-6%)	947(-6%)
	Ensemble mean	**917(-9%)**	**932(-8%)**

Most of the individual RCMs (S-RCMs) projected a reduction of mean annual rainfall (Table 6.3) except REMO models. The individual RCM simulations project a reduction of rainfall in the order of -48% (CCLM4(CNRM-CM5)) to an increase of 2% (REMO (MPI-ESM-LR)) under the near term and RCP4.5, RCP8.5 and RCP2.6 emission scenarios. And in the long term future, reduction of rainfall from -42% (CCLM4(CNRM-CM5)) to 12% (REMO (EC-EARTH)) under RCP4.5, RCP8.5 and RCP2.6 emission scenarios was discerned. Whereas, RCMs ensemble (E-RCMs) simulation project a reduction of rainfall in the order of 8% to 23% under near and long-term period and under RCP2.6, RCP4.5 and RCP8.5 emission scenarios. Unpredictably, higher reduction of rainfall is projected in the near-term (23%) under RCP8.5 emission scenario than long-term climate scenario (21%) under RCP4.5 emission scenario. The projected future rainfall had the same spatial pattern with the observed rainfall, where lower rainfall is projected in the northern part of the sub-basin (Figure 6.9). This means drier area of the sub-basin will become more drier under future climate scenarios.

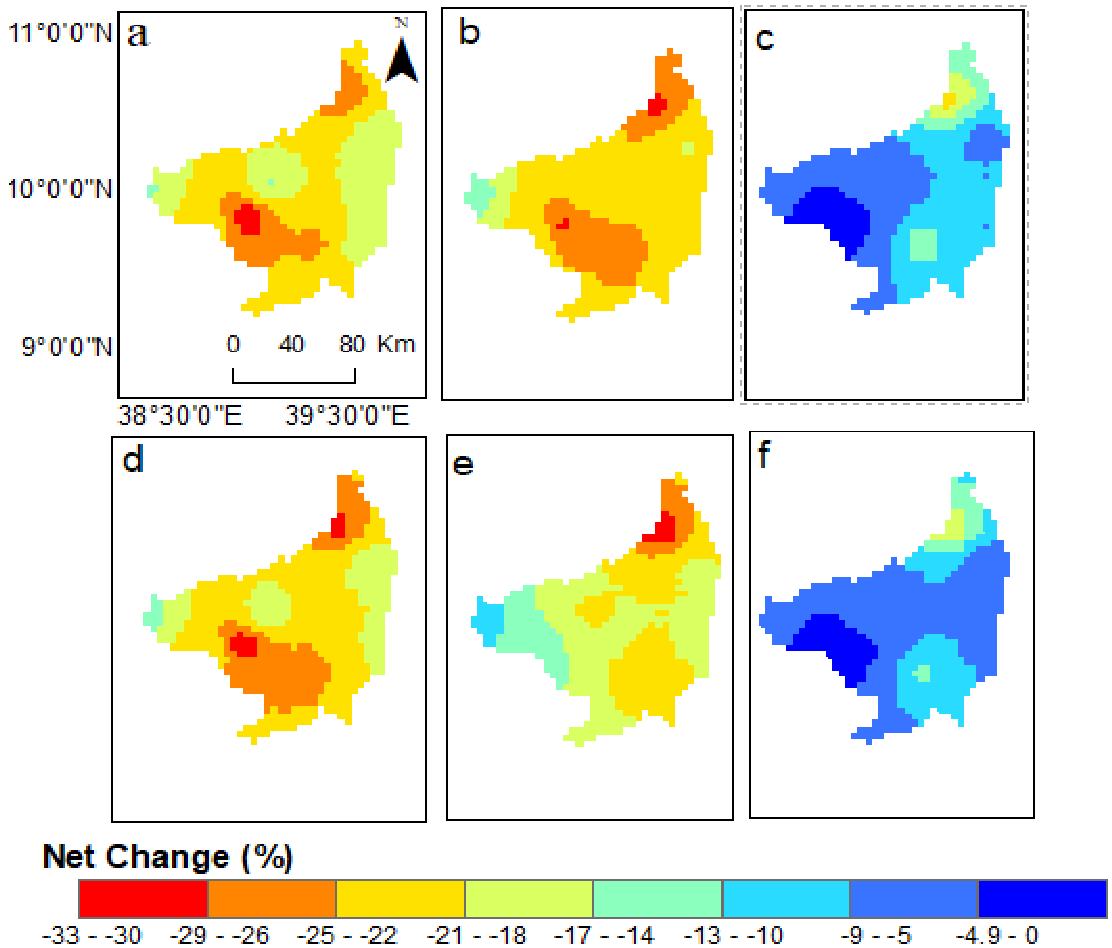


Figure 6.9 Net change (%) in mean annual rainfall between baseline and future climate scenarios. a) RCP4.5 (2021-2050) climate scenario, b) RCP8.5 (2021-2050) climate scenario, c) RCP2.6 (2021-2050) climate scenario, d) RCP4.5 (2071-2100) climate scenario, e) RCP8.5 (2071-2100) climate scenario, f) RCP2.6 (2071-2100) climate scenario. The scenarios were developed based on the ensemble mean of six RCMs.

In the near-term and long-term climate scenarios developed based on RCP4.5, RCP8.5 and RCP2.6 emission scenarios, the mean monthly rainfall was projected to decrease. All RCM outputs showed a decrease in mean monthly rainfall in the near-term and long-term futures except GCMs downscaled using the REMO model (Figure 6.10). Consequently, the ensemble mean monthly rainfall projections showed a decrease under all RCP scenarios in the near and long-term future. Though the raw simulation of CCLM4 models was characterized by overestimation in simulating historical rainfall, higher monthly rainfall is projected from REMO models than CCLM4 models (Figure 6.10). In autumn months, particularly in October, a steady increase of rainfall is projected under all climate scenarios.

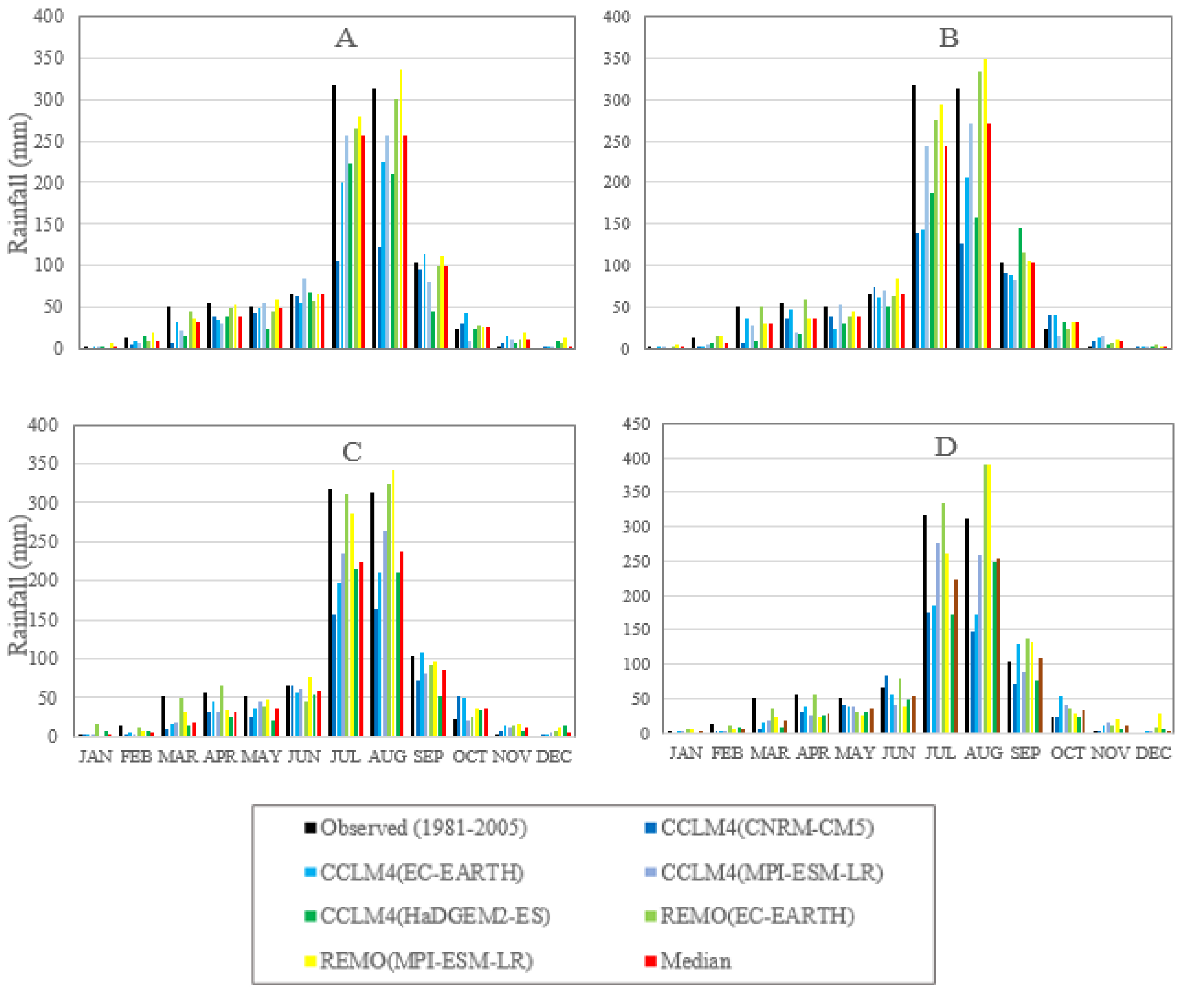


Figure 6.10 Mean monthly rainfall (mm) of baseline and future climate scenarios. A) RCP4.5 (2021-2050) climate scenario, B) RCP8.5 (2021-2050) climate scenario, C) RCP4.5 (2071-2100) climate scenario and D) RCP8.5 (2071-2100) climate scenario. The scenarios were developed based on the ensemble mean of six RCMs. Values are area-weighted across the Jemma basin.

Seasonally, all seasons showed a reduction of rainfall except autumn season in which persistent increase of rainfall in future climate scenarios is projected (Table 6.4). High volumetric reduction of rainfall is projected in the summer season, but high percentage reduction of rainfall is estimated in spring (March-May) followed by winter (December–February) seasons than summer under future climate scenarios. Positive change on autumn rainfall indicates there will be slight shifts of rainfall from summer to autumn. Concomitantly, the multi-model ensemble mean projects a shift in seasonal patterns of rainfall, with decreasing and increasing of rainfall in the June to July and August to November respectively in the Upper Blue Nile Basin (Liersch et al., 2016). In contrast to change on the dry seasons (spring and winter), Worqlul et al., (2018) has investigated an increase of dry season rainfall in future climate in Upper Blue Nile Basin using the downscaled outputs of HadCM3 climate model.

Table 6.4 - Mean seasonal rainfall (mm) of future climate scenarios under emission scenarios of RCP4.5 and RCP8.5 compared to baseline climate (1981-2014). The scenarios were developed based on the ensemble mean of six RCMs and the values are area-weighted across the Jemma sub-basin.

Rainfall (mm yr^{-1})	**Baseline (1981– 2014)**	**Near-term 2021-2050 (RCP4.5)**	**Near-term 2021-2050 (RCP8.5)**	**Long-term 2071-2100 (RCP4.5)**	**Long-term 2071-2100 (RCP8.5)**
Summer (June - September)	786	637(-19%)	628(-20%)	626(-20.35%)	673(-14%)
Spring (March - May)	168	118(-30%)	108(-36%)	101(-40%)	90(-46%)
Winter (December - February)	48	20(-58%)	17(-65%)	16(-67%)	19(-60%)
Autumn (October - November)	36	39(8%)	41(14%)	45(25%)	49(36%)

Studies (e.g., Beyene et al., 2010; Dile et al., 2013) show a similar trend of rainfall in the Upper Blue Nile Basins in the future period. For example, Dile et al. 2013 found a decrease in rainfall by about -30% during 2010-2040 in Gilgel Abay watershed using statistically downscaled outputs of the HadCM3 model. Conversely, there are other studies (e.g., Mekonnen and Disse, 2016; Liersch et al., 2016) which project a positive trend of future rainfall in the Blue Nile Basin using GCM outputs. There are also other studies reported inconsistent or no trend of future rainfall (Elshamy et al., 2009; Setegn et al., 2011). Elshamy et al. (2009), using an ensemble of seventeen GCM outputs, showed almost no change in the future (2081 – 2098) annual rainfall in the Upper Blue Nile Basin. Likewise, Setegn et al. (2011) studied the hydro-meteorological change in the Lake Tana sub-basin using 11 CMIP3 GCM outputs. They found an inconsistent trend of future rainfall; of the eleven CMIP3 GCM outputs, nine of them indicated a decrease in rainfall. Concomitant to this study, an increase of autumn rainfall was projected for future climate period from ensemble of GCMs in the central highlands and the eastern region of Ethiopia (FDRE:MoWIE, 2015).

In all climate scenarios, TMAX and TMIN showed an increasing trend under RCP4.5, RCP8.5 and RCP2.6 scenarios. The individual RCM simulations project an increase of TMAX in the order of 0.88°C to 1.39°C in the near future and from 1.72°C to 4.11°C in the long-term future under RCP4.5 and RCP8.5.

In the ensemble mean of RCMs, an increase of TMAX by 1.01 °C and TMIN by 1.14 °C in the near-term under RCP4.5 emission scenario and an increase of TMAX by 1.25 °C and TMIN by 1.59°C in the near-term under RCP8.5 emission scenario. The highest increase was observed in the long-term future and for the RCP8.5 scenario, where the multi-model ensemble provided an increase of TMAX by 3.13 °C and TMIN by 5.00 °C (Table 6.5). Corresponding to the assumption of emission scenarios, less increase of TMAX and TMIN is projected under RCP2.6 (Table 6.5). The projected future TMAX and TMIN showed a consistent spatial pattern with the observed TMAX and TMIN where lower values were projected in the eastern and northern part of the sub-basin (Figure 6.11).

Table 6.5 - Mean annual TMAX and TMIN (°C) of future climate scenarios under emission scenarios of RCP4.5, RCP8.5 and RCP2.6 compared to baseline climate (1981-2014). The values are area-weighted across the Jemma sub-basin.

Emission Scenario	**RCMs**	**Mean Annual TMAX(°C)**		**Mean Annual TMIN(°C)**	
		2021-2050	**2071-2100**	**2021-2050**	**20171-2100**
RCP4.5	Baseline (1981-2014)	21.16	21.16	9.83	9.83
	CCLM(CNRM-CM5)	22.04 (+0.88)	22.99(+1.83)	10.82 (+0.99)	12.14 (+2.30)
	CCLM(EC-EARTH)	22.28 (+1.11)	23.09(+1.93)	11.11 (+1.27)	12.34(+2.50)
	CCLM(MPI-ESM-LR)	22.19 (+1.02)	22.88(+1.72)	11.14 (+1.30)	12.17(+2.34)
	CCLM(HadGEM2-ES)	22.17 (+1.00)	23.33(+2.17)	10.44(+0.61)	11.75(+1.92)
	REMO(EC-EARTH)	22.28 (+1.12)	23.08(+1.91)	11.17 (+1.33)	12.53(+2.70
	REMO(MPI-ESM-LR)	22.07(+0.91)	23.04(+1.8)	11.17(+1.33)	12.34(+2.50)
	Ensemble mean	**22.17 (+1.01)**	**23.07(+1.9)**	**10.97(+1.14)**	**12.21(+2.38)**
RCP8.5	CCLM(CNRM-CM5)	22.15(+0.99)	24.46(+3.30)	11.13(+1.30)	14.24(+4.41)
	CCLM(EC-EARTH)	22.55 (+1.39)	21.79(+0.63)	11.44 (+1.60)	14.87(+5.04)
	CCLM(MPI-ESM-LR)	22.54(+1.37)	24.81(+3.64)	11.47(+1.63)	15.07(+5.23)
	CCLM(HadGEM2-ES)	22.41(+1.25)	24.69(+3.53)	11.41(+1.57)	14.25(+4.41)
	REMO(EC-EARTH)	22.34(+1.17)	24.74(+3.57)	11.55(+1.71)	15.11(+5.28)
	REMO(MPI-ESM-LR)	22.48(+1.31)	25.28(+4.11)	11.58 (+1.75)	15.46(+5.62)
	Ensemble mean	**22.41(+1.25)**	**24.29(+3.13)**	**11.43(+1.59)**	**14.83(+5.00)**
RCP2.6	REMO(EC-EARTH)	21.91(+0.75)	22.00(+0.84)	10.70(+0.88)	10.86(+1.03)
	REMO(MPI-ESM-LR)	21.92(+0.76)	21.86(+0.70)	10.83(+1.00)	10.76(+0.94)
	Ensemble mean	**21.915(+0.75)**	**21.93(+0.77)**	**10.77(+0.94)**	**10.81(+0.98)**

The findings of projected TMAX and TMIN trends in the Jemma sub-basin were also similar to other studies in the Blue Nile Basin (e.g. Elshamy et al., 2009; Liersch et al., 2016; Mekonnen and Disse, 2016), and other regional and global reports (Beyene et al., 2010; IPCC, 2013). For example, IPCC (2013) projected an increase in the mean temperature from 2081-2100 by 2.6°C to 4.8°C under the RCP8.5 scenario, which is comparable to the temperature trend estimated for the Jemma sub-basin. In the Blue Nile Basin, an increase in temperature in the future with different magnitude is projected from different models (Elshamy et al., 2009; Liersch et al., 2016; Mekonnen and Disse, 2016).

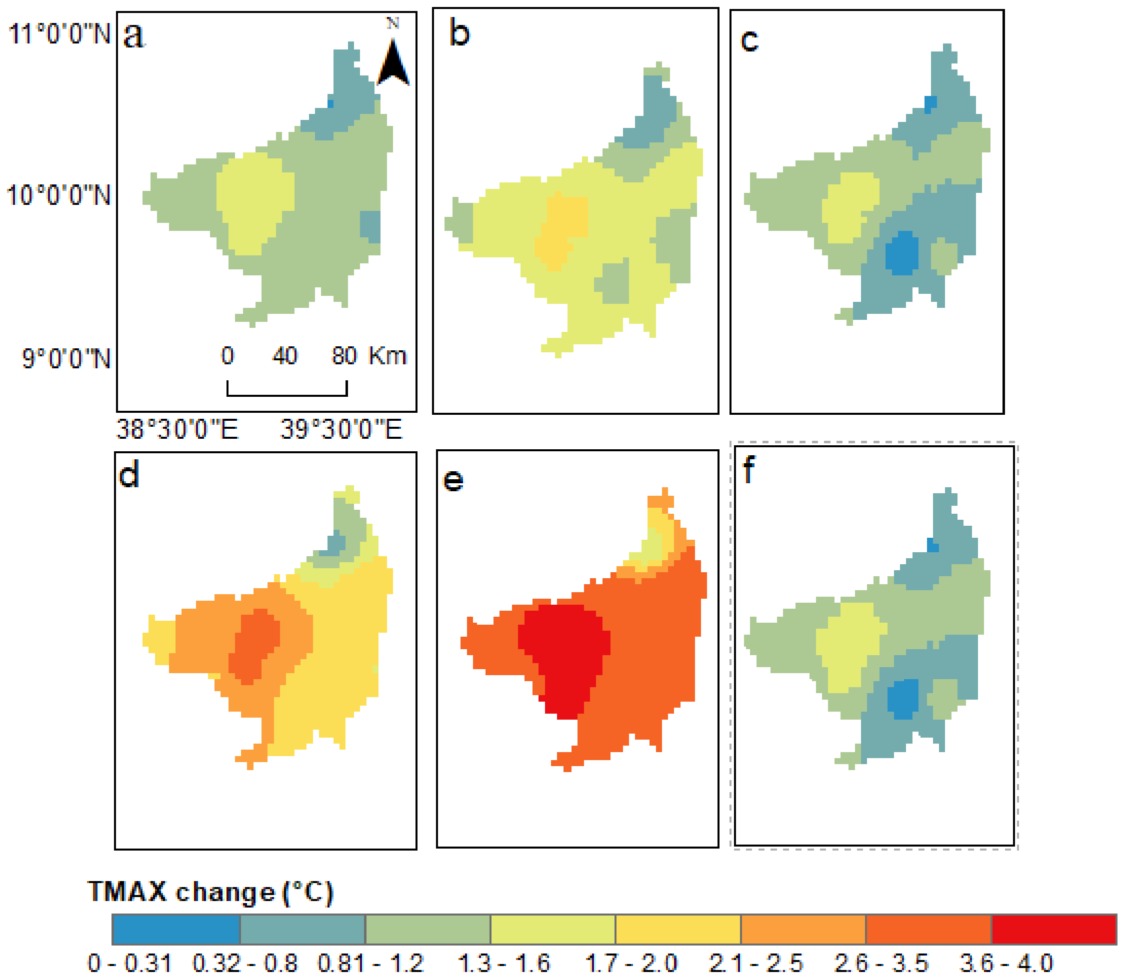


Figure 6.11 –Net Change in TMAC (°C) between baseline and future climate scenarios. a) RCP4.5 (2021-2050) climate scenario, b) RCP8.5 (2021-2050) climate scenario, c) RCP2.6 (2021-2050) climate scenario, d) RCP4.5 (2071-2100) climate scenario, e) RCP8.5 (2071-2100) climate scenario f) RCP2.6 (2071-2100) climate scenario. The scenarios were developed based on the ensemble mean of six RCMs.

6.3.3 Rainfall and temperature extremes under future climate scenarios

The annual rainfall and daily rainfall frequency analysis under different climate scenarios showed that the future climate will be under extreme rainfall events. Eventhough, a reduction of mean annual rainfall is projected, there are days with high rainfall values than observed climate. In Figure 6.12 and Figure 6.13, there is a discernible difference in the frequency of rainfall values at daily and annual time steps. In the observed climate, rainfall above 22mm/day can occur within 100days, while within 100days, rainfall above 30mm/day can occur in most RCMs. In contrast, 56.73% and 74.61% of days under the observed climate and future RCM outputs have rainfall less than 1mm/day, respectively. Further, 35.81% of days in the observed climate have rainfall in the order of 1-10mm/day, while in the future RCM outputs, 19.70% of days will have rainfall in the order of 1-10mm/day. In a daily time step, high frequency of extreme rainfall values is ascertained in the future climate scenarios than baseline climate scenario. In contrast, a higher frequency of extreme annual rainfall is depicted in the baseline climate scenario than future climate scenarios (Figure 6.12 and Figure 6.13). In parallel, an increase in high and low streamflow (which is governed by climate variability) is projected by different studies for the 2050s and 2080s at the upper Blue Nile River Basin (Taye et al., 2015).

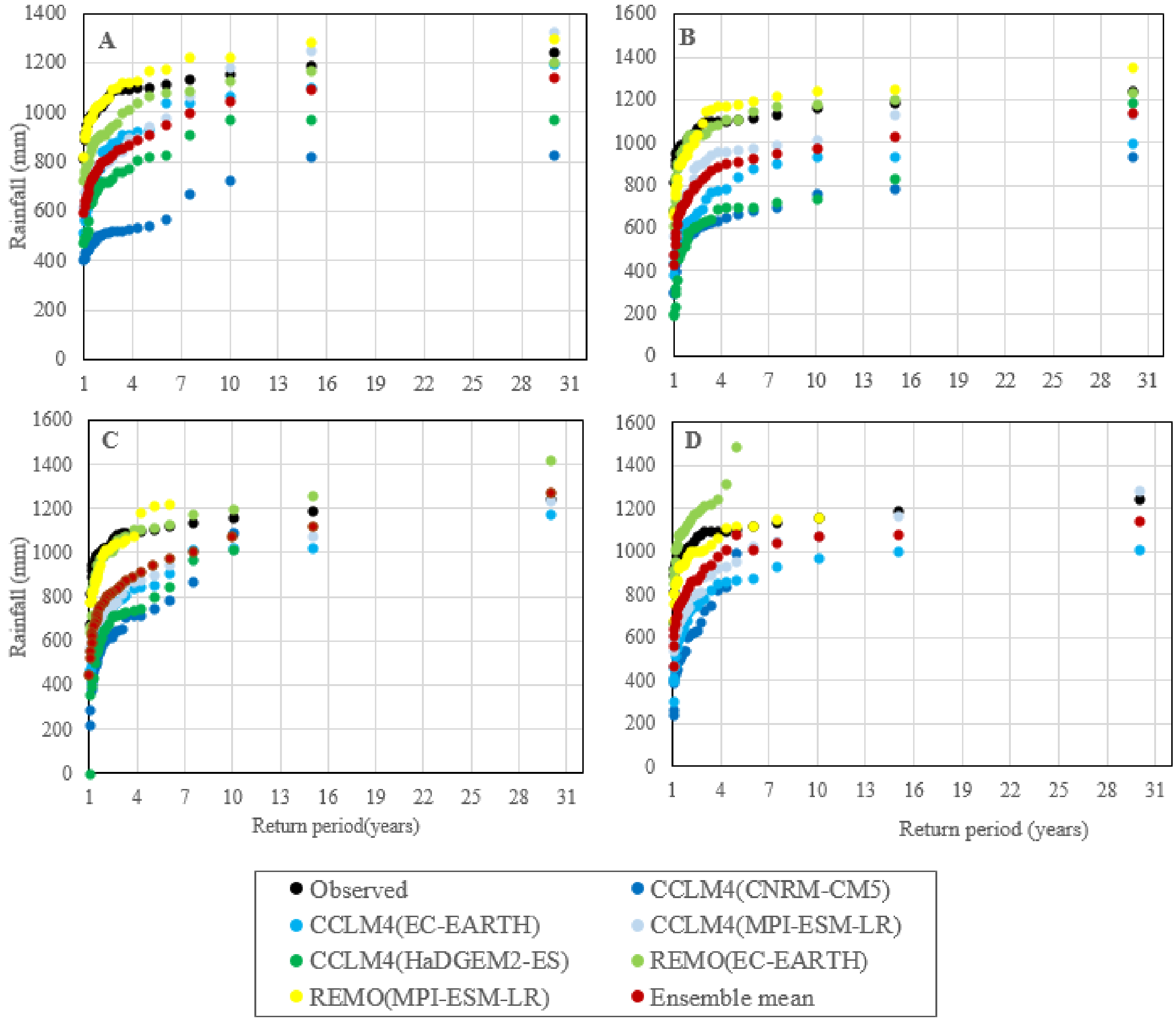


Figure 6.12 - Return period of annual rainfall in baseline and future climate scenarios. A) RCP4.5 (2021-2050) climate scenario, B) RCP8.5 (2021-2050) climate scenario, C) RCP4.5 (2071-2100) climate scenario and D) RCP8.5 (2071-2100) climate scenario. Values are area-weighted across the Jemma basin.

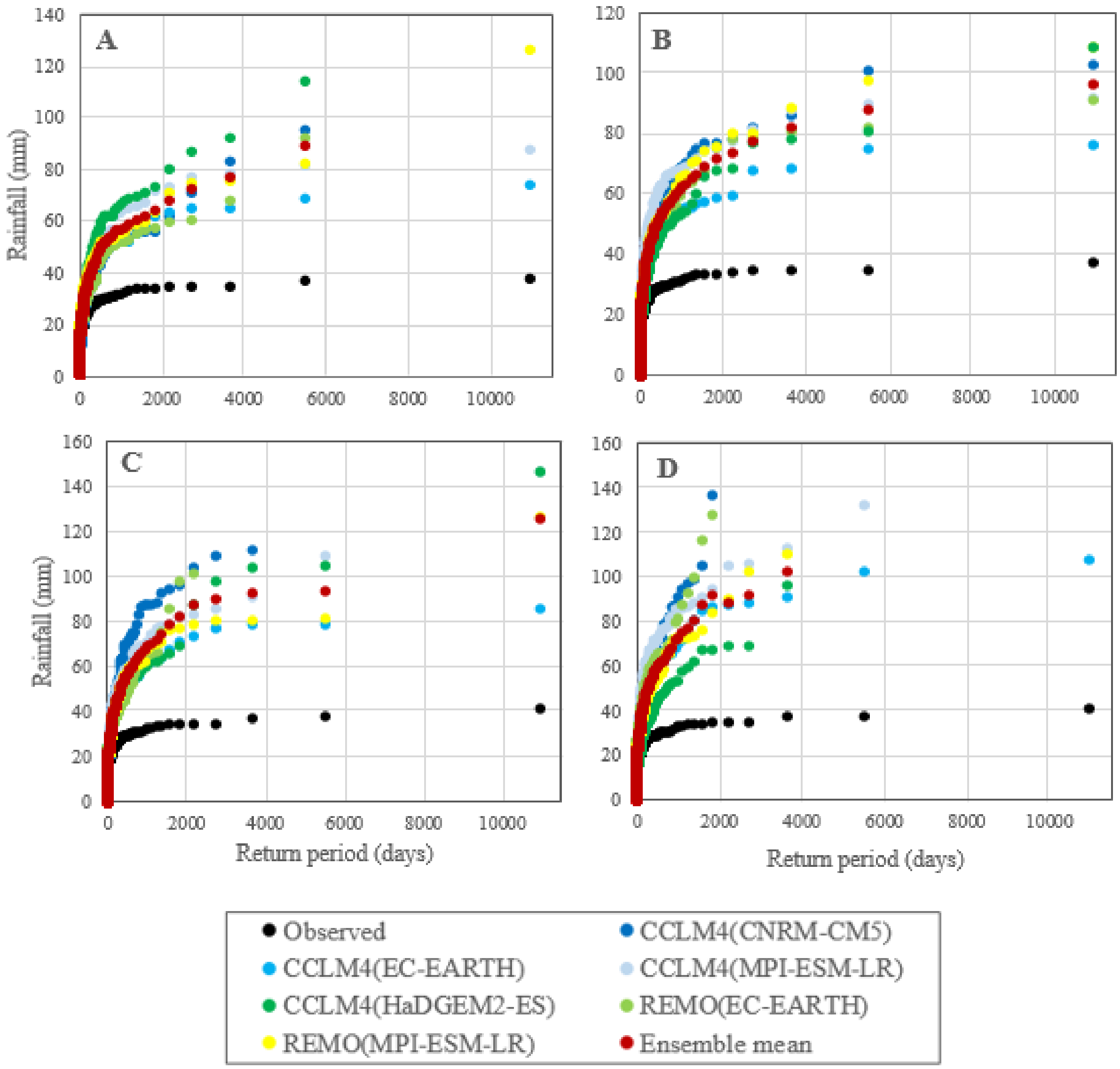
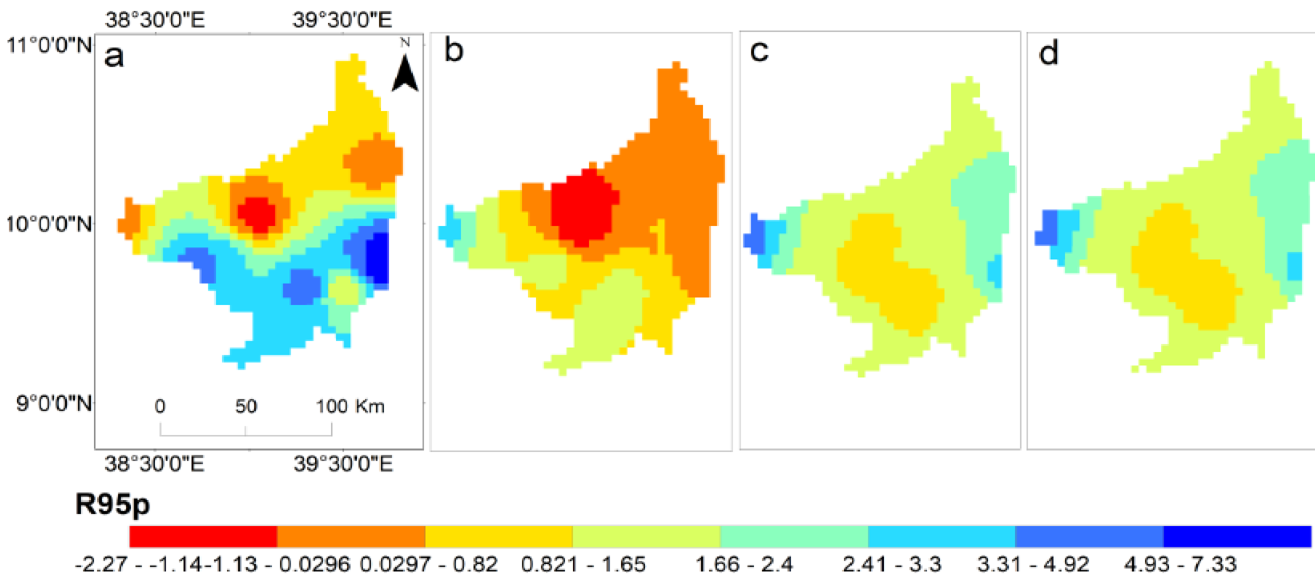
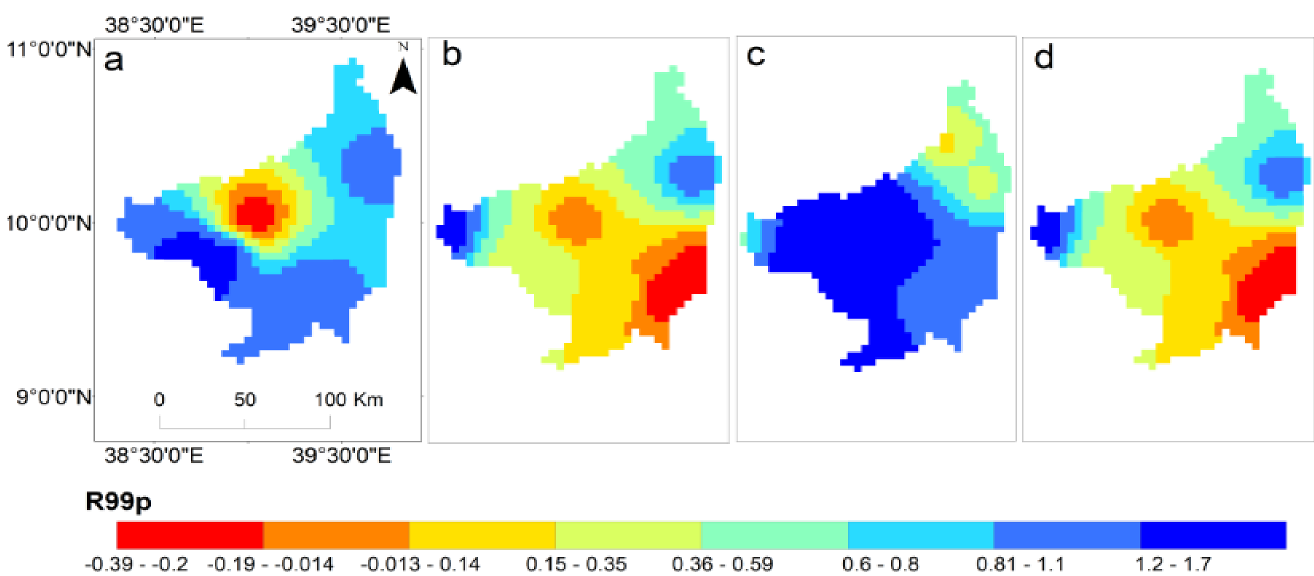


Figure 6.13 – Return period of daily rainfall of baseline and future climate scenarios. A) RCP4.5 (2021-2050) climate scenario, B) RCP8.5 (2021-2050) climate scenario, C) RCP4.5 (2071-2100) climate scenario and D) RCP8.5 (2071-2100) climate scenario. The scenarios were developed based on the ensemble mean of six RCMs. Values are area-weighted across the Jemma basin.

