Local Adaptation Practices in Response to Climate Change in the Bilate River Basin, Southern Ethiopia

by

GETAHUN GAREDEW WODAJE

Submitted in accordance with the requirements

for the degree

Doctor of Philosophy in

ENVIRONMENTAL SCIENCES

At the

University of South Africa (UNISA)

SUPERVISOR: Dr Zewdu Eshetu

CO-SUPERVISOR: Dr Mekuria Argaw

MARCH 2017

DEDICATION

I dedicate this work to my beloved family for giving me the encouragement, support and inspiration. May God bless them all!

DECLARATION

I, **Getahun Garedew Wodaje,** hereby declare that the dissertation which I hereby submit for the degree of **Doctor of Philosophy in Environmental Science** at the University of South Africa is my own work and has not previously been submitted by me for a degree at this or any other institution. To the best of my knowledge and belief, except as acknowledged in the text, the dissertation does not contain any written work presented by other persons whether written, pictures, graphs or data or any other. I also declare that I have complied with the rules, requirements, procedures and policy of the university.

Student signature: _____ Date: **March 2017.**

ACKNOWLEDGEMENTS

I would like to thank the Lord Almighty for giving me the ability, health, strength, and motivation to start and come to this stage of my study.

I had the privilege of working under the supervision and mentorship of Dr Zewdu Eshetu and Dr Mekuria Argaw. I am grateful for their supervision, support, encouragement and inspiration. Thanks to Dr Zewdu for the constructive support and critical comments throughout the research work and for your really fatherly encouragement. Thanks to Dr Mekuria for the comments, the inspiration and enthusiasm. Every communication I made with both of you were sources of encouragement and fruitful.

I am thankful for the following organizations for sponsoring my study, providing data and facilitating the research work: Wolaita Sodo University, National Meteorological Agency, Ministry of Water, Irrigation and Energy, NASA Goddard Institute for Space Studies (GISS), The Agricultural Model Intercomparison and Improvement Project (AgMIP), and the UNISA Akaki Regional Learning Centre. Without the support of these institutions my research work would not have been realized.

The number of the people I wish to thank cannot fit into a single acknowledgement section. However, I would like to mention the following people for their valuable contributions: Muse G/Silase, Dr. Fisaha Behulu, Yalew Bezu, Gashaw Gismu, Dr. Desalegn Wana, Samuel Urkato, Dr. Yesuneh Gizaw, Dr. Brehantshay Teklewold, Fikadu Getachew (Melkassa ARC), Dr. Alexander C. Ruane (Nasa, GISS), Professor Assefa Mekonnen (FIU).These were people helped me since the proposal stage by GIS analysis, SWAT model procedures, statistical downscaling methods and the organization of the paper. Thank you all for your support and guidance. I wish to thank all farmers who willingly provided the necessary information about their environment and to Development Agents who coordinated the field data collection.

Special thanks to my family members and my parents (Gashe and Eto), Ato Ayele Haile, Melkamu Garedew, Mesay Garedew, Senait Tekle. You have been there for me all the time I needed you. Most importantly, I would like to forward my love and thanks to my

helpful wife, Kuri Ayele, for her support and encouragement. Kuratu, without your understanding and patience this achievement would have not been possible. Special thanks go to my lovely daughter, Malaliya Getahun. You were my refreshment and moral support whenever I was tired.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS

AfDB	-African Development Bank
AgMIP	-Agricultural Model Intercomparison and Improvement Project
AI	-Aridity Index
AOGCMs	-Atmosphere–Ocean General Circulation Models
ASTER	-Advanced Spaceborne Thermal Emission and Reflection Radiometer
ATA	-Agricultural Transformation Agency
BRW	-Bilate River Watershed
CMIP	-Coupled Model Intercomparison Project
CSA	- Central Statistical Agency
DEMs	-Digital elevation models
DOY	-Day of a Year
ENSO	-El Nino–Southern Oscillation
ESM	-Earth System Models
FAO	-Food and Agricultural Organisation of UN
FAR (AR5)	- Fifth Assessment Report of IPCC
GCM	-Global climate model
GHA	-Greater Horn of Africa
GHG	-Greenhouse gases
IPCC	-Intergovernmental Panel on Climate Change
ITCZ	-Inter-Tropical Convergence Zone

LGP	-Length of Growing Period
MERRA	-Modern-Era Restrospective Analysis for Research and Applications
MoA	-Ministry of Agriculture
MoWE	-Ministry of Water and Energy
NMA	-National Meteorological Agency of Ethiopia
NMA	-National Meteorological Agency of Ethiopian
PCI	-Precipitation Concentration Index
RAI	-Rainfall anomaly Index
RCMs	-Regional Climate Models
RCPs	-Representative Concentration Pathways
SRES	-Special Report on Emission Scenarios
SSTs	-Sea Surface Temperatures
SWAT	-Soil and Water Assessment Tool
UNDP	-United Nations Development Program
WCRP	-World Climate Research Program

ABSTRACT

The study was conducted in the Bilate River Watershed. Bilate River is one of the inland rivers of Ethiopia that drains in to the northern watershed of the Lake Abaya-Chamo Drainage Basin which forms part of the Main Ethiopian Rift and in turn is part of an active rift system of the Great Rift Valley in Africa. This study examined the extent and nature of rainfall variability from recorded data while estimation of evapotranspiration was derived from recorded weather data. Future climate scenarios of precipitation and temperature for the Bilate Watershed were also generated. Analysis of rainfall variability was made by the rainfall anomaly index, coefficient of variance and Precipitation Concentration Index. The FAO-56 reference ET (ETo) approach was used to determine the amount of evapotranspiration. Estimation of the onset and the end of the growing season, and the length of the growing period was done using Instat software. The results show that mean annual rainfall of the upper (2307 m.a.s.l), middle (1772 m.a.s.l) and lower (1361 m.a.s.l) altitude zones of the watershed are in the order of 1100 mm, 1070 mm and 785 mm with CV of 12%, 15% and 17% respectively. Based on the rainfall data record of the latest 30 years, there was a high temporal anomaly in rainfall between 1980 and 2013. The wettest years recorded a Rainfall Anomaly Index of +5, +6 and +8 for stations in the upper, middle and lower altitude zones respectively, where the driest year recorded value is -5 in all the stations. The average onset date of rainfall for the upper zone is April 3± 8 days, for the middle zone April 10 ± 10 days and for the lower zone April 11± 11 days with CV of 23%, 26% and 29% respectively. The average end dates of the rainy season in the upper and middle zones are October 3± 5 days and September 25± 7 days with CV 5% and 7%. The main rainy season ends earlier in the lower zone; it is on July 12 ± 10 days with CV of 14%.

Climate change scenarios were generated for two Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5 using 20 GCMs from CMIP5 bias-corrected under three future time slices, near-term (2010-2039), mid-century (2040-2069) and end-century (2071-2099). Rainfall is projected to increase in total amount under all-time slices and emissions pathways but with pronounced inter and intra-variability. Minimum temperature will significantly increase during mid-century by 1.81^{0}C (RCP 4.5) and

2.55^0C (RCP 8.5) and by 2.1^0C (RCP 4.5) and 4.27^0C (RCP8.5) during end-century. The projected increase in maximum temperature during mid-century is 1.43^0C under RCP 4.5 and 1.99 ^{0}C under RCP 8.5 and during end-century by 1.65^0C under RCP 4.5 and 3.5^0C under RCP8.5 during end-century.

The Soil and Water Assessment Tool (SWAT) model was selected to simulate stream flow of the watershed. The Alaba Kulito gauging station monthly stream flows from 1990 to 1996 and 1997 to 2002 were used for stream flow calibration and validation respectively. The respective statistical results of the coefficient of determination (R^2), Nash–Sutcliffe coefficient (NSE) and percent bias (PB) are 0.79, 0.78 and 0.56 for the calibration period and 0.64, 0.60 and -21.7 for the validation period which show that the model predicted the stream flow at the Alaba Kulito gauging station reasonably. The annual stream flow increased progressively throughout the century for all time periods under both RCP scenarios. The increases under RCP 8.5 scenario are the larger compared to RCP 4.5 scenarios, approximately 42.42% during the 2080s period. The six GCMs selected to see the uncertainties related to GCMs suggest that the river flow will change by small amounts of −6.18 to 7.83% change compared with the baseline. The simulated runoff in the Bilate River depends on the projected amount of rainfall embedded in the GCM structures selected to simulate the future climate and is less dependent on the local temperature increment.