Analysis of changes in rainfall extremes in the near-term and long-term future was also analyzed using ETCCDI and revealed that there will be an increase in rainfall extremes, which is in contention with the decreasing trend of future mean annual and monthly rainfall estimated in the sub-basin. In the near-term future under the RCP8.5 scenario, there will be a significant ($p \leq 0.05$) increase in the number of heavy rainfall days (R10mm) and very heavy rainfall days (R20mm). An increase of extreme wet-days (R99p) and very wet-days (R95p) is also projected, but not significant. In comparison with the trends of baseline rainfall extremes (1981-2014) in the Jemma sub-basin (Worku et al., 2018a), an increasing trend of R20mm, R10mm and R95p is low, while the trend in extreme wet-days (R99p) is high than observed extreme rainfall trends (Figure 6.14).





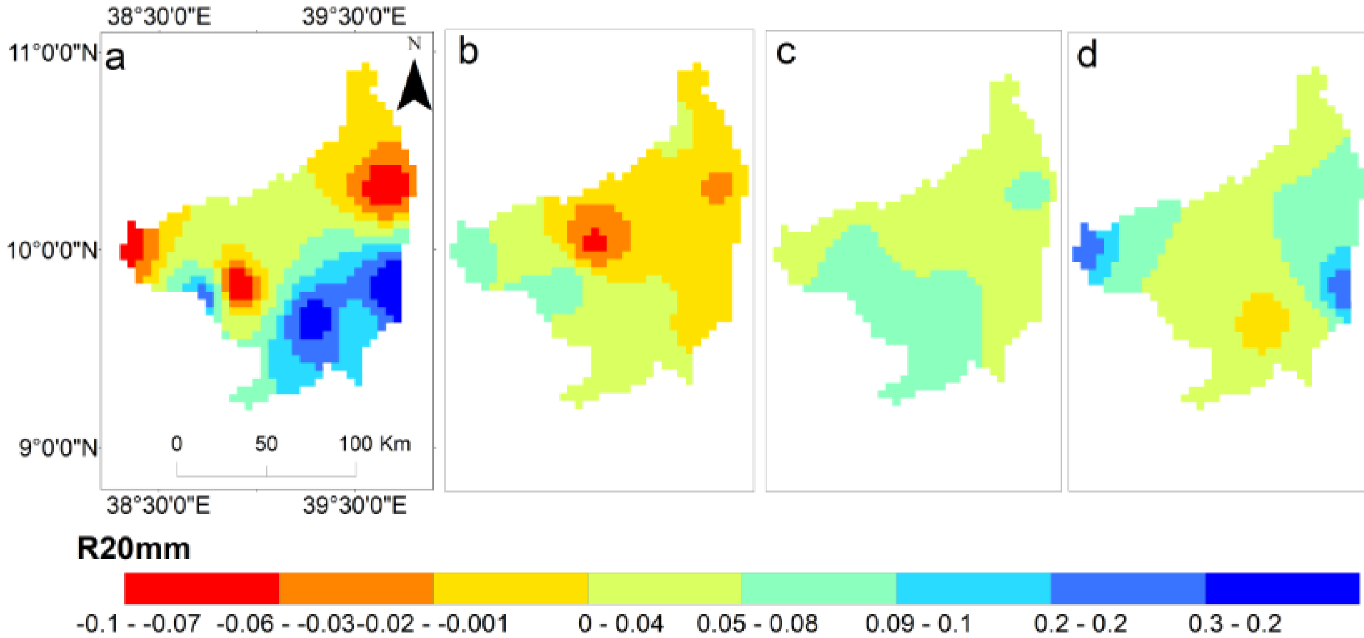
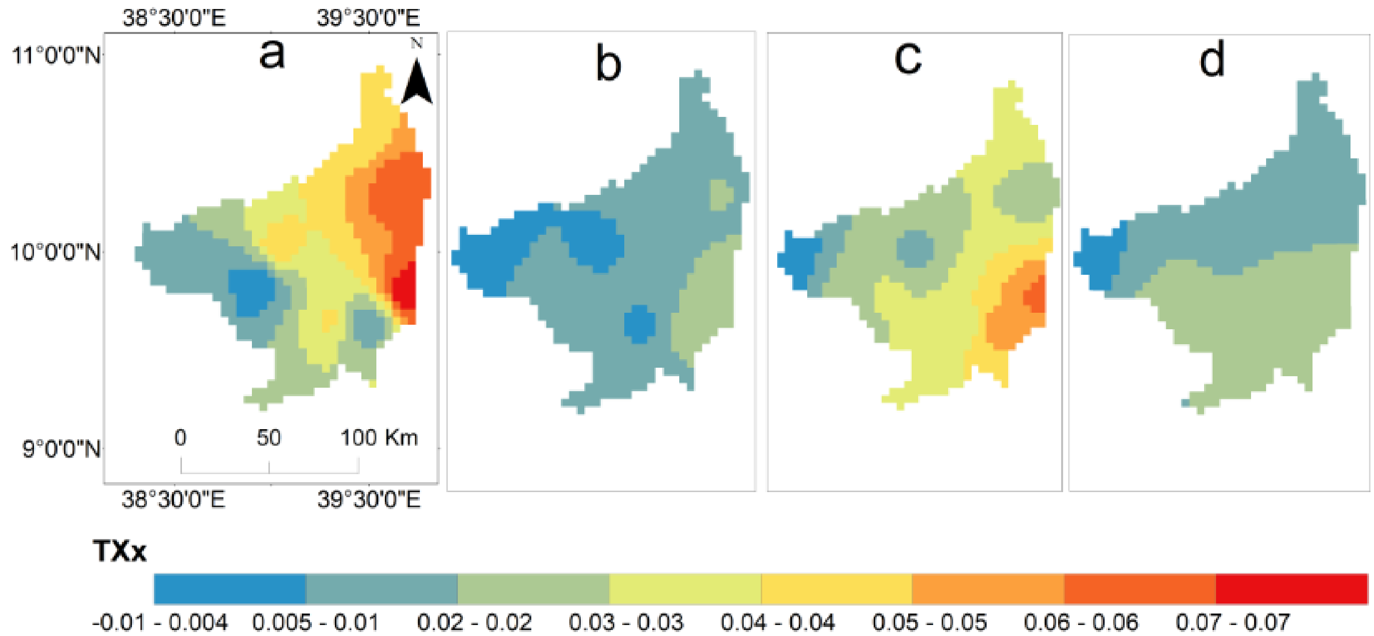


Figure 6.14 Trends (mm/year) of R95p (Very wet days), R99p (extreme wet days) and R20mm (Number of very heavy precipitation days) under baseline and future climate scenarios. a) Baseline climate (1981-2014), b) RCP4.5 (2021-2050) climate scenario, c) RCP8.5 (2021-2050) climate scenario, d) RCP4.5 (2071-2100) climate scenario. The scenarios were developed based on the ensemble mean of six RCMs.

An increase in temperature extremes in the near-term and long-term future under both RCP scenarios in the entire sub-basin was projected (Figure 6.15). All temperature indices showed an increase in temperature extreme events in the future climate. For instance, in the long-term future under RCP8.5 scenario, significant increasing trends are projected in TXx (Max TMAX), TXn (Min TMAX), TX90p (Warm days), TX10p (Cool days), TN10p (Cool nights) and TN90p (Warm nights) which substantiates as there would be more warming in the future. The magnitude of the trends in these temperature extremes indices is comparable with the baseline trend of temperature extremes indices in the sub-basin (Worku et al., 2018a). Higher spatial homogeneity is observed in the trend of temperature extremes in future climate than trends of temperature extreme indices of historical climate, which is characterized by higher diversity among different areas of the sub-basin. Most temperature extremes indicate more warming trend in the future in the entire parts of the sub-basin (Figure 6.15).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TXx
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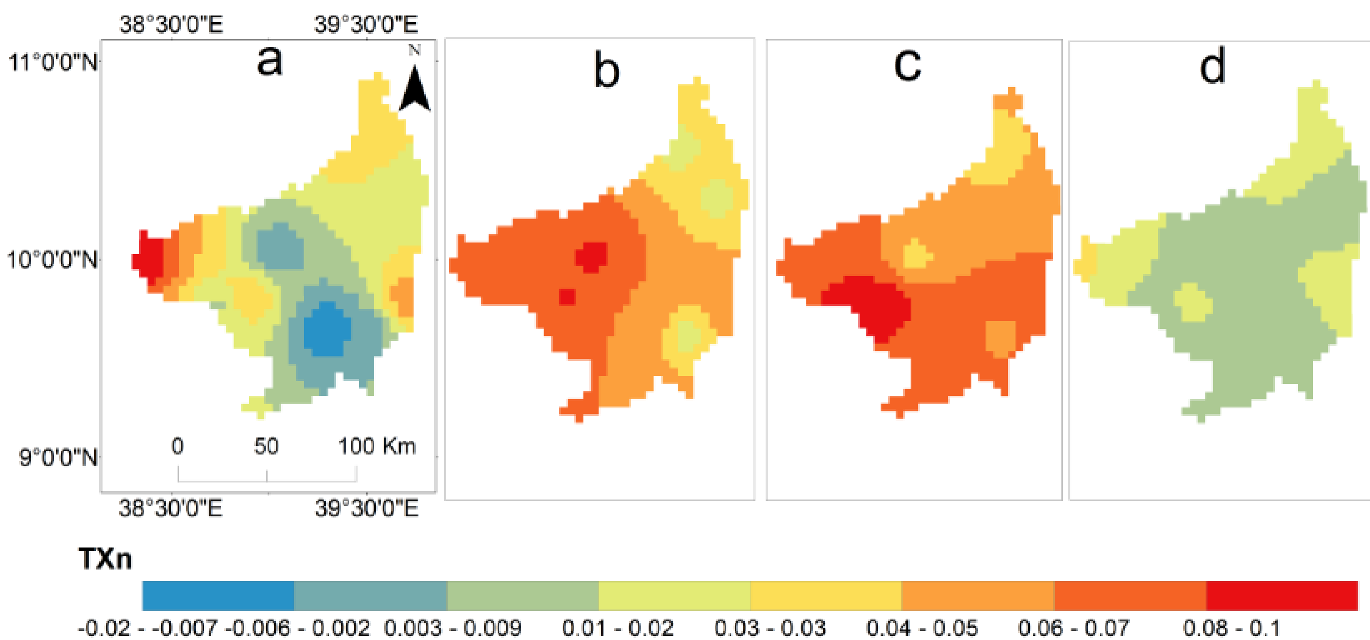
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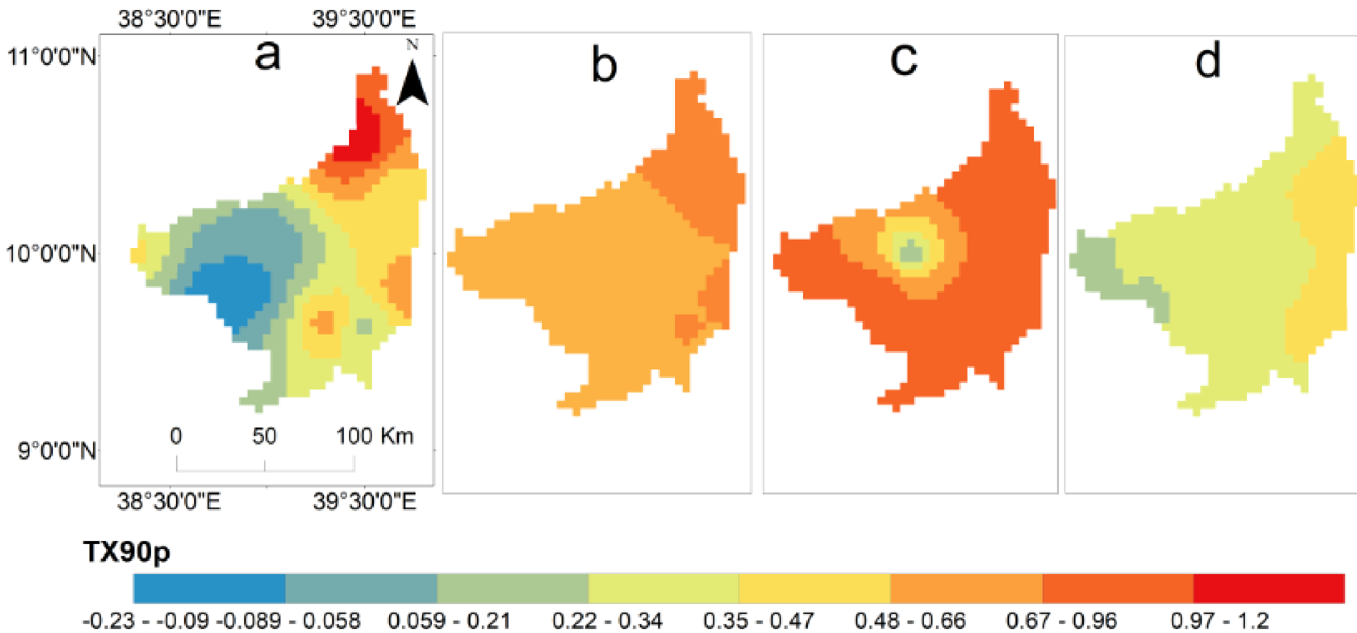

Figure 6.15 Trends of TXx(Max TMAX, ˚C year^{-1}), TXn (Min TMAX, ˚C year^{-1}) and TX90p (Warm days, % year^{-1}) under baseline and future climate scenarios. a) Baseline climate (1981-2014), b) RCP4.5 (2021-2050) climate scenario, c) RCP8.5 (2021-2050) climate scenario, d) RCP4.5 (2071-2100) climate scenario. The scenarios were developed based on the ensemble mean of six RCMs.

An increase in rainfall and temperature extremes is not only in our study, but there are also various studies which have investigated an increase of extremes in future climate. For instance, IPCC (2013) projected more frequent hot and fewer cold temperature extremes over most land areas of the world. In Australia, a significant increase in the number of warm nights, heatwaves and extreme rainfall were projected (Alexander and Arblaster, 2009). Extreme rainfall events are projected to increase over different regions of North America at the end of the 21st century under RCP 8.5 scenario (Wang and Kotamarthi, 2015). In general, the future climate will be characterized by high rainfall and temperature extreme events and needs caution in designing adaptation structures.

6.3.4 Uncertainties

This study was based on the blending of four GCMs (CNRM-CM5, EC-EARTH, HadGEM2-ES and MPI-ESM-LR), two RCMs (CCLM4 and REMO) and three emission scenarios (RCP2.6, RCP4.5 and RCP8.5). The mean monthly pattern of observed rainfall, TMAX and TMIN were captured by the raw simulation of RCMs and it is within the uncertainty range of rainfall simulated by different RCMs (Figure 6.16 and Figure 6.17). The ensemble mean of the RCMs is also within the uncertainty range of different RCMs simulation and captures the pattern of mean monthly observed rainfall. Uncertainty could also arise from bias correction methods. In this study, bias correction did not trigger change on the climate change signal of rainfall. Both the raw RCM simulations and the bias corrected outputs show a comparable reduction of rainfall in the main rainy season and an increase in autumn (September to October) season. GCMs downscaled through REMO model showed a slight increase before and after bias correction.

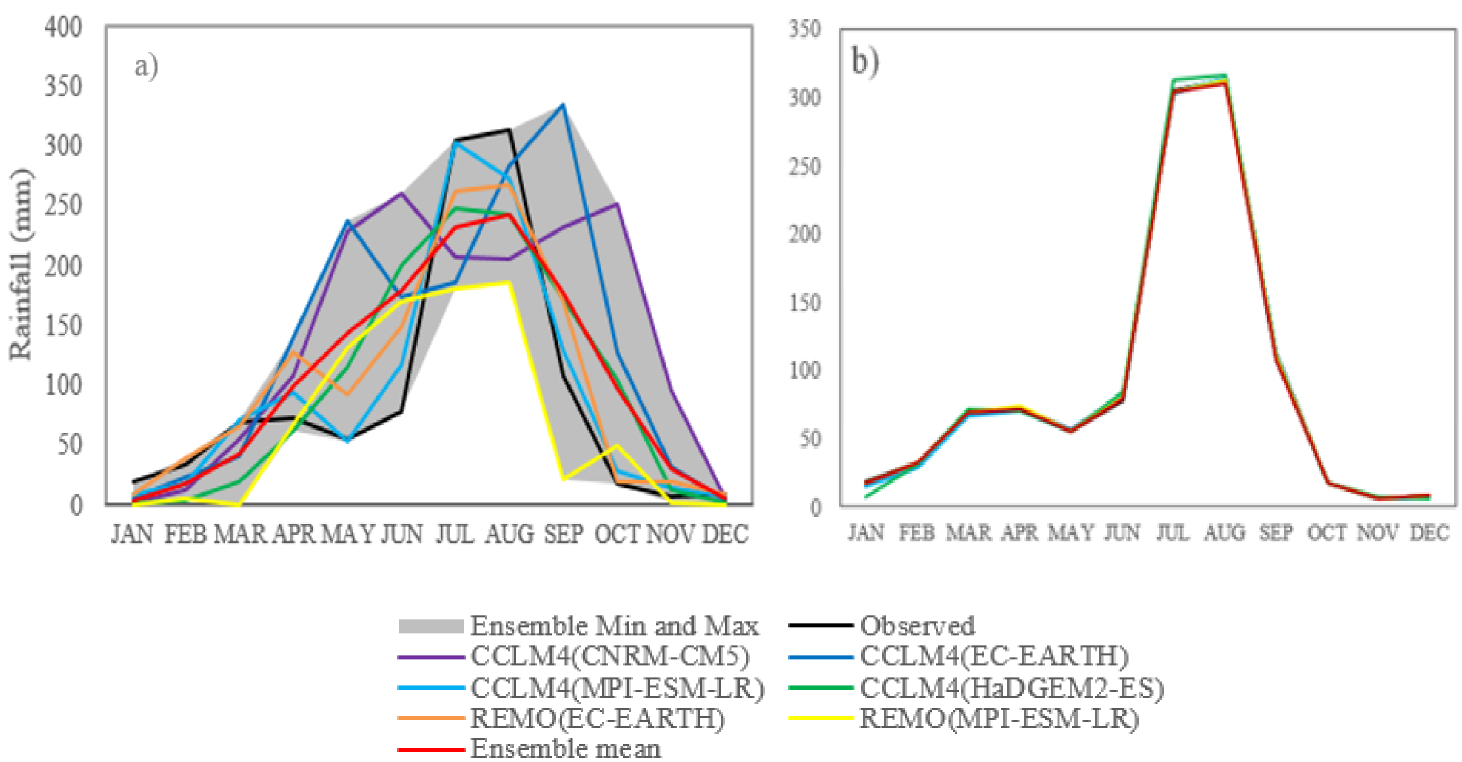

Figure 6.16 RCMs simulation (a) and bias corrected RCM outputs (b) of mean monthly rainfall in comparison with observed rainfall for the historical period (1981–2005) in the Jemma sub-basin. The RCM simulations is bias corrected using distribution mapping method.

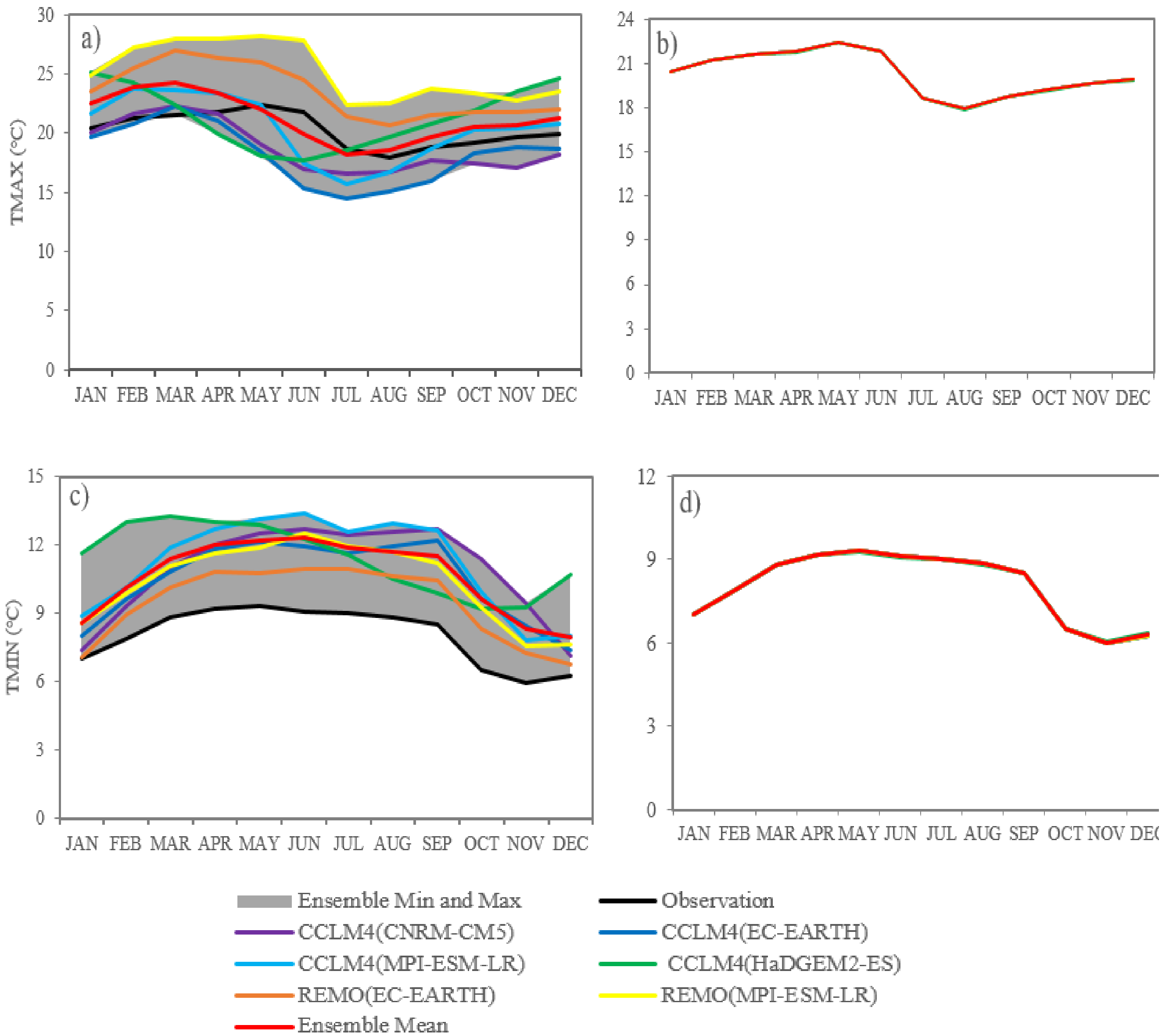

Figure 6.17 Observed, RCM simulations and bias corrected mean monthly TMAX and TMIN for the historical period (1981–2005). a) RCM simulations of TMAX, b) bias corrected TMAX, c) RCM simulations of TMIN and d) bias corrected TMIN. Bias correction based on distribution mapping.

The RCMs and the ensemble mean of RCMs showed uniformity in the climate change signal, but with different magnitude. Strong similarity in rainfall change signal is found among the ensemble mean of the RCMs(E-RCMs) than among the individual RCM (S-RCMs) simulation (Table 6.3). The GCMs downscaled through REMO model project lower reduction of rainfall in the future climate than GCMs downscaled by CCLM4 model. The difference among the RCMs to simulate rainfall could be attributed to the variation in the parametrization schemes used to represent sub-grid processes (local forcing) such as convective rainfall. Thus, RCMs selection during climate scenario development could be crucial for climate change projection and climate change impact assessment.

The variation among emission scenarios is lower than the difference among the RCMs. In the RCP4.5 emission scenario, higher reduction of rainfall is projected in the long-term climate condition than the near-term climate condition. Conversely, higher reduction of rainfall is projected in the near-term than long-term climate condition under RCP8.5 emission scenario. This entails that emission scenarios could trigger changes in some rainfall drivers, for instance, emission scenarios may reduce convective activity and moisture of the lower atmosphere over the airfields of the Central Highlands of Ethiopia. This also accentuates local and regional forcings (internal variability) are to be also important drivers of rainfall of the Jemma sub-basin and the central highlands of Ethiopia. Another potential reason could be the variation in the projected tropical ocean warming in the near and long-term future.

Considering the Paris agreement, future rainfall and temperature under RCP2.6 were also investigated. Rainfall projection has shown a lower reduction under RCP2.6 emission scenarios. The RCMs (REMO(EC-EARTH) and REMO(MPI-ESM-LR)) under RCP4.5 and RCP8.5 also showed a lower reduction of rainfall. This further emphasizes that larger uncertainty is found among the RCMs than the emission scenarios. However, in the Paris climate agreement which requires 10% reduction of emission by 2030 from 2015 level to realize RCP2.6 and to limit warming to 2°C above preindustrial level looks not within reach.

In contention with the projected rainfall, a large difference in projected TMAX and TMIN is observed among emission scenarios than among RCMs (Table 6.5). Corresponding with the projected concentration of greenhouse gases, a high increase of TMAX and TMIN is projected in the long-term future than the near-term future and in the RCP8.5 than RCP4.5 and RCP2.6. Lower increases of TMAX and TMIN are projected under RCP2.6 emission scenario. The fifth IPCC assessment report has also attributed that emission scenarios are major drivers of temperature change (IPCC, 2013). The individual RCM and the ensemble mean of the RCMs project higher increase of TMIN than TMAX under near and long-term climate scenarios. In general, the steady increase of TMAX and TMIN has shown strong agreement with the projected global temperature.

6.4 Conclusion

Statistical bias correction is essential to get reliable climate data from GCMs and RCMs for climate impact studies and subsequently climate change adaptations and mitigation policymaking. This study has intercompared statistical bias correction methods which range from some simple additive or multiplicative bias corrections methods to most robust distribution based bias correction methods using different statistical metrics. For this endeavour, rainfall and temperature simulations of six RCMs were used. The raw RCM simulations particularly GCMs downscaled using CCLM4 model were characterized by overestimation and underestimation of rainfall in the higher and lower elevation areas of the sub-basin, respectively. This bias of RCMs could stem from the initial boundary condition (GCMs) and RCMs convective cloud parametrization schemes. Thus, for other studies, it is worthwhile to use RCMs driven by reanalysis datasets such as ERA dataset to disentangle whether the biases are arises from RCMs or driving GCMs. This study was based on six RCMs, however, it is also non-trivial to use more number of RCMs to develop climate and climate impact scenarios.

This study ascertains a comparable performance among bias correction methods in reproducing mean rainfall and temperature values. This unfolds as bias correction methods use similar scale parameters. However, most additive or multiplicative bias corrections methods struggle to adjust frequency and intensity based metrics such as wet-day probability and the 90th percentiles. Distribution mapping method showed superior performance in adjusting wet-day probability and the 90th percentiles. Consequently, the distribution mapping method can be used to analyse extreme values like drought and flood and to design engineering structures to reduce the impacts of extreme events. The performance of distribution mapping method to cope with non-stationary climate conditions also warrants as this method can be used in other sub-basins of the Blue Nile Basin. But, this study questions the use of linear scaling and power transformation to adjust RCM simulations and to develop climate scenarios. Further, future studies can be designed using other frequency-based indices such as consecutive dry days, consecutive wet days and other indices to analyse the sensitivity of bias correction methods.

This study also develops climate scenarios using multiple GCMs and RCMs, emission scenarios and robust statistical bias correction method. Most RCMs and all ensemble mean of RCMs (E-RCMs) showed an agreement on climate change signal which revealed that the future climate will be characterized by drier condition and more warming. It is also projected that the future climate will be characterized by extreme rainfall and temperature events. The change in climate and extremes events could trigger profound impacts on the natural and anthropogenic systems. To reduce anticipated impacts of climate change and extreme events, it is essential to develop and apply robust climate scenarios in designing optimal adaptation and mitigation structures in the Jemma sub-basin and other similar sub-basins of the Blue Nile Basin. Climate change and extreme values could also have a compound impact through triggering flood or drought in the Jemma sub-basin. Therefore, it is worthwhile to simulate the impact of projected climate change on the hydrology of the Jemma sub-basin using well-calibrated and validated hydrological model. Moreover, climate science and climate modelling are under continuous improvement that further increase climate models reliability and reduce uncertainty. Thus, climate scenario developed in this study may be refined in the future.

Chapter 7

Hydrological processes under climate change scenarios in the Jemma Basin, upper Blue Nile Basin of Ethiopia

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Abstract

This study examines the response of hydrological processes to different climate change scenarios in the Jemma basin of upper Blue Nile Basin. Future near-term (2021-2050) and long-term (2071-2100) climate scenarios under Representative Concentration Pathways 4.5 and 8.5 (RCP4.5 and RCP8.5) were developed from six statistically bias corrected Regional Climate Models (RCMs). The output of these climate models were used as input to a calibrated and validated Soil and Water Assessment Tool (SWAT) model to assess the impact of climate change on the hydrology of the basin. For a robust hydrologic representation, the SWAT model was calibrated and validated at three river gauging stations and provided an acceptable result. The climate scenarios developed from bias corrected RCMs project an increase in temperature in all models and a subsidence of rainfall in the ensemble mean of the models in the near-term (2021-2050) and long-term (2071-2100) climate scenarios. Climate change may cause a consistent decrease in surface runoff and total water yield and an increase in evapotranspiration under all climate scenarios. This warrants the implementation of climate change adaptation strategies which can conserve water for agriculture and other ecosystem services in the Jemma basin and other similar basins in Ethiopia.

Keywords; climate change, hydrology, SWAT, RCP, Blue Nile Basin

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This Chapter is based on **Worku, G., Teferi, E., Bantider, A., Dile, Y.T., 2019. Hydrological processes under climate change scenarios in the Jemma Basin, upper Blue Nile Basin of Ethiopia**. ***Journal of Arid Environment, Under Review.***

7.1 Introduction

Climate change is unequivocally influencing the availability of freshwater resources through changes in evaporation, soil water and relative humidity (Bates et al., 2008; IPCC, 2013). The most significant potential effects of climate change may include increased frequency and magnitude of droughts and floods, and changes in water supplies due to the likely changes in rainfall, temperature, humidity, soil moisture, runoff and other important components of the hydrologic cycle (Bates et al., 2008). For example, a rise in temperature will lead to increased evapotranspiration and in turn, further increases the demand for irrigation water (Wang et al., 2012). On the other hand, the conceivable increase in intensities of rainfall will lead to higher rates of surface runoff and an increased risk of flood. Such hydrologic changes will impact nearly every aspect of human well-being such as water supply, agricultural productivity and energy production. For instance, globally it was projected that the number of people who face water stress will increase from 12 to 81 million in the 2020s and from 79 to 178 million in the 2050s (Arnell, 2004). Thus, to underpin water management under a changing climate, the impact of climate change on freshwater needs to be quantified.

Several studies have been made to assess the impact of climate change on hydrological processes and water availability at local (e.g Olsson et al., 2013) and regional and global scales (e.gArnell, 2004; Elshamy et al., 2009). Some of these studies directly apply outputs of GCMs and RCMs (e.g. Beyene et al., 2010; Setegn et al., 2011), others bias-adjusted and downscaled climate models output before applying for hydrological estimations (e.g. Elshamy et al., 2009; Teutschbein and Seibert, 2012; Liersch et al., 2016). However, the standard procedure of climate change impact assessment includes downscaling of GCMs output into regional scales, tailoring (bias correction) of RCMs output, hydrological simulation and analysis of changes exclusively due to climate change (Olsson et al., 2016). When assessing the effects of climate change on water resources, it is also very important to understand the effect of spatial scale. Due to coarse spatial resolution, climate models are characterized by uncertainty to simulate local scale climate variables that are used to input for hydrological models. For this, it is recommendable to downscale and fine-tune climate models simulation before using for hydrological impact assessment (Teutschbein and Seibert, 2012).

Hydrological simulations using the bias corrected climate models output provide a reliable estimate of hydrological components for instance surface runoff, evapotranspiration and water yield than hydrological simulation without bias correction of climate models (Hagemann et al., 2011; Teutschbein and Seibert, 2012). For instance, Fang et al., 2015 has investigated that RCM simulations without bias correction showed large biases of streamflow simulation, while bias corrected RCMs were effective in streamflow simulation. Bias correction has also shown improved performance in simulating rainfall and discharge characteristics (Liersch et al., 2016). However, sometimes bias corrections trigger biases (Maraun, 2013; Wang and Kotamarthi, 2015). In Canada and Central North America, bias corrected WRF (Weather Research and Forecasting) RCM has shown larger wet bias than the non-bias corrected WRF simulation (Wang and Kotamarthi, 2015). Therefore, it is important to identify the appropriate bias correction method and apply bias correction on climate models simulation before using for various applications. It is important, however, to note that there are limited studies in Ethiopia (Elshamy et al., 2009; Liersch et al., 2016; Chaemiso et al., 2016) which use bias corrected RCM outputs for climate change impact assessment and climate adaptation decision analysis.

In Ethiopia, the current climate has caused drought, floods, heavy rains and frosts. Among these impacts of climate, drought is the most severe impact of climate change which affect the country frequently (NMA, 2007). There are also various watershed and basin-scale studies which account the impact of climate change on the water resource. In the Awash Basin, a decrease in runoff which ranges from 10% to 34% was projected using a single GCM with coarse resolution (Hailemariam, 1999) which could be subject to uncertainty. Taye et al., (2018) has also projected a decrease in water resources in the future period at Awash River Basin using three GCMs from the CMIP5. In contrast to the case of Awash River Basin, an increase in surface runoff and total water yield was projected for the 2030s and 2090s climate using bias corrected RCM output in the Omo-Gibe River Basin of Ethiopia (Chaemiso et al., 2016). The difference in signals of change on water resources at different basins due to climate change highlights the need to investigate hydrological impacts of climate change using appropriate climate change scenarios that could capture local scale climate variables.

In the Upper Blue Nile Basin, there are some hydrological climate change impact studies which apply ensemble of various GCMs (e.g Elshamy et al., 2009; Setegn et al. 2011) and statistically and dynamically downscaled GCMs output (Worqlul et al., 2018; Adem et al., 2016; Mekonnen and Disse, 2016; Dile et al., 2013; Soliman et al., 2009). However, there are limited studies which use bias-corrected outputs of GCM and RCM (Elshamy et al., 2009; Liersch et al., 2016) as inputs to hydrological models. There are also studies which use a single emission scenario (Soliman et al., 2009) and different emission scenarios (Worqlul et al., 2018; Adem et al., 2016; Liersch et al., 2016). The findings from these studies provided a non-conclusive impact of climate change on hydrological processes. For example, some studies (e.g. Worqlul et al., 2018; Adem et al., 2016; Liersch et al., 2016) simulated an increase in steam flow while others (e.g. Elshamy et al., 2009) simulated a decrease in streamflow. Other studies existed which projected a non-linear trend of climate change impact on streamflow (e.g. Setegn et al., 2011). This suggested that there is no conclusive consensus on the impact of climate change on streamflow in the Upper Blue Nile Basin. Thus, it is worthwhile to recognize and characterize the uncertainties of climate change in the basin.

Jemma basin of the Upper Blue Nile Basin is characterized by extreme temperature and rainfall events (Worku et al., 2018a). The livelihood of the majority of the inhabitants is based on rain-fed agriculture which is frequently affected by climate variability. This suggests that climate change will significantly affect the livelihoods of the smallholder farmers, which warrants detailed studies to support policy on climate change adaptation and mitigation. To develop climate change adaptation decisions for current and near and long-term future climate conditions, bias corrected RCMs rainfall and temperature output under different emission scenarios are essential. Bias correction has been found crucial because, even though, RCMs are able to capture mean annual and monthly rainfall and distribution of rainfall events, RCMs showed wet bias in the higher elevation (>2700m above sea level) areas of the Jemma basin (Worku et al., 2018b). This highlights the need to bias adjusts RCM simulations before using for hydrological climate change impact assessment. There is no such study in the basin which has assessed the impact of climate change on water availability for agriculture and other services using bias corrected outputs of RCMs.

This study, therefore, aims to assess the impact of different climate scenarios on hydrologic components in the Jemma basin using the Soil and Water Assessment Tool (SWAT). For the Jemma basin, different climate scenarios were developed based on robust bias corrected RCM outputs (Worku et al., 2019). The SWAT model is developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions (Arnold et al., 1998). The model is successfully applied in Blue Nile Basin to study hydrological processes and other environmental applications (Setegn et al., 2011; Betrie et al., 2011; Griensven et al., 2012).

7.2 Data and Methodology

7.2.1 Input Data

The SWAT model requires temporal and spatial data to simulate hydrological processes. The temporal data used in the modelling process are the climatic and streamflow data. Baseline climate (1981-2014) data include daily rainfall, TMAX and TMIN, solar radiation, sunshine, wind speed and relative humidity of climatic stations of the Jemma basin (Figure 7.1) were obtained from the Ethiopian National Meteorological Services Agency. These climatic data were used to calculate weather stations statistics which is needed to create SWAT's weather generator input file (Arnold et al., 2012). Daily rainfall, TMAX and TMIN were also used to statistically bias correct RCM simulations. Daily streamflow data of Beressa (1991-2008), Robi-Gumero (1988-2002) and Jemma (1996-1997) gauge stations was obtained from Ethiopian Ministry of Water, Irrigation and Electricity. These climatic and hydrologic data were used to calibrate and validate the hydrological model and to develop baseline climate and hydrologic balance components. Beressa, Robi-Gumero and Jemma hydrological stations are located at the upstream, middle stream and downstream of the Jemma sub-basin (Figure 7.1).

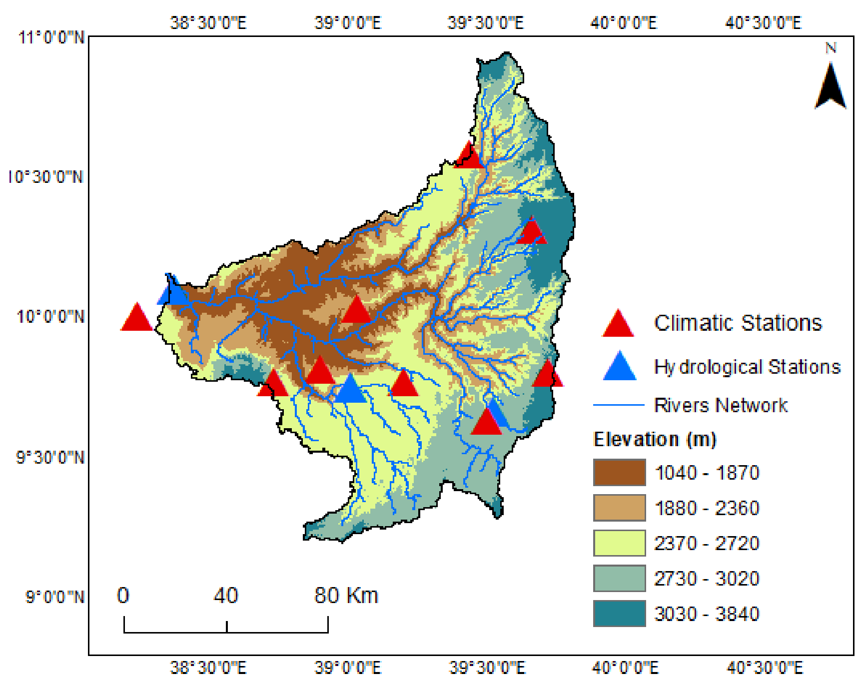

Figure 7.1 Distribution of the climatic and hydrological gauge stations used for calibration and validation of the hydrological model.

The spatial data include Digital Elevation Model (DEM), slope, soil and land use and land cover data (Figure 7.2). The DEM data which has a 30m resolution was obtained from the Shuttle Radar Topographic Mission (SRTM). The DEM data was used to create the basin boundary and stream networks. The slope generated from the DEM data was used to define Hydrological Response Units (HRU) together with the soil and land use data. The soil data was obtained from the Ministry of Water, Irrigation and Electricity of Ethiopian. Soil parameters such as soil saturated hydraulic conductivity, available water capacity, soil texture, etc) are obtained from the Water and Land Resources Centre of Ethiopia and the Harmonized World Soil Database. The land use/land cover data for the year 2008 was derived from Landsat satellite imagery and supervised image classification was done using maximum likelihood algorithm. The land use land cover map was prepared with Kappa (K) statistics and overall accuracy of 0.81% and 83% respectively. After the different land use classes were identified, they were redefined according to SWAT land use database code. Thus the land use/land cover of 2008 was used to represent the land use of the baseline period. All the spatial data were projected into the projection parameters for Ethiopia, which is UTM Zone of WGS 1984, 37N.

The other data used for this study was RCM simulations of rainfall and temperature. Six RCMs which have shown good performance in capturing the historical (1981-2005) mean monthly and annual rainfall and frequency of rainfall events of the Jemma basin (Worku et al., 2018b) were considered and acquired from the Earth System Grid Federation web portal. In each RCM, RCP8.5 which represents radiative forcing pathway of 8.5W/m^2 by 2100, and RCP 4.5 which represents intermediate emission levels of 4.5 W/m^2 that could start stabilization after 2100 (Moss et al., 2010) were used.

7.2.2 Bias correction of regional climate models data

The intercomparison of different statistical bias correction methods shown that distribution mapping method is superior in capturing mean values and the 90th percentile of observed rainfall and temperature and wet day probability of observed rainfall than other bias correction methods (Worku et al., 2019). Moreover, different from other bias correction methods (linear scaling, variance scaling, power transformation, etc.), distribution mapping method adjusted the CDF of RCM-simulated rainfall and temperature values with the CDF of observed rainfall and temperature values. Thus, in this study, the

RCM simulations of rainfall and temperature bias adjusted using distribution mapping method was used to run the hydrological model.

7.2.3 Hydrological model set up

The SWAT model for the Jemma basin was discretized into 150 sub-basins using a threshold area of 45 km^2 (Figure 7.2). Within each sub-basin, Hydrological Response Units (HRUs) were created. HRUs are unique combinations of slope, soil and land use. Multiple HRUs were defined in a basin to allow heterogeneity within the basin. The slope was classified into 0-8%, 9-20% and >20% to define the HRUs. The HRU definition processes created 958 HRUs (Figure 7.2). The Soil Conservation Service (SCS) Curve Number method (USDA-SCS, 1972) was used to estimate surface runoff. The applicability of curve number method in estimating surface runoff in three catchments of the Upper Blue Nile basin was evaluated and concluded that CN method can be used to estimate surface runoff in the region of Blue Nile Basin and other tropical regions (Dile et al., 2016). Potential evapotranspiration (PET) was estimated using the Penman-Monteith method.

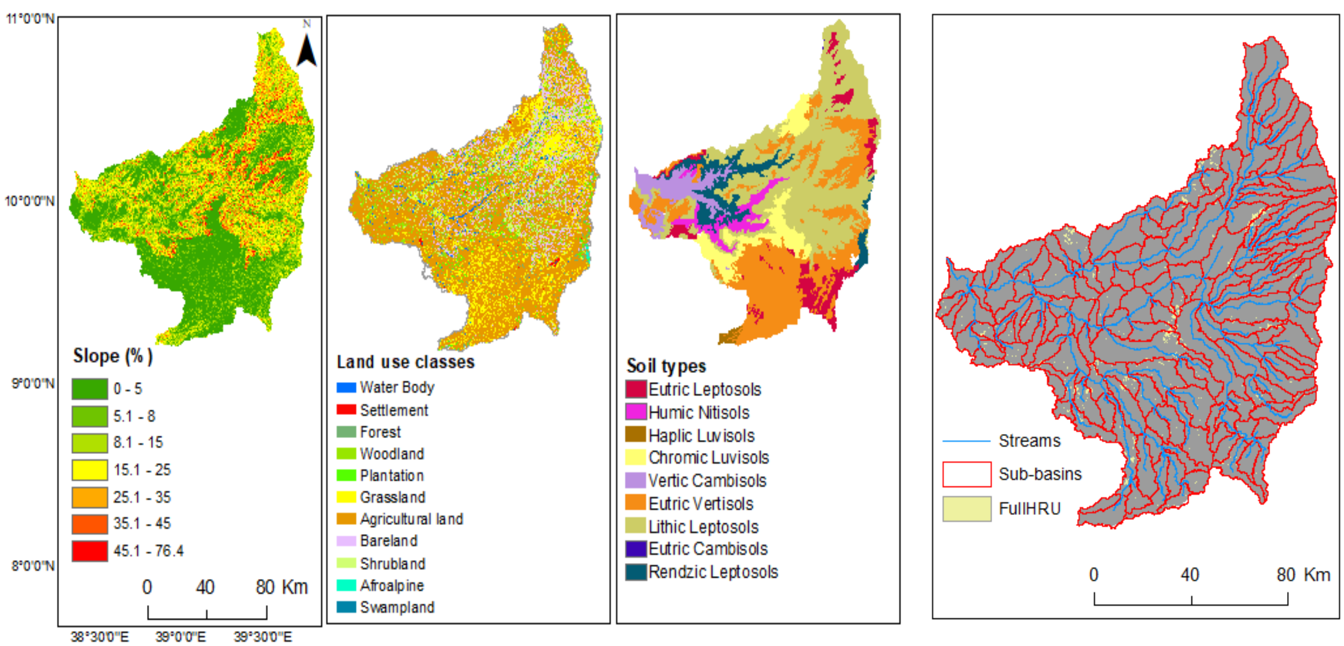

Figure 7.2 Slope, land use, soil types, streams and sub-basins of the Jemma basin. Based unique combinations of slope, land use and soil types, HRUs were created.

7.2.4 Model calibration and validation

Before the analysis of climate change impacts, the hydrological model was calibrated and validated to represent the biophysical conditions of the basin. The calibration of the model parameters was conducted using SUFI-2 in SWAT-CUP (Abbaspour et al, 2004). Since the SWAT model has hundreds of parameters, the most sensitive parameters which affect the simulation outputs were identified through sensitivity analysis. Parameters related to soil water, runoff, groundwater and evapotranspiration were considered for the sensitivity analysis. The highest sensitive parameters which have smaller p-value and larger t-stat were selected.

The Jemma basin is large in area and its topography is rugged. Therefore, multi-site calibration and validation (Cao et al., 2006; Arnold et al., 2012) approach was applied to capture the hydrological processes across the basin. At Beressa and Robi Gumero gauge stations which are located at the upper and middle part of the Jemma basin (Figure 7.1), streamflow data is available from 1991-2008 and 1988-2002, respectively. However, at the Jemma River gauging stations (outlet) of the Jemma basin, streamflow data is available only from 1996-1997. Using semi-automatic calibration procedure (Arnold et al., 2012), the model was calibrated at Beressa (2002-2008) gauge station using observed streamflow data of this station. Since the period from 1991 to 1995 was government transition period in Ethiopia, we assume the quality of data after 1995 is better and consequently we use the streamflow data after 1995 for model calibration. The calibrated model was also validated at Beressa (1991-1999), Robi Gumero (1991-2002) and Jemma (1996-1997) using observed streamflow of these gauge stations. Due to data scarcity, only validation was performed at outlet gauge, the Jemma gauge station. Similar calibration and validation procedure was followed at the Gerda catchment of the Upper Blue Nile Basin (Lemann et al., 2016)

The performance of the model during calibration and validation was evaluated using Nash and Sutcliffe simulation efficiency (NSE) and percent Bias (PBIAS), which are fundamental goodness-of-fit evaluation criteria (Moriasi et al., 2015). The NSE is normalized statistics that measures the relative magnitude of the residual variance compared to the observed data variance (Nash and Sutcliffe, 1970). Generally, the NSE value ranges between 1 (when measured data and simulated are alike) and $-\infty$. An NSE value > 0.50 is considered as an acceptable level of performance for streamflow simulation (Moriasi et al., 2015). PBIAS measures the average tendency of the simulated data to be larger or smaller than the observed data.

A PBIAS value ranges from -∞ to ∞ and an optimal value of PBIAS is 0 (Moriasi et al., 2015). A positive value of PBIAS indicates model underestimation and negative values indicates model overestimation.

The uncertainty of model simulation was evaluated using P-factor and the r-factor on the SUFI-2 algorithm (Abbaspour et al, 2004). The SUFI-2 estimates uncertainty at the 95 percent prediction uncertainty (95PPU). The P-factor is the percentage of the measured data bracketed within the 95PPU while the r-factor measures the thickness of the uncertainty band. P-factor of 1 and an r-factor of 0 indicates an exact fit of simulation with measurement (Abbaspour, 2015).

7.2.5 Estimating hydrological climate change impact

To simulate the hydrological impact of climate change, the ensemble mean of RCMs/GCMs is recommended (Teutschbein and Seibert, 2010; Taylor, et al, 2012). Thus, the ensemble mean of six statistically bias corrected RCMs rainfall and temperature output under RCP4.5 and RCP8.5 emission scenarios at each climatic station was used as input to the hydrological model. The calibrated and validated SWAT model was used to estimate surface runoff, evapotranspiration and total water yield under baseline climate and future climate scenarios. The impact of climate scenarios on the hydrological variables was studied dividing the coming century into near-term (2021-2050) and long-term (2071-2100) future. The impacts of climate change were therefore analysed by comparing the ensemble mean of RCMs under RCP4.5 and RCP8.5 emission scenarios with the baseline climate. Besides to the ensemble mean of the RCMs, the hydrological simulation was made using the input of the RCM (i.e CCLM4(MPI-ESM-LR)) which was better in capturing the rainfall and temperature of the baseline period. As a result, CCLM4(MPI-ESM-LR) model was used as input to the hydrological model and the output was compared with the hydrology simulated with the ensemble mean output.

7.3 Result and Discussion

7.3.1 Model Calibration and Uncertainty Analysis

Using the global sensitivity analysis, sensitivity of twenty-six hydrological parameters for streamflow was tested. The Global sensitivity analysis showed that CN2 (Curve number), ESCO (Soil evaporation compensation factor), SOL_AWC (Available water capacity of the soil), OV_N (Manning's "n" value for overland flow) and CH_N2 (Manning's "n" value for the main channel) are the most sensitive parameters (Table 7.1 and Figure 7.3). Most of the sensitive parameters are related to surface runoff and processes occurring at the soil and channel. However, Groundwater related parameters; ALPHA_BF (Base-flow alpha-factor) and GWQMN (Threshold water depth in the shallow aquifer required for return flow to occur) are also considered in the calibration based on the literature (e.g Betrie et al., 2011; Griensven et al., 2012) in the Upper Blue Nile Basin. The groundwater parameters are considered to maintain the hydrological mass balance since the surface and groundwater processes are intertwined. Unlike other studies in the Upper Blue Nile Basin, this study found OV_N as a sensitive parameter to streamflow simulation. OV_N was useful to adjust the pattern of simulated monthly streamflow with the observed monthly streamflow.

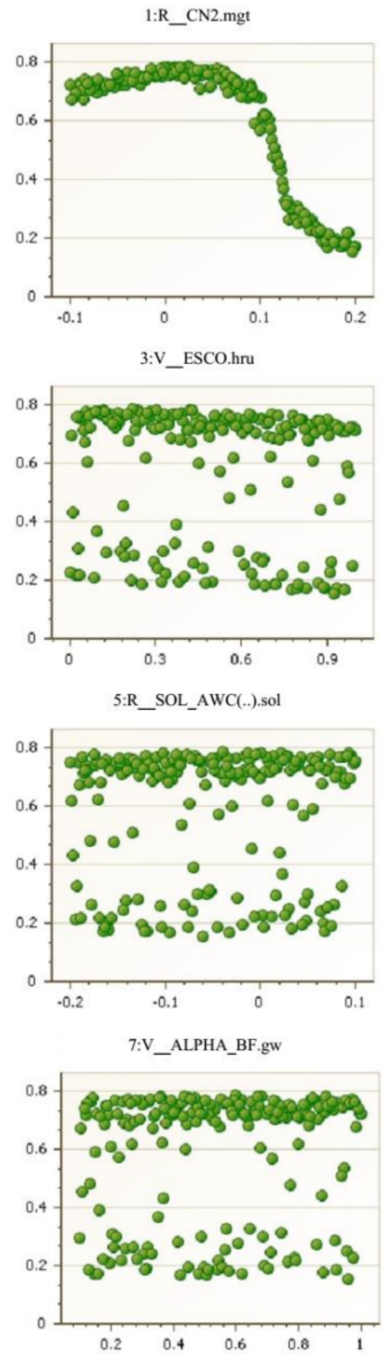

Figure 7.3 Dotty plots of SWAT parameters used for calibration. The plots show parameter values in the x axis versus objective function, Nash-Sutcliffe (NS) in the y axis.

Table 7.1 Calibrated model parameters, studied parameter ranges, and final fitted values using observed monthly streamflow at the Beressa River gauge station of the Jemma basin. The model was calibrated for the period 2002–2008.

Sensitive Parameters	Parameter description	Parameter ranges	Final Fitted values
r__CN2.mgt	Curve number	-0. 1- 0.2	-0.057
v__ESCO.hru	Soil evaporation compensation factor	0.0-1.0	0.2175
r__SOL_AWC.sol	Available water capacity of the soil (mm)	-0.2 - 0.1	-0.040
r__OV_N.hru	Manning's "n" value for overland flow	-0.2 - 0.2	-0.179
v__CH_N2.rte	Manning's "n" value for the main channel	-0.0 1– 0.3	0.054
v__ALPHA_BF.gw	Base-flow alpha factor (days)	0.0 - 1.0	0.597
v__GWQMN.gw	Threshold water depth in the shallow aquifer required for return flow to occur (mm)	0.0 - 500	131.250

The qualifier (r_) refers to a relative change in the parameter where the default values are multiplied by 1 plus a factor in the parameter range, while (v_) refers to the substitution of the default parameter by a calibrated value. The extensions (e.g., .hru, .bsn, .gw, etc.) indicate the SWAT parameter family.

The comparison between the observed and simulated monthly streamflow showed a very good model performance during calibration and validation periods. For example, the NSE and PBIAS values during the calibration of the model at the Beressa river gauge station were 0.78 and -4.2% respectively (Table 7.2 and Figure 7.4a). Similarly during the validation, the model showed NSE of 0.59 and PBIAS of 9.4 which can be considered as acceptable model performance (Moriasi et al., 2015) at Beressa gauge station. Likewise, the model validation using observed monthly streamflow at the Robi Gumero and Jemma river gauging stations showed NSE of 0.64 and 0.85 respectively. PBIAS values of -5.0% and 10.4% were also found during validation at Robi Gumero and Jemma river gauging stations respectively (Table 7.2, Figure 7.5).

Table 7.2 Calibration and validation performance of the SWAT model at the Beressa, Robi Gumero and Jemma river gauging stations of the Jemma basin. Beressa, Ribit-Lemi and Jemma river gauging stations are located at the upper, middle, and most downstream locations in the Jemma basin.

Objective functions	River Stations			
	Beressa		Robi Gumero	Jemma
	Calibration (2002-2008)	Validation (1991-1999)	Validation (1991-2002)	Validation (1996-1997)
NSE	0.78	0.59	0.61	0.85
PBIAS	-4.2	9.4	-2.1	10.4
P-factor (%)	80	71	68	64
r-factor	0.65	0.30	0.85	0.51

The uncertainty analysis of the calibrated model provided more than satisfactory P-factor and r-factor (P-factor >70% and r-factor of close to 0) (Abbaspour, 2015). The calibrated model at Beressa river gauging station bracketed 80% and 71% of the observed data within the 95PPU during the calibration and validation periods, respectively. At Robi Gumero and Jemma river gauging stations, P-factor of 68% and 64% respectively were also obtained. The measure of the uncertainty using the r-factor also showed performance of 0.65 during the calibration at the Beressa river gauging station. The validation of the model at the Beressa, Robit-Gumero and Jemma river gauging stations provided an r-factor of 0.3, 0.85 and 0.51, respectively. The best r-factor (i.e. smallest uncertainty band) was observed during the validation period at the Beressa and Jemma river gauging station (Table 7.2).

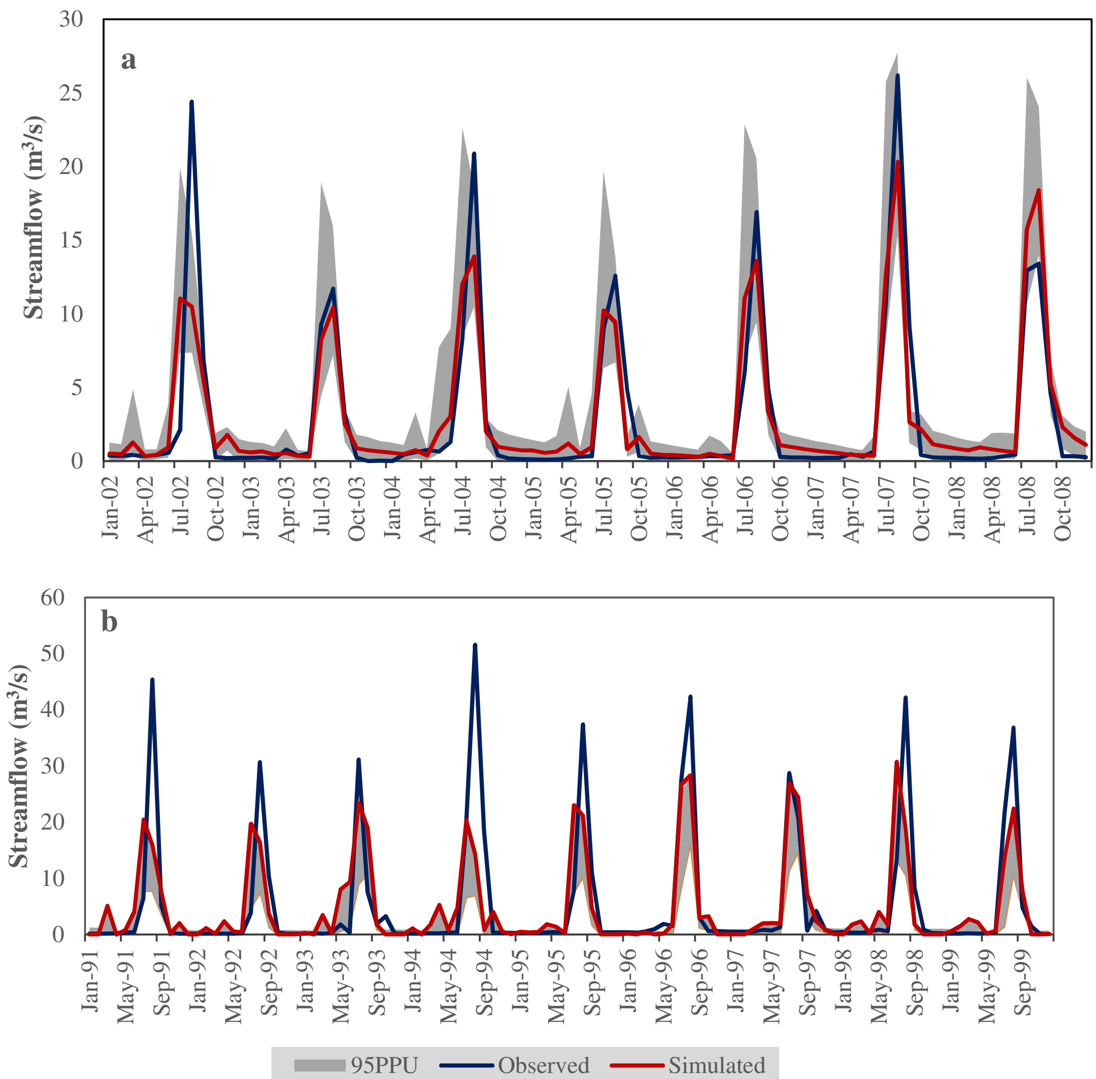

Figure 7.4 Simulated and validated hydrographs of (a) calibration (2002 – 2008) and (b) validation (1991 – 1999) at Beressa gauge station of Jemma basin.

Even though the model evaluation in terms of goodness-of-fit criterion showed very good performance, the validation at Beressa river gauging station could not capture the peak streamflow and also showed substantial volumetric differences (Figure 7.4b). This may be associated to the poor quality of climate and/or streamflow data. Evaluation of the calibrated parameter sets based on the Beressa River gauging station to reproduce streamflow at the Robit-Gumero River gauging sites provided reasonable estimates. This suggests that the parameter sets are representative across the Jemma basin in different periods. However, the model performance in terms of NSE was higher at the basin outlet than at the watershed level (Table 7.2, Figure 7.5b), which suggests that calibrating hydrological models only at the basin outlet may overrate performance of models than evaluating them at the watershed level. Similarly, Cao et al., (2006) and Begou et al., (2016), reported better performance of models at the watershed outlet than sub-watershed outlets at a large mountainous catchment of New Zealand and Bani Catchment of Niger River, respectively.

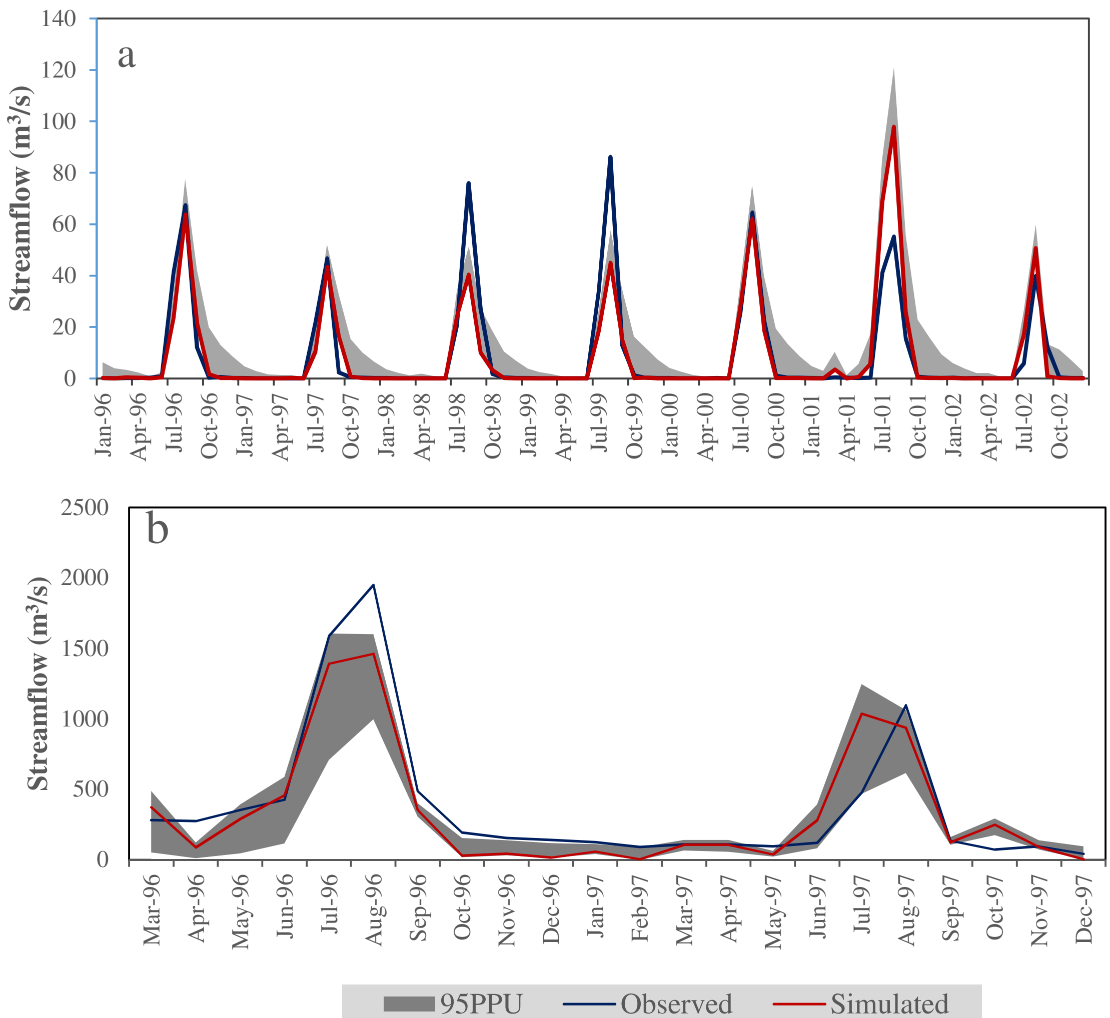

Figure 7.5 Validation of the SWAT model at Robi Gumero and Jemma gauge stations using the same parameter sets calibrated and validated at Beressa station of the Jemma basin. a) validation at Robi Gomero gauge station b) validation at Jemma gauge station.

7.3.2 Hydrologic processes under baseline climate scenario

The long-term mean annual water balance analysis of the basin showed that a large proportion of the rainfall is evapotranspiration (53.41%) and surface run-off (38.40%) (Table 7.3). Water yield refers to the sum of surface runoff, lateral flow and groundwater minus transmission losses and Jemma basin has a total water yield of 501mm which is 46.48% of the total rainfall. In this basin, surface runoff is the major contributor (87%) to the total water yield. This is in contrast to the headwaters of the Upper Blue Nile basin where, for example, Setegn et al. (2010) reported that in the Lake Tana sub-basin, groundwater flow contribution is higher than surface runoff contribution.

Hydrologic balance dynamics at dry (2002) and wet (1997) years and in different seasons (Table 7.3) of the study period was examined. Here, the term "dry" and "wet" is relative which represent years with lower and higher rainfall during the baseline climate. During these dry and wet years, surface runoff has shown large deviation than other components of hydrological balance. During the wet year (1996), there is high surface runoff and water yield and in this wet year, 90% of the water yield is generated from surface runoff (Table 7.3).

The hydrological system of the Jemma basin is strongly responsive to rainfall occurrence and has high rainfall-runoff coefficient (45%) during the rainy season. Comparative estimates have also reported the rainfall to runoff conversion in different catchments of the Jemma basin. For example (Hurni et al., 2005) reported 55% rainfall is converted into a runoff in Andit-Tid catchment of the Jemma basin, whereas Gebrehiwot and Ilstedt (2011) reported that the rainfall-runoff coefficient at Beressa and Weizer catchment of the Jemma basin is 57% and 80%, respectively. Thus, water resources management strategies which focus on surface runoff are to be designed for sustainable water resources development in the Jemma basin.

Seasonally, there is high water yield and surface runoff during the rainy season (June - September) and low water yield and surface runoff during the dry season (December –February) (Table 7.3). This shows that the hydrological system of the Jemma basin is strongly responsive to rainfall occurrence and has high rainfall-runoff coefficient (45%) during the rainy season.

Table 7.3 - Hydrological balance components of the Jemma basin in annual, dry and wet years. The estimates are based on the calibrated and validated model under baseline climate. The values are mean of all sub-basins.

	Baseline (1981-2014)	Dry Year (2002)	Wet Year (1996)	Dry Season (Dec-Feb)	Rainy Season (Jun-Sep)
Rainfall (mm yr^{-1})	1039	801	1286	47.97	786.28
ET(mmyr^{-1})	537.30	510	645	50.00	282
SURQ(mm yr^{-1})	419.33	268	554	9.79	351
GWQ(mm yr^{-1})	67.81	27	77	3.43	41
LATQ(mm yr^{-1})	15.59	14	20	3.00	9.0
WYLD(mm yr^{-1})	500.84	303	642	16	390
PERC(mm yr^{-1})	86.12	27	81	0.72	57

ET = evapotranspiration, SURQ = surface runoff, GWQ = groundwater contribution to stream flow, LATQ = lateral flow into stream, WYLD = SURQ + LATQ + GWQ-LOSSES, PERC = percolation below root zone (groundwater recharge).

7.3.3 Rainfall and temperature under future climate scenarios

Future climate scenarios for the Jemma basin were developed by blending different GCMs, RCMs, emission scenarios and robust bias correction method i.e distribution mapping (Worku et al., 2019). In the ensemble mean of RCM (E-RCMs), a consistent reduction of rainfall which ranges from 19% to 23% under all climate scenarios is detected. A large difference in rainfall change signal is observed among RCMs (S-RCMs) than among the ensemble mean of RCMs in the near and long-term climate scenarios. In the individual RCMs (S-RCMs), reduction of future rainfall is in the order of -43% to 0.5% for the near-term future and from -42% to 12% for the long-term future under RCP8.5 scenario. Whereas, an unpredictable response of rainfall to emission scenarios is projected. Higher reduction of rainfall is projected in the near-term than long-term climate condition under RCP8.5 emission scenario (Figure 7.6). In the RCP4.5 emission scenario, higher reduction of rainfall is projected in the long-term climate condition than the near-term climate condition. The detail in the rainfall and temperature changes under different climate scenarios is given in (Worku et al., 2019).

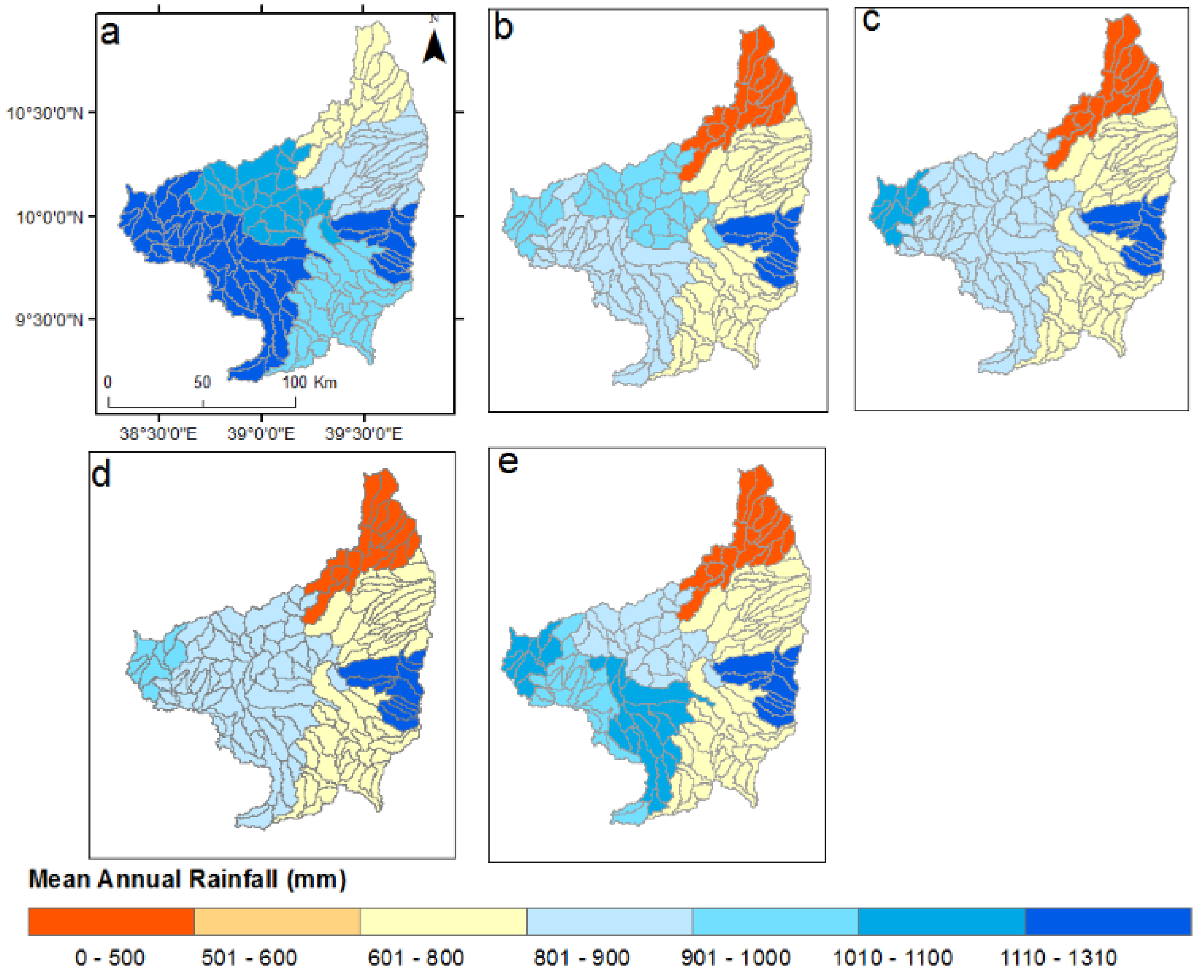

Figure 7.6 Mean annual rainfall (mm) of baseline and future climate scenarios in each sub-basin of the Jemma basin. a) Baseline climate (1981-2014), b) RCP4.5 (2021-2050) climate scenario, c) RCP8.5 (2021-2050) climate scenario, d) RCP4.5 (2071-2100) climate scenario and e) RCP8.5 (2071-2100)climate scenario. The scenarios were developed based on the ensemble mean of six RCMs.