The study also assessed the farmers' perceptions of the changes on climatic variables and their adaptation options to the impacts of climate variability and change. The determinant factors that influence the choice of farmers to climate change adaptation were also investigated. Above 92% of the surveyed farm households perceived variability and change in climatic variables but 59% of the households participated in one or other of the six major adaptation strategies which most prevailed inside farmers of the watershed. Changing crop variety, using water harvesting scheme, intensifying irrigation, using cover crop or/and mulching, reducing the number of livestock owned and getting off-farm jobs are the main adaptation strategies used by the farming households. The results from the binary logistic model further showed that age and educational level of the household head, farm size and the income level of the household are household

characteristics that significantly affect the choice of adaptation options, while access to climate information in the form of seasonal forecasts and local agro ecology are other factors that determined the selection of adaptation methods by the farming households in the study area. The main constraints to adaptation to climate change in the study area were seen to be the knowledge gap in the form of lack of information, shortage of labour and minimal land size. These were the three most explained constraints to climate change as explained by responding household heads.

Chapter 1: Introduction

1.1 General background

Climate change is emerging as one of the major challenges facing scientific and policy communities and the largest known impact of climate change is upon agriculture because of the size and sensitivity of the sector (Mendelsohn, 2009). Climate change could result in a variety of impacts on agriculture, both adverse and beneficial. Some of these effects are biophysical, some are ecological, and some others are economic, including changes in production patterns due to the changing temperatures and precipitation patterns. Since climatic factors serve as direct inputs to agriculture, any change in climatic factors is bound to have a significant impact on crop yields and production (Asha latha et al., 2012) and sustainable agriculture is about climate resilient cropping, as well as soil and water management systems that reduce climate-related risks for smallholder farmers and enhance the natural resource base (ATA, 2014). The effects of climate change on agriculture and other natural resources may vary across agro-ecological regions and within agriculture it is the rainfed agriculture that will be most impacted by climate change (Asha latha et al., 2012).

In sub-Saharan Africa, agriculture remains the main contributor to socio-economic development but the sector is already vulnerable to the effects of climate change and variability and that this will worsen in the future as its variability increases (Ojwang et al., 2010). In Ethiopia, rain-fed agriculture is the primary source of food production. As a result, the various impacts of climate change and variability, such as unpredictable rains, droughts, and floods, often overweigh the smallholder farmers of the country (ATA, 2014). Timely preparedness and adaptation to climate change is needed, not only to tap emerging opportunities; but also to reduce the adverse impacts of climate change in all sectors of the economy in general and agriculture, livestock, forest and water resources in particular (Hussain, 2013).

Identifying the local impact of climate change at a watershed level and quantitative estimates of hydrological effects of climate change is crucial for solving potential challenges in water resource management (Alemayehu et al., 2015). A watershed is an

area that drains water to a common outlet, and consists of upstream and downstream areas which are linked through bio-physical and socio-economic factors. So, a watershed is not simply the hydrological or development unit but also a socio-political-ecological entity which plays a crucial role in determining food, social, and economical security and provides life support services to the rural people (Wani and Garg , 2009).

Water resource management at watershed level requires information on water availability including the quantification of the spatial and temporal changes of hydrological processes and evapotranspiration plays a major role in this hydrological cycle. Evaporation from the land surface and transpiration from plants combine to return available moisture at the surface layer back to the bulk atmosphere in a process referred to as evapotranspiration (ET) (Su et al., 2005). Evapotranspiration (ET) plays a critical role in ecological and hydrological processes and influences local weather and climate (Sun et al., 2001; Huizhi and Jianwu, 2012) and also has great importance in agriculture (Ishak et al., 2010). Accurate and timely estimates of ET are essential for agricultural and water resource planning as well as for understanding the impacts of climate variability on terrestrial systems (Kim and Hogue, 2008).

Incorporating the influences of global climate change and variability into regional water resources planning and management at watershed level is increasingly necessary to more accurately predict future supplies. Climate models are the primary tools available to simulate future climate impacts under different emission scenarios (Liu et al., 2014). But there is an agreement among the scientific community that global climate model (GCM)-simulated climate data cannot be directly used as input to hydrological models (Li and Smith, 2009; Liu et al., 2014). In order to use the output of a GCM for conducting hydrological impact studies, downscaling is used in this study, which is a process of converting the coarse spatial resolution of the GCM output into a fine resolution.

Decision-makers face the challenge of adapting to a changing climate because the public perceptions of the risk posed by climate change and variability and support for adaptation policies vary from place to place (Moss et al., 2013; Taylor et al., 2014). The science of climate has a role in the governance of adaptation in terms of developing

climate scenarios, assessing the variations of regional impacts and vulnerabilities, by identifying adaptation needs, options, and priorities and evaluating the effectiveness of the existing adaptation strategies and polices (Ford, 2008; Bauer et al., 2012). There are many advantages in pursuing adaptation planning at the community level, because organizations can move quickly to create adaptation strategies which will directly benefit their communities (Picketts et al., 2012). The elements of climate and aspects of hydrology, coupled with human-landscape features have sensitive interactions that ultimately affect the availability of water for the rainfed agro-ecological landscapes currently provide food and livelihoods for the predominantly rural population of the area. Local climate studies are needed to provide fine scale climate information for impact assessment and localized adaptation planning and implementation.

The Bilate River watershed stretches across different topographical zones, sections of the watershed are located in the Ethiopian Highlands and display mountainous characteristics while other areas are part of the Rift Valley and thus, are almost flat or undulating. Intensive agriculture is dominating in the Highlands while the lower elevation part of the Rift Valley is dominantly extensive pasture. Any variability in local weather conditions is likely to have a huge impact on the agriculture sector and livelihoods of farmers. So, there is a need for a comprehensive study of climate variability and its impacts with the resulting adaptation costs in the watershed of the Bilate River. The population distribution of the watershed has two characteristics. The first one is maximum rural population density in the upper and middle course areas of the western part of the basin, while the second is the eastern part that is dominantly known for agro-pastoralism and relatively sparse population distribution.

1.2 Statement of the problem

Many Sub-Saharan African countries experience either water stress (less than 1,700 m^3 per capita per annum) or water scarcity (less than 1,000 m^3 per capita per annum) or both (Ngigi, 2009) and more than 80% of the agricultural land is rain-fed; in these regions, crop productivity depends solely on sufficient precipitation to meet evaporative demand and associated soil moisture distribution (FAO, 2003). Moreover, food

insecurity remains endemic throughout much of Africa, with climate induced risks following rainfall variability a major cause. For example, in 2006, 25 African countries required food aid, largely due to recurring drought. Poverty and food insecurity are linked to low agricultural productivity aggravated by climate change and variability (Ngigi, 2009).

Developing countries have specific needs for adaptation due to their high vulnerability, and they will carry a great part of the global costs of climate change (Mertz et al., 2009). Developing countries have very context specific circumstances and the specific impacts of climate change on a country depend on the climate it experiences as well as its geographical, social, cultural, economic and political situations (UNFCCC, 2007). Many literature (Smit et al., 1996; Belliveau et al., 2006; Maddison, 2006; Gbetibouo, 2009) argue that climate change impact studies often assume certain adaptations and little explicit examination of how, when, why, and under what conditions adaptation actually occurs in economic and social systems.

Adaptation to climate change is being given increasing international attention as the confidence in climate change projections is getting higher. Computational advancements and availability of satellite data to extract valuable spatial information provide confidence to better analyse watershed hydrologic processes (Wagesho, 2014). The current debate on climate change and variability is too much focused on the impact of global climate change and insufficiently addresses the local climatic interrelationships that prevail in Ethiopia (Wood, 2007) and country or location specific comprehensive attempt to know the local variability and erratic nature of the climate has been receiving little attention.

Thus, as part of a more recent adaptation research, there is a need to investigate climate change impacts at watershed scale and actual adaptations at the farm level, as well as the factors that appear to be driving them. The response of a catchment, that is, the runoff process is time and space variant and influenced by anthropogenic and climatic factors (Wagesho, 2014).

In the past watershed development plans were made with relatively straightforward objectives in mind. However, activities in the Bilate River watershed have more complex, direct and indirect relationships. The planning and implementation of watershed interventions takes a variety of comprehensive, integrated and holistic forms. Impact of these interventions in addressing the adverse effects of climate change is hardly documented. A study which uses a multi-disciplinary approach combining climate science with hydrology and social science in investigating climate change impacts and adaptation over the Bilate River watershed is needed to address the gaps. This study examined the impact of climate change on water resource availability and dry spell and length of growing period analysis at a watershed scale. The focus is on the evaluation of how climate change would influence the availability of water resources for the Bilate river basin in south central Ethiopia using downscaled Global Climate Model (GCM) outputs. This research analyses the interactions between climate and hydrology that affect water availability and extreme hydrological events.

1.3 Objectives of the research

The goals of this research is to provide policy makers and development planners with scientific evidence on detailed watershed exploration of biophysical and socio-economic characteristics, identified potentials and problems in the Bilate River watershed for making informed decisions on integrated watershed development addressing the adverse effects of climate change on local livelihoods by:

- Presenting estimates of current and future climate variability and its impact on the hydrology of the Bilate River Watershed and
- Examining local perceptions and adaptation mechanisms to climate variability and change.