In all climate scenarios, an increase of TMAX and TMIN is projected in the RCMs and in the ensemble mean of RCMs. In the ensemble mean of RCMs, a consistent increase of TMAX which ranges from 1.01°C to 3.13°C is detected under future climate scenarios. Similarly, a consistent increase of TMIN which ranges from 1.14°C to 5°C is projected under future climate scenarios. In contrast to the projected rainfall, a large difference in projected TMAX and TMIN is detected among emission scenarios than among RCMs. Higher increase of TMIN and TMAX is estimated from climate scenarios under RCP8.5 emission scenarios. The Fifth IPCC assessment report has also attributed that emission scenarios are major drivers of temperature change (IPCC, 2013). Again in agreement with the projected concentration of greenhouses gases, high increase of TMAX and TMIN is projected in the long-term future than the near-term future. The individual RCM and the ensemble mean of RCMs project higher increase of TMIN than TMAX under near and long-term climate scenarios. In general, TMAX and TMIN under all climate scenarios have shown strong agreement with the projected global temperature. This substantiates there will be high increase of temperature unless substantial and sustainable measures are to limit greenhouse gases emission by the global society are realized.

7.3.4 Hydrologic components under future climate scenarios

The change in rainfall and temperature due to the future climate change was seen to cause a change on the water balance components in the Jemma basin. Although there is a difference in magnitude, the surface runoff showed a decline under all the future climate scenarios and RCMs. The highest reduction of surface runoff (-65%) was estimated in the near-term period (2021-2050) under RCP8.5 climate scenario. Over long-term (2071-2100), the reduction in surface runoff was smaller both in the RCP4.5 and 8.5 climate scenarios (Table 7.4 and Figure 7.7). This may be attributed to the higher projected rainfall in the long-term climate scenarios compared to the near-term scenarios. Generally, the reduction in surface runoff is related to the reduction in rainfall, and an increase in evapotranspiration. However, surface runoff showed strong disproportional change to rainfall reduction. Rainfall reduction in the order of 19% to 22% triggers a reduction of surface runoff in the order of 48% to 58% under all climate scenarios (Table 7.4). The highest reduction in surface runoff occurred during the main rainy season (June-September) (Figure 7.10). Spatially, in the southern areas of the basin, there will be a higher reduction of surface runoff under the near-term and long-term climate scenarios (Figure 7.7).

Table 7.4 Mean annual hydrological components under baseline and future climate scenarios. The changes in the hydrologic balance components were estimated for an ensemble mean of six RCMs under RCP4.5 and RCP8.5 emission scenarios. The values are mean of all sub-basins.

	Baseline (1981– 2014)	**Near-term 2021-2050 (RCP4.5)**	**Near-term 2021-2050 (RCP8.5)**	**Long-term 2071-2100 (RCP4.5)**	**Long-term 2071-2100 (RCP8.5)**
Rainfall (mm yr^{-1})	1039	799 (-20%)	782(-22%)	791 (-21%)	812(-19%)
ET(mm yr^{-1})	537.30	584.39(9%)	574.60(7%)	565.40(5%)	557.29(4%)
SURQ (mm yr^{-1})	419.33	191.46(-57%)	185.27(-58%)	190.41(-57%)	226.07(-48%)
GWQ (mm yr^{-1})	67.81	37.61(-44%)	36.20(-47%)	32.17(-52%)	40.41(-40%)
LATQ(mm yr^{-1})	15.59	11.99(-23%)	8.73(-44%)	10.95(-29%)	8.62(-45%)
WYLD (mmyr^{-1})	500.84	231.02(-54%)	220.02(-56%)	222.19(-56%)	266.03(-47%)
PERC(mmyr^{-1})	86.12	47.77(-44%)	45.90(-47%)	40.83(-53%)	51.28(-40%)

ET = evapotranspiration, SURQ = surface runoff, GWQ = groundwater contribution to stream flow, LATQ = lateral flow into stream, WYLD = SURQ + LATQ + GWQ-LOSSES, PERC = percolation below root zone (groundwater recharge).

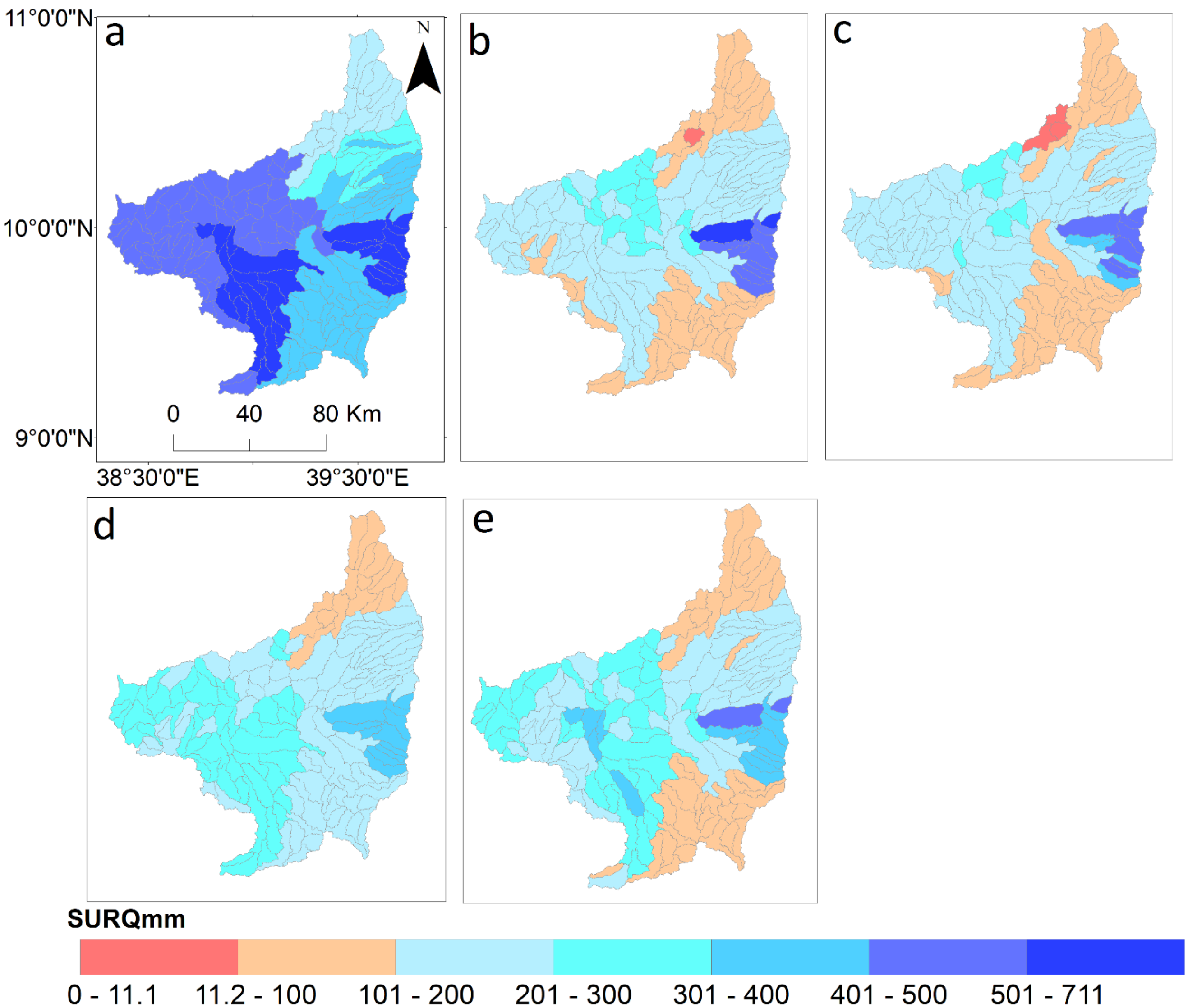

Figure 7.7 Mean annual surface runoff (SURQmm) of baseline and future climate scenarios in each sub-basin of the Jemma basin. a) Baseline climate (1981-2014), b) RCP4.5 (2021-2050) climate scenario, c) RCP8.5 (2021-2050) climate scenario, d) RCP4.5 (2071-2100) climate scenario and e) RCP8.5 (2071-2100)climate scenario. The scenarios were developed based on the ensemble mean of six RCMs.

For the years to come, annual rainfall and surface runoff may decrease, however evapotranspiration may increase. The increase in actual evapotranspiration is in part due to a consistent increase in temperature. Similar to the surface runoff, there will be lower actual evapotranspiration in the northern part of the basin under all future climate scenarios (Figure 7.8). Lower surface runoff and rainfall in the northern part of the basin could result in low actual evapotranspiration.

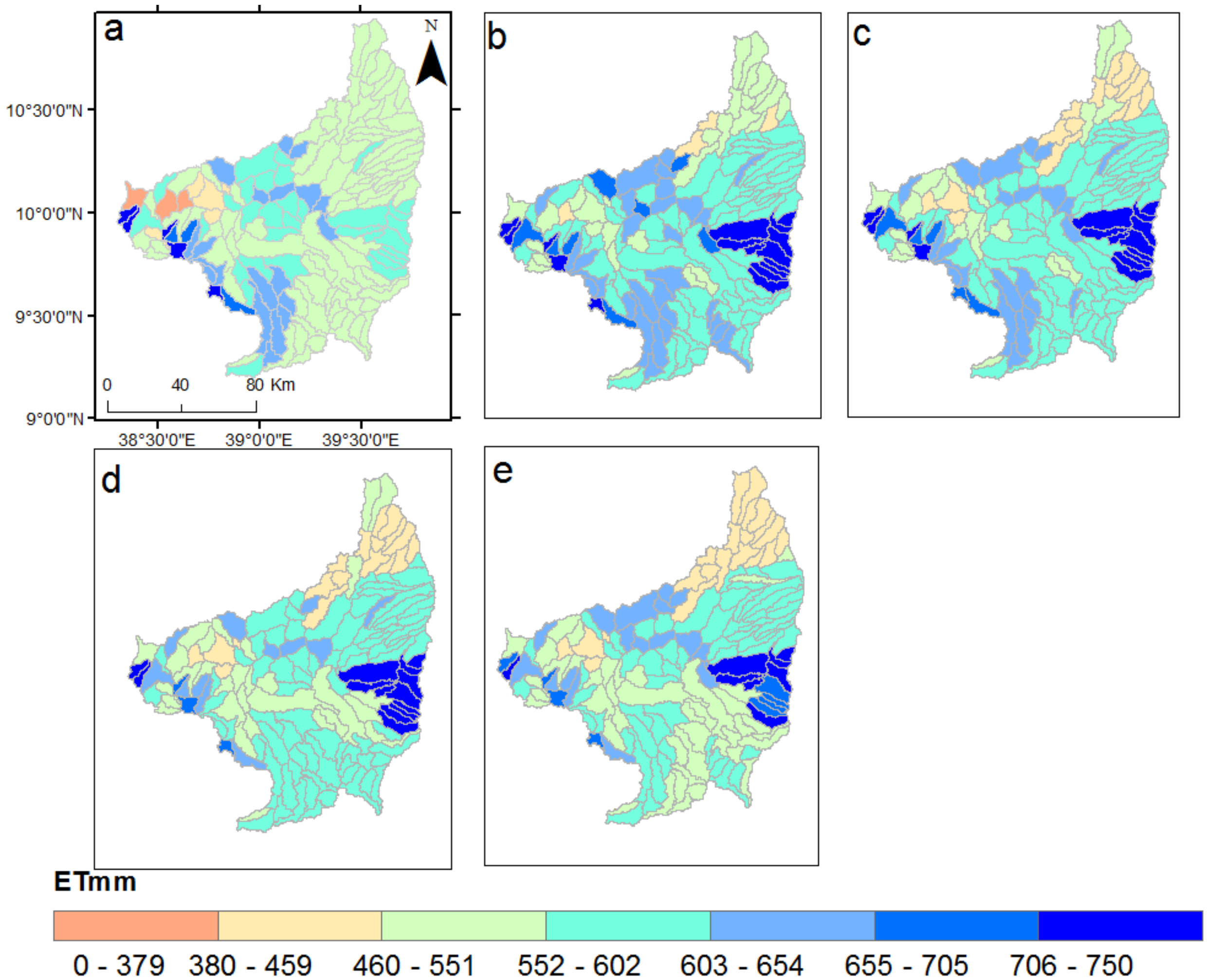

Figure 7.8 Mean annual actual evapotranspiration (ETmm) of baseline and future climate scenarios in each sub-basin of the Jemma basin. a) Baseline climate (1981-2014), b) RCP4.5 (2021-2050) climate scenario, c) RCP8.5 (2021-2050) climate scenario, d) RCP4.5 (2071-2100) climate scenario and e) RCP8.5 (2071-2100)climate scenario. The scenarios were developed based on the ensemble mean of six RCMs.

The total water yield may decrease in the coming century due to the impact of future climate change. The magnitude and spatial pattern of change in water yield was similar to the impact on surface runoff (Table 7.4). The largest reduction of water yield (-58%) was observed in the near-term ensemble mean of RCP8.5, where the highest reduction of rainfall and surface runoff was projected (Figure 7.9). Higher water yield is projected in the long-term ensemble of RCP8.5 than other future climate scenarios primarily due to the higher projected rainfall and surface runoff in this climate scenario (Table 7.4). Seasonally, the highest reduction of water yield was observed in the main rainy season (Table 7.5). The reduction of total water yield may cause rampant impacts on the agriculture, domestic and livestock water supply and other ecosystem services in the Jemma basin. The northern and the southern parts of the basin will be characterized by lower water yield than other areas of the basin (Figure 7.9). The northern areas of the basin are also characterized by low water yield under the baseline climate scenario and in these areas, low surface runoff is projected.

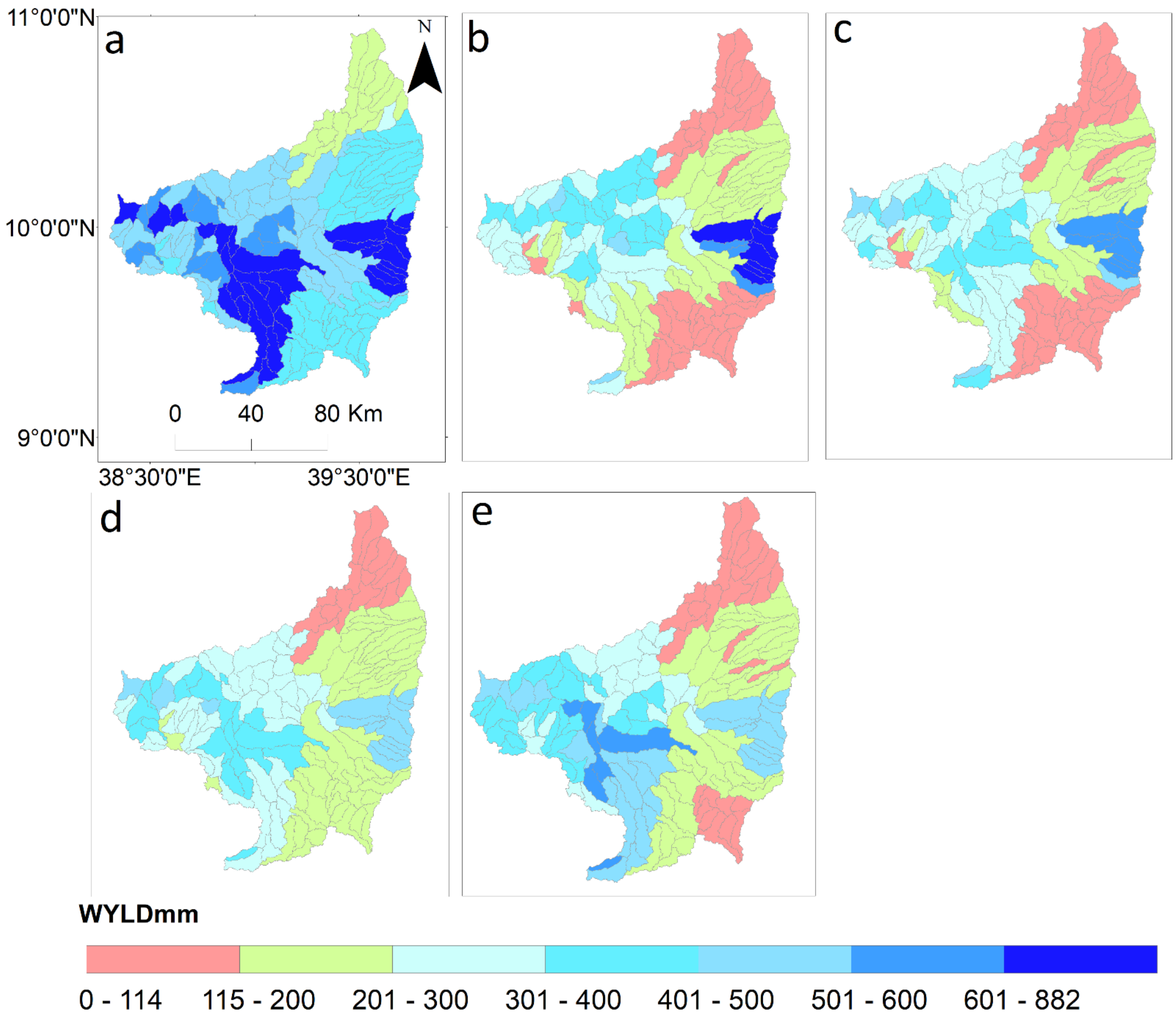

Figure 7.9. Mean annual water yield (WYLDmm) of baseline and future climate scenarios in each sub-basin of the Jemma basin. a) Baseline climate (1981-2014), b) RCP4.5 (2021-2050) climate scenario, c) RCP8.5 (2021-2050) climate scenario, d) RCP4.5 (2071-2100) climate scenario and e) RCP8.5 (2071-2100) climate scenario. The scenarios were developed based on the ensemble mean of six RCMs.

Groundwater is another water balance component which will be affected by anticipated climate change. In this study, there will be a higher drop of groundwater under climate scenario of RCP4.5 (2071-2100) (Figure 7.10d). This could be due to high loss of water through evapotranspiration in this climate scenario in which higher evapotranspiration is projected than other climate scenarios. Different from surface runoff and total water yield, there is no sharp decline of groundwater in September to November, the maximum groundwater flow is during September (Figure 7.10d). The monthly hydrography of the groundwater flow also indicates there is one-month lag-time between surface runoff and groundwater flow (Figure 7.10a and 7.10d).

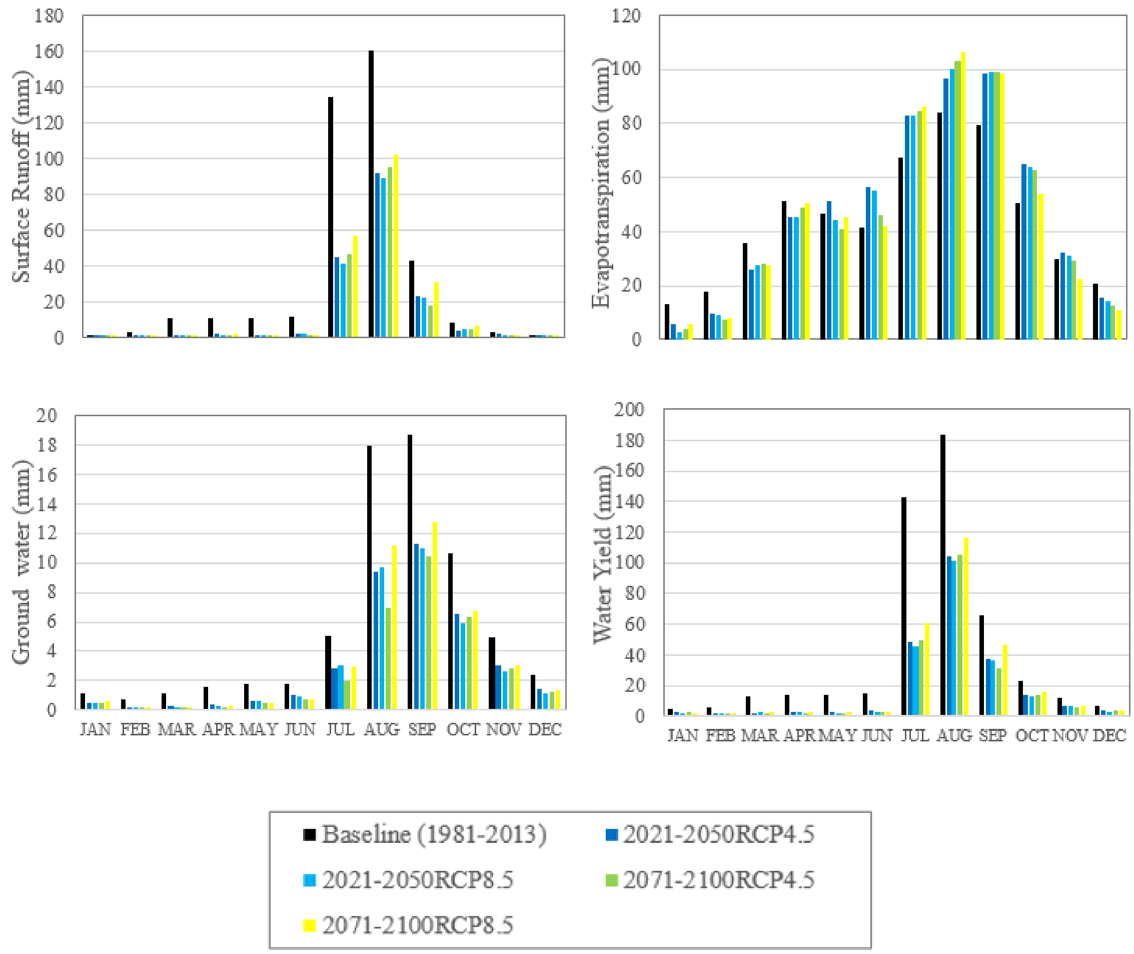

Figure 7.10 Mean monthly values of hydrologic components for baseline, near term (2021-2050) and long-term (2071-2100) climate scenarios under RCP4.5 and RCP8.5 emission scenarios. The scenarios were developed based on the ensemble mean of six RCMs. And values are mean of all sub-basins.

Seasonally, a reduction of surface runoff, groundwater discharge and water yield is estimated in all seasons under future climate scenarios. However, the magnitude of change is different among seasons. High volumetric reduction is estimated in the summer season, while high percentage reduction of surface runoff, groundwater discharge and water yield are estimated in spring (March-May) followed by winter

(December - February) seasons than summer season under future climate scenarios (Table 7.5). This indicates dry seasons will be more water constrained in the future climate condition. When we see the volumetric change, there will be more reduction of water availability during the summer season than other months. Even though, persistent increase in autumn season rainfall is projected under future climate scenarios, this season is among the seasons showed higher subsidence of water availability.

In contrast to surface runoff, groundwater and water yield, the future climate will be characterized by an increase and more loss of water through evapotranspiration during different seasons. This might be attributed to an increase in temperature in the future climate scenarios. The increase in evapotranspiration alone could trigger the basin to become more water constrained, which is the case for the Blue Nile Basin (Elshamy et al., 2009). Lower loss of water through evapotranspiration is estimated in spring and winter seasons under future climate scenarios than the baseline scenario. This might be due to the reduction of water available for evapotranspiration in the spring and winter seasons (Table 7.5).

Table 7.5 Mean seasonal hydrologic components under baseline and future climate scenarios. The outputs of the water balance components were estimated for an ensemble mean of RCMs under RCP4.5 and RCP8.5 emission scenarios. The scenarios were developed based on the ensemble mean of six RCMs. The values are mean of all sub-basins.

	Baseline (1981– 2014)	Near-term 2021-2050 (RCP4.5)	Near-term 2021-2050 (RCP8.5)	Long-term 2071-2100 (RCP4.5)	Long-term 2071-2100 (RCP8.5)
ET(mm)					
Summer (June – September)	271.83	333.89(23%)	337.01(24%)	332.26(22%)	332.48(22.3%)
Spring (March-May)	133.86	122.29(-9%)	116.76(-13%)	117.43(-12%)	123.90(-7.4%)
Winter(December–February)	51.32	30(-41%)	26.20(-49%)	23.64(-54%)	24.34(-53%)
SURQ (mm)					
Summer (June – September)	362.49	172.86(-54%)	166.26(-56%)	172.24(-54.3%)	203.52(-45%)
Spring (March-May)	37.53	8.69(-89%)	8.98(-88%)	7.90(-91%)	9.69(-86%)
Winter(December–February)	8.49	3.28(-77%)	3.99(-82%)	4.53(-72%)	4.68(-69%)
GWQ (mm)					
Summer (June – September)	43.50	24.54 (-44%)	24.69 (-43%)	20.16 (-54%)	27.52 (-37%)
Spring (March-May)	4.44	1.24 (-72%)	1.18 (-73%)	0.88 (-80%)	0.97 (-78%)
Winter(December–February)	4.22 ()	2.18 (-48%)	1.82 (-57%)	1.97 (-53%)	2.15 (-49%)
WYLD (mm)					
Summer (June – September)	406.76	194(-52%)	186.11(-54%)	188.72(-54%)	226.36(-44%)
Spring (March-May)	41.69	7.62(-82%)	7.39(-82.3%)	6.15(-85%)	7.96(-81%)
Winter(December–February)	17.35	8.41(-52%)	7.07(-59%)	7.84(-55%)	8.45(-51%)

The repercussion of climate change on water balance components was also investigated using the bias corrected output of CCLM4(MPI-ESM-LR), which has shown better performance in capturing the rainfall and temperature of the historical (1981-2005) period. A concomitant change on hydrologic balance components is estimated using the output of CCLM4(MPI-ESM-LR) and ensemble mean of RCMs. However, lower subsidence of surface runoff, water yield and groundwater flow is estimated using CCLM4(MPI-ESM-LR) model than the ensemble mean of RCMs. For instance, a decrease of surface runoff by 47%, 51%, 54% and 53% was estimated using CCLM4(MPI-ESM-LR) model under, 2021-2050

(RCP4.5), 2021-2050 (RCP8.5), 2071-2100 (RCP4.5) and 2071-2100 (RCP8.5) climate scenarios respectively (Table 7.6). Correspondingly, a decrease of surface runoff by 57%, 58%, 57% and 48% was projected using the ensemble mean of RCMs under, 2021-2050 (RCP4.5), 2021-2050 (RCP8.5), 2071-2100 (RCP4.5) and 2071-2100 (RCP8.5) climate scenarios respectively (Table 7.4). In general, a comparable signal of change on rainfall, evapotranspiration, total water yield and groundwater was estimated using the output of ensemble mean of RCMs and CCLM4(MPI-ESM-LR) model.

Table 7.6 Mean annual water balance components under baseline and future climate scenarios. The changes in the water balance components were estimated for CCLM4(MPI-ESM-LR) model under RCP4.5 and RCP8.5 emission scenarios. The values are area-weighted across the Jemma basin. The values are mean of all sub-basins.

	Baseline (1981– 2014)	**2021-2050 (RCP4.5)**	**2021-2050 (RCP8.5)**	**2071-2100 (RCP4.5)**	**2071-2100 (RCP8.5)**
Rainfall (mm yr^{-1})	1039	828 (-18%)	808(-20%)	782(-22%)	804 (-20%)
ET(mm yr^{-1})	537.30	567.42 (7%)	561(4.4%)	559(4%)	558(4%)
SURQ (mm yr^{-1})	419.33	232.46(-47%)	213.67(-51%)	201.84(-54%)	206.34(-53%)
GWQ (mm yr^{-1})	67.81	39.82(-41%)	37.68(-44%)	35.35(-48%)	36.25(-46%)
LATQ(mm yr^{-1})	15.59	11.24(-28%)	9.45(-39%)	8.78(-44%)	9.47(-39%)
WYLD (mmyr^{-1})	501.01	265.53(-47%)	250.8(50%)	235.97(-53%)	242.06(-52%)
PERC(mmyr^{-1})	86.12	58.373(-32%)	51.62(-40%)	47.66(-45%)	50.36(-41%)

In the Upper Blue Nile Basin, there are different studies which project the negative and positive impact of climate change on the water resource base of the basin. For instance, in Tana sub-basin of Upper Blue Nile basin, a reduction in surface runoff and an increase in evapotranspiration is also projected using the output of 15 GCMs and SWAT hydrologic model (Setegn et al., 2011). Worqlul et al., 2018 also project a reduction of average streamflow and an increase of evapotranspiration in the Beles basin of the Upper Blue Nile Basin. In polarity, an increment of streamflow is projected using the output of single GCM (HadCM3) and SWAT hydrological model in the Upper Gilgel Abay Catchment of Blue Nile basin (Adem et al., 2016). Even with and without a change on rainfall, an increase in temperature and potential evapotranspiration lead reduced wet season runoff and the Upper Blue Nile Basin may become more moisture constrained in the future (Elshamy et al., 2009). In Jemma basin and other studies particular to Upper Blue Nile Basin (Elshamy et al., 2009; Setegn et al., 2011; Liersch et al., 2016; Worqlul et al., 2018), a consistent increase in temperature is projected and this could intensify a decline in water availability through evapotranspiration.

7.4 Conclusion

Since rainfall is the main source of the total water yield and surface runoff in the Jemma basin (Hurni et al., 2005; Gebrehiwot and Ilstedt, 2011), a change in climate will triggers a direct impact on the hydrology of the basin. This study quantified the impact of climate change on the hydrologic balance components of the Jemma basin using the SWAT model. Multi-site calibration and validation of the model reproduced the baseline hydrological conditions of the basin very well. The sensitivity analysis showed that the hydrologic processes are highly sensitive to surface water processes. A strong relationship was found among rainfall, surface runoff and total water yield both spatially and seasonally.

A decrease in rainfall and an increase in temperature and evapotranspiration may cause a diminish in surface runoff and water yield under different future climate impact scenarios. The highest decrease in water yield may be observed during the rainy season (June – September) suggesting that the rainfed agricultural production will be severely impacted. This rainy season is the main agricultural cultivation season, as a result, a decline on rainfall and water yield could decrease crops growing season, soil water availability for crops, crops productivity and water availability to livestock and other domestic uses.

Climate change and its hydrologic impact in the Jemma basin prompts to implement sustainable surface water resource management strategies. To avert future climate change impact on the basin, surface runoff management alternatives would be essential to maintain water availability, since surface runoff contributes a large proportion to the total water yield. To develop surface water resource management strategies, the projected climate scenarios and the simulated impacts of climate change are to be incorporated in the adaptation decisions analysis. Such strategies may provide optimal benefits in maintaining the water resources availability and to mitigate and adapt the adverse impacts of climate conditions and thereby maintain or even enhance agricultural production. However, a detailed study is warranted to ascertain water management technologies that suit different climate conditions and the biophysical and socio-economic conditions in the Jemma basin.

Chapter 8

Prioritization of Optimal Watershed Management Alternatives under Climate Change Scenarios in the Jemma sub-basin, Upper Blue Nile Basin

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Abstract

This study identifies watershed management strategies that can ensure optimal climate change adaptation benefits under different climate and climate impact scenarios in the Jemma sub-basin of the Upper Blue Nile basin. The analysis applied multi-criteria decision analysis and hydrologic modelling. The climate scenarios were developed using the statistically bias-corrected, multi-model ensemble mean under the Representative Concentration Pathways 4.5 and 8.5 (RCP 4.5 and RCP 8.5) emission scenarios. The hydrological impact of the climate change was assessed using a multi-site calibrated and validated hydrologic model, Soil and Water Assessment Tool (SWAT). The observed terrace and other physical soil and water management structures were also identified using Google Earth Image, 2016 and field survey. The best watershed management strategies were discerned using a multi-criteria decision analysis that intercompared eight watershed management alternatives under seven watershed management criteria through the Analytic Hierarchy Process (AHP). The findings revealed a consistent decline of rainfall, surface runoff and total water yield under all climate scenarios and climate impact scenarios. Water harvesting structures were the most prioritized watershed management alternatives to adapt the changing climate. More than half of the watersheds of the Jemma sub-basin are highly and optimally suitable for in-situ water harvesting in the baseline and future climate scenarios. Observed terrace and in-situ water

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This chapter is based on **Worku, G., Teferi, E., Bantider, A. and Dile, Y. 2019. Prioritization of Watershed Management Scenarios under Climate Change in the Jemma sub-basin, Upper Blue Nile Basin.** ***Journal of Hydrology: Regional Studies, Accepted.***

harvesting structures significantly ($p<0.05$) reduced surface runoff and thereby significantly increase soil water retention both in the baseline and future climate scenarios. Ex-situ water harvesting structures significantly reduce surface runoff under some climate scenarios, and no significant change in soil water is estimated. Filter strips trigger no significant change in surface runoff and soil water under any climate scenario. However, both in-situ and ex-situ water harvesting structures and filter strips caused an insignificant change in the total water yield under the baseline and future climate scenarios. Based on the findings, we conclude that implementing in-situ water harvesting structures increase green water storage that can further increase agricultural production and improve livelihood without a decline in blue water and environmental flow under baseline and future climate scenarios.

Keywords; climate change, watershed management scenarios, multi-criteria decision analysis, Jemma sub-basin, Blue Nile Basin

8.1 Introduction

Contemporary water management practices are not up to the challenges of the plausible climate change in several regions of the world (Snover et al., 2003; Bates et al, 2008; WMO, 2009). As a result, there is a strong consensus that water resources management decisions should consider climate change information (IPCC, 2007; Bates et al, 2008; Yang et al., 2012). However, in several regions of the world, existing climate adaptation strategies were developed based on historical hydro-climatic data, which has a narrow margin to buffer future climate change impacts (WMO, 2009). Different climate change adaptation strategies that consider future climate change scenarios are essential to adapt a wide range of climate change conditions (IPCC, 2007; Hallegatte, 2009). Therefore, an array of robust climate adaptation options are required to reduce future climate change and climate extreme impacts.

Furthermore, designing water management systems that can cope with climate change impacts is challenging due to uncertainties in climate change projections (Yang et al., 2012; Kundzewicz et al., 2018). The uncertainties can stem from assumptions in the future socio-economic development scenarios and associated greenhouse gas emission scenarios, the conceptualization of the GCMs and downscaling methods (IPCC, 2013; Kundzewicz et al., 2018). The uncertainties in climate models curtail from directly using the outputs of climate models to develop adaptation strategies (Hallegatte, 2009). To address uncertainties, the ensemble of several climate model outputs generated using multiple climate scenarios has been recommended (Snover et al., 2003; Yang et al., 2012). Further, climate scenarios with low uncertainty are essential to develop robust climate adaptation strategies that can provide optimal benefits of reducing the impacts of future climate change (IPCC, 2007; Kuikman et al., 2009; Haque, 2016).

Besides the uncertainty in the science of climate change, developing a robust climate change adaption policy is also influenced by the trade-offs between environmental and economic objectives (Chung and Lee, 2016). Therefore, climate change adaptation decisions should balance the societal, technological and institutional responses to ensure long-term sustainability (USAID, 2013). Consequently, relevant stakeholders at all levels should be involved to ensure policies that transcend generations (Haque, 2016). To this end, decision support systems will play a critical role to inform a balanced accounting of environment and economic factors. Multi-Criteria Decision Analysis (MCDA) systems have been considered as critical approaches to develop climate change adaptation strategies that can incorporate economic, environmental and social factors so as to ensure optimal benefits (IPCC, 2007; Kuikman et al., 2009; Haque, 2016). Multi-criteria decision systems enable comparing different but competing criteria and selecting the best alternatives (Malczewski, 2006). The Ethiopian National Adaptation Programmes of Action (NAPAs) has used the MCDA to identify and prioritize the national climate change adaptation strategies (NMA, 2007).

In Ethiopia, the community-based watershed development guideline was developed in 2005 (Desta et al., 2005) having appropriate site selection and implementation of watershed management technologies as its main objectives. The guideline considered observed climatic conditions, especially rainfall as its main criteria, however, it fails to recognize a potential change in the climate. It is recognized that climate change affects the potential of existing water resources management structures and less likely to be effective under future climate conditions (Hallegatte, 2009). There are also mounting evidence which revealed climate change may impact water quantity, soil erosion and nutrient loading and also may amplify water variability (IPCC 2013). To reduce such climate change impacts, water resources and watershed management are among the priority areas of adaptation (IPCC, 2007; Bates et al, 2008; IPCC, 2013). Therefore, watershed management planning should account climate change to design resilient adaptation and mitigation measures under the scrutiny of different criteria.

In the upper Blue Nile Basin, there are studies that use multi-criteria analysis in natural resources management and other socio-economic planning. For instance, Amdihun et al. (2014) has used GIS-based multi-criteria analysis to evaluate the effectiveness of soil and water conservation technologies based on different biophysical criteria in the Blue Nile Basin and reported that the efficiency of existing soil and water management structures is not comparable to socio-economic and environmental challenges. Dile et al. (2016) has also applied GIS-based multi-criteria analysis to identify suitable sites for water harvesting that further build resilience against climatic shocks in Upper Blue Nile Basin under historical climate condition. Different from the previous studies, the current study considered different climate scenarios, climate impact scenarios, existing biophysical settings and the perspectives of the stakeholders to identify watershed management alternatives under changing climate conditions in the watersheds of the Jemma sub-basin.

An increase in rainfall and temperature extremes, which could exacerbate the repercussion of climate change on water resources and agricultural systems is reported in the Jemma sub-basin of the Upper Blue Nile Basin (Worku et al., 2018a). The sub-basin may experience a decrease in mean annual rainfall in different future climate change scenarios (Worku et al., 2019). Therefore, it is worthwhile to devise watershed management technologies that sustain water resources availability in the face of climate change in the watersheds of the Jemma sub-basin. In fact, through the "food for work" program different watershed management interventions such as *Fanya Juu,* cutoff drains, stone and soil bunds and afforestation have been implemented since the 1970s (Hurni, 1985; Herweg and Ludi, 1999). However, watershed management structures were implemented on only about 42% of the watersheds of the Jemma sub-basin up until 2016 (Google Earth, 2016), whilst huge and optimal soil and water management investment is essential.

Moreover, watershed management technologies that could provide optimal adaptation benefits and their areas of suitability were not identified. The objective of this study is to develop watershed management alternatives to adapt the impacts of climate change and to evaluate their effectiveness under different climate scenarios in the watersheds of the Jemma sub-basin. Consequently, the study straddles climate scenarios, hydrological climate change impact assessment, biophysical settings and stakeholders view through GIS-based MCDA to develop watershed management planning in the face of climate change. The outputs from climate and hydrological models were used in the MCDA to prioritize watershed management alternative in each watershed of the Jemma sub-basin.

The methodological framework and the findings of this study will underpin climate change adaptation programs in the watersheds and river basins of Ethiopia. In Ethiopia's National Adaptation Plan (FDRE, 2019) and the water and energy sector of Climate Resilience Strategy of Ethiopia (FDRE: MoWIE, 2015), watershed and water management are the among the prioritized strategies to build climate change resilience. However, an insufficient link between climate information and climate adaptation strategies are realized to reduce climate change impacts in Ethiopia (World Bank, 2006; Conway and Schipper, 2011). Thus, this study will help the national climate adaptation plans of Ethiopia to identify optimal watersheds-based climate adaptation alternatives through integrating climate scenarios, hydrological climate change impact assessment, biophysical settings and stakeholders' perspectives in the wake of climate change. This study also recommends watershed development policies and programs in Ethiopia should thoroughly use robust climate change scenarios and realize climate-sensitive watershed planning.

8.2 Data and Methodology

8.2.1 Framework of the study

This study integrates climate scenarios, climate impact scenarios (hydrological climate impact assessment), biophysical settings and stakeholders' perspectives to prioritize optimal watersheds based adaptation alternatives that could reduce the anticipated impact of climate change. As a result, baseline climate scenarios, future climate scenarios and hydrological climate impact scenarios were developed. Subsequently, GIS-based multi-criteria decision analysis was used to bridge spatial data such as climate and hydrological models output with non-spatial data such as stakeholders' perspectives (Malczewski, 2006). The hydrological model was also used to evaluate the effectiveness of prioritize watershed management alternatives. Figure 8.1 presents the integration of climate change scenarios, climate impact scenarios, biophysical factors and the multi-criteria decision analysis to develop optimal watersheds-based adaptation decision making.

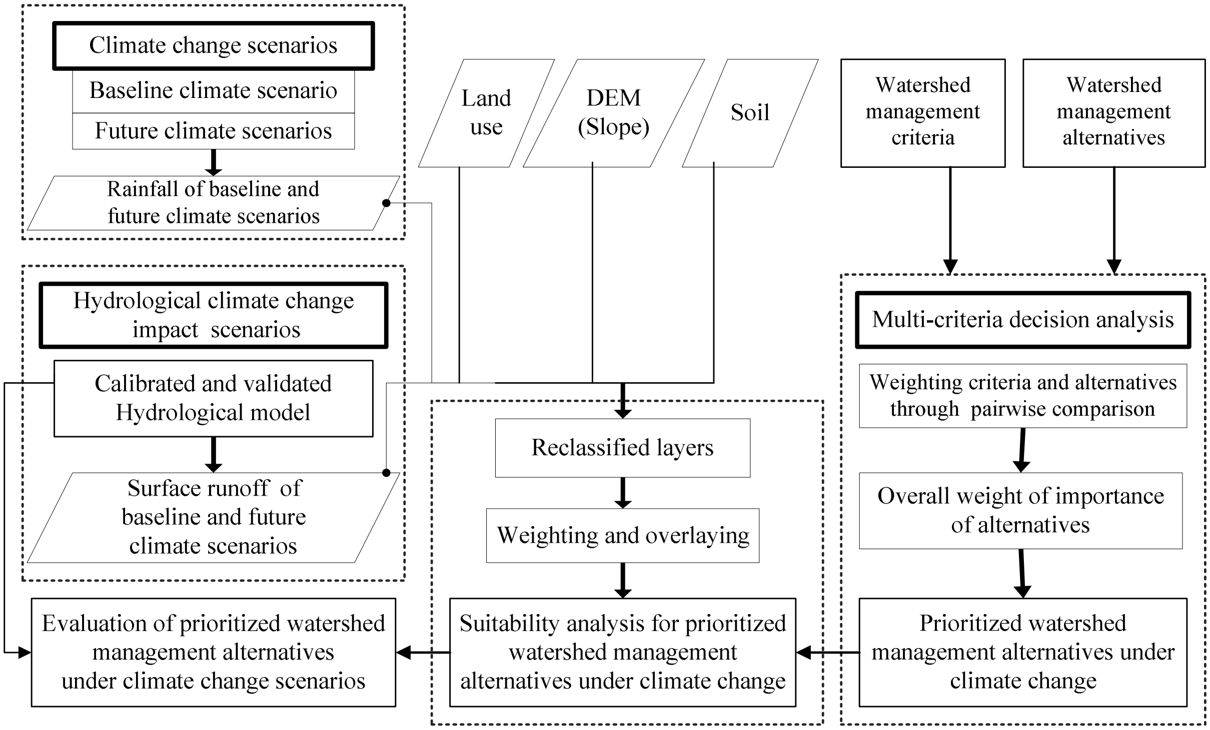

Figure 8.1 Analytical framework of the study. The square dot boxes comprise the main processes of the study and the parallelograms are the input layers to the GIS based multi-criteria decision analysis.

8.2.2 Observed climate and hydrological data

Observed climate data was required to establish baseline climate scenarios, future climate scenarios and hydrological climate impact scenarios. Thus, observed (1981-2014) data of daily rainfall, TMAX, TMIN, solar radiation, sunshine, wind speed and relative humidity of nine climatic stations of the Jemma basin were obtained from the Ethiopian National Meteorological Services Agency. Daily streamflow data of gauge stations was obtained from Ethiopian Ministry of Water, Irrigation and Electricity. The hydrologic data was used to calibrate and validate the hydrological model and to develop baseline hydrologic balance components.

8.2.3 Regional climate models data

Historical (1981-2005) and future (2021-2100) RCM simulations driven by four CMIP5 GCMs were used in this study. The CMIP5 GCMs which were used as initial boundary conditions were CNRM-CM5, EC-EARTH, HadGEM2-ES and MPI-ESM-LR. Whilst, the RCMs which were used to regionalize these GCMs are the CCLM4 (COnsortium for Small-scale MOdeling (COSMO) Climate Limited-Area Model (CCLM) version 4.8) and REMO (Max Planck Institute Regional Model). RCM simulations driven through the Representative Concentration Pathways 8.5 (RCP8.5) and RCP 4.5 (Moss et al., 2010) were considered. Detail on RCMs selection is given in Worku et al., 2018b.

8.2.4 Biophysical data

The spatial data which include slope, soil texture and land use data were acquired from different sources (Figure 8.2). Slope map was generated from 30m resolution Digital Elevation Model (DEM) which was obtained from the Shuttle Radar Topographic Mission (SRTM). The land use map for the year 2008 was derived from Landsat satellite imagery. Supervised image classification using maximum likelihood algorithm was performed to develop the land use map. The soil data which include soil texture and other physical and chemical properties of soil was obtained from the Ministry of Water, Irrigation and Electricity of Ethiopian and Water and land resources Center of Ethiopia (WLRC, 2016). All the spatial data were projected into the projection parameters for Ethiopia, which is UTM Zone of WGS 1984, 37N.

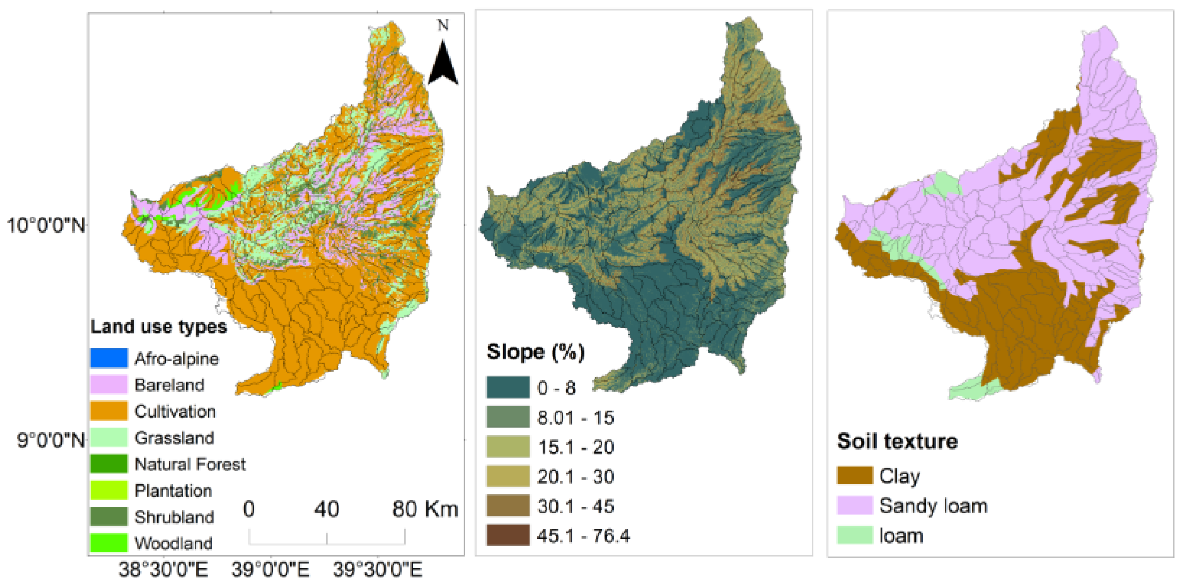

Figure 8.2 Biophysical factors used to assess the suitability of a land for prioritized watershed management alternatives in the Jemma sub-basin.

8.2.5 Land and water management data

Land and water management structures such as terraces and other physical soil and water management structures that were implemented in the watersheds of the Jemma sub-basin since the 1980s were identified through Google Earth satellite images and field surveys (Figure 8.3 and Figure 8.4). Particularly, Google Earth Image, 2016 was used to map observed soil and water management structures in the watersheds. Besides, field observations were made to identify soil and water management structures in different areas of the sub-basin. Using google earth image of 2016, terrace and other physical soil and water management structures were observed on 6,562 km^2 (42.71%) land of the sub-basin. Land and water management was largely implemented on slopes >18% and in the elevation classes range from1040m to 2360m (Figure 8.3).

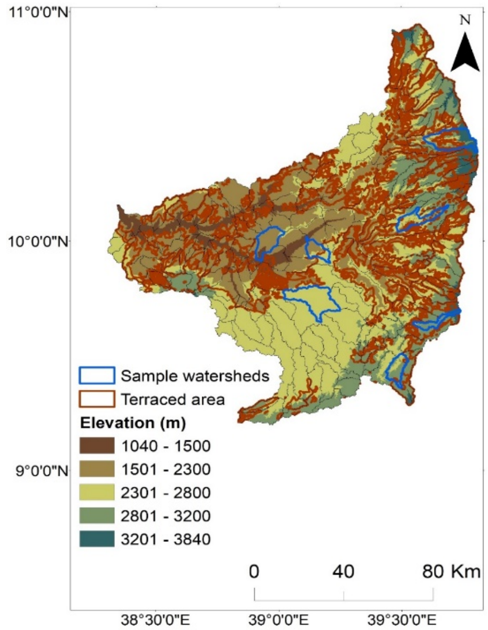

Figure 8.3 Terraces coverage and sample watersheds in the Jemma sub-basin.

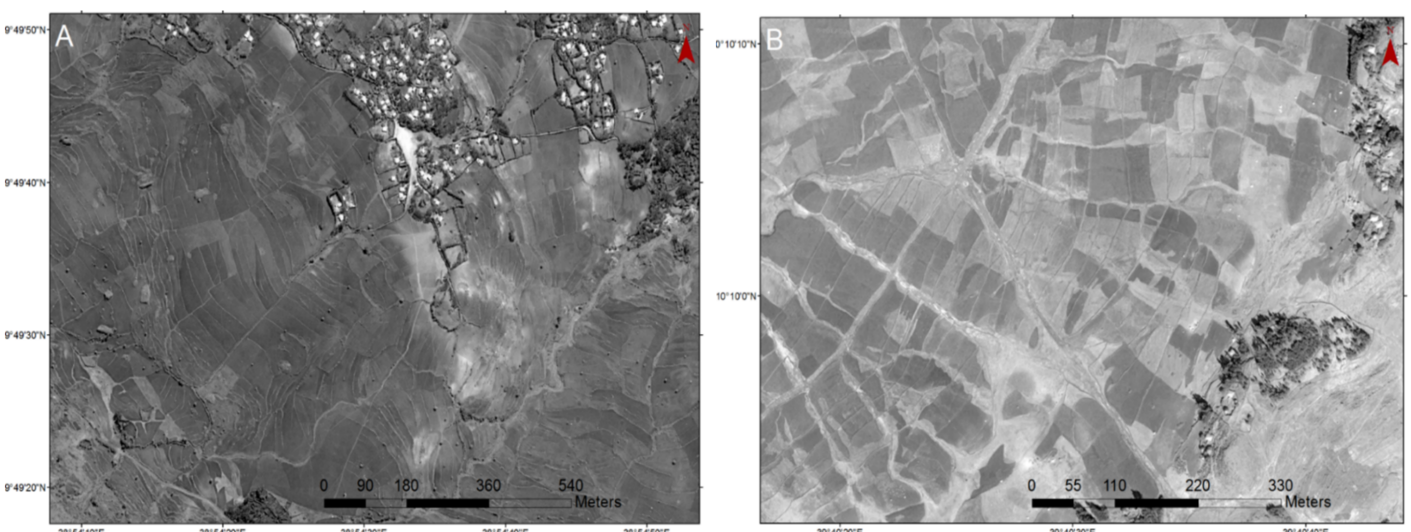

Figure 8.4 Google Earth satellite images, 2016 showing terraces implemented in the watersheds located A) lower stream and B) upstream watersheds of the Jemma sub-basin. Soil bunds, *fanya juu*, micro-basins and trenches were also observed on cultivated lands, grazing lands and degraded lands through field observations.

8.2.6 Qualitative data

Qualitative data was collected through interviews and focused group discussions with farmers and natural resources and watershed management experts. Seven sample watersheds were selected to cover all elevation classes of the sub-basin (Figure 8.3). In these sample watersheds, 56 farmers were interviewed (8 from each watershed), however, two questionnaires were not complete. Besides, focused group discussions (6 farmers at each focused group discussion) were also conducted with farmers at five of the watersheds of the sub-basin. During interview and focused group discussion, farmers were requested to list watershed management alternatives that could provide optimal benefits of climate change adaptation, particularly climate change characterized by a reduction of rainfall and water availability. Interview was also conducted with 13, 5 and 12 natural resources and watershed management experts at *woreda, zonal* and federal offices, respectively. The experts were requested to list and prioritize the criteria and alternatives of watershed management for climate change adaptation.

8.2.7 Climate change scenarios

The study used the period 1981-2014 as a baseline scenario to assess the change in climate. To develop future climate scenarios, RCM simulations that better reproduce the historical climate of the Jemma sub-basin were used (Worku et al., 2018b). RCM simulations were further adjusted using a robust bias correction technique. For this, different statistical bias correction methods were intercompared using different metrics. The distribution mapping method was superior to other techniques to adjust mean values, intensity and frequency of RCM simulations with observed counterparts (Worku et al., 2019). Consequently, RCM simulations bias adjusted using distribution mapping technique were used to develop climate change scenarios for the near-term future (2021-2050) and long-term future (2071-2100). To execute different statistical bias correction techniques, this study has used the qmap package which is built-in R statistical software (Gudmundsson, 2015) and CMhyd tool (Rathjens et al., 2016).

8.2.8 Hydrological climate impact scenarios

To develop climate impact scenarios, the hydrological model i.e the Soil and Water Assessment Tool (SWAT) model was used. Based on slope, land use and soil, the SWAT model discretizes the Jemma sub-basin into Hydrological Response Units (HRUs). The Soil Conservation Service (SCS) Curve Number method and the Penman-Monteith method were used to estimate surface runoff potential evapotranspiration (PET), respectively. The SWAT model was calibrated and validated using multi-site calibration and validation approach (Cao et al., 2006) on SUFI-2 in SWAT-CUP (Abbaspour et al, 2004).

The performance of the model during calibration and validation was evaluated using Nash and Sutcliffe simulation efficiency (NSE) and percent Bias (PBIAS) (Moriasi et al., 2015). The uncertainty of model simulation was also evaluated using P-factor and the r-factor on the SUFI-2 algorithm (Abbaspour et al, 2004). Eventually, the calibrated SWAT model was used to simulate hydrological processes under baseline and different future climate scenarios. Detail of hydrological climate change impact assessment is given in Worku et al., under review.

8.2.9 Multi-criteria Decision Analysis Technique and Procedures

8.2.9.1 Define the Problem and the Stakeholders

Climate change scenarios at the Jemma sub-basin revealed a reduction of rainfall in the near and long-term future (Worku et al., 2019). This indicates that climate change will be a major factor to the agriculture and water-related sectors. Such findings suggest that watershed management interventions need to be implemented to address the likely water shortage that may occur due to climate change. In this study, farmers and experts (at woreda, zonal and federal level) were the main stakeholders and involved to identify and prioritize criteria and watershed management alternatives in the wake of climate change.

8.2.9.2 Defining and weighting Criteria

Criteria to prioritize watershed management alternatives under climate change were identified through interviews with experts. Besides, the National Climate Adaptation Action Plan of Ethiopia (NMA, 2007) was also used to identify criteria. We conducted interviews with 30 watershed management and natural resource officers at woreda, zonal and national levels. Such a process helped to identify the most critical criteria and assign weight for each criterion.

The Analytic Hierarchy Process (AHP) was used to estimate the weights of the criteria. AHP is a structured multi-criteria decision analysis technique that is used to estimate the weight of different but competing criteria (Saaty, 1990). It uses a matrix of pairwise comparisons to assign a weight for each criterion and determine the relative importance of two or more criteria. As such, AHP creates a hierarchical structure of the criteria and it tests whether the pairwise comparisons are consistent or not using a Consistency Ratio (CR) (Saaty, 1994). The CR was calculated as:

$$CR = CI/RI$$

Where CI is the Consistency Index which is expressed as:

$$CI = ((\lambda\text{max} - n)/(n - 1))$$

Where λ_{max} the maximum eigenvalue of the matrix and n is the order of the criteria. RI is the random index which is the randomly generated index of the matrix (Saaty, 1994). If the CR is 0.1 (10%) or less, the criteria weighting is considered reasonable otherwise it is considered less consistent and requires a revision of criteria analysis (Saaty, 1990).

8.2.9.3 Defining and weighting watershed management alternatives

Watershed management alternatives under climate conditions characterized by a reduction in rainfall and water availability were listed out through interviews and focused group discussions with farmers and experts. Besides, the Community Based Participatory Watershed Management Guideline (Desta et al., 2005) of Ethiopia was also used to identify potential watershed management alternatives. Based on these approaches, eight watershed management alternatives (Table 8.1) were found relevant for climate change adaptation in the Jemma watershed. Further, experts' opinion was used to intercompare and prioritize the most important alternatives through pairwise comparison matrix.

Watershed management alternatives under each criterion were also compared and weight was assigned for each alternative using AHP. By comparing eight alternatives under seven criteria, the overall priority of alternative (P_i) was estimated as the weight of criterion multiplied by the weight of the alternative under each criterion.

The P_i of alternative A_i is calculated as;

$$P_i = \sum_{j=1}^{N} a_{ij} W_j$$

Where a_{ij} is the weight of alternative *i* with respect to criterion *j*, and W_j is the weight of criterion *j* (Saaty, 1990).

Table 8.1 Description of watershed management alternatives

No.	Alternatives	Description
1	Physical & biological soil and water management	These include different physical structures such as terraces, soil and stone bunds, check dams and *Fanya Juu* and biological structures such as vegetative strips, afforestation, mulching minimum or zero tillage, etc mainly to reduce soil erosion
2	Crop change	This include changes from annual to perennial crops, from one cereal to another cereal or introducing cash crops
3	Water harvesting structures	Include different in-situ and ex-situ structures like micro basins (Zaï), terraces/trenches/bunds, percolation pits, ponds and farm catchment water harvesting
4	Land use change	Changes like from grazing land to cropland, forest land to cropland, cropland to Eucalyptus land, expand irrigation, or from agricultural land to other land use types.
5	Reclaim degraded lands	This represents rehabilitation of degraded lands through micro-basins, plantation, introducing cash crops and others.
6	Introduce new crop varieties	Introduce early mature crops and crops with high production
7	Area closure	Closure mostly degraded hillsides and large gully networks and incorporate different water harvesting structures
8	Agroforestry and biological measures	Include alley cropping, grass strip, trees with croplands and grazing lands, orchards

8.2.10 Suitability Analysis using Weighted Overlay Analysis

After identifying and prioritizing watershed management alternatives, suitability analysis was performed to identify a suitable spatial implementation of prioritized watershed management alternatives using GIS-based weighted overlay analysis (Malczewski, 2000). In the multi-criteria decision analysis, water harvesting structures were prioritized followed by physical and biological soil and water management structures. According to FAO (2003) guideline, climate, hydrology, topography, agronomy and soil are the most important criteria to identify suitable sites for water harvesting structures. Therefore, rainfall and surface runoff outputs of climate scenarios and hydrological climate impact scenarios were used as factors to the suitability analysis. All input layers which include rainfall, surface runoff, land use, slope and soil texture were reclassified into five suitability classes (suitability score) before overlaying these layers (Table 1 and 2). The suitability score of in-situ and ex-situ water harvesting structures were developed based on literature (Desta et al, 2005; Mati, 2007; Dile et al., 2016; Hurni et al., 2016).

Table 8.2 Suitability classes for in-situ water harvesting structures

No.		Suitability score (xi)				
		Not Suitable (1)	**Marginally suitable (2)**	**Moderately suitable (3)**	**Highly suitable (4)**	**Optimally suitable (5)**
1	Rainfall(mm/year)	<200	>1200	201-500	901-1200	501-900
2	Slope (%)	>61	31-60	0-7	16-30	8-15
3	Soil texture	NA	NA	Loam sandy	Clay	Loam
4	Surface runoff(mm/year)	<50	50-150	151-250	251-350	>350
5	Land use	Waterbody, Settlement, swampy	woodland, forest, afro-alpine, plantation	Grazing land, shrubland, bare land	NA	Cultivated land

Table 8.3 Suitability classes for ex-situ water harvesting structures

Criteria	Suitability score (xi)				
	Not Suitable (1)	**Marginally suitable (2)**	**Moderately suitable (3)**	**Highly suitable (4)**	**Optimally suitable (5)**
Rainfall (mm)	<200	201-500	>1200	501-900	901-1200
Slope (%)	>20	12-20	9-12	3-8	<2
Soil texture	NA	NA	Loam sandy	Clay	Loam
Land use	Waterbody, swampy, settlement	Cultivated land, Afro alpine, forest, woodland	NA	NA	Grazing land, shirb land, bare lands,
Surface runoff(mm)	<100	101-200	201-300	301-500	>500

Similar to the weighting of criteria and alternatives, the AHP was also used to assign a weight (w_i) to rainfall, surface runoff, slope, land use and soil texture. Expert opinion was used to assign weight to these factors through the pairwise comparison matrix. Through this process, high weight was given to rainfall, surface runoff and slope, respectively to map suitable areas for in-situ water harvesting structures.

Whereas, slope, surface runoff and rainfall, respectively were constraints for which high weight was given to identify suitable areas for ex-situ water harvesting structures.

Finally, the suitability of alternative i.e. the overall weight of alternative was calculated as;

$$S = \sum w_i x_i$$

Where: S is the final suitability, w_i is the weight of constraint i and x_i is suitability score of constraint i (Malczewski, 2000).

Table 8.4 Pair-wise comparison matrix and weights of factors for in-situ and ex-situ water harvesting

	Weight (%)	
	In-situ water harvesting structures	**Ex-situ water harvesting structures**
Rainfall	31.2	20.4
Slope	19.0	30.2
Soil texture	7.9	11.0
Surface runoff	24.1	24.8
Land use	17.9	13.8

Consistency Index was 0.08% and 0.06% during in-situ and ex-situ water harvesting pairwise comparison of criteria

8.2.11 Evaluation of Effectiveness of Watershed Management Scenarios

The effectiveness of prioritized watershed management alternatives (after multi-criteria decision analysis and suitability analysis) and observed terrace in reducing the negative impact of baseline and future climate change was evaluated using the SWAT model. Specifically, there were three main scenarios and subject to comparison;

Scenario-0 (Baseline): this scenario is used to show the water balance components under baseline and future climate scenarios. In this scenario, observed terrace and any prioritized watershed management alternatives were not considered and represented on the SWAT model. This scenario embraces sub-scenarios from a-e (Table 8.5).

Scenario-1 (Climate Change + Observed Terrace): this scenario was used to assess the effectiveness of observed terrace on water balance components under baseline and future climate scenarios. Currently, on 6562 km^2 (42.71%) of the watersheds of the sub-basin, terrace and other physical soil and water management structures are implemented. Watersheds under observed terrace were identified and represented on the SWAT model to detect changes on surface runoff, soil water and total water yield.

Terraces have the effect of reducing slope which thereby reduces surface runoff and peak flow by impounding water in small depressions. Thus, observed terraces were represented by modifying slope length (SLSUBBSN) (Desta et al., 2005; Hurni et al., 2016), Curve number (CN) (Arnold et al., 2012) and USLE_P (Universal Soil Loss Equation management factor) (Gebremichael et al., 2005) (Table 8.6). This scenario encompasses the sub-scenarios from f-j (Table 8.5).

Scenario-2 (Climate change + watershed management alternatives prioritized using multi-criteria decision analysis (MCDA) and Suitability Analysis (SA): this scenario was used to evaluate the effect of prioritized watershed management alternatives on water balance components under baseline and future climate scenarios. Watersheds suitable for prioritized watershed management alternatives were identified and represented on the SWAT model to analyze changes on surface runoff, soil water and total water yield. Similar to scenario 1, the SLSUBBSN, CN and USLE_P were modified to represent prioritized watershed management alternatives (in-situ and ex-situ water harvesting structures and biological soil and water management) (Table 8.6). The in-situ water harvesting structures were represented in the SWAT model based on Hurni et al., 2016; Arnold et al., 2012; Gebremichael et al., 2005) recommendations. Whereas, the ex-situ water harvesting structures were represented in the SWAT model as recommended by Waidler et al. (2011) and biological alternatives i.e filter strips were based on Betrie et al., (2011); Hurni et al., (2016). Scenario 2 embraces sub-scenarios from k-o (Table 8.5).

Table 8.5 Summary description of watershed management scenarios developed in this study

Scenarios	Sub-scenario	Analysis
Scenario-0: Baseline scenario	a. Baseline climate (1981-2014) b. Near-term 2021-2050 (RCP4.5) c. Near-term 2021-2050 (RCP8.5) d. Long-term 2071-2100 (RCP4.5) e. Long-term 2071-2100 (RCP8.5)	Baseline and future climate change analysis
Scenario-1: Climate change + Observed terrace (observed terrace)	f. Baseline climate (1981-2014) + observed terrace g. Near-term 2021-2050 (RCP4.5) + observed terrace h. Near-term 2021-2050 (RCP8.5) + observed terrace i. Long-term 2071-2100 (RCP4.5) + observed terrace j. Long-term 2071-2100 (RCP8.5) + observed terrace	Effectiveness of observed terrace under different climate scenarios
Scenario-2: Climate change + watershed management alternatives identified using multi-criteria analysis (MCA) and suitability analysis (SA)	k. Baseline climate (1981-2014) + MCA and SA l. Near-term 2021-2050 (RCP4.5) + MCA and SA m. Near-term 2021-2050 (RCP8.5) + MCA and SA n. Long-term 2071-2100 (RCP4.5) + MCA and SA o. Long-term 2071-2100 (RCP8.5) + MCA and SA	Effectiveness of watershed management scenarios developed using multi-criteria analysis and suitability analysis

Changes in soil water, surface runoff and total water yield as a response to observed terrace under baseline and future climate scenarios (**Scenario 1**) and as a response to prioritized in-situ and ex-situ water harvesting structures and vegetative soil and water management structures under baseline and future climate scenarios (**Scenario 2**) were analyzed. Differences in effectiveness between the various scenarios were studied using t-tests ($p<0.05$).

Table 8.6 Watershed management scenarios representation in the SWAT model

	Watershed management alternatives	SWAT parameter		Value with the scenario	Reference
1	In-situ water harvesting structures (Terrace, trenches, microbasins, Soil bund, *Fanya Juu)*	SLSUBBSN (.hru)	0–10%	17.5m	Desta et al., 2005*; Hurni et al., 2016
			11-20%	13.5	Desta et al., 2005*; Hurni et al., 2016
			>20%	8m	Desta et al., 2005*; Hurni et al., 2016
		CN2 (.mgt)	Cultivated land	61	Arnold et al., 2012**
			Grazing land	49	Arnold et al., 2012**
			Shrubland	48	Arnold et al., 2012**
			Woodland and forest	45	Arnold et al., 2012**
			Bareland	77	Arnold et al., 2012**
		USLE_P (.mgt)		0.32	Gebremichael et al., 2005
2	Ex-situ water harvesting (Ponds and farm dams)	PND_FR (.pnd)		0.42	Waidler et al., 2011***; Arnold et al., 2012**
3	Filter strips (vegetative and grass strips)	FILTERW (.hru)		1m	Betrie et al., 2011; Hurni et al., 2016

* - Community Based Participatory Watershed Development Guideline, 2005

** - SWAT input/output documentation version 2012

*** - Conservation Practice Modeling Guide for SWAT and APEX, 2011

SLSUBBSN – Average slope length in (m)

CN2 – Initial SCS curve number for moisture condition II

PND_FR – Fraction of sub-basin area that drains into ponds

USLE_P – USLE equation management practice factor

8.3 Result and Discussion

8.3.1 Climate and hydrological conditions under different climate scenarios

The baseline climate (1981-2014) exhibited an increasing trend of mean annual and mean summer season rainfall in more than 78% of the stations and a subsidence trend of spring season rainfall in most of the stations (Worku et al., 2018a). However, future climate change scenarios describe a decrease in mean annual rainfall (Figure 8.5). The statistical bias corrected output of ensemble mean of RCMs showed a decline of mean annual rainfall in the range of 23% in the near-term (2021-2050) and 19% in the long-term (2071-2100) climate condition under RCP4.5 and RCP8.5 emission scenarios (Worku et al., 2019). The projected future rainfall had the same spatial pattern with the observed rainfall, where lower rainfall is projected in the northern part of the sub-basin.

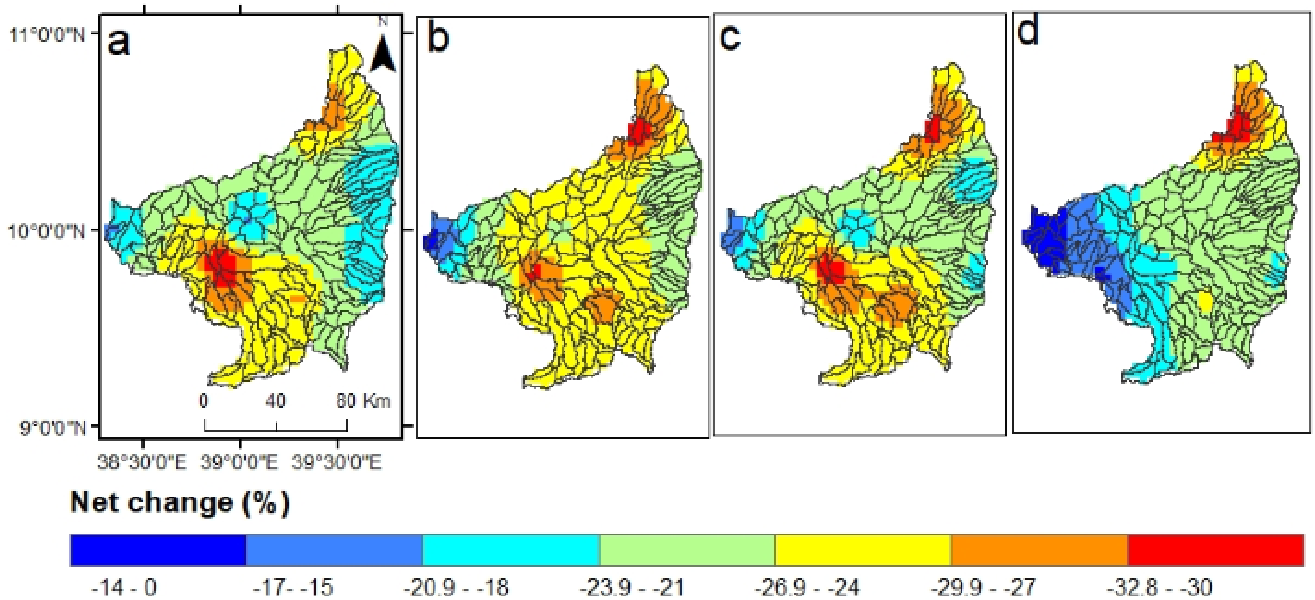

Figure 8.5 Net change (%) in mean annual rainfall between baseline and future climate scenarios. a) RCP4.5 (2021-2050) climate scenario, b) RCP8.5 (2021-2050) climate scenario, c) RCP4.5 (2071-2100) climate scenario and d) RCP8.5 (2071-2100) climate scenario.