The specific objectives are the following:

- To examine climate variability and its impact on the hydrology of the Bilate River watershed,

- To statistically downscale and produce future climate scenarios under different representative pathways.
- To evaluate the response of the stream flow of the Bilate watershed to climate change using the SWAT model.
- To examine the extent of farmers' level of awareness and perceptions of climate variability and change, and the types of adjustments they have made in their farming practices in response to these changes,
- To model adaptation options to climate variability and to examine the factors influencing farmers' adaptation options.

1.4 Research questions

The current research work was designed to address the following research questions:

- What is the level of climate variability in the Bilate River watershed?
- What is the future scenario of climate variables (rainfall and temperature) in Bilate River Watershed?
- What is the level of hydrologic variability in response to climate variability?
- How do farmers perceive long term changes in local climatic conditions?
- How farmers do adapt their farming systems in response to perceived changes in climate?
- What factors determined farmers' adaptation options?

1.5 Outline of the thesis

The thesis is structured in the standard monograph type of thesis writing with five chapters. In the current chapter the overall background of the research with the objectives of the research and the structural overview of the research is presented. Chapter two is a review about climate change and local adaptations including literature on climate models and the underlying downscaling methods. The detailed materials and

methods of the research are presented in chapter three. Chapter four presents the results and discussions with sub headings on: - i.) the variability of rainfall distribution and evapotranspiration over Bilate Watershed, ii.) application of statistical downscaling in the Bilate Watershed, iii.) the impact of climate change on the stream flow of the Bilate River Watershed, using a CMIP5 General Circulation Models ensemble projected precipitation and temperature data as input, iv.) local perceptions and adaptation to climate variability and change in the Bilate Watershed are discussed. Finally, the general conclusions and perspectives are given in chapter Five.

Chapter 2 : Review of Literature

2.1 Climate Change

Climate is the average pattern of weather in one locality averaged for at least 30 years, so it is based on long period measurements and records of meteorological data. Climate fluctuates yearly above or below a long-term average value (climate variability) or by the long-term continuous change (increase or decrease) to average weather conditions or the range of weather (climate change) (IPCC, 2007). Droughts, storms and floods are some of the manifestations of climate variability and change and often causing serious agricultural losses and human suffering around the world (Wilbank and Kates, 2010).

There are many doubts about how climate change impacts on agriculture, and how farmers respond. The impacts of global climate change are not only physical and economic, but also social and cultural, therefore altering environmentally-based livelihoods in many areas of the world (Hageback et al., 2005; Kyomuhendo and Muhanguzi, 2008). A better understanding of the social and economic factors influencing farmers' perceptions and their responses to a changing climate is needed.

Atmospheric temperature, rainfall, humidity, solar radiation, etc. are dominant climatic factors closely linked with agricultural production (Monzurul et al., 2015). Rainfall is of major importance in water resources assessment and therefore considerable research has been devoted toward characterizing its spatial and temporal variability (Alemseged et al., 2009). However, accurate estimation of space–time variability of rainfall is one of the major challenges in hydrometeorology in the interest of providing fine scale climate information for impact assessment and adaptation planning and operational decisions (Tsidu, 2012).

A change in global average temperatures due to anthropogenic greenhouse gases emission is evidenced in many recent studies confirming that the period from 1983 to 2012 was likely the warmest 30-year period of the last 1400 years in the Northern Hemisphere (IPCC, 2014) and it is believed to have led to a larger proportion of rainfall derived from intense precipitation events (Houghton et al., 2001; Trenberth et al., 2003; Raisanen, 2007). Even at times when our competency of separating the signal of anthropogenic influences from the 'noise' of natural climate variability has increased, the challenge of framing and communicating about climate change and variability is a manifestation of the challenge of understanding and reasoning about the complex climate system (Curry, 2011). Curry (2011) reasons, the very large number of subsystems and complexity in linking them, and the nonlinear and chaotic nature of the atmosphere for difficulty of understanding the climate system. With all the uncertainties to define it, global warming has been recognized since the 1970s and the amount of research concerning climate oscillations for both natural and anthropogenic reasons has increased sharply since then (Gruza and Rankova, 2004). IPCC (2014) also reports that each of the last three decades has been successively warmer than any preceding decade since 1850.

Adaptation to climate change has not been the focus of the international climate change studies, but as the confidence in climate change projections is getting higher, adaptation to climate change and variability is given increasing international attention (IPCC, 2007; Mertz et al., 2009). Most of the early time approaches to adaptation move from global climate model scenarios to sectoral impact studies and then to assessments of adaptation options (AfDB, 2003; Van Aalsta et al., 2008). By the growing dissatisfaction with this top-down scenario driven approach which uses global model scenarios far into the future, adaptation methods that begin with the assessment process closely involving local stakeholders, based on actual experience at local scales has emerged (UNDP, 2005; Van Aalsta et al., 2008).

Despite our experiences with historical climate variability, most attention today is given to anthropogenic climate change with the assumption that the damages caused by the current variability will end up in increased uncertainty. This has captured the attention of

policy makers at national and international levels (Thurlow et al., 2012). Climate variability threatens households' livelihoods and undermines economic development, especially in Sub-Saharan Africa, where most countries rely on rainfed agriculture (Thurlow et al., 2012).

2.2 Climate variability

Variability is a very important inherent characteristic of climate and it varies on all timescales. There has been much recent public and scientific interest in climate variability (the way climate fluctuates yearly above or below a long-term average value) and the possible role of human activity in changing the climate in space and time (Braganza et al., 2003). Climate variability and climate change impacts are determined elements and livelihood sources. So far, most studies have focused on measuring the impacts of changes in climatic averages on different sectors (Kucharik and Serbin, 2008; Lobell and Burke, 2008; Lobell and Field, 2008; Tao et al., 2008; Rowhani et al., 2011). Global scale assessments of climate change impacts on livelihoods and economic factors are commonly based on averages rather than on the analysis of the variability or extremes (Adams et al., 1990; Penalbaa and Vargasa, 2008). Observations, however, suggest that climate change and climate variability impacts on society result primarily from extreme events that induce disaster risks (such as drought, flood) (IPCC, 2007). This is because, in addition to changes in climate means, climate variability is expected to increase in some regions in the future, including the frequency and intensity of extreme events (IPCC, 2007). Some have proposed that changes in extremes will have a more adverse impact on crop production than changes in climate averages alone (Morton, 2007; Tubiello et al., 2007).

Climate variability is not uniform in space. It can be described as a combination of some preferred spatial patterns. The most prominent of these are known as modes of climate variability, which affect weather and climate on many spatial and temporal scales. The best known and truly periodic climate variability mode is the seasonal cycle. Others are quasiperiodic or of wide spectrum temporal variability (Blunden et al., 2011). One of the challenges that captured most interests of the climate science community is the

description and analysis of climate variability because the origins of these variations are uncertain, although there are many studies that try to connect them with climate forcing factors such as solar forcing and atmospheric circulation indices (Branstator and Selten, 2009; Roderiguez-Puebla et al., 1998). Climate variability may be due to natural internal processes within the climate system itself (internal variability), or to variations in natural or anthropogenic external forcing (external variability) (Werner et al., 2007) and the common view about the response of the climate system to external forcing will tend to have a structure that is similar to the structure of the system's leading intrinsic modes of variability (Branstator and Selten, 2009).

The Third Assessment Report of IPCC evaluated the available evidence and concluded that 'there is new and stronger evidence that most of the warming observed over the last 50 years is attributable to human activities (Winkler, 2005). But some external influences, such as changes in solar radiation and volcanism, occur naturally and contribute to the total natural variability of the climate system (IPCC, 2007). Internal climate variability is also present on all time scales. Internal climate variability is produced by processes like condensation of water vapour in clouds and coupled interactions among components, such as is the case with the El-Niño Southern Oscillation (IPCC, 2007). Atmospheric processes that generate internal variability are known to operate on time scales ranging from virtually instantaneous up to millenia.

Human perceptions of the climate, its variability and its potential change, have become an important challenge in understanding climate-society interactions (Elisabeth, 2004). The majority of climatic change studies try to identify variations of central tendency values of temperature and less frequently for rainfall series. However, the variability pattern was rarely considered in this type of study. But variability is a major descriptive parameter for observational series climate data; for example, total precipitation is not the only factor that determines the hydrological characteristics of a given area, as the variability of precipitation is of comparable importance (Jurkovic and Pasaric, 2012).

Rainfall variability receives higher attention among other climatic elements especially in relation to agriculture. The variability in rainfall can be explained either temporally or

spatially or both depending on the purpose needed (Song et al., 2014). A better understanding of the spatial and temporal variations of precipitation on different timescales and the adjustment of specific theoretical models like models that generate design storms and models that allows for the simulation of continuous time series at a point or spatially distributed are important for many applications (Vernieuwe et al., 2015). The resulting models will lead to a better management of a great variety of problems associated with variations in precipitation and will make it possible to improve statistical weather forecasts and climate monitoring (Penalbaa and Vargasa, 2008). Characterizing and quantifying these variability is of fundamental importance, not only for purposes of detection and attribution, but also for strategic approaches to adaptation and mitigation.

Precipitation distributions over tropical East Africa exhibit pronounced regional variations, and the seasonal cycle is complicated (Cook and Vizy, 2012). In most regions, there are two peak rainfall seasons that are nominally associated with solar heating maxima in the equinox seasons; sea surface temperature forcing, and teleconnections to the West African and Indian monsoon systems are among the other important factors influencing the timing and intensity of seasonal rainfall (Cook and Vizy, 2013). Topography is another factor that determines spatial distribution regardless of the impact of the equinox (Hession and Moore, 2011). Rainfall in tropical East Africa, within about 15^0 of the equator, is often delivered during two seasons, which are governed by the seasonal oscillation of the intertropical convergence zone (ITCZ). As a result, one rainy period occurs during boreal spring, known as the spring rain *Belg* in Ethiopia. A second rainy period occurs in the boreal fall over much of the region, and is known as the summer rain *Keremt* (Cook and Vizy, 2013).

Rainfall and evapotranspiration are two major climatic factors affecting agricultural production (Tilahun, 2006), and agricultural water resources face two major problems. One is the lack of available water supply in rain-fed agriculture, and the loss of available water through evapotranspiration (Wriedt et al., 2009; Derbile, 2013; Mou et al., 2014). Droughts are apparent after a long period without precipitation and the main natural causes of agricultural, economic, and environmental damage. Determining the onset,

extent, and end of drought and objectively quantifying its characteristics in terms of intensity, magnitude, duration, and spatial extent is difficult (Vicente-Serrano et al., 2010). In recent years, there have been many attempts to develop new drought indices, or to improve existing ones (Tsakiris et al., 2007; Vicente-Serrano et al., 2010). Generally, climatic characteristics of a given area can be used in different ways. For example, variations in the mean level of seasonal rainfall can be described statistically by coefficient of variation, while one can describe annual rainfall variability by the rainfall anomaly index (RAI) (Rooy, 1965). The Aridity index (AI) of an area can be expressed in terms of the results of precipitation and evapotranspiration (Rodier, 1985) and to study monthly variability of rainfall, the Precipitation Concentration Index (PCI) can also be used (Mulugojjan and Ferede, 2012).

2.3 Evapotranspiration

Evapotranspiration (ET) is an important hydrological process and its estimation is needed for many applications in diverse disciplines such as agriculture, hydrology, and meteorology (Suleiman et al., 2008). In the literature, there are three terms usually used to describe evapotranspiration: the first is *free water evaporation* ET0 (the amount of evaporation from open/free water surface), the second is *actual evapotranspiration* ETa (all the processes by which liquid water at or near the land surface becomes atmospheric water vapour under natural conditions) and the third is *potential evapotranspiration* ETp (water loss that occurs if at no time is there a deficiency of water in the soil for use of vegetation) (Xu and Chen, 2005; Shi et al., 2008; Li et al., 2010). Actual evapotranspiration is perhaps the most difficult and complicated component of the hydrological cycle, because it is the only connecting term between water balance and energy balance and also because of complex interactions in the land-plant-atmosphere system (Xu and Singh, 2005; Gao et al., 2007). Determined basically by climatic factors, evapotranspiration is more complicated, since it is also mediated by the vegetation cover of an area and by soil characteristics, and it is constrained by the amount of available water (Xu and Singh, 2005). The estimation of ET needs measurements of many weather variables such as atmospheric pressure, wind speed, air temperature, net

radiation and relative humidity, but these weather variables are not easily obtainable from practical measurements in weather stations (Ishak et al., 2010) as the most prevailing weather stations in Ethiopia are class III meteorological stations that can collect only air temperature and rainfall and class IV stations that can collect only rainfall.

Potential evapotranspiration (PET) is defined as the maximum ability to evaporate under the assumption of a well-watered surface. Accurate and timely estimates of PET are essential for agricultural and water resource planning as well as for understanding the impacts of climate variability on terrestrial systems (Kim and Hogue, 2008) and reference evapotranspiration (ETo) is the evapotranspiration from the reference surface, which is a hypothetical grass reference crop with an assumed height of 0.12m, a fixed surface resistance of 70 S/m, and an albedo of 0.23, and closely resembles an extensive surface of green, well-watered grass of uniform height, actively growing and completely shading the ground (Allen et al., 1998). The quantity ETo can be considered to be an upper limit of actual ET. The Food and Agriculture Organization (FAO) adopted and modified (as FAO 56) the Penman–Monteith (PM) equation as the standard ETo estimation method (Allen et al., 1998). Because of the usefulness of evapotranspiration for hydrological and agricultural research, a considerable literature has accumulated on the subject and the accuracy of evapotranspiration (ET) (McVicar et al., 2005; Sumner and Jacobs, 2005). From all the methods, the FAO-56 Penman–Monteith (PM) equation (Allen et al., 1998) has been widely used and considered as the standard method for estimating reference crop evapotranspiration (ETo), and for evaluating the performance of other methods (Allen et al., 1998; Ishak et al., 2010).

2.4 Climate models in climate change studies

Climate models, class of computer driven models, are defined as a mathematical representation of the climate system based on physical, biological and chemical principles (Goosse et al., 2010) and they are the primary tools available for investigating the response of the climate system to various forces (IPCC, 2013; Flato et al., 2013). Many climate models have been developed to understand the level of climate change in

response to the emission of greenhouse gases (GHG). The population size and lifestyle including energy and land use are the main drivers of anthropogenic GHG emissions and the representative concentration pathways (RCPs) are projections of GHG concentrations based on these factors. The RCP2.6 is for the strict mitigation scenario, RCP4.5 and RCP6.0 are for two intermediate mitigation scenarios and RCP8.5 is for very high GHG emissions (IPCC, 2014).

Knowing how temperature and precipitation are projected to change in the future on average is not very useful to decision-makers planning for specific types of impact studies of climate change on agriculture or water supply (Girvetz et al., 2012). But climate models that can be used to create more useful climate metrics and impact modelling results are needed, which in turn will be used directly to inform the development of climate adaptation responses for weather forecasting, understanding climate and projecting climate change. There are wide ranges of climate models identified by IPCC for impact assessment studies (IPCC, 2000; IPCC, 2007; IPCC, 2013).

There is no single model which is appropriate for all purposes. Models used in climate research vary from simple energy balance models to complex earth system models (ESMs) (Goosse et al., 2010; Flato et al., 2013). The following are climate models evaluated in the IPCC's Fifth Assessment Report (AR5).

2.4.1 Atmosphere-Ocean General Circulation Models

Atmosphere-Ocean General Circulation Models (AOGCMs) are developed to simulate the present climate and also used as a major tool for projections of future climate change using different emission scenarios. Global climate model information can be enhanced to better represent the conditions we know to have occurred in specific places by using historically observed local climate information from weather stations (Girvetz et al., 2012). But to assess the hydrological impacts of climate change at the watershed and the regional scale, the GCM outputs cannot be used directly due to the mismatch in the spatial resolution between the GCMs and hydrological models (Hashmi et al., 2009). Outputs from many GCMs are available in the public domain for academics and

research, mainly in the Coupled Model Intercomparison Project phase 5 (CMIP5) multi-model dataset of the World Climate Research Programs (WCRPs). CMIP5 is meant to provide a framework for coordinated climate change experiments for the IPPC AR5 and beyond and it promotes a standard set of model simulations in order to provide projections of future climate change on two time scales, near term (out to about 2035) and long term (out to 2100 and beyond).

Most of these GCMs have spatial resolutions that are usually no higher than 70–120 km (Solomon, 2007; D'onofrio et al., 2013). But to properly predict impacts of climate change and variability it needs information on a spatial scale in the order of 10km, but global climate models (GCMs) rarely have a spatial resolution finer than the order of 100km. This mismatch in spatial resolution creates the gap between the information available from GCMs and that needed to inform climate change adaptation strategies. This is mainly true for models that can benefit from higher spatial resolutions than global models provide. The best example is hydrological simulations, which are sensitive to elevation, local soil properties, topography, and slope orientation, and so on (Pierce et al., 2014).

2.4.2 Earth System Models

Earth System Models (ESMs) are the current state-of-the-art models, which are expanded on Atmosphere-Ocean General Circulation Models (AOGCMs) by incorporating the biogeochemical cycles (Flato et al., 2013). Adding biological and chemical components to a climate model due to the strong interactions associated with climate With the assumption that climate system is not only driven by physical processes specifically, the concentrations of major greenhouse gases are not only affected by man-made emissions but are also involved in chemical reactions and interactions with the biological components of the Earth system. So, ESM is developed with the aim of quantifying feedback on climate through the Earth system interactions.