The baseline and future climate impact scenarios output e.g., surface runoff used in this study is based on (Worku et al, under review). All future climate scenarios presented a decline of surface run-off, but in different magnitude. The climate scenario of RCP8.5 (2021-2050) will be characterized by maximum reduction of surface runoff (-65%) followed by the scenario of RCP4.5 (2021-2050) for which -63% reduction of surface runoff was estimated (Figure 8.6). In long-term climate scenarios (2071-2100 under RCP4.5 and 8.5), lower reduction of surface runoff is projected, mainly attributed to the higher rainfall projected in the long-term climate scenarios than the near-term scenarios.

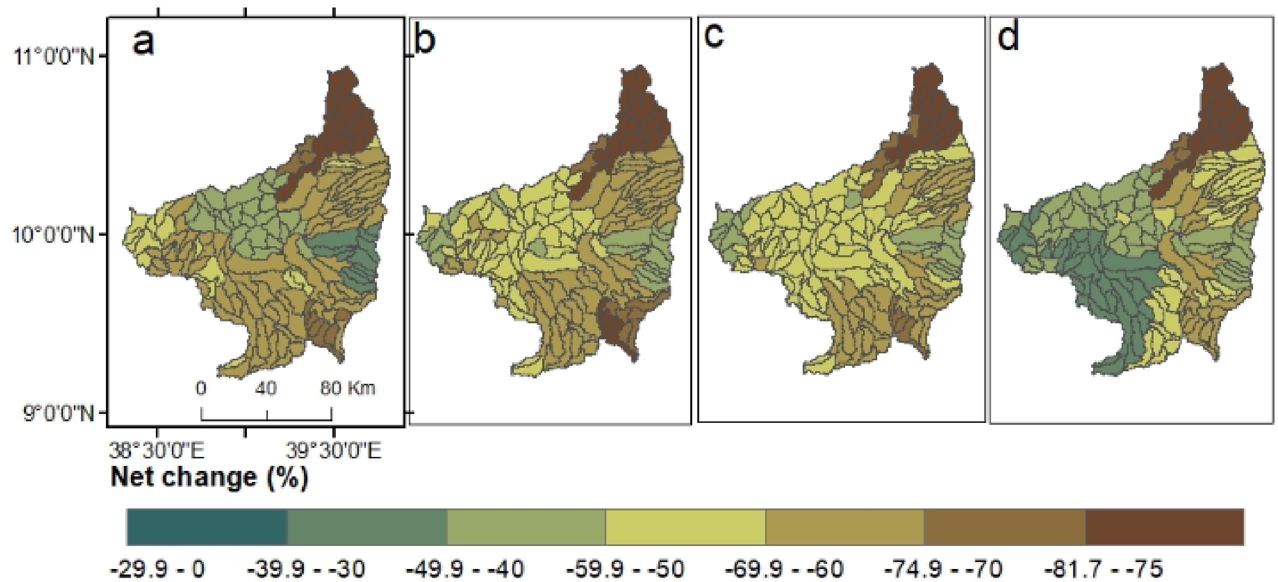

Figure 8.6 Net change (%) in mean annual surface runoff between baseline and future climate scenarios. a) RCP4.5 (2021-2050) climate scenario, b) RCP8.5 (2021-2050) climate scenario, c) RCP4.5 (2071-2100) climate scenario and d) RCP8.5 (2071-2100) climate scenario.

8.3.2 Criteria and Alternatives of Watershed Management

In the multi-criteria decision analysis, contribution to retain water is the most prioritized criteria to select watershed management alternatives for climate change adaptation in the Jemma sub-basin (Table 8.7). Contribution to reduce flood and soil erosion and contribution to the economy are other important criteria. Conversely, less weight is given to the criterion i.e 'coherence of the intended alternatives with the objectives of Climate Resilient Green Economy (CRGE) strategies of Ethiopia and other development programs'. The inexpensiveness of technology in terms of money and labor has also given less weight (Table 8.7). This might be due to good access to labor for watershed management in the study area.

Table 8.7 Pairwise comparision matrix and weights of criteria used to select watershed management alternatives for climate adaptation

	Contribution to reduce flood and soil erosion	Contribution to retain water	Degree of community acceptance	Contribution to economy	Inexpensive (labor and cost)	Similarity with CRGE and	Availability and simplicity of technology	**AHP weight (%)**
Contribution to reduce flood and soil erosion	1	1/2	2	3	5	7	5	**24.9**
Contribution to retain water	2	1	3	3	5	7	4	**31.4**
Degree of community acceptance	1/2	1/3	1	1/3	3	5	2	**11.5**
Contribution to economy	1/3	1/3	3	1	5	4	4	**17.4**
Inexpensive (labor and cost)	1/5	1/5	1/3	1/5	1	2	1/3	**4.4**
Similarity with national climate adaptation action plan	1/7	1/7	1/5	1/4	1/2	1	1/3	**3.0**
Availability and simplicity of technology	1/5	1/4	1/2	1/4	3	3	1	**7.3**

The consistency Ratio (CR) = 0.08

Through pairwise comparison matrix, water harvesting structures which include in-situ and ex-situ water harvesting structures are the most prioritized watershed management alternative for climate change adaptation (Table 8.8). The in-situ water harvesting (micro catchments) are structures that capture and store rainfall where it falls. Terraces, soil bunds, stone bunds, trenches, micro-basins and *Fanya Juu* are categorized as in-situ water harvesting systems (Mati et al, 2006; Biazin et al., 2012). The ex-situ water harvesting structures (macro-catchment) collect water from a large area (water collection catchment) and store rainwater using storage structures. Structures like ponds and dams are categorized as ex-situ water harvesting structures (Mati et al, 2006; Biazin et al., 2012). Next to water harvesting, physical and biological soil and water management are the most prioritized watershed management alternatives (Table 8.8).

Table 8.8 Pairwise comparision matrix and weights of watershed management alternatives

	Water harvesting structures	Physical & biological soil and water management	Crop change	Land use change	Reclaim degraded lands	Introduce new crop varieties	Area closure	agroforestry	AHP weight (%)
Water harvesting structures	1	2	5	5	5	5	5	5	**32.7**
Physical & biological soil and water management	1/2	1	5	3	5	5	5	3	**24.8**
Crop change	1/5	1/5	1	1/3	1/3	1/2	1/2	1/2	**3.5**
Land use change	1/5	1/3	3	1	1/2	2	2	2	**8.9**
Reclaim degraded lands	1/5	1/5	2	2	1	5	2	3	**12.3**
Introduce new crop varieties	1/5	1/5	2	1/2	1/5	1	1/3	1/2	**4.4**
Area closure	1/5	1/5	2	1/2	1/2	3	1	2	**7.3**
Agroforestry	1/5	1/4	3	1/2	1/3	2	1/2	1	**6.2**

Consistence Ratio = 0.09

The weight of each alternative under each criterion was also compared. The overall priority ranking (Table 8.9) showed that water harvesting structures are the most preferred alternatives to build resilience for future climate. Under a few criteria for instance, contribution to the economy, high weight is given to other alternatives i.e crop change and introducing new crop varieties than water harvesting structures (Table 8.9).

Table 8.9 Summary to obtain overall priority ranking for watershed management alternatives

	Criteria and weight	Contribution to economy (0.174)	Contribution to retain water (0.314)	Contribution to reduce flood and soil erosion (0.249)	Degree of community acceptance (0.115)	Cost (labor and cost) (0.044)	Coherence with CRGE objectives (0.03)	Availability & simplicity (0.073)	**Overall Priority (%)**
1	Physical & biological soil and water management	0.105	0.216	0.231	0.119	0.256	0.202	0.238	**19.2**
2	Crop change	0.236	0.033	0.031	0.229	0.121	0.129	0.104	**10.2**
3	Water harvesting structures	0.122	0.289	0.282	0.150	0.214	0.269	0.238	**23.4**
4	Land use change	0.078	0.060	0.068	0.070	0.068	0.054	0.050	**6.6**
5	Reclaim degraded lands	0.060	0.164	0.149	0.046	0.070	0.051	0.073	**11.4**
6	Introduce new crop varieties	0.219	0.038	0.032	0.229	0.138	0.135	0.136	**10.4**
7	Area closure	0.043	0.123	0.130	0.082	0.044	0.067	0.072	**9.7**
8	Agroforestry (alley cropping, strip grass)	0.137	0.078	0.076	0.074	0.088	0.092	0.090	**8.9**

Similar to this study, the IPCC fourth assessment report has also recommended the expansion of water harvesting storage structures and indigenous practices for sustainable water use (IPCC, 2007). There are also other studies which prioritize water harvesting for climate change adaptation and adaptation under uncertainty (Hallegatte, 2009; Haque, 2016). In the Ethiopian climate resilience strategy, water harvesting was identified as among the strategies to buffer the negative impact of climate change (FDRE, 2019). However, to get optimal benefit from water harvesting, optimal site identification is the most important step (Mbilinyi, 2007; Dile et al., 2016).

8.3.3 Suitability Analysis

The weighted overlay suitability analysis has shown that most watersheds of the Jemma sub-basin are suitable for in-situ water harvesting structures. More than 50% of the watersheds are highly and optimally suitable for in-situ water harvesting structures under baseline, near and long-term future climate scenarios (Figure 8.7 and Table 8.10). This is because more weight is given for rainfall and the amount of rainfall under baseline and future climate scenarios is highly and optimally suitable for in-situ water harvesting structures. About 74% of the watersheds are suitable for in-situ water harvesting under the baseline climate scenario.

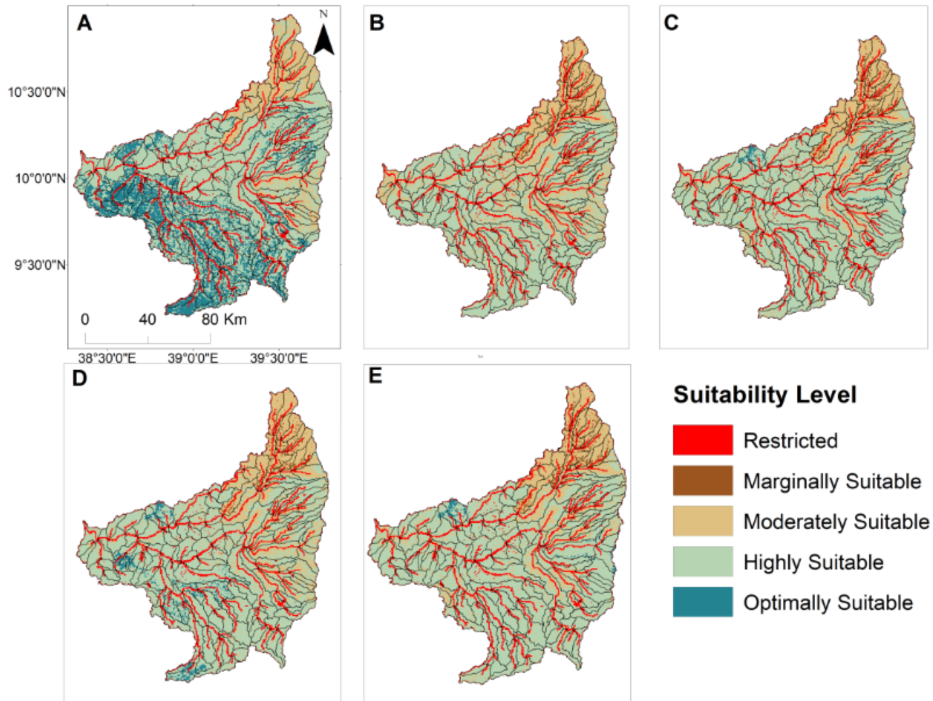

Figure 8.7 In-situ water harvestibg suitability analysis under different climate scenarios. A) baseline scenario (1981-2014), B) RCP4.5(2021-2050) climate scenario, C) RCP8.5 (2021-2050) climate scenario, D) RCP4.5 (2071-2100) climate scenario and E) RCP8.5 (2071-2100) climate scenario.

Unlike the baseline climate scenario, less than 62% of the watersheds are optimally and highly suitable for in-situ water harvesting structures under future climate change scenarios (Table 8.10). The projected decline of rainfall in future climate scenarios is the main constraint to find large areas of the watersheds highly and optimally suitable for water harvesting structures. The watersheds in the northern part of the sub-basin are moderately suitable for ex-situ water harvesting mainly attributed to low rainfall under baseline and future climate scenarios. The lower slope (<8%) is considered as not highly and optimally suitable, because designing in-situ harvesting structures in this slope class could trigger waterlogging (Herweg and Ludi, 1999; Desta et al., 2005).

Table 8.10 The suitability levels for in-situ water harvesting in the Jemma sub-basin (area in percent) under baseline and future climate scenarios

	Baseline	2021-2050 RCP4.5	2021-2050 RCP8.5	2071-2100 RCP4.5	2071-2100 RCP8.5
Restricted	14.87	14.87	14.87	14.87	14.87
Marginally Suitable	0.00	11.40	11.10	7.19	11.11
Moderately Suitable	11.59	24.39	17.78	15.56	17.78
Highly Suitable	54.31	48.99	51.12	47.36	51.12
Optimally Suitable	19.23	0.21	4.99	14.90	5.00

Comparable to this study, about 60% of the central Rift Valley of Ethiopia was mapped as a highly suitable area for in-situ water harvesting structures under historical climate condition using GIS-based Multi-criteria analysis (Moges, 2009). Using the weighted overlay analysis, 6–24% and 50% of the Upper Blue Nile Basin was also identified as highly and moderately suitable (respectively) for water harvesting structures under historical climate condition (Dile et al., 2016). The study also revealed that more areas of the Upper Blue Nile Basin can be considered as highly suitable for water harvesting structures through assigning more weight to slope and rainfall parameters. Mati et al., 2006 has also identified that most of Ethiopia is suitable for in-situ water harvesting structures under historical climate condition.

The area of the watersheds highly and optimally suitable for ex-situ water harvesting are lower than the area of the watersheds suitable for in-situ water harvesting (Figure 8.8). It is only under the baseline climate condition where about 37% of the watersheds are highly and optimally suitable for ex-situ water harvesting (Table 8.11). In the near and long-term climate scenarios, less than 13% of the area of watersheds are highly and optimally suitable. The main constraint to find large suitable sites for ex-situ water harvesting structures is a slope where only less than 8% of the slope is highly and optimally suitable. Another constraint is surface runoff, which is projected to decline under near and long-term climate scenarios. Equivalent to the in-situ water harvesting suitability, the watersheds in the northern part of the sub-basin are moderately suitable for ex-situ water harvesting structures mainly attributed to low surface runoff and rainfall in future climate and climate impact scenarios.

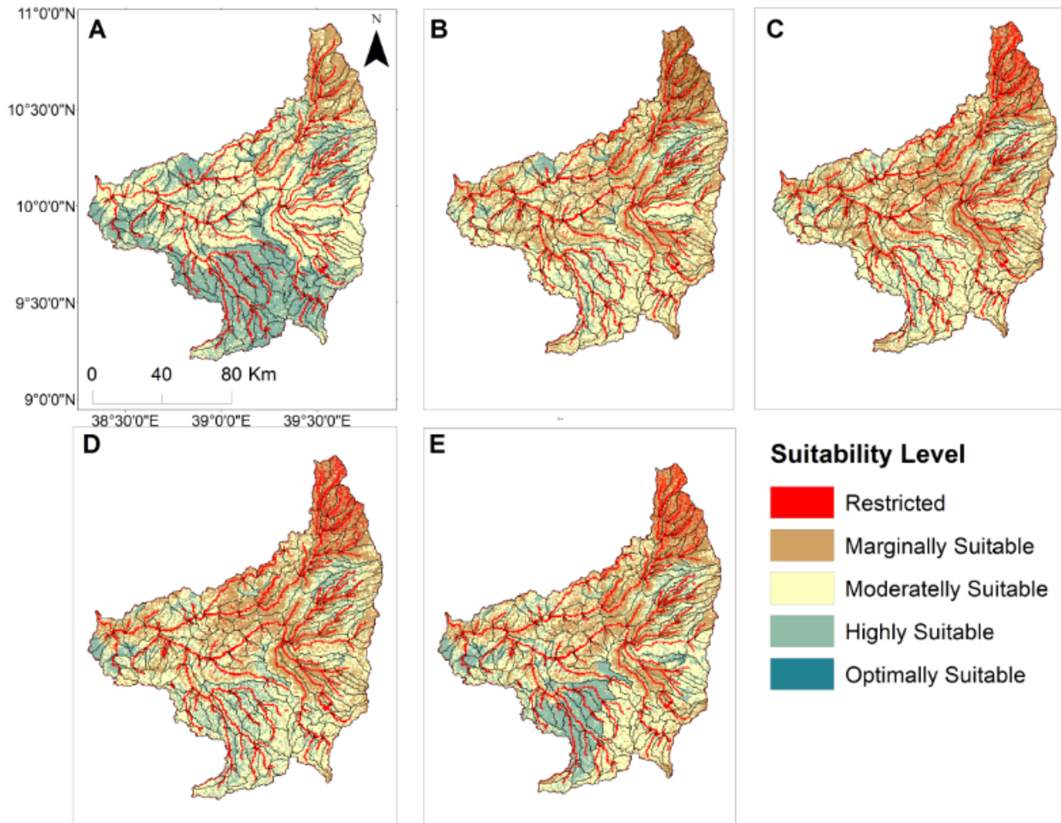

Figure 8.8 Ex-situ water harvestibg suitability analysis under different climate scenarios. A) baseline scenario (1981-2014), B) RCP4.5(2021-2050) climate scenario, C) RCP8.5 (2021-2050) climate scenario, D) RCP4.5 (2071-2100) climate scenario and E) RCP8.5 (2071-2100) climate scenario.

Table 8.11 The suitability levels for ex-situ water harvesting of the Jemma sub-basin area (in percent) under baseline and future climate scenarios

Suitability level	Baseline	2021-2050 RCP4.5	2021-2050 RCP8.5	2071-2100 RCP4.5	2071-2100 RCP8.5
Restricted	14.87	18.97	19.57	17.43	16.76
Marginally Suitable	7.27	30.36	35.71	30.56	30.73
Moderately Suitable	40.81	41.42	37.10	38.54	39.65
Highly Suitable	36.18	9.22	7.75	13.30	12.65
Optimally Suitable	0.74	0.00	0.00	0.01	0.06

Both in-situ and ex-situ water harvesting suitability analysis showed the area of the watersheds suitable under near-term and long-term climate scenarios is lower than the baseline climate scenario. About 15%

of the area of the watersheds is river channels, settlements, swamp areas and restricted to implement any of the water harvesting structures. As a result, it is essential to consider the second prioritized watershed management alternatives to design on the main river channels and areas not suitable for water harvesting structures. Physical and biological soil & water management technologies were the second alternative prioritized by the multi-criteria decision analysis.

Biological soil and water management alternatives (vegetative measures) that could slow runoff water leaving the catchments and increase water availability in the soil are to be designed. Filter strips (grass and vegetative) are soil and water management technologies which include plantation of grasses and vegetation along with the river channels, degraded (bare lands) and cultivated lands (Desta et al., 2005; Waidler et al., 2011). In this study, we identify suitable areas of the Jemma sub-basin for filter strips under different climate scenarios. The river channels, bare lands, cultivated lands, rainfall (>500mm), slope (0-15%), surface runoff (>150mm) are highly and optimally suitable to design filter strips (Desta et al., 2005; Hurni et al., 2016). Figure 8.9 shows suitable areas for filter strips under different climate scenarios.

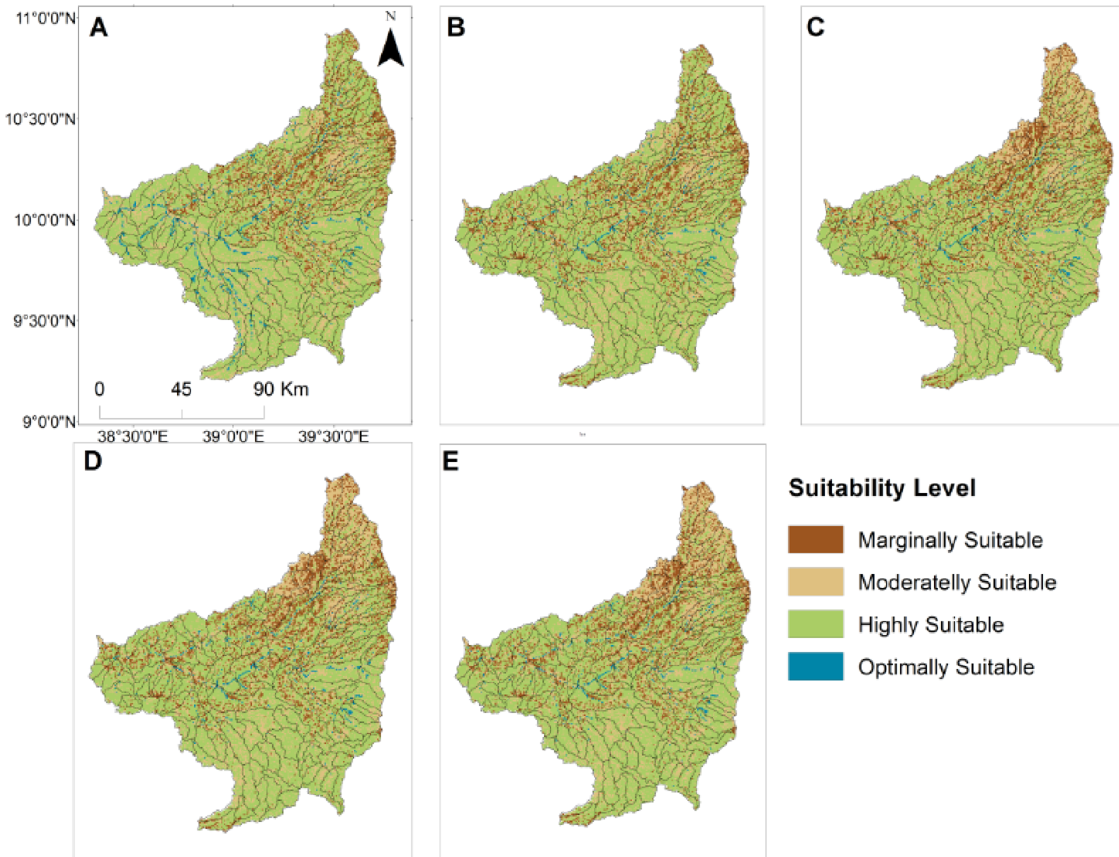

Figure 8.9 Suitability analysis for vegitative strips under different climate scenarios. A) baseline scenario (1981-2014), B) RCP4.5(2021-2050) climate scenario, C) RCP8.5 (2021-2050) climate scenario, D) RCP4.5 (2071-2100) climate scenario and E) RCP8.5 (2071-2100) climate scenario.

Comparable to in-situ water harvesting structures, about 64% (10015km^2) of the watersheds are highly and optimally suitable for filter strips under the baseline climate scenario. In the future climate scenarios, less than 56% of the watersheds will be highly and optimally suitable for filter strips. Similar to water harvesting structures, large areas of the watersheds in the northern part of the sub-basin are moderately suitable for filter strips under future climate scenarios (Figure 8.9). The main constraint to locate highly and optimally suitable areas for filter strips under future climate scenarios is rainfall. In future climate scenarios, the annual rainfall is reduced and watersheds in the northern part of the sub-basin have an annual rainfall of less than 500mm.

Validation was done using the layer of observed terrace and the in-situ water harvesting suitability analysis under the baseline climate. The analysis revealed that 4592km^2 (70%) of the observed terraced landscape was identified as suitable for in-situ water harvesting structures. The suitability analysis showed the northern part of the sub-basin is not highly and optimally suitable for water harvesting attributed to rainfall and surface runoff amount. However, on the northern part of the sub-basin, terraces are built and it is already a terraced landscape.

8.3.4 Effectiveness of watershed management alternatives under climate change scenarios

Prioritized watershed management alternatives and observed terraces have the effect to increase soil water and reduce surface runoff, but at different magnitude (Figure 8.10- 8.11 and Table 8.12). In the baseline climate, observed terraces have the effect to reduce surface runoff by 27.7%. At sub-basin scale, observed terrace could result 35.12%, 35.00%, 32.97% and 32.08% reduction of surface runoff under RCP4.5(2021-2050), RCP8.5(2021-2050), RCP4.5(2071-2100) and RCP8.5(2071-2100) climate scenarios, respectively. In the baseline climate scenario, there will be 56.66% reduction of surface runoff under in-situ water harvesting structures. At sub-basin scale, in-situ water harvesting structures could result 63.45%, 75.80%, 74.70% and 72.98% reduction of surface runoff under RCP4.5 (2021-2050), RCP8.5(2021-2050), RCP4.5(2071-2100) and RCP8.5(2071-2100) climate scenarios, respectively. The change in surface runoff under observed terrace and in-situ water harvesting in baseline and future climate scenarios is statistically significant ($p<0.05$) (Table 8.12).

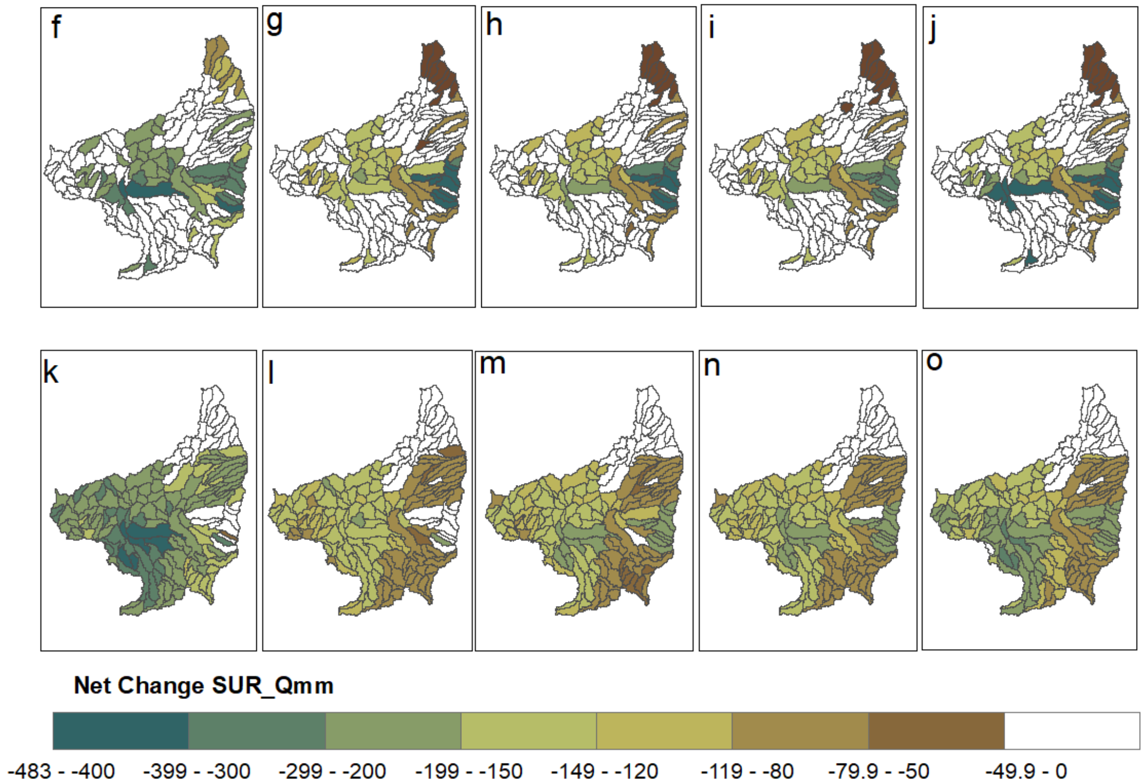

Figure 8.10 Net change in mean annual surface runoff (mm) under scenario – 1 and Scenario -2. f) baseline climate with observed terrace, g) RCP4.5(2021-2050) climate scenario with observed terrace, h) RCP8.5 (2021-2050) climate scenario with observed terrace, i)RCP4.5 (2070-2100) climate scenario with observed terrace j) RCP8.5 (2071-2100) climate scenario with observed terrace, k) baseline climate with in-situ water harvesting, l) RCP4.5(2021-2050) climate scenario with in-situ water harvesting, m) RCP8.5 (2021-2050) climate scenario with in-situ water harvesting, n) RCP4.5 (2070-2100) climate scenario with in-situ water harvesting and o) RCP8.5 (2071-2100) climate scenario with in-situ water harvesting.

At the watersheds scale, observed terraces trigger a reduction of surface runoff in the range of 1% to 88%. In the watersheds located in the central part of the sub-basin, higher reduction of surface runoff (28%-88%) was estimated, where as in the watersheds located northern part of the sub-basin, observed terraces trigger lower reduction of surface runoff (1% - 23%) under baseline and future climate scenarios. On 73% of the watersheds, in-situ water harvesting structures resulted in a reduction of surface runoff in the range of 13% to 88%. In the watersheds located northern part of the sub-basin, no change in surface runoff is estimated due to in-situ water harvesting since the watersheds in this region are not suitable for in-situ water harvesting (Figure 8.10).

Analogous to this study, in situ water harvesting structures reduced surface runoff in the order of 13% to 60% in the semi-arid region of northern Ethiopia (Araya and Stroosnijder, 2010). Besides, in-situ water harvesting structures also trigger a reduction of surface runoff by 28% in the watershed of Central Highlands of Ethiopia (Adimassu et al., 2012). There might be a difference in the performance of in-situ water harvesting structures probably due to the difference in area coverage of in-situ water harvesting structures, local topographic condition and variations in measurement scale between the Jemma sub-basin and other study areas.

Prioritized watershed management alternatives and observed terraces have also significant effect to increase soil water under baseline and future climate scenarios (Figure 8.11 and Table 8.12). In the baseline climate scenario, there could be 8% increase in soil water as a response to the observed terrace. At the sub-basin scale, observed terrace could result 13.24%, 14.06%, 13.68% and 12.24% increase of soil water in RCP4.5 (2021-2050), RCP8.5(2021-2050), RCP4.5(2071-2100) and RCP8.5(2071-2100) climate scenarios, respectively. In the baseline climate scenario, a 14% increase in soil water was estimated as a response to in-situ water harvesting structures. Whereas, in-situ water harvesting triggers an increase of soil water by 19%, 24%, 23% and 21% under RCP4.5(2021-2050), RCP8.5(2021-2050), RCP4.5(2071-2100) and RCP8.5(2071-2100) climate scenarios, respectively at sub-basin scale. The increase in soil water as a response to the observed terrace and in-situ water harvesting under baseline and future climate scenarios is statistically significant ($p<0.05$) (Table 8.12).

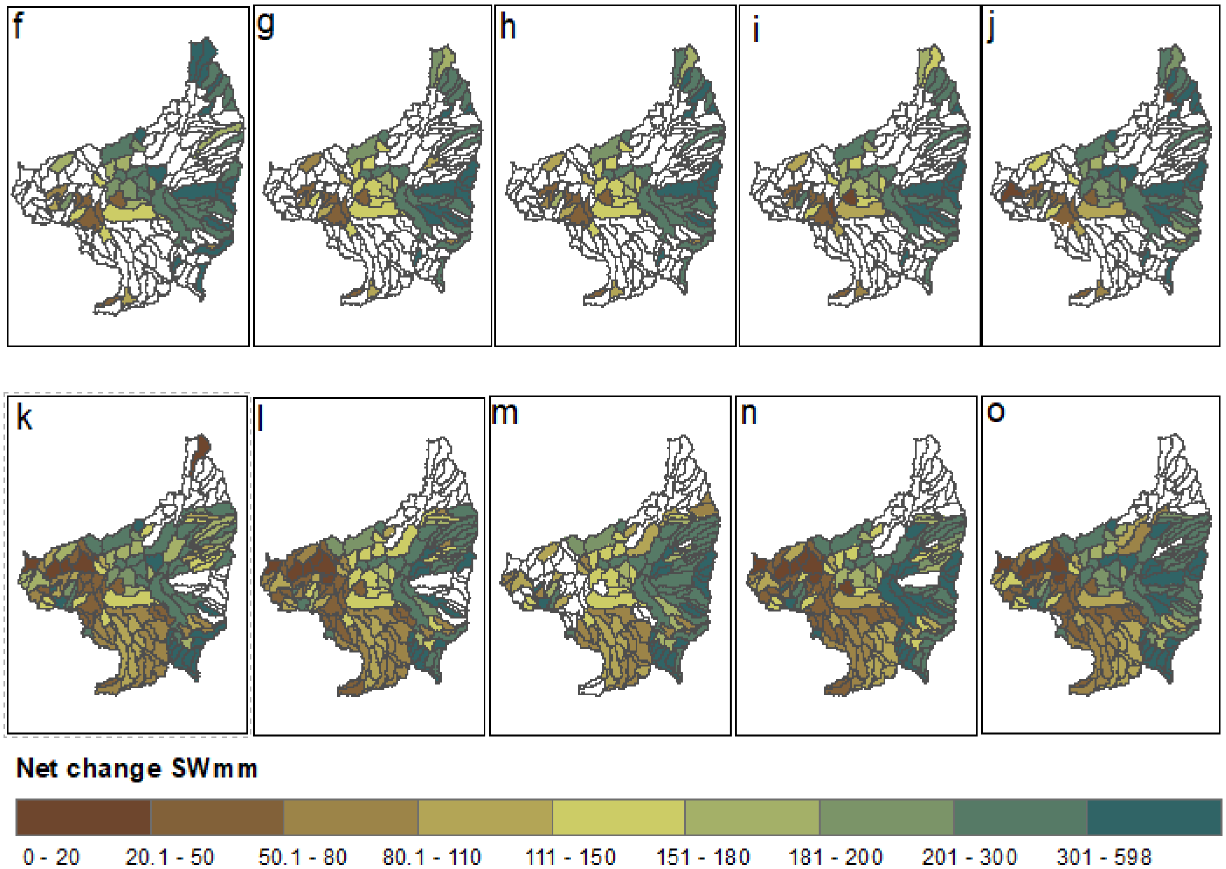

Figure 8.11 Net change in mean annual soil water (mm) under Scenario – 1 and Scenario -2. f) baseline climate with observed terrace, g) RCP4.5(2021-2050) climate scenario with observed terrace, h) RCP8.5 (2021-2050) climate scenario with observed terrace, i)RCP4.5 (2070-2100) climate scenario with observed terrace j) RCP8.5 (2071-2100) climate scenario with observed terrace, k) baseline climate with in-situ water harvesting, l) RCP4.5(2021-2050) climate scenario with in-situ water harvesting, m) RCP8.5 (2021-2050) climate scenario with in-situ water harvesting, n) RCP4.5 (2070-2100) climate scenario with in-situ water harvesting and o) RCP8.5 (2071-2100) climate scenario with in-situ water harvesting.

Among the watersheds, a large difference of soil water is estimated as a response to in-situ water harvesting and observed terrace (Figure 8.11). The watersheds in the eastern part of the sub-basin showed a higher increase of soil water (34%-48%) as a response to observed terrace under baseline and future climate scenarios. The watersheds in the southern part of the sub-basin revealed no change in soil water to observed terrace since no terraces were represented in this area of the sub-basin (Figure 8.11). On more than 74% of the watersheds, in-situ water harvesting resulted in an increase of soil water in the range of 19% to 48% under baseline and future climate scenarios. In the watersheds of the northern part of the sub-basin, low soil water is estimated under in-situ water harvesting than observed terrace scenario.

Because, in this region of the watersheds, observed terraces were identified and represented in the SWAT model. Whereas, this region is not highly and optimally suitable for in-situ water harvesting structures under climate change scenarios and no watershed management structure is represented in the SWAT model that further resulted no change of soil water (Figure 8.11). Comparable to the effect of observed terrace and in-situ water harvesting structures under baseline and future climate scenarios in this study, an increase of soil water (30%) was investigated as a response to in-situ water harvesting structures in Ethiopia and other sub-Saharan African countries (Biazin et al., 2012).

In contrast to the response of surface runoff and soil water response to observed terrace and in-situ water harvesting, an insignificant ($p<0.05$) change was estimated on total water yield (Figure 8.12 and Table 8.12). This indicates there will be insignificant reduction of streamflow from the watersheds of the Jemma sub-basin to the downstream rivers as a response to the observed terrace and in-situ water harvesting structures. In total water yield, the contribution of surface runoff showed a decrease while contribuion of groundwaterflow to total water yield has shown an increase under the observed terrace and in-situ water harvesting.

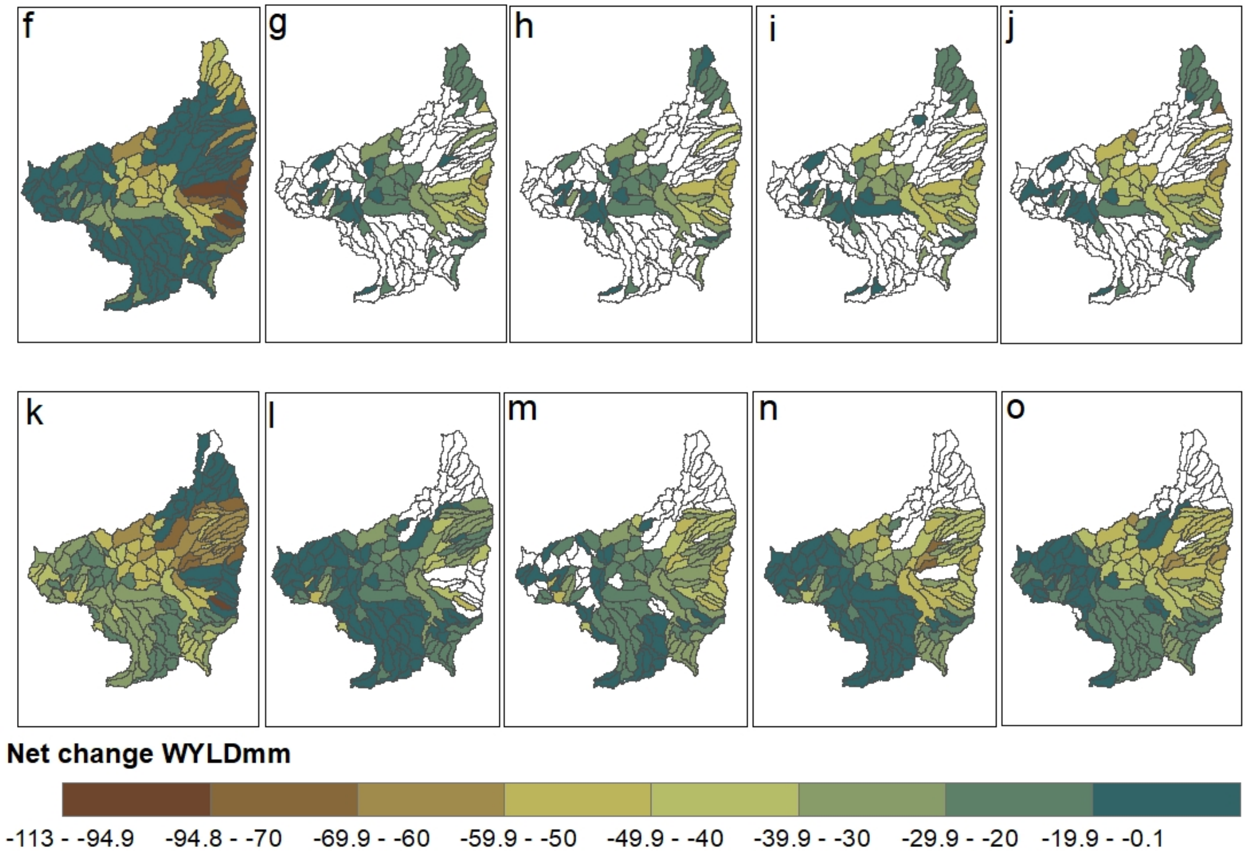

Figure 8.12 Net change in mean annual water yield (mm) under Scenario – 1 and Scenario -2. f) baseline climate with observed terrace, g) RCP4.5(2021-2050) climate scenario with observed terrace, h) RCP8.5 (2021-2050) climate scenario with observed terrace, i)RCP4.5 (2070-2100) climate scenario with observed terrace j) RCP8.5 (2071-2100) climate scenario with observed terrace, k) baseline climate with in-situ water harvesting, l) RCP4.5(2021-2050) climate scenario with in-situ water harvesting, m) RCP8.5 (2021-2050) climate scenario with in-situ water harvesting, n) RCP4.5 (2070-2100) climate scenario with in-situ water harvesting and o) RCP8.5 (2071-2100) climate scenario with in-situ water harvesting.

Eventhough, insignificant reduction of mean annual streamflow was simulated, the water harvesting structures will cause a slight change in the hydrography of the streamflow. There will be far low streamflow in July and increase in the consecutive months as a response to the observed terrace and in-situ water harvesting structures (Figure 8.13). In September - November, there will be high streamflow under in-situ water harvesting. And an increase in groundwater and prolonged dry season flow was simulated under watershed management structures than the climate change scenarios (Figure 8.13). This could be due to the storage and release effects of the water harvesting structures. This storage and realse effects of water harvesting structures could improve soil moisture, reduce soil erosion and increase crop growing period in the Jemma sub-basin. In the downstream to the Jemma sub-basin, this situation will reduce flood frequency and increase water availability in dry seasons.

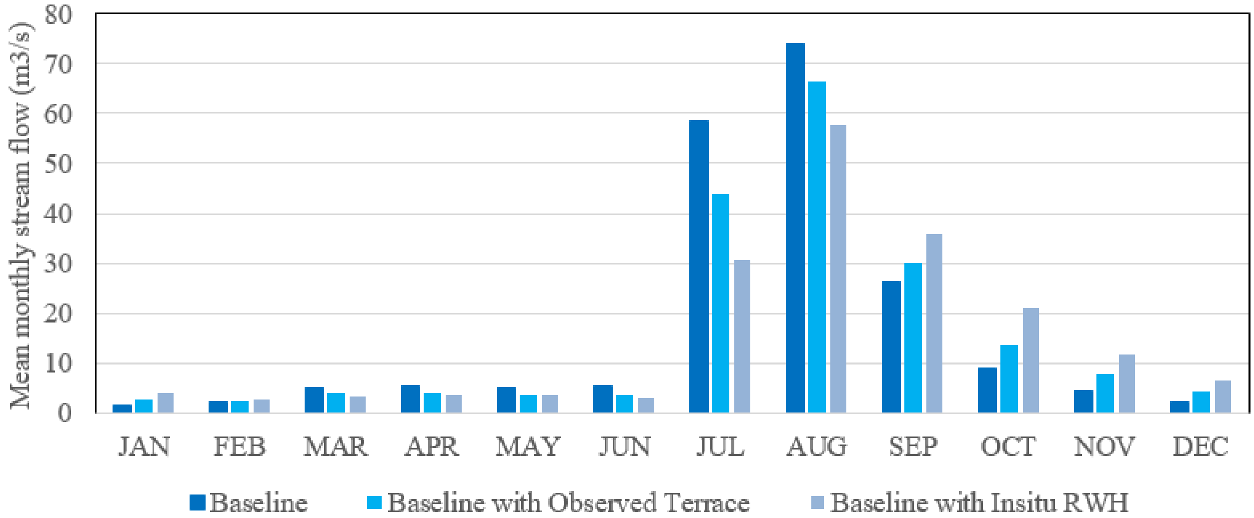

Figure 8.13 Mean monthly streamflow (m^3/s) under baseline climate condition and watershed management scenarios.

This finding strongly corroborates with Rockstro¨m et al., 2009; Lemann et al., 2016 and Dile et al., 2016. For instance, Rockstro¨m et al., 2009 has explored that water harvesting structures are among the strategies to realize global water availability and food production through increasing green water availability under future climate change and population growth. The study of Lemann et al., 2016 also revealed an insignificant change in blue water (discharge) to downstream stakeholders as a response to soil and water management in the Upper Blue Nile Basin of Ethiopia. More analogously, it was simulated that water harvesting structures have the effect to increase dry season flow (low flow) and decrease high flows that further increase in-situ agricultural production and a reduced flood damages in the downstream areas of the Lake Tana sub-basin of Blue Nile Basin (Dile et al., 2016).

Ex-situ rainwater harvesting and filter strips have lower effect on soil water and surface runoff. Ex-situ water harvesting structures will significantly reduce surface runoff under baseline and long term climate scenarios (Figure 8.14). However, ex-situ water harvesting structures will have no benefits to increase soil water under any of the climate scenarios (Figure 8.14 and Table 8.12). This is attributed to the difference in the area of land suitable for ex-situ water harvesting structures, where only less than 37% and 15% of the sub-basin is suitable for ex-situ water harvesting structures under baseline and future climate scenarios, respectively. Filter strips showed insignificant change on soil water, surface runoff and water yield under all climate change scenarios (Table 8.12). However, vegetative strips may have optimal benefits in reducing soil erosion and other environmental benefits under the wake of climate change.

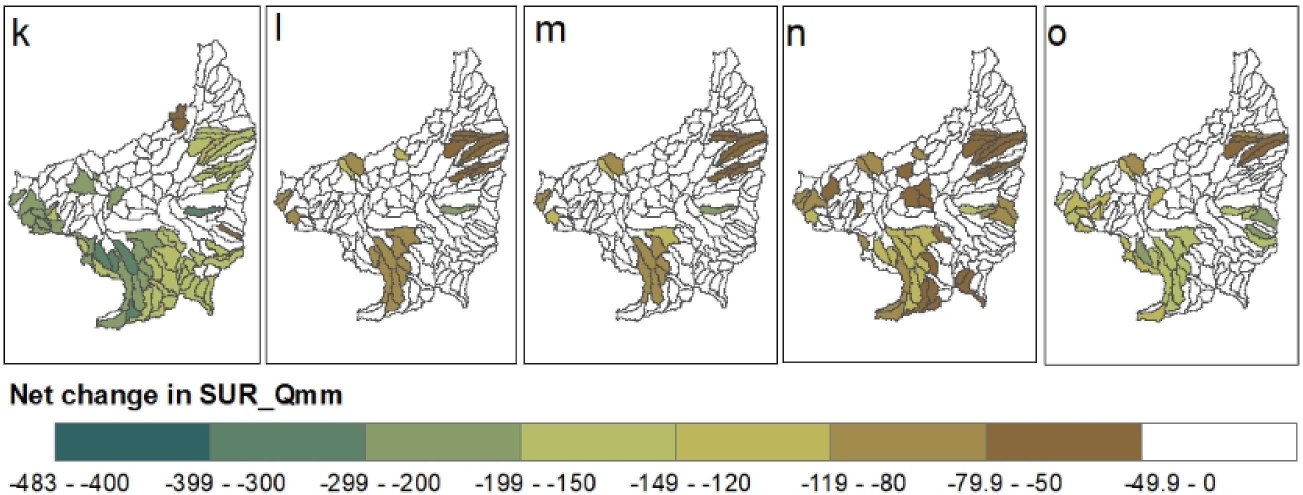

Figure 8.14 Net change in mean annual surface runoff (mm) under Scenario -2. k) Baseline climate with ex-situ water harvesting, l) RCP4.5(2021-2050) climate scenario with ex-situ water harvesting, m) RCP8.5 (2021-2050) climate scenario with ex-situ water harvesting, n) RCP4.5 (2070-2100) climate scenario with ex-situ water harvesting and o) RCP8.5 (2071-2100) climate scenario with ex-situ water harvesting.

In other areas of Ethiopia, ex-situ water harvesting structures result significant increase in water availability and reduce surface runoff tremendously. For instance, in the Lake Tana sub-basin of Upper Blue Nile Basin, a reduction of surface runoff that further result a decrease of total water yield in the order of 14% to 33% is estimated under different rainfall years (Dile et al., 2016). In some regions of Ethiopia and the Sub-Saharan region, runoff is collected from the upstream part of the catchment and stored in the storage structures and used for supplementary irrigation (Biazin et al., 2012).

Table 8.12 Significant differences (p-values) in watershed management scenarios performance in reduction of surface runoff and water yield and increasing soil water under baseline and future climate scenarios. Up arrows are to represent a significant increase, and down arrows are to represent a significant decrease.

Watershed management scenarios	Climate Scenarios	Surface runoff (SUR_Q_{mm})	Soil water (SW_{mm})	Total water yield ($WYLD_{mm}$)
Observed terrace	Baseline (1981-2014)	**0.00↓**	**0.01↑**	0.31
	2021-2050RCP4.5	**0.00↓**	**0.02↑**	0.40
	2021-2050RCP8.5	**0.00↓**	**0.00↑**	0.30
	2071-2100RCP4.5	**0.00↓**	**0.00↑**	0.31
	2071-2100RCP8.5	**0.00↓**	**0.02↑**	0.34
In-situ Water harvesting	Baseline (1981-2014)	**0.00↓**	**0.00↑**	0.14
	2021-2050RCP4.5	**0.00↓**	**0.00↑**	0.18
	2021-2050RCP8.5	**0.00↓**	**0.00↑**	**0.03↓**
	2071-2100RCP4.5	**0.00↓**	**0.00↑**	0.06
	2071-2100RCP8.5	**0.00↓**	**0.00↑**	0.08
Ex-situ Water harvesting	Baseline (1981-2014)	**0.00↓**	0.48	0.47
	2021-2050RCP4.5	0.11	**0.39**	0.93
	2021-2050RCP8.5	**0.14**	**0.97**	0.98
	2071-2100RCP4.5	**0.00↓**	**0.98**	0.97
	2071-2100RCP8.5	**0.00↓**	**0.98**	0.99
Filter strips	Baseline (1981-2014)	0.21	0.41	0.37
	2021-2050RCP4.5	0.23	0.47	0.39
	2021-2050RCP8.5	0.26	0.51	0.44
	2071-2100RCP4.5	0.23	0.49	0.41
	2071-2100RCP8.5	0.22	0.51	0.41

8.4 Conclusion

Climate change unequivocally triggers changes in freshwater availability and as a response it is worthwhile to design watershed management strategies that could provide optimal benefits under different climate conditions. This study was intended to develop watershed management scenarios for climate change adaptation using multi-criteria decision analysis which blended climate scenarios, climate impact scenarios, stakeholders view and the existing biophysical settings. There was intercomparison among a portfolio of alternatives and criteria using the multi-criteria decision analysis tool, the Analytical Hierarchy Process (AHP). Through this process, water harvesting structures were identified as appropriate watershed management alternatives for existing and future climate change adaptation. This is primarily because water harvesting structures can retain and increase soil water availability and provide benefits in reducing the impact of extreme events like drought and flood. Thus, water harvesting structures will reduce the effects of uncertainties stem from climate scenarios and climate impact scenarios by providing benefits under negative and positive changes in climate.

Suitability analysis showed at least 50% of the watersheds of the Jemma sub-basin are highly and optimally suitable to design water harvesting and biological soil and water management structures under baseline and future climate conditions. In contrast, the watersheds in the northern part of the Jemma sub-basin are moderately suitable for water harvesting structures mainly due to low rainfall and surface runoff. On the other hand, the watersheds in eastern parts of the Jemma sub-basin are not highly and optimal suitable for in-situ water harvesting structures exclusively due to high rainfall and runoff that needs graded structures to circumvent waterlogging effects. Due to slope, surface runoff and rainfall, the area suitable for ex-situ water harvesting is lower under baseline and future climate scenarios. Both in-situ and ex-situ water harvesting suitability analysis accentuates climate change will be the limiting factor to design adaptation options.

Representation of prioritized watershed management alternatives particularly in-situ water harvesting on hydrological model resulted in significant increase of soil water, significant reduction of surface runoff and insignificant change on water yield. This corroborates the need to implement and expand water harvesting structures and other water management structures to increase water retention and water availability in different climate scenarios. However, terrace and other physical soil and water management structures are implemented on about 42% of the watersheds of the Jemma sub-basin up until 2016. Concurrently, existing and prioritized water management structures need to be regularly maintained since there are studies which show the decrease of the effectiveness of such structures after a certain time (Herweg and Ludi, 1999).

The National Adaptation Plan of Ethiopia (FDRE, 2019) has also prioritized water harvesting as among the main strategies to ensure climate change adaptation. However, water harvesting implementation is far low from its potential for climate adaptation, food security and other objectives. Lack of data and information related to effectiveness of water harvesting structures, insufficient information on potentials of different areas for water harvesting structures and lack of advanced research and extension services are among the constraints of water harvesting techniques in the Blue Nile Basin of Ethiopia (Johnston and Mccartney, 2010). This accentuates the need to involve the stakeholders in dialogues and discussion forums and to develop a strong database which shows the capability of each land for water harvesting under different climate conditions, biophysical and socio-economic condition.

Chapter 9

Watershed management technologies under climate change scenarios in selected watersheds of the Jemma sub-basin – a case study

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9.1 Introduction

In our prioritization of watershed management alternatives, we have identified one alternative i.e water harvesting for the entire Jemma sub-basin. As a result, there were watersheds which were not optimally and highly suitable for water harvesting. For instance, the watersheds in the northern and eastern part of the sub-basin were not suitable for water harvesting under climate change scenarios. From this, we realize there is no watershed management technology which could fits all. Because, watersheds are different in their soil, topography, agroecology, land use, climate and socio-economic aspects. Therefore, it is essential to identify watershed management technologies for each watershed. There are also evidence and recommendations which suggest watershed management planning at smaller scale (e.g Desta et al., 2005). At such spatial scales, it is non-trivial to identify suitable area of watersheds for different soil and water management structures to maximize water availability and agricultural productivity under changing environmental conditions (Mbilinyi et al., 2007). There are also empirical evidences which observe and simulate an increase in effectiveness of watershed management technologies due to their optimal placement (e. g Mbilinyi et al., 2007; Xie et al., 2015; Dile et al., 2016).

Besides, we also recognize there are watersheds which require other watershed alternatives parallel to water harvesting. For instance, the watersheds characterized by Vertisols and gentle slope may need other

[‡]This chapter is based on **Worku, G., Teferi, E., Bantider, A., Dile, Y.T. Watershed management technologies under climate change scenarios in selected watersheds of the Jemma sub-basin**. Under preparation

alternatives. The Shewa plateau has large areas with Vertisols which are characterized by good moisture holding capacity and fair fertility (FAO, 1986). However, Vertisols have poor drainage and workability which are hard when dry and very sticky when wet. On such soils with above average rainfall conditions, water harvesting structures may create water-logging. As a result, in soils with above average rainfall (mean annual rainfall greater than 700mm), graded soil and water management structures are appropriate (Desta et al., 2005; Georgis, 2015). Besides using drainage, Broad Bed and furrow Maker (BBM), improved crop varieties for waterlogged Vertisols and precise application of fertilizers can be taken as among Vertisols management practices.

Economic importance of watersheds based soil and water management technologies is to be emphasized as high as environmental benefits. Focusing on economic importance of watershed management technologies further help to get community acceptance. Different from past watershed management paradigms which focus on integration of socio-economic issues in watershed management, current watershed management systems consider watershed management as part of local socio-economic development processes (FAO, 2006). Thus, in this case study, we have included watershed management technologies which could have high economic benefits. At all, watershed management technologies taken into account in this case study include conservation agriculture (conservation tillage), Vertisols management, precision agriculture, double cropping, fruit trees plantation and revegetation using different vegetation and grass species.

In this case study we have selected watersheds from different agroecological zones of the Jemma sub-basin (Figure 9.1). The agroecological zonation is based on elevation, cropping pattern, rainfall, temperature, soil and length of growing period (MoA, 2000). Thus, there could be high diversity in sample watersheds taken from different agroecologies. Besides, soil types, rainfall amount, land use and slope classes of the selected watersheds were used to identify suitable areas for watershed management technologies under changing climate. The climate, slope, land use, soil and agro-ecological requirements for each technology was specified based on different literature (see sec 9.2.4).

9.2 Method and Material

9.2.1 The study area

For this case study, primarily watersheds which were not highly and optimally suitable for water harvesting structures were selected (Figure 9.1). The watersheds in the northern part of the sub-basin and the watersheds in the high rainfall areas were not suitable for water harvesting. Besides, we have also observed that terraces are not implemented on watersheds in gentle slope and dominated by Vertisols. The Vertisols may be also not suitable for in-situ water harvesting structures when there is more rainfall (greater than 700mm per annum). Due to the better potential of retaining soil water, Vertisols can be used for double cropping (small scale irrigation) through integrating with ex-situ water harvesting. Such watersheds are located in the southern part of the Jemma sub-basin (Figure 9.2).

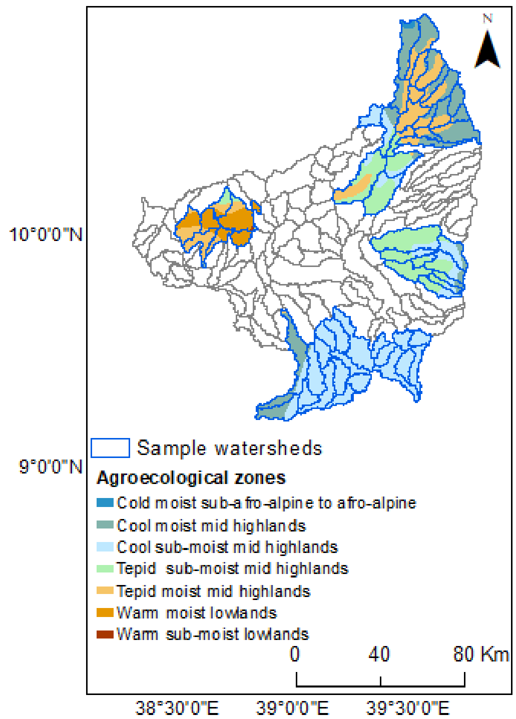

Figure 9.1-Agroecological zones of sample watersheds

9.2.2 Spatial datasets

The mean annual rainfall under different climate scenarios, land use, soil types, agroecological zones and slope data were collected from different sources and used in this case study (Figure 9.2). The baseline mean annual rainfall is generated from the observed (1981-2014) rainfall of different climatic stations. Mean annual rainfall of future climate scenarios is generated from the output of statistically bias corrected RCM simulations (Worku et al., 2019). The elevation and slope maps are based on the DEM data of 30m resolution obtained from the Shuttle Radar Topographic Mission (SRTM). The 2008 land use/land cover data was derived from Landsat satellite imagery and supervised image classification was done using maximum likelihood algorithm. The soil data was obtained from the Ministry of Water, Irrigation and Electricity of Ethiopian and the Water and Land Resources Centre of Ethiopia. Eutric Vertisols (28.07%) which cover large area in the southern part of the sub-basin and Lithic Leptosols (37.44%) are the major soil types in the watersheds of the Jemma sub-basin. Data of agroecological zones which range from cold moist sub-afro alpine to warm sub-moist lowlands were also used (MoA, 2000).

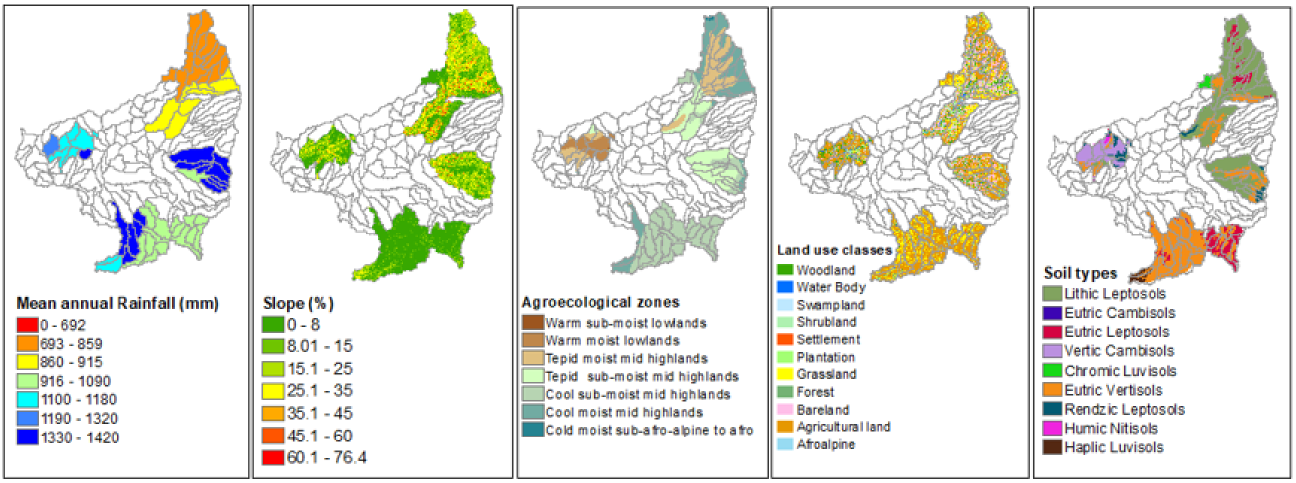

Figure 9.2 Biophysical characteristics of selected watersheds. These biophysical characteristics were used to identify suitable area of watersheds for different watershed management technologies. The rainfall map is based baseline climate scenario.

9.2.3 Data processing

The datasets acquired from different sources were clipped to include only the area extent of selected watersheds. All datasets were projected into coordinate system of UTM zone 37N, which is the projection system of Ethiopia. All vector (shape files) were converted into raster layers since the overlay analysis works in a grid data format. The slope (in percent) raster was generated from the DEM using the spatial analyst tool in ArcGIS.

9.2.4 Methods

For each watershed management technology, we have identified the biophysical and climatic requirements (factor) which determine the suitability of each watershed management technology (Desta et al., 2005; Hurni et al., 2016; Georgis, 2015). Based on the factors, area of the watersheds suitable for each watershed management technology under each climate scenario were identified. The suitability of watershed area for different watershed management technologies was assessed using GIS-based suitability analysis method called a Boolean approach (Malczewski, 2006)). The Boolean approach particularly, the AND Boolean analysis identifies the area of the watersheds which can fulfill all suitability criteria are included in the suitability analysis.

From different watershed management technologies, conservation agriculture is one of. Conservation agriculture can be implemented on all agroecologies except moist *berha* and at elevation which ranges from 500-3700m.a.s.l. Watersheds which have mean annual rainfall in the order of 300 to 1500mm is also suitable for conservation agriculture (Georgis, 2015). From the land use and land cover types, cultivated lands are suitable for conservation agriculture. At all soil types, conservation agriculture can be implemented (Hurni et al., 2016).

Vertisols management is essential at watersheds dominated by Vertisols and gentle slopes. In areas where there are Vertisols, waterlogging is the common problem and needs particular management system. Thus, different Vertisols management practices which enhance water drainage, aeration, permeability and crop productivity of Vertisols is essential. Vertisols management can be realized at all agroecological zones particularly in moist and waterlogged areas, cultivated lands and elevation which ranges from 500-3700m.a.s.l.

Areas which are suitable for ex-situ water harvesting and dominated by Vertisols can be ideal area of watersheds for small scale irrigation during dry seasons. Vertisols have high moisture holding capacity which allows to cultivate crops in dry and wet seasons. Thus, in areas where there are Vertisols and water harvesting structures such as ponds and dams, double cropping can be realized. On Vertisols, early planting of short maturing crop varieties and collecting excess water from Vertisols is an opportunity to get more land for double cropping.

Revegetation through area closure, replantation and other methods can be designed on areas with mean annual rainfall of less than 900-140mm, degraded land, barelands, terraces, bunds and other physical structures Hurni et al., 2016). There are degraded lands, bare lands, grazing lands and shrub lands which were not suitable for water harvesting structures due to low rainfall amount particularly in future climate scenarios. Thus, in these areas, watershed management through replantation of different indigenous trees and improved grass and forage and fodder varieties, legumes, vitivier grasses is essential. All soil types, mean annual rainfall of less than 900 to 1400mm and all agroecologies except *berha* are suitable for replantation of trees, shrubs and different grass species (Hurni et al., 2016).

Precision agriculture cannot be constrained by most of the biophysical and climatic parameters and can be designed on all area of the watersheds where there are cultivated lands. In areas which have mean annual rainfall of greater than 500mm, cultivation of most crop can be practiced (Georgis, 2015). And in areas where there is cultivation of crop, precision agriculture can be practiced. This strategy intends to get optimal benefits of agricultural production and ecosystem services through efficient use of nutrients and other inputs. All agroecologies except *berha* can be ideal for precision agriculture.

Taking the ever growing food demand and the need for more food production, fruit tree planting can be non-trivial under changing climate. Fruit trees can be planted on all land use classes except settlement, barelands and water bodies. Besides, fruit trees can be designed along different bunds, bench terraces, micro basins and other water collection structures. Fruit trees such as Apple, Mango, Watermelon and other fruit tree species can be cultivated in the warm moist and sub-moist lowlands, cool moist mid-highlands. In the dry area of the watersheds, drought resistant fruit tree species should be cultivated to underpin food production and ecosystem rehabilitation.

9.3 Result and discussion

The Boolean analysis showed that large area of the watersheds is suitable for conservation agriculture, precision agriculture and revegetation under all climate scenarios (Figure 9.3 and Table 9.1). This is primarily because such watershed management technologies can be implemented in large area including low rainfall areas. In the watersheds located in the northern part of the Jemma sub-basin which were not suitable for water harvesting, conservation agriculture can be implemented on large area of cultivated lands under all climate scenarios with annual rainfall greater than 300mm. In these watersheds, conservation agriculture may triggers an increase in soil water, soil organic matter and soil fertility and a reduction in surface runoff and soil erosion. Concurrently, in the soil sector of Climate-Resilient Green Economy Strategy of Ethiopia, conservation agriculture is also among the strategies identified to lower emissions of CO_2 by more than 40Mt per year in 2030 (FDRE:2011). However, more work is needed to get recognition of smallholder farming community who is practicing conventional agriculture which is characterized by intensive tillage. Chronically low and continuous decline of productivity and ever growing soil degradation may push the smallholder community to practice conservation agriculture.

Different from conservation agriculture, precision agriculture needs higher rainfall (mean annual rainfall greater than 500mm) to cultivate crops. In the baseline climate all watersheds have mean annual rainfall greater than 500mm and thus suitable for precision agriculture. However, there is shrinkage of area of the watersheds suitable for precision agriculture under future climate scenarios owing to reduction of rainfall (Figure 9.3 and Table 9.1). Other than the northern part of the watersheds, other watersheds located in the central and southern part of the Jemma sub-basin can be also benefited from precision agriculture through efficient and site specific application of fertilizers, seeds and pesticides. In all watersheds and under all climate scenarios, precision agriculture may increase crops production, environmental sustainability and mal-climate change mitigation and adaptation through more efficient and targeted use of agricultural inputs. Thus, precision agriculture can be taken as a no-regret action which can benefit the physical environment and the agricultural production even without climate change.

Fruit trees plantation management is another watershed management technology which has revealed no change in area of the watersheds suitable for fruit trees management within baseline and future climate scenarios (Figure 9.3 and Table 9.1). However, few agroecological zones i.e warm moist lowlands, warm sub-moist lowlands and cool moist mid-highlands are suitable for fruit trees. In the warm moist and sub-moist lowlands agroecologies, fruit trees such as Mango, Watermelon and other trees can be planted on different land uses including degraded lands. While, in the cool moist mid-highlands, fruit trees such as Apple plantation can be planned (Figure 9.3). Integrating fruit trees management with water harvesting may help to get optimal economic and environmental benefits and better acceptance by the community. In Ethiopia, there are experiences of plantation of fruit trees and high value crops through integrating with different ex-situ water harvesting structures such as runoff and flood farming (Mekdaschi Studer and Liniger, 2013).

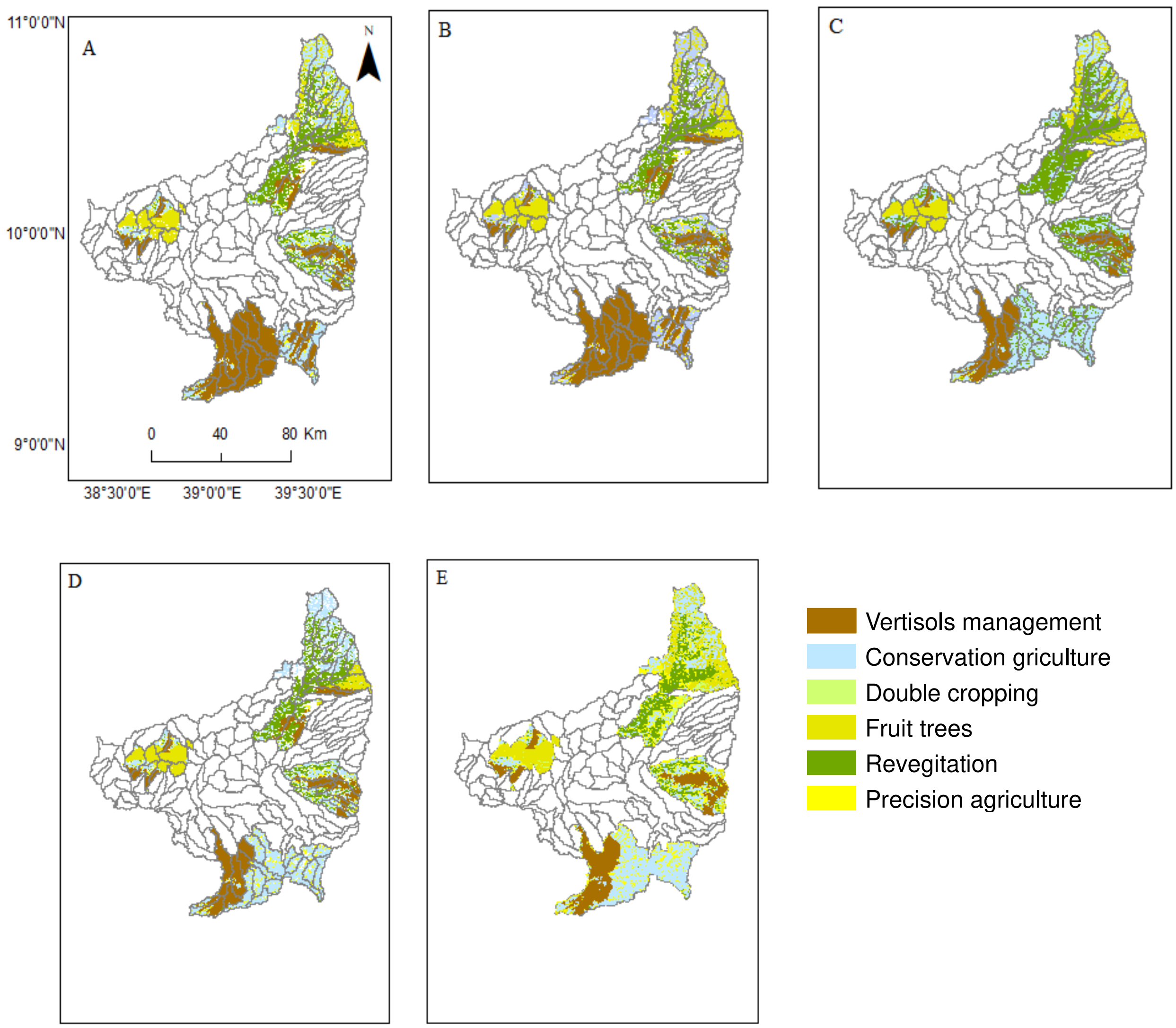

Figure 9.3-Watershed management technologies suitability analysis under different climate change scenarios. A) baseline scenario (1981-2014), B) RCP4.5(2021-2050) climate scenario, C) RCP8.5 (2021-2050) climate scenario, D) RCP4.5 (2071-2100) climate scenario and E) RCP8.5 (2071-2100) climate scenario.