2.4.3 Earth System Models of Intermediate Complexity

In some instances more focused modelling systems aim to answer specific scientific questions concerning long term climate change and climate sensitivity, or for developing large model ensembles, and for these projects lower resolution models called Earth System Models of Intermediate Complexity (EMICs) are used. Intermediate-complexity models are models which describe the dynamics of the atmosphere and/or ocean in less detail than conventional General Circulation Models (Flato et al., 2013).

2.4.4 Regional Climate Models (RCMs)

Regional Climate Models (RCMs) or limited-area models use large-scale and lateral boundary conditions and sea surface temperatures (SSTs) from GCMs to produce higher resolution outputs (Fowler et al., 2007). They have higher spatial resolution in the order of 10-50 kms. The higher resolution of RCMs compared to GCMs makes it possible to realistically simulate regional climate features such as orographic precipitation, extreme events, and regional scale climate anomalies, or non-linear effects (Fowler et al., 2007). The use of RCMs gained higher interest of scholars in recent years and the ability of RCMs to reproduce the present-day climate has substantially improved (Van Roosmalen et al., 2010). Unfortunately, using a RCM provides additional uncertainty to that inherent in GCM output because RCMs are subject to systematic biases when comparing simulated meteorological variables for the current climate to observations and these biases can affect hydrological simulations considerably (Van Roosmalen et al., 2010). There has now been much assessment of the ability of RCMs to simulate climate variables, particularly those relevant to hydrological impact studies (Hagemann et al., 2004; Leung et al., 2004; Fowler et al., 2007). RCMs are used to dynamically ‘downscale’ global model simulations for some particular geographical region to provide more detailed information, but they require considerable computing resources and are expensive to run (Flato et al., 2013).

2.5 Downscaling of climate models

The issue of climate change and its impacts on a global scale are the focus of strong, wide, international research efforts in natural and social sciences. However, understanding the nature and potential consequences of climate change at regional levels remains a challenge (El-Jabi et al., 2013). To determine the future changes in climate, the climate change research needs to address three different questions: How will emission rates change in the future? How will the climate respond to such changed emissions? And How large is the climate variability irrespective of changing emissions? (Ekström et al., 2015). Observed changes in the earth's climate over the past ~250 years are now widely considered to have been enhanced by anthropogenic activities of using fossil fuel (IPCC, 2007) and global climate models (GCMs) are the typical tools used to simulate the changes in climate as a result of increases in the concentrations of GHGs (Ekström et al., 2015). A number of Global Climate Models (GCMs) have been developed to simulate global climatology including precipitation and multiple GCMs have been used to simulate historic climate and project future climate based on different emissions scenarios (IPCC, 2007; Swain et al., 2014). The Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (AR5) describes emissions scenarios as plausible trajectories of different aspects of the future that are constructed to investigate the potential consequences of anthropogenic climate change. Scenarios represent many of the major driving forces - including processes, impacts (physical, ecological, and socioeconomic), and potential responses (IPCC, 2013).

GCMs are the best tools to estimate future global climate changes resulting from greenhouse gas concentration with different emissions scenarios in the atmosphere (Dibike and Coulibaly, 2005; Cheng et al., 2012). However, due to their coarse spatial resolution, the outputs from these models may not be used directly in impact studies. Hydrological models, for instance, deal with small or sub-catchment scale processes whereas GCMs simulate planetary scale and parameterize many regional and smaller-scale processes. Therefore, there is a scale mismatch between GCMs and hydrological models and these need downscaling of GCMs to catchment or sub-catchment processes (Coulibaly et al., 2005; Chen et al., 2012; Chen et al., 2013). So one of the important issues for the analysis of climate change impact is the part related to the downscaling of GCM data and the studies on downscaling techniques that have arisen from the issue on

the resolution of GCM (Kim et al., 2014). Several downscaling methodologies have been developed to transfer the GCM simulated information to local scale. In general, local scale is defined on the basis of geographical or physiographic considerations (Anandhi et al.,2008; Bhattacharjee and Zaitchik, 2015).

Climate models sometimes have difficulty in realistically simulating climatic variables on smaller scales, which in turn affects the confidence that can be placed in their attempts to simulate future changes (Hewitson and Crane, 2006; Li and Smith, 2009). In order to use the output of a GCM for conducting hydrological impact studies, downscaling is used, which is a process of converting the coarse spatial resolution of the GCM output into a fine resolution. It involves generation of station data by using the GCM climatic output variables. The current trend of increasing the resolution of GCMs is limited by the vast computational and storage resources required.

Global or regional climate models are still relatively coarse so that they cannot explicitly capture the fine-scale structure that characterises climatic variables at the local scale which is needed for impact assessment studies. The spatial resolution gap between currently available climate models and what impact assessment studies require can be bridged through the application of "downscaling" techniques. Thus, downscaling is required for climate impact studies at local scale. Agricultural and hydrologic impact assessment models require daily climate data, but the lack of availability of daily future climate projections has been a barrier to doing climate change impact assessments for specific places throughout the world. The daily downscaled data now provides a means for using these types to assess future climate change impacts (Girvetz et al., 2012).

There are two main approaches to downscaling i.e. dynamical, using regional climate models, and statistical, using empirical relationships (Christensen et al., 1998; Fowler et al., 2007; Anandhi et al., 2008).

- **Dynamical downscaling**: Dynamical downscaling uses regional climate models (RCMs) that transform outputs from GCMs into finer spatial and temporal resolution outputs. Their primary contribution is through the inclusion of more realistic topography and land use/vegetation (Brown et al., 2008).

- **Statistical downscaling**: Statistical downscaling utilizes relationships between GCM output and historical data to produce finer spatial and temporal resolution climate data at the regional level (Brown et al., 2008).

Dynamical downscaling typically employs the use of a regional climate model (RCM) embedded within or driven by output from a larger-scale global model (Megan et al., 2014). Dynamical downscaling of RCMs often includes statistical modelling in the form of "bias correction" to provide realistic output and minimize systematic errors that inevitably occur (Brown et al., 2008). RCMs are recommended at times when topographic features, such as strong orography, land use and vegetation play a significant role in regional climate (Brown et al., 2008). The major drawback of RCM, which restricts its use in climate impact studies, is its complicated design and high computational cost with the uncertainties that accompany complex models that outweigh the benefits of dynamical downscaling where these features are not significant. The spatial resolution that can be achieved is in the order of tens of kilometres (Anandhi et al., 2008).

Statistical downscaling involves developing a relationship between the large and local scales using historical data and then applying this relationship to adjust independent large-scale data down to the local scale (Megan et al., 2014). It is based on the use of statistical tools and rules to develop local scale hydro-meteorological data using the GCM outputs. In Hashim et al. (2009) statistical downscaling approaches are classified into three broad categories, namely: (1) weather typing, (2) weather generators, and (3) regression-based downscaling. Even if they come out to be different categories, fundamentally in their operation, they represent the following three basic assumptions (Hashim et al., 2009):

1. Selected predictor variables are relevant to the study and the host GCM is able to simulate them realistically.
2. The empirical relationships/rules developed under the present climate conditions are also valid for future climate change conditions.
3. Selected predictor variables are able to capture the climate change signal.

Statistical downscaling methods are typically as effective as and less expensive than dynamical downscaling and especially useful for temporal downscaling (from monthly to daily values) (Brown et al., 2008). In chapter five of this thesis statistical downscaling of selected GCMs from the Coupled Model Intercomparison Project phase 5 (CMIP5) is performed for precipitation and temperature at the watershed of the Bilate River.

2.6 Watershed modelling

A model is a simplified representation of a real world system and consists of a set of simultaneous equations or a logical set of operations contained within a computer programme (Wheater et al., 2008). A watershed model is series of algorithms applied to watershed characteristics and meteorological data to simulate naturally occurring, land-based processes over an extended period, including hydrology and pollutant transport. A watershed model is a useful tool for providing a quantitative linkage between external forcing and in-stream response by its capacity to simulate in-stream processes (EPA, 2013).

Based on the nature of algorithms used, watershed modelling approaches can be categorized as empirical, conceptual or physically-based where empirical models consist of functions used to approximate or fit available data (Daniel et al., 2011). Based on the techniques involved in the modelling process, models can be categorized as deterministic where outcomes are obtained through known relationships among states and events or stochastic where their inputs are represented by statistical distributions which determine a range of outputs (Erik Jorgensen et al., 2014). On a spatial basis models can be categorized as lumped, semi-distributed or distributed models. Semi-distributed and distributed models account for the spatial variability of hydrologic processes and boundary conditions within the watershed while the lumped modelling approach considers a watershed as a single unit for computations where the watershed parameters and variables are averaged over this unit (Wi et al., 2015). Watershed models can also be categorised as event-based which simulates individual precipitation-runoff events or continuous-process models which explicitly account for all runoff components while considering soil moisture redistribution between storm events (Daniel et al., 2010; Daniel et al., 2011).