Area of watersheds suitable for Vertisols management revealed variation among climate change scenarios (Figure 9.3 and Table 9.1). In the baseline climate scenario, every area of the watershed which has Vertisols is ideal to implement different Vertisols management practice. However, in future climate scenarios, there are areas which will receive mean annual rainfall less than 700mm. Such areas are not suitable for Vertisols management since there will be no rainfall which can cause waterlogging and other related Vertisols problems. In the RCP4.5 (2021-2050), there are large area of the watersheds that can be important to implement Vertisols management. This could be due to lower reduction of rainfall particularly in areas where there are Vertisols. However, under RCP 8.5 (2021-2050), RCP 4.5 (2071-2100) and RCP 8.5 (2071-2100) climate scenarios, there is 56.30%, 47.83% and 56.30% reduction of area of the watersheds suitable for Vertisols management (Table 9.3). Vertisols management practices, particularly using improved varieties and early planting of short maturing crops such as wheat and teff can surface the opportunity to integrate such practices with double cropping. For instance, on the Vertisols of Central Highlands of Ethiopia, it was investigated that double cropping of early-maturing crops and residual soil moisture-based planting of chickpea and grass pea resulted an increase in land productivity and improve feed availability (Minta et al., 2014).

Table 9.1-Area of sample watersheds suitable for different watershed management technologies under baseline and future climate change scenarios.

	Baseline climate	**RCP 4.5 (2021-2050)**	**RCP 8.5 (2021-2050)**	**RCP 4.5 (2071-2100)**	**RCP 8.5 (2071-2100)**
Vertisols management	1840	1836	804	960	804
Double cropping	1243	117	117	309	503
Fruit trees	1380	1380	1380	1380	1380
Revegetation	1501	1441	1483	1501	1501
Precision agriculture	2890	2356	2356	2356	2356
Conservation agriculture	2780	2780	2780	2780	2780

The reduction of rainfall in the future climate triggers decreasing of area of watersheds suitable for double cropping (Figure 9.4 and Table 9.1). In areas with mean annual rainfall greater than 500mm can be potential area to practice double cropping through integrating with ex-situ water harvesting structures. However, the reduction in rainfall also causes a reduction of area of land for ex-situ water harvesting systems. This eventually effects low area of watersheds suitable for double cropping. A decrease of rainfall under RCP 4.5 (2021-2050) and RCP 8.5 (2021-2050) climate scenarios effects 90.59% reduction of area of the watersheds suitable for double cropping. In RCP 4.5 (2071-2100) and RCP 8.5 (2071-2100) climate scenarios, there is also 75.14% and 59.53% reduction of area of watersheds suitable to apply double cropping, respectively (Table 9.3).

More inclusively, double cropping can be suited to areas with mean annual rainfall of less than 500mm. However, this is only due to high moisture holding capacity of Vertisols which help crop production in arid environment with uncertain and heavy rainfall. It is also estimated to double or triple crop yields and to cultivate crops with high risk of crop failure through harvesting 10-25% of rainwater under any climate scenario (Mekdaschi Studer and Liniger, 2013). Analogously, it was simulated that more than 25% of surface runoff generated from rainfall can be stored in the soil using different water harvesting structures (see sec 8.3.4) which could further increase water availability for double cropping.

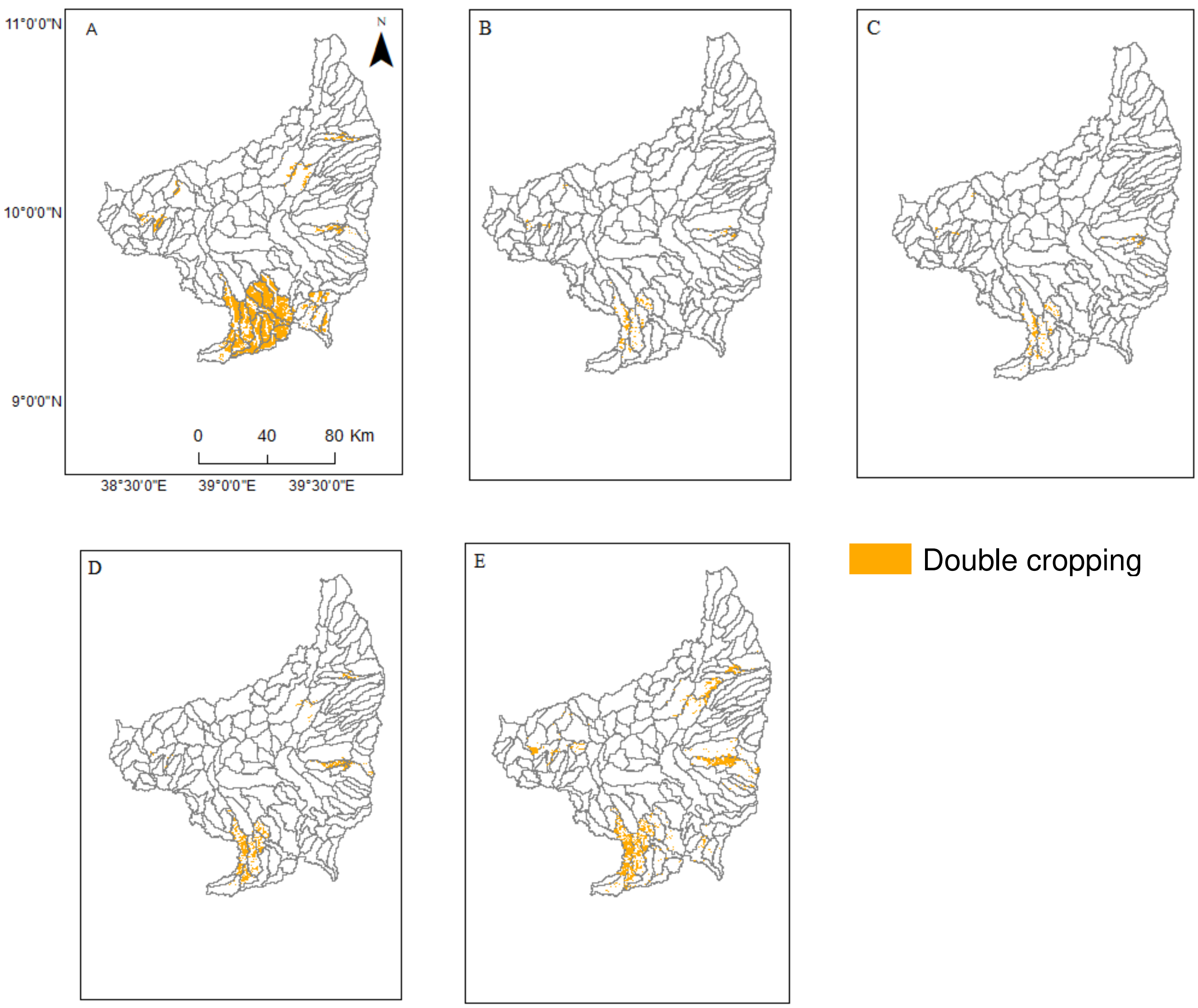

Figure 9.4 – Watersheds suitable for double cropping under climate change scenarios. A) baseline scenario (1981-2014), B) RCP4.5(2021-2050) climate scenario, C) RCP8.5 (2021-2050) climate scenario, D) RCP4.5 (2071-2100) climate scenario and E) RCP8.5 (2071-2100) climate scenario.

9.4 Conclusion

Watersheds level suitability analysis for different watershed management technologies under climate change scenarios is germane to further optimize benefits from the technologies. This case study showed the difference in the potential of watersheds to different technologies and climate scenarios. Watershed management technologies related to Vertisols management and double cropping found selective of the biophysical and climate conditions of the watersheds. Only watersheds where there are Vertisols and mean annual rainfall greater than 700mm are suitable for Vertisols management and double cropping. Even though climate condition is not a constraint, fruit tree plantation can be designed in some agroecological zones of the watersheds. Fruit trees and double cropping systems could increase climate change resilience through boosting food security and efficient use of water which can be available under any climate conditions.

Watershed management technologies such as conservation agriculture, precision agriculture and revegetation can be implemented on large area of the watersheds. There is no climate and other biophysical constraints to select conservation agriculture and revegetative measures. These technologies also can be considered as no-regret actions which can provide economic and environmental benefits even without climate change. For instance, decisions toward precision agriculture underpins an increase in agricultural productivity and environmental sustainability of farmlands and surrounding environ.

PART III: SYNTHESIS, CONCLUSIONS AND RECOMMENDATIONS

Chapter 10

Synthesis, Conclusions and Recommendations

10.1 Synthesis

This dissertation was intended to develop watershed management scenarios which could provide optimal benefits of adaptation under different climate and climate impact scenarios. The dissertation comprises a study of plausible future climate condition, its impact and response strategies which can provide optimal benefits of adaptations to relieve the adverse impact of climate change. To explicitly analyze the plausible impact and response strategies of climate change, the study has applied scenario planning framework. Scenario planning requires developing a robust baseline climate scenario, future climate scenarios, climate impact scenarios and optimal adaptation scenarios which include stakeholders' involvement. Baseline climate scenario development comprises ensuring the quality of observed climate data and characterizing the observed climate that can be a frontier against which future climate scenarios were assessed. Accordingly, this dissertation starts with maintaining the quality of the observed data and developing baseline climate (1981-2014).

10.1.1 Baseline climate

In the baseline climate scenario, an increasing trend in mean annual rainfall and summer season rainfall is detected in most climatic stations of the Jemma sub-basin. In contrast, the second rainy season (March-May) rainfall has shown a downward trend. Parallel with change signal of annual and main rainy season rainfall, most intensity and frequency indices of extreme rainfall, for instance, Very wet days (R95p), extremely wet days (R99p), Max 5-day rainfall amount (Rx5DAY), R20mm (number of very heavy rainfall days) show increasing trend in the baseline scenario in all but one climatic station of the Jemma sub-basin. Different from other extreme rainfall indices, the trend in Simple Daily Intensity Index (SDII) is negative in most of the stations. Generally, extreme rainfall events in most stations of the sub-basin showed similar trend of global extreme rainfall events, which revealed an increase since the 1950s (IPCC, 2013). This corroborates that the mean rainfall and extreme rainfall events of the Jemma sub-basin could be further perturbed in the near and long-term future following changes on the pressure systems and the sea surface temperature of the equatorial east Pacific, Gulf of Guinea, Atlantic and Indian Oceans in the future period.

The trend of mean TMAX and TMIN and intensity and frequency of temperature extremes indices emphasis strong warming in most climatic stations of the Jemma sub-basin. In the afro-alpine climatic station, minimum temperature has disclosed a negative trend which conforms cold region of the sub-basin are becoming colder. Perhaps, extreme cool nights may trigger a negative trend of minimum temperature in the afro-alpine regions of the sub-basin where an exceptional increase of cool nights was observed. Warm extreme indices are increasing whereas cold extreme indices are reduced under the baseline scenario.

10.1.2 Regional climate models evaluation

After establishing the baseline climate scenario, it was non-trivial to develop different future climate scenarios using climate models. Due to the difference in initial boundary conditions, local forcings, the parameters considered and parametrization of variables, climate models have different performance in simulating the climate of a specific geographic region. Thus, it is essential to identify GCMs/RCMs which can simulate the historical climate of the study region. The historical simulations of climate models are initiated from an arbitrary point of a quasi-equilibrium control run and the simulations are not to occur at the same time with observational records. However, climate models have to show some fidelity with the observed mean values and the major drivers (teleconnections) of the climate of the study region.

Comparatively, GCMs dynamically downscaled using REMO and CCLM4 regional models are better in simulating mean and frequency of rainfall values than RCA4 model in the Jemma sub-basin. However, all models particularly, GCMs downscaled by CCLM4 and RCA4 regional models struggle to simulate rainfall of high and low elevation areas which show overestimation in the high elevation areas and underestimation in the low elevation areas. The relative difference in simulating the rainfall of the sub-basin and elevation-dependent biases among the RCMs could be because of the variation in the parametrization schemes used to represent sub-grid processes (local forcings) such as convective rainfall and other elevation-dependent parameters. For instance, RCA4 model uses the Kain-Fritsch scheme (Kain and Fritsch, 1993), however, CCLM4 and REMO models use a mass flux scheme (Tiedtke, 1989) to parametrize cloud formation. The biases in RCMs may also stem from the boundary conditions (GCMs). Different RCMs forced with alike boundary conditions (GCMs) may show different performance. In such a case, it is reasonable to use the RCM which show better performance under different metrics. Further, it is recommended to use the ensemble mean of RCMs simulation to reduce the uncertainty caused by the underestimation and overestimation. In this study, the ensemble of RCMs(E-RCMs) is superior in capturing monthly and seasonal rainfall and in correlation metric.

10.1.3 Evaluation of statistical bias correction methods

Even though, some RCMs have shown relatively better performance in simulating the rainfall climatology of the Jemma sub-basin, elevation-dependent bias is to be adjusted to develop robust climate scenarios. Bias adjustment could help to reduce uncertainties arises from systematic biases in the RCMs. But, there are bias correction procedures which trigger bias. Besides, bias correction algorithms assume the bias correction algorithms and its parameterization for baseline climate conditions are also valid under future climate conditions. Thus, this was worthwhile to ascertain a robust bias correction method which can adjust the mean and extremes of RCM simulations and applicable under different climate conditions.

The statistical bias correction methods were effective and showed comparable performance in adjusting some elevation-dependent biases and mean rainfall and temperature simulations of RCM with observed rainfall and temperature values. However, most bias correction methods (linear scaling, power transformation and variance scaling) have struggled in fitting the frequencies and intensities of rainfall and temperature simulations of RCM with corresponding observed counterparts. Distribution mapping method was better than other methods in fine-tuning wet day probability and the 90th percentile of RCM simulations of rainfall and temperature with corresponding observed values. Another skill of distribution mapping method is its viability under different climate conditions (non-stationary condition). Such skills of distribution mapping method guarantee to use RCMs bias corrected using distribution mapping method for climate scenarios, climate impact scenarios development and for climate adaptation decision analysis.

10.1.4 Rainfall and temperature in future climate scenarios

Eventually, future climate scenarios were developed by blending four GCMs (CNRM-CM5, EC-EARTH, HadGEM2-ES and MPI-ESM-LR), two RCMs (CCLM4 and REMO), three emission scenarios (RCP4.5 RCP8.5 and RCP2.6) and robust bias adjusting method. In correspondence with the projected strong tropical ocean warming (IPCC, 2013), the climate scenarios reveal a consistent decrease of rainfall in the near and long-term future over the Jemma sub-basin. Large difference in rainfall change signal is detected among RCMs than among emission scenarios. Higher reduction of rainfall is projected in the near-term than long-term climate condition under RCP8.5 emission scenario. In the RCP4.5 emission scenario, higher reduction of rainfall is projected in the long-term climate condition than the near-term climate condition. Different from the trend of mean annual and summer season rainfall, an increase on autumn season rainfall is detected under all climate scenarios.

In all climate scenarios, an increase of TMAX and TMIN is projected in the RCMs and the ensemble mean of RCMs. In contrast to the projected rainfall, large difference in projected TMAX and TMIN is detected among emission scenarios than among RCMs. In correspondence with the Fifth IPCC assessment report which attributed that emission scenarios as major drivers of temperature change, higher and lower increase of TMIN and TMAX is estimated from climate scenarios under RCP8.5 and RCP2.6 emission scenarios, respectively. Again, in agreement with the projected concentration of greenhouses gases, high increase of TMAX and TMIN is projected in the long-term future than the near-term future. In general, TMAX and TMIN under all climate scenarios have shown strong agreement with the projected global temperature. This substantiates that there will be low increase of temperature if the Paris Agreement and other substantial measures to limit greenhouse gases emission by the global society are realized.

10.1.5 Hydrological climate change impact scenarios

The baseline hydrologic balance of the Jemma sub-basin shows that a large proportion of the rainfall becomes loss through evapotranspiration (51.68%). The remaining portion of rainfall contributes to water yield which is highly dependent on rainfall. More than 80% of water yield is generated from rainfall which is highly variable following change in seasons. Thus, change in rainfall immensely triggers a change in surface runoff and the total water yield of the sub-basin. The response of this baseline water balance to different climate scenarios discloses a decrease of surface runoff and water yield. And an increase in evaporation could further triggers water loss. Similar with rainfall under different climate scenarios, higher and lower reduction of surface runoff and water yield is estimated in the near future under RCP8.5 emission scenario and in the long-term future under RCP4.5 emission scenario, respectively.

10.1.6 Prioritization of optimal watershed management alternatives under different climate scenarios

Based on climate scenarios, climate change impact scenarios, existing biophysical conditions and stakeholders' perspective, watershed management alternatives which can provide optimal benefits in climate change adaptation were developed. The multi-criteria decision analysis is the most essential decision support system to straddle the science and community perspectives and to undertake due caveat during the selection of adaptation strategies. The multi-criteria analysis has prioritized that retaining rainwater and increase water availability is the most critical criteria of watershed management strategies under changing climate. In parallel, engineering and technological options which can increase water storage in the soil are the most prioritized watershed management alternatives under different criteria. Particularly, water harvesting structures are ascertained as the most prioritized watershed management alternatives under different climate scenarios. The spatial suitability analysis of water harvesting structures also showed more than half of the watersheds of the Jemma sub-basin are suitable for in-situ water harvesting structures under all climate scenarios.

A significant increase of soil water and a significant decrease of loss of water through direct surface runoff was estimated as a response to in-situ water harvesting structures under different climate scenarios. Conversely, no significant decline of streamflow (blue water) is estimated as a response to in-situ water harvesting structures. However, no significant increase in soil water was estimated as a response to ex-situ water harvesting.

10.2 Conclusions

From the above syntheses, the following conclusions are drawn

Conclusion 1: in the baseline climate, discernible increase in mean annual and summer season rainfall, mean TMAX and TMIN, extreme rainfall events and extreme temperature events was detected. Whereas, a subsidence in spring season rainfall was detected.

The observed climate which was used as baseline scenario is characterized by an increase of mean annual and main rainy season rainfall (June-September) and subsidence of second rainy season (March-May) rainfall in most climatic station of the Jemma sub-basin. This substantiates that the rainfall pattern in the Jemma sub-basin is shifted into a unimodal pattern of rainfall and could cause crop failure and livestock losses due to lack of water and pasture in spring season. Corresponding with mean annual and main rainy season rainfall, most intensity and frequency indices of extreme rainfall show positive trend under the baseline scenario. However, Simple Daily Intensity Index revealed a decline of daily rainfall. This suggested that the daily rainfall has been declining and the total rainfall is dominated by extreme rainfall events. The trend of mean TMAX and TMIN and intensity and frequency of temperature extremes indices show strong warming in the baseline climate scenario. Changes in extreme rainfall and temperature events could trigger multifarious impacts on human's livelihoods and natural ecosystems and escalate the risks of future climate change.

Conclusion 2: GCMs dynamically downscaled using REMO and CCLM4 regional models are better in simulating historical mean annual and monthly rainfall and frequency of rainfall events. The ensemble mean of RCMs is superior in some metrics.

The evaluation of different RCMs performance specifies that GCMs downscaled through RCA4 regional model are characterized by high overestimation in the higher elevation areas and high underestimation in the lower elevation areas. GCMs downscaled using CCLM4 regional model also showed overestimation in the high elevation areas. Relatively, REMO regional model simulates the historical rainfall of the Jemma sub-basin better than RCA4 and CCLM4 models. This highlights the selection of RCMs during climate scenario development could be central for climate change projection and climate change impact assessment. The multi-model ensemble mean is superior in correlation metric and capturing monthly and seasonal rainfall of corresponding baseline climate.

Conclusion 3: distribution mapping bias correction technique has superior performance in adjusting mean values, wet day probability and the 90th percentile of rainfall and temperature of raw RCM simulations.

Statistical bias correction methods were effective and showed comparable performance in adjusting mean rainfall and temperature simulations of RCM. However, most bias correction methods, struggle to adjust frequency and intensity of rainfall and temperature simulations of RCM. This corroborates that bias correction methods have used different algorithms to develop shape parameters which further determine the frequency of rainfall and temperature events. Another skill of distribution mapping method is its viability under different climate conditions (non-stationary condition). These skills of distribution mapping suggest that this method is applicable in developing future climate scenarios.

Conclusion 4: future climate scenarios describe steady reduction of rainfall and an increase in temperature. In the future climate scenarios, there will be an increase in extreme rainfall and temperature events.

The climate scenarios reveal a consistent decrease of rainfall and an increase in extreme rainfall events in the near and long-term future over the Jemma sub-basin. The rainfall under different climate scenarios also shows unpredictable impact of emission scenarios on rainfall. This highlights local and regional forcings (internal variability) are also important drivers of rainfall of the Jemma sub-basin and the central highlands of Ethiopia. The steady increase of TMAX and TMIN and temperature extreme events are detected in the near-term and long-term climate scenarios. High increase of temperature is projected under climate scenarios based on RCP8.5 and in the last decades of the 21stC. Such changes of temperature and rainfall under different climate scenario may happen in the 21stC and beyond unless sustainable and substantial reduction of greenhouse gas emissions are realized.

Conclusion 5: future climate impact scenarios describe the Jemma sub-basin will be more water constrain.

Climate impact scenarios developed based on multi-model ensemble mean and multi-gauge calibration highlights the strong implication of future climate scenarios on the hydrology of the Jemma sub-basin. Future climate scenarios will trigger dwindling of surface runoff, water yield and an increase in evapotranspiration. Future climate may cause compound effects (reduction of rainfall and water yield) on the water resources base of the sub-basin. Consequently, compound effects may cause multifarious repercussion on the biophysical and socio-economic components of the sub-basin unless elegant adaptation strategies are designed. Besides, compound extremes (extremes of climate and hydrology) will amplify the consequence of climate change in the sub-basin.

Conclusion 6: water harvesting is the most prioritized watershed alternative through the multi-criteria decision analysis, GIS and hydrological model. Water harvesting will contribute a significant increase in soil water availability under all climate scenarios.

Retaining rainwater and water harvesting structures are the most prioritized criteria and alternatives of watershed management under different climate scenarios, climate impact scenarios and stakeholders view. Water harvesting structures, particularly the in-situ water harvesting structures significantly reduce surface runoff and significantly increase soil water availability, however no significant change in total water yield is estimated. Therefore, water harvesting structures could increase green water that can further increase agricultural production without a decline in blue water and environmental flow under future climate scenarios. In regions like the Jemma sub-basin, water harvesting structures strategies could have co-benefits to realize existing and forthcoming GTPs of Ethiopia which have strategies focus on the agriculture and water sectors. The increase in water availability will increase land for irrigation, agricultural production and youth employment. This will help to achieve GTP II plan of expanding irrigation land to about 5 million hectares, predominantly using surface water. Besides, water harvesting will reduce the pressure on marginal lands and natural ecosystems through reducing the expansion of agricultural land.

Conclusion 7: water harvesting structures could provide other co-benefits which are to be maximized.

Further, water harvesting structures could be elegant climate resilient pathways that reduce climate change impacts, improve livelihood, sustain interaction of upstream and downstream stakeholders. Even, such climate adaptation strategies would have co-benefits to achieve some sustainable development goals. However, caution is to be made in the design of water harvesting structures particularly ex-situ water harvesting structures to reduce seepage, evaporation loss and sediment load.

Conclusion 8: Watershed management technologies under climate change scenarios in selected watersheds.

On watersheds not suitable for water harvesting under climate scenarios, other watershed management technologies such as Vertisols management, double cropping, conservation agriculture and fruit tree plantation can be designed. Particularly, double cropping can be integrated with ex-situ water harvesting to obtain optimal crops production under the wake of climate change.

10.3 Recommendations

10.3.1 Development oriented recommendations

This PhD dissertation has suggested the following recommendations for water and other natural resources and socio-economic development under changing climate.

a) **Establish a robust climate service system;** In the Jemma sub-basin and other similar basins, establishment of robust climate service system is highly recommended in order to increase climate information to the stakeholders. In the Jemma sub-basin, for instance, climate extremes were detected under baseline and future climate scenarios and such information will have a pivotal role for the stakeholders in their adaptation decision analysis. The climate services system can avail information related to seasonal variations in rainfall and temperature that further helps farmers to adjust their agronomic calendar. Climate science and climate modeling are continuing to improve that could enhance climate models reliability and reduce uncertainty. Consequently, climate service system can surface the way to use advancements from climate modelling. Climate service system can be also extended into a hydro-climatic service system for the Jemma sub-basin.

b) **Climate change scenarios based watershed management planning**; climate and climate impact scenarios are to be the base for watershed management planning. In Ethiopia, watershed development programs and design of hydraulic structures for water management should thoroughly use robust climate scenarios and realize climate-sensitive watershed planning. Otherwise, the hydraulic structures may not be effective in the wake of climate change.

c) **Surface water management based climate adaptation;** surface runoff which is highly dependent on rainfall contributes a large proportion to stream flow and water availability in the soil. Consequently, robust climate adaptation decision systems which are based on surface water management are non-trivial to reduce observed and projected impacts of climate change and climate extremes on agriculture water sectors.

d) **Extension activities;** Parallel to the efforts to increase water availability through water harvesting, due caution is needed to reduce water losses through seepage and evaporation. Other water management techniques to increase water productivity are also to be explored. Extensions activities, training, communications and networking activities will be far important to lower water losses and to increase water productivity from water harvesting structures.

10.3.2 Future research

a) Climate change scenarios can be developed using more number of RCM simulations than this study. Besides, it is important to evaluate RCM simulations which are driven by reanalysis datasets, for instance ERA-Interim reanalysis. That would help to identify and disentangle whether biases are stem from driving model or RCMs schemes.

b) The outputs of Convective-Permitting Models are to be used. Regional climate models are characterized by overestimation of rainfall in high elevation areas. Convective-Permitting Models may reduce such biases through effectively solve clouds and convective process in high elevation areas.

c) This study struggles to locate highly and optimally suitable areas for water harvesting structures and other vegetative strips in the northern areas of the sub-basin under all climate scenarios. Thus, other watersheds based climate adaptation alternatives are to be designed in these areas of the sub-basin.

d) Studies to investigate the contribution of water harvesting structures on sustainable development objectives such as agricultural production, livelihood security, poverty reduction and access to clean water under different climate scenarios can be designed. This can help to well incorporate climate adaptation strategies with development policies and strategies.

e) Climate adaptation scenarios development which integrates other factors like population, agriculture and land use change can be designed.

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Curriculum vitae of Gebrekidan Worku Tefera

Gebrekidan Worku was born on October 27, 1987 in Shewa, Ethiopia. He completed his secondary school education in June, 2006 and joined Jimma University, Ethiopia. He obtained his bachelor degree in June 2009 from Department of Geography and Environmental Studies of Jemma University. He was graduated with great distinction. In September, 2009 Gebrekidan has joined Department of Geography and Environmental studies of Dilla University, Ethiopia to pursue his second degree and obtained his Masters degree (Msc) with specialization in 'Sustainable Natural Resources Management' in October, 2011. His masters thesis was focused on GIS and remote sensing based analysis of land use and land cover dynamics and its effect on the physical and chemical properties of soils in Ameleke Watershed, south Ethiopia. He was also graduated with great distinction. In November, 2011 Gebrekidan was assigned to Debretabor University by the Ministry of Education, Ethiopia. At Debretabor university, Gebrekidan has worked as a lecturer and department head of Natural Resources Management (Sep, 2012 – July, 2014).

In October, 2014 Gebrekidan was admitted as a PhD student at center for Environment and Development Studies of Addis Ababa University. Since then, he has conducted research focused on climate extremes, climate models evaluation and bias correction, hydrological climate change impact assessment, developing watershed management scenarios for climate adaptation, environmental analysis and climate change adaptation in urban areas. Gebrekidan was also working as a short term consultant at Water and Land Resources Center of Addis Ababa University in the 'Sustainable Land Management Project' and in at the World Bank Independent Evaluation Group (IEG). Gebrekidan has obtained fellowships from the Netherlands Fellowship Program (NFP) and the Indian Technical and Economic Cooperation (ITEC) for short courses and research grant from International Foundation for Science (IFS). He has published and contributed different articles which focus on climate. Gebrekidan has also presented different research papers at national and international conferences since 2013.

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ORIGINAL PAPER

Observed changes in extremes of daily rainfall and temperature in Jemma Sub-Basin, Upper Blue Nile Basin, Ethiopia

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Abstract

Climate variability has been a threat to the socio-economic development of Ethiopia. This paper examined the changes in rainfall, minimum, and maximum temperature extremes of Jemma Sub-Basin of the Upper Blue Nile Basin for the period of 1981 to 2014. The nonparametric Mann-Kendall, seasonal Mann-Kendall, and Sen's slope estimator were used to estimate annual trends. Ten rainfall and 12 temperature indices were used to study changes in rainfall and temperature extremes. The results showed an increasing trend of annual and summer rainfall in more than 78% of the stations and a decreasing trend of spring rainfall in most of the stations. An increase in rainfall extreme events was detected in the majority of the stations. Several rainfall extreme indices showed wetting trends in the sub-basin, whereas limited indices indicated dryness in most of the stations. Annual maximum and minimum temperature and extreme temperature indices showed warming trend in the sub-basin. Presence of extreme rainfall and a warming trend of extreme temperature indices may suggest signs of climate change in the Jemma Sub-Basin. This study, therefore, recommended the need for exploring climate induced risks and implementing appropriate climate change adaptation and mitigation strategies.

1 Introduction

Compelling evidence exists that climate change is occurring globally and concerns have arisen about its impact. Global land and ocean surface temperature has increased by 0.85 °C for the period 1880–2012 (Intergovernmental Panel on Climate Change (IPCC) 2013). Similarly, the last three successive decades were warmer globally compared to any other decades since 1850 (Folland et al. 2002; IPCC 2013). Temperature has been showing an increasing trend in almost all regions of the world. While the trend and magnitude of change on rainfall is not conclusive, it may vary by regions and seasons (Tank et al. 2006; Alexander et al. 2006; IPCC 2013; Maidment et al. 2015). An increase in rainfall by 0.5–1% per decade over most middle and high latitudes of the Northern Hemisphere and by 0.2–0.3% per decade over the tropical land areas was estimated in the twentieth century (IPCC 2001, 2013). Likewise, an increase in annual rainfall in the Sahel and Southern Africa regions and a decrease in March–May rainfall in East Africa region was observed over the period from 1983 to 2010 (Maidment et al. 2015). While the focus of most long-term climate change studies have been on changes in average climates. Extreme climate events are more sensitive to climate changes (Alexander et al. 2007; World Metrological Organization (WMO) 2009).

Change in the extremes of rainfall and temperature was observed at various regions of the world. For example, a decrease of the number of cold days and nights, an increase in number of warm days and nights, frequency of extreme high temperatures, and frequency of heavy rainfall were discerned on the second half of the twentieth century (IPCC 2001, 2012, 2013). Changes in extreme climate have profound impacts on society by causing property damage, injury, poverty, loss of life, and biodiversity (IPCC 2012). Moreover, extreme events speedup changes in the ecosystem structure and function more than the average climate (Peterson and Manton 2008; Tierney et al. 2013). Such extreme events demand rigorous risk

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Evaluation of regional climate models performance in simulating rainfall climatology of Jemma sub-basin, Upper Blue Nile Basin, Ethiopia

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ABSTRACT

This study examines the performance of 10 Regional Climate Model (RCM) outputs which are dynamically downscaled from the fifth phase of Coupled Model Inter-comparison Project (CMIP5) GCMs using different RCMs parameterization approaches. The RCMs are evaluated based on their ability to reproduce the magnitude and pattern of monthly and annual rainfall, characteristics of rainfall events and variability related to Sea Surface Temperature (SST) for the period 1981–2005. The outputs of all RCMs showed wet bias, particularly in the higher elevation areas of the sub-basin. Wet bias of annual rainfall ranges from 9.60% in CCLM4 (HadGEM2-ES) model to 110.9% in RCA4 (EC-EARTH) model. JJAS (June-September) rainfall is also characterized by wet bias ranges from 0.76% in REMO (MPI-ESM-LR) model to 100.7% in RCA4 (HadGEM2-ES) model. GCMs that were dynamically downscaled through REMO (Max Planck Institute) and CCLM4 (Climate Limited-Area Modeling) performed better in capturing the rainfall climatology and distribution of rainfall events. However, GCMs dynamically downscaled using RCA4 (SMHI Rossby Center Regional Atmospheric Model) were characterized by overestimation and there are more extreme rainfall events in the cumulative distribution. Most of the RCMs' rainfall over the sub-basin showed a teleconnection with Sea Surface Temperature (SST) of CMIP5 GCMs in the Pacific and Indian Oceans, but weak. The ensemble mean of all 10 RCMs simulations was superior in capturing the seasonal pattern of the rainfall and had better correlation with observed annual (Correl = 0.6) and JJAS season rainfall (Correl = 0.5) than any single model (S-RCM). We recommend using GCMs downscaled using REMO and CCLM4 RCMs and stations based statistical bias correction to manage elevation based biases of RCMs in the Upper Blue Nile Basin, specifically in the Jemma sub-basin.

1. Introduction

Global Climate Models (GCMs) are instrumental to assess relative change in the climate system due to various radiative forcing and make climate predictions on seasonal to decadal time scales and projections of future climate (IPCC, 2013). Many GCMs were

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ORIGINAL PAPER

Statistical bias correction of regional climate model simulations for climate change projection in the Jemma sub-basin, upper Blue Nile Basin of Ethiopia

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Abstract

This study evaluates bias correction methods and develops future climate scenarios using the output of a better bias correction technique at the Jemma sub-basin. The performance of different bias correction techniques was evaluated using several statistical metrics. The bias correction methods performance under climate condition different from the current climate was also evaluated using the differential split sample testing (DSST) and reveals that the distribution mapping technique is valid under climate condition different from the current climate. All bias correction methods were effective in adjusting mean monthly and annual RCM simulations of rainfall and temperature to the observed rainfall and temperature values. However, distribution mapping method was better in capturing the 90th percentile of observed rainfall and temperature and wet day probability of observed rainfall than other methods. As a result, we use the future (2021–2100) simulation of RCMs which are bias corrected using distribution mapping technique. The output of bias-adjusted RCMs unfolds a decline of rainfall, a persistent increase of temperature and an increase of extremes of rainfall and temperature in the future climate under emission scenarios of Representative Concentration Pathways 4.5, 8.5 and 2.6 (RCP4.5, RCP8.5 and RCP2.6). Thus, climate adaptation strategies that can provide optimal benefits under different climate scenarios should be developed to reduce the impact of future climate change.

1 Introduction

Global climate models (GCMs) are essential to study changes in the climate of the earth and to make climate change projections (Edwards 2011; Intergovernmental Panel on Climate Change (IPCC) 2013). Since mainly the 1950s, GCMs are under development and there are vital improvements. For instance, the Earth System Modelling Framework is the most essential step in climate modelling (Taylor et al. 2012; Edwards 2011). In fifth phase of Climate Model Intercomparison Project (CMIP5), several GCMs have been developed into Earth System Models by incorporating the representation of biogeochemical cycles (Taylor et al. 2012). Better than the earlier phases of IPCC models, the atmosphere and the ocean components of CMIP5 models have higher spatial resolution (Taylor et al. 2012; Woldemeskel et al. 2015; Yang et al. 2018). Consequently, CMIP5 GCMs reproduce the global scale mean surface temperature and the seasonal cycle of sea ice extent of oceans (Flato et al. 2013; Taylor et al. 2012).

Despite several improvements, CMIP5 GCMs perform less effectively in simulating cloud cover and rainfall of mountainous and coastal regions (Randall et al. 2007; Flato et al. 2013; Woldemeskel et al. 2015; Yang et al. 2018). Model parameterization, greenhouse emission scenarios, and internal climate variability are the key sources of uncertainties in GCMs (IPCC 2013). Low spatial resolution of GCMs is another source of uncertainty that hiders GCMs to reproduce the local

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