Understanding and quantifying the responses of hydrological processes to CO_2 emission induced climate change is critical for developing appropriate mitigation and adaptation strategies for sustainable water resources management within agricultural systems (Ficklin et al., 2009). Many studies have been conducted to investigate long-term hydrologic variability associated with climate change. Hydrologic models combined with climate scenarios generated from GCMs are used to produce potential scenarios of climate change impacts on water resources (Ficklin et al., 2009) and assessment of the sensitivity of a model to climate change provides insights into the sensitivity of the hydrological systems to the changing climate (Arnell and Liv, 2001; Ficklin et al., 2009).

Understanding the hydrologic response of watersheds to physical (land use) and climatic (rainfall and air temperature) change is an important component of water resource planning and management (Mango et al., 2011). Study of the hydrologic behaviour of a watershed involves the quantitative characterization of the variability of water balance components, as influenced by orographic effects, natural climate variability and the changes associated with warming climate conditions. Effective planning of water resource use under changing conditions requires the use of basin runoff models that can simulate flow regimes under different scenarios of change (Mango et al., 2011).

Since the availability of continuous observational data at high spatiotemporal resolution is limited, studies often rely on hydrologic models to understand and predict the hydrologic behaviour of basins (Sridhar and Nayk, 2010). Several operational, lumped or ‘conceptual’ watershed models have been developed through time. The Stanford Watershed Model (Crawford and Linsley, 1966), SSARR (Rockwood et al., 1972), the Sacramento Model (Burnash et al., 1973), the Tank Model (Sugawara et al., 1976), HEC-1 (Hydrologic Engineering Centre, 1981), and HYMO (Williams and Hann, 1973) are examples of these models described by differential equations of hydraulic laws and empirical algebraic equations and have been reviewed by Arnold and Fohrer (2005). More recent conceptual models have incorporated soil moisture replenishment, depletion and redistribution for the dynamic variation in areas contributing to direct runoff and efforts to simulate hydrology and water quality of complex watersheds. Varying soils,

land use and management resulted in models that can reflect changes in land use and agricultural management on stream flow and sediment yield (Arnold and Fohrer, 2005).

Spatially distributed models allow a multi-objective evaluation of the watershed spatial impact on the hydrological responses but the data demands for these models are substantial, especially high-precision data cannot directly be met since the data is simply not available or it does not comply with standard quality targets. They require high-resolution digital elevation models (DEMs) and land use and soil maps to generate accurate prediction (Ye et al., 2011).

Soil and Water Assessment Tool (SWAT)

The SWAT model is a watershed scale model created to run with readily available input data so that general initialization of the modelling system does not require complex data gathering or calibration. It was originally intended to model long-term run-off and nutrient losses from rural watersheds, particularly those dominated by agriculture (Arnold et al., 1998; Easton et al., 2008; Pervez and Henebry, 2015). SWAT is a semi-distributed, continuous time model that operates on a daily time series (Narsimlu et al., 2015). The capabilities of SWAT in simulating various hydrological processes in different part of the world is discussed in scientific literature (Gassman et al., 2007; Gassman et al., 2014; Krysanova and Whiteb; 2015) and up to date publications are also available in the SWAT literature database at (https://www.card.iastate.edu/swat_articles/).

The Soil and Water Assessment Tool (SWAT) model has been used as an effective tool to model impacts of land cover changes and climatic change on hydrological and biogeochemical cycles in a variety of watersheds (Arnold, 1998; Wu and Johnston, 2008; Ye et al., 2011). Simulation models such as the Soil and Water Assessment Tool (SWAT) are frequently used to project the responses of watershed processes to climate change and provide a link between climate changes and water yields through simulation of hydrologic processes within watersheds (Butcher et al., 2014). Hydrologic models also allow various simulations to be performed based on user needs (Ficklin et al., 2009).

In SWAT the simulation of the hydrology of a watershed is performed in two phases, the first is the land phase of the hydrological cycle while the second is the routing phase of the hydrologic cycle. The land phase controls the amount of water, sediment, nutrient and pesticide loadings to the main channel in each sub basin and simulates the canopy storage, infiltration, redistribution, evapotranspiration, lateral subsurface flow, surface runoff, ponds, tributary channels and return flow. The routing phase can be defined as the movement of water, sediments, nutrients and organic chemicals through the channel network of the watershed to the outlet (Neitsch et al., 2005; Setegn, 2010).

The hydrological components of the SWAT model are governed by the water balance equation which is depicted as follows (equation 2.1) (Neitsch et al., 2005; Narsimlu et al., 2015):

$$SW_t = SW_0 + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \qquad (2.1)$$

where: SW_t is the final soil water content (mm); SW_0 is the initial soil water content on day i (mm); R_{day} is the amount of precipitation on day i (mm); Q_{surf} is the amount of surface runoff on day i (mm); Ea is the amount of evapotranspiration (ET) on day i (mm); W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm); Q_{gw} is the amount of return flow on day i (mm).

General circulation models (GCMs) projected precipitation and temperature data are often used as input to a calibrated hydrological model to simulate the future hydrological cycle (Dessu and Melese, 2013). GCMs are commonly utilized for local-scale forecasts under global warming scenarios (Ryu et al., 2011). CMIP5 includes comprehensive GCMs including finer spatial resolution associated with more complex orography of the region and different greenhouse gases emission scenarios (Taylor et al., 2012). The statistical downscaling approach such as the Delta approach is often applied in hydrological impact studies due to its simplicity, flexibility and low computation cost (Wilby et al., 2002).

SWAT is a conceptual, continuous time and physically-based hydrologic model developed by the U.S. Department of Agriculture-Agriculture Research Service in the early 1990s to assist water resources managers in assessing the impact of climate risks

and its management on water supplies and non-point source pollution in agricultural watersheds and large river basins (Arnold and Fohrer, 2005). The SWAT model is developed to predict the impact of land management practices on hydrologic and water quality response of complex watersheds with heterogeneous soils and land use conditions (Arnold, 1998; Chaubey et al., 2005). Performance of the SWAT model in Ethiopia was documented in some previous studies (Setegn et al., 2009; Easton et al., 2010; Betrie et al., 2011; White et al., 2011). In other east African Countries also satisfactory performance and applicability of SWAT was reported (Jayakrishnan et al., 2005; Mulungu and Munishi, 2007; Mango et al., 2011a; Dessu and Melesse, 2012).

Watershed model selection criteria

Several watershed simulation models have been developed so far, but it is not easy to choose the most suitable model for a particular watershed to address a particular problem. Even though there are no clear rules for making a choice from the existing watershed models, some guidelines can be considered (Fiseha, 2013). An extensive review on published literature related to calibration, validation, and application of watershed models in similar scenario is needed to get a watershed model which is commonly used, accepted, and recommended in published literature; and all depending on the objective of the study at hand (Moriasi et al., 2007).

For this particular study the Soil and Water Assessment Tool (SWAT) model was selected to simulate the stream flow of the Bilate River watershed based on the following criteria as suggested by Fiseha (2013):

i. Considering the availability of input data
ii. Considering the nature and type of hydrologic process needs to be simulated
iii. Considering the availability of the watershed simulation model itself
iv. Considering the nature of data handling mechanisms (storage, retrieval and manipulation with use of Geographical Information Systems (GIS)).

The performance of SWAT in other parts of Ethiopia is also considered as criteria for selection of the model (Setegn et al., 2009; Easton et al., 2010; Betrie et al., 2011; White

et al., 2011) and in other east African countries also satisfactory performance and applicability of SWAT was reported (Jayakrishnan et al., 2005; Mulungu and Munishi, 2007; Mango et al., 2011a; Dessu and Melesse, 2012).

2.7 Local adaptations to climate change

Climate change is a global environmental threat to all economic sectors, particularly the agricultural sector (Chandrasiri, 2013). Climate is a key factor influencing agricultural production, and agriculture also affects climate change, which means higher temperatures, reduced rainfall and increased rainfall variability reduce crop yield and threaten food security in low income and agriculture-based economies (Deressa et al., 2011). In recent decades, there exist substantially more impacts attributable to climate change (IPCC, 2014). Impacts are due to observed climate change, irrespective of its cause, indicating the sensitivity of natural and human systems to changing climate and societies have adjusted to and coped with climate variability and extremes with varying degrees of success. The use of information about present and future climate change to evaluate the suitability of current and future practices is adaptation (Fussel, 2007). Adaptation can also be defined as actions taken to minimize negative effects or maximize any potential benefits of climate change (Smit and Wandel, 2006). According to the IPCC (2001) adaptation is adjustment in ecological, social, or economic systems in response to actual or expected climatic stimuli and their effects or impacts. Generally adaptation refers to the adjustment in natural or human systems in response to actual or expected climatic variability or change and their effects that can minimize harm or take advantage of beneficial opportunities (Parry et al., 2007; Green and Weatherhead, 2014).

Adaptations may occur before or after impacts have happened (Lindseth, 2005). In the early days the concern of scientific society was to produce knowledge of the potential impacts of a changing climate and how to reduce anthropogenic greenhouse gas emissions, but recently emphasis has been given to adaptation and the promotion of a risk management approach (Martens et al., 2009). The science of climate has a role in the governance of adaptation in terms of developing climate scenarios, assessing the variations of regional impacts and vulnerabilities, by identifying adaptation needs,

options, and priorities and evaluating the effectiveness of the existing adaptation strategies and polices (Ford, 2008; Bauer et al., 2012).

Adaptation to climate change is attracting international attention as the confidence in climate change projections is getting higher, because it can no longer be ignored (Wilbanks and Kates, 2010).Adaptation in the context of climate change refers to any adjustment that takes place in natural or human systems in response to actual or expected impacts of climate change, aimed at moderating harm or exploiting beneficial opportunities (Smit and Wandel, 2006; Picketts et al., 2012). Adapting to climate variability and change has been part of human practice for long period and the historical record includes many cases of successful adaptations (Wilbanks and Kates, 2010).

The impacts of climate change are typically discussed at the global, continental or national levels and developing countries are recognised as the most vulnerable to adverse impacts of climate change and have less capacity to adapt (Lindseth , 2005). But the impacts of climate change are most acutely felt at local level, so there are many advantages to pursuing adaptation planning at this level (Juholaa et al., 2012) and there are a lot of studies conducted on farm-level adaptation to climate change across different disciplines in various countries which explore farmers' adaptive behaviour and its determinants (Deressa et al., 2009; Bryan et al., 2013; Abid et al., 2015). The impact of climate change is detrimental to countries that depend on agriculture as the main livelihood (Deressa et al., 2011) and Ethiopia is fundamentally an agrarian country, with its agriculture sector continuing to be the most dominant aspect of the economy, accounting for nearly 46% of GDP, 73% of employment, and nearly 80% of foreign export earnings (ATA, 2014). To guide future adaptation strategies, it is important to understand how local communities perceive and adapt to climate change because adaptation to climate change is a two-step process; the first step requires the community to perceive a change in climate and the second step requires the community to decide and act through adaptation (Deressa et al., 2011). In order to understand what context specific adaptation options are needed by the local communities and how the perceptions of farmers are affected, it is important to identify the climatic and non-climatic factors that influence the sensitivity of rural livelihoods to climate change. Non-climatic factors

include, among others, age or farming experience of farmers, exposure to mass media and income level of rural household, all of which may affect perceptions of climate change (Ishaya and Abaje, 2008; Semenza et al., 2008; Akter et al., 2009). A number of studies show that in one way or the other farmers perceive that the climate is changing and also try to adapt to reduce the negative impacts of climate change (Mertz et al., 2009; Deressa et al., 2011).

Many governments and international development organizations have begun to develop strategies to adapt to the effects of climate change (UNDP, 2003). The UNDP climate adaptation programme has a well-defied framework that guides implementation of the adaptation programmes of nations to climate change. Different communities tend to be impacted differently, thereby exhibiting different adaptation needs and uncoordinated action at household levels (Paavola and Adger, 2005). Adaptation activities are national, regional or local issues rather than international. At the national level adaptation activities may include formulation of climate change policy geared toward vulnerable sectors and the development of policies and institutions that support adaptation at community levels and encourage private sector participation, allowing for greater dedication of resources to development of adaptive technologies and innovations (Paavola and Adger, 2005; Ngigi, 2009). The recent focus of studies of adaptation to climate change is on the local level and effective adaptation measures require understanding of how climate variables are likely to change and the level of uncertainty at local levels (Amundsen et al., 2010; Dannevig et al., 2012).

Locally at the community level adaptation activities include prioritization of local adaptation measures and giving feedback to stakeholders and provision of knowledge, technology, policy and institutional support for the vulnerable communities (Paavola and Adger, 2005; Ngigi, 2009). The importance of adaptation to climate change is increasingly emphasised and human adaptation to climate change is a heterogeneous process influenced by more than economic and technological development (Pielke et al., 2007; Nielsen and Reenberg, 2010). There are many advantages to pursuing adaptation planning at the community level, because small organizations can move quickly to create adaptation strategies which will directly benefit their communities (Picketts et al.,

2012). Systems ability to adjust to climate change to minimize potential damages, to take advantage of opportunities or cope with the adverse consequences of climate change is its adaptive capacity (IPCC, 2007; Juholaa et al., 2012). Adaptive capacity is highly varied within a society or among communities and often influenced by social factors such as education, gender, health, social status and ethnicity (Nielsen et al., 2010).

Chapter 3 : Methodology

3.1 Description of the Study Area

3.1.1 Location and general characteristics

Bilate River is one of the inland rivers of Ethiopia whose source is located at Gurage Mountains in central Ethiopia. The river drains to the northern watershed of the Lake Abaya-Chamo Drainage Basin. The basin forms part of the Main Ethiopian Rift which is part of an active rift system of the Great Rift Valley. The Bilate River watershed (BRW) covers an area of about 5625 square kilometres and is located in the southern Ethiopian Rift Valley and partly in the western Ethiopian Highlands. The Bilate River catchment includes part of the SNNPRS regional zones which include: Hadiya, Kambata Tambaro, Gurage, Silte, Wolaita, Sidama, and Alaba special woreda and small parts of the south-central Oromiya regional states. The Bilate River Watershed stretches across different ecological zones ranging from the mid-south-west Ethiopian Highlands to the lowlands of the Rift Valley. The altitude of the watershed ranges from 1,146 at Lake Abaya to 3,393 meters above sea level at Mt. Ambaricho. Geographically, its location, extends from 6º 36'N 38º00'E at Lake Abaya Wolaita Zone SNNPR to 8º05'N 38 º12'E at Gurage and Silte Zones border, SNNPR; and from7º18'N 46'E at Kambata Zone to7º12'N38º22'E Sidama Zone.

The Bilate River is the longest river in the Abaya Chamo Basin, with a length of about 255 km. It is also the only river which flows into Lake Abaya from the north. The main

river flows straight southwards to Lake Abaya. Most of the perennial tributaries come from the western side, while the eastern side has mainly intermittent streams, and hence the water contribution from the eastern side is relatively low. From the regional location point of view, the watershed covers mainly the north-eastern part of the SNNPR and some parts of the south central Oromiya Regional States. Although the upper course lies in Silte and Gurage Zones, most of its tributaries with large volumes of water come from Kambata, Wolaita and Hadiya mountains respectively.

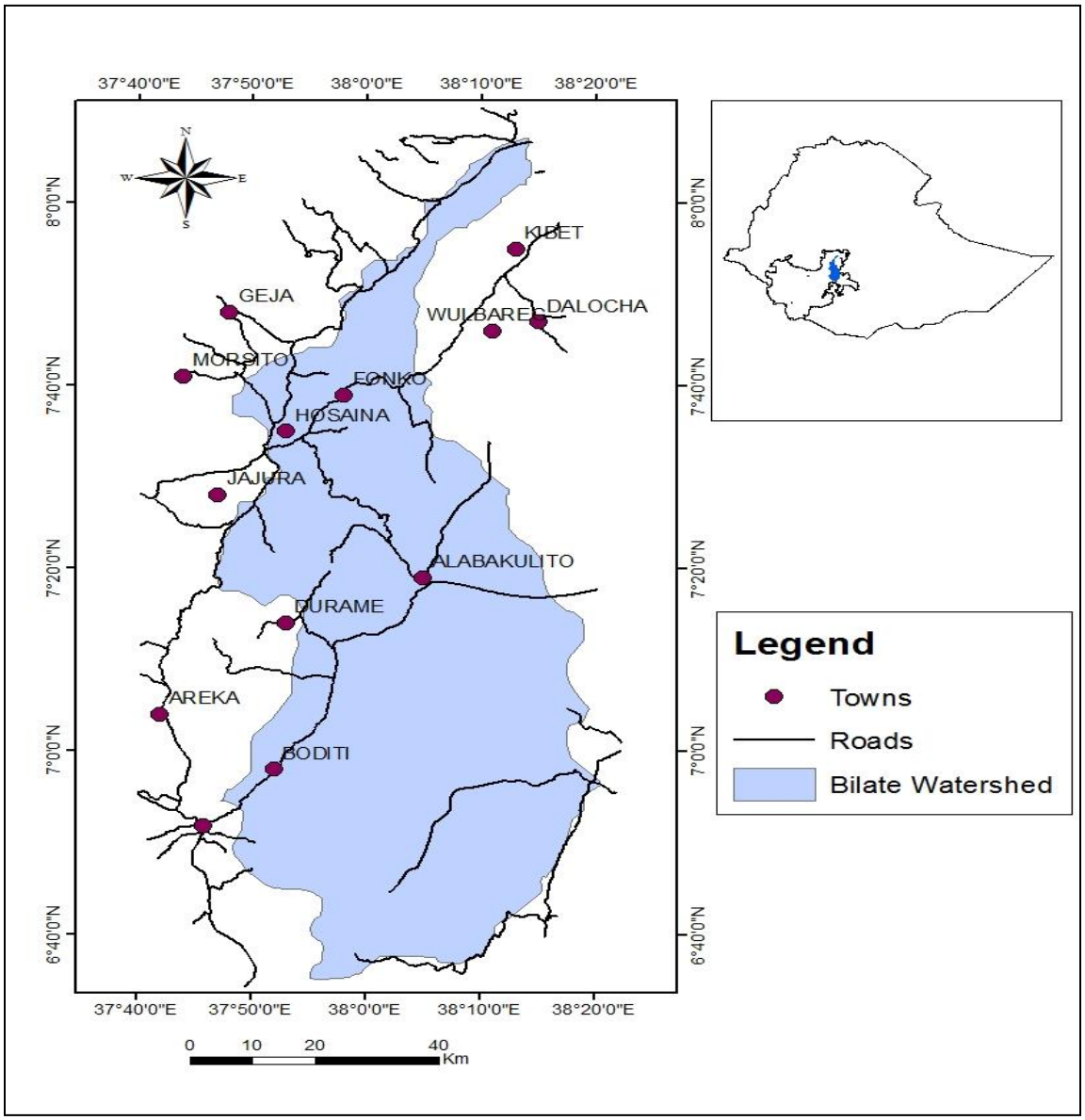


Figure 3-1: Location map of Bilate River Watershed

The population distribution of the watershed has two characteristics. The first one is maximum rural population density in the upper and middle course areas of the western part of the basin, while the second is the eastern part that is dominantly known for agro-pastoralism and relatively sparse population distribution. The high population density in the western part of the basin is related to the suitability of agro-climatic conditions, soil type and availability of water resources. In these areas maximum rural population density is the highest in Ethiopia, which exceeds 500 persons per square km (CSA, 2013).

The ethnic and cultural distribution within the watershed is highly diversified. There are more than eight ethnic groups dwelling within the watershed. Their impact on the environment depends on their cultural agricultural and land management practices. For example, the ethnic groups living at the lowest elevation of the Bilate River or northern part of Lake Abaya are more of agro-pastoralists. On the other hand, the people living in the western part of the watershed are known for their intensive and mixed farming culture.

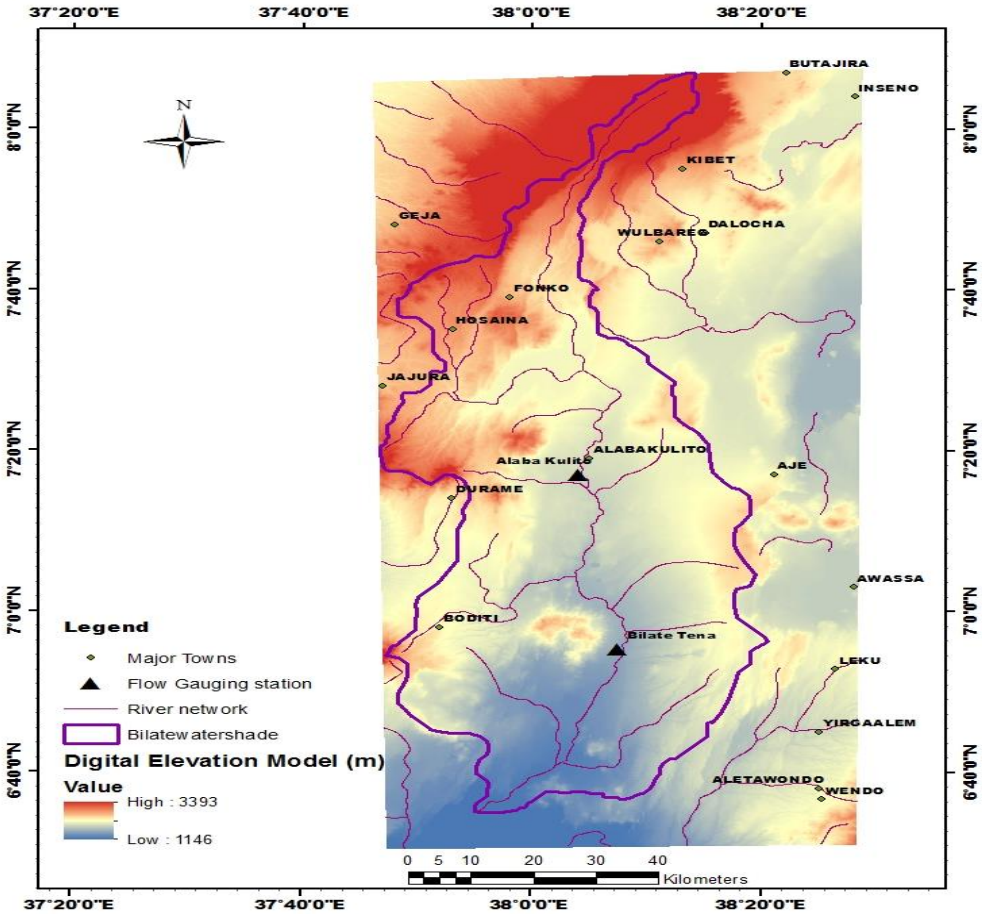


Figure 3-2: Digital Elevation Model (DEM) and River networks in BRW

3.1.2 Topography, geology, land use and soils

Topography

The watershed and topographic characteristics of BRW has been extracted from a Digital Elevation Model (DEM) with 30m resolution which was acquired from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). The topography of the BRW varies from the lowlands of altitude 1,146 metre above sea level (m.a.s.l.) near Lake Abaya to the highlands with peak elevation of 3,393 metre above sea level towards the northern realm of the watershed.

According to Wemmer, (2004) the relative relief of the Bilate area is divided into three parts: the first is a relatively steep profile with relative relief of 0.29, and is separated into several convex partitions from the headwaters to approximately 61 km downstream; the second part is a convex profile from approximately 61 km to 193 km with relative relief of 0.05, and the third is a smooth and straight profile from 193 km to Lake Abaya with relative relief of 0.04.

Geology

BRW forms part of the geological foundations of East Africa known to be formed from a complex of metamorphic and volcanic rocks, which can be assigned to the era of the Precambrian and the Palaeozoic (Forch and Althoff, 2009). The relief of today's Ethiopia as well as the one of the Bilate River catchment is strongly influenced by the geological conditions and therefore structurally strongly dependent. Only limited amounts of information specific to the geology of the Bilate watershed itself are available. Geological information published by FAO (1998) provides the Oligocene-Miocene basalts dominating the Bilate River Catchment. These basalts can be found in the central area between Alaba Kulito and Bilate Tena, accompanied by Quaternary rhyolites and trachytes in the north and Holocene lacustrine sequences in the south of the catchment. Furthermore, on the southwest border, many subordinated Oligocene and Miocene volcanics can be found. Geophysical studies by Thiemann et al., (2004) show that the entire Main Ethiopian Rift is situated in a hot zone with a width of around 1000km, which displays low density and thickness while the Western Ethiopian Highlands are characterised by quaternary Rhyolites and Trachytes. Lake Abaya, which is in close proximity to the watershed, is typified by Holocene lake and swamp deposits.

Physiographically the Bilate River basin is a tectonic valley. Along its length much of the valley is bounded by fault scarps or steep slopes on either side, as described in Tenalem et al. (2008) and therein cited references. The floor of the valley is mostly flat plain and appears to be in part a remnant of the depositions floor of an ancient large water basin. The study area is part of the western rift margin which is characterized by chain ridge, hills, deep and wide valleys of small and large streams, and narrow flat lands between the valleys having gentle slopes. It is due to the uplift and subsequent rifting phenomena that created localized and regional fractures and faults.

Soil

The soil types within the watershed can only be roughly estimated, due to the inadequate scale of the available soil data. The soil data used in this research was obtained from the Food and Agriculture Organization of the United Nations data base (FAO, 2003). According to the FAO Soil Map the soil depths in the study area is between 1.00 and 2.00m and the dominant soil types are Eutric Nitosols, Plinthic Ferralsols, Eutric Cambisols, Ochric Andosols and Haplic Xerosols. The occurrence of different soil types is related to geology, although the relief has a significant influence on the development of soil types in some areas.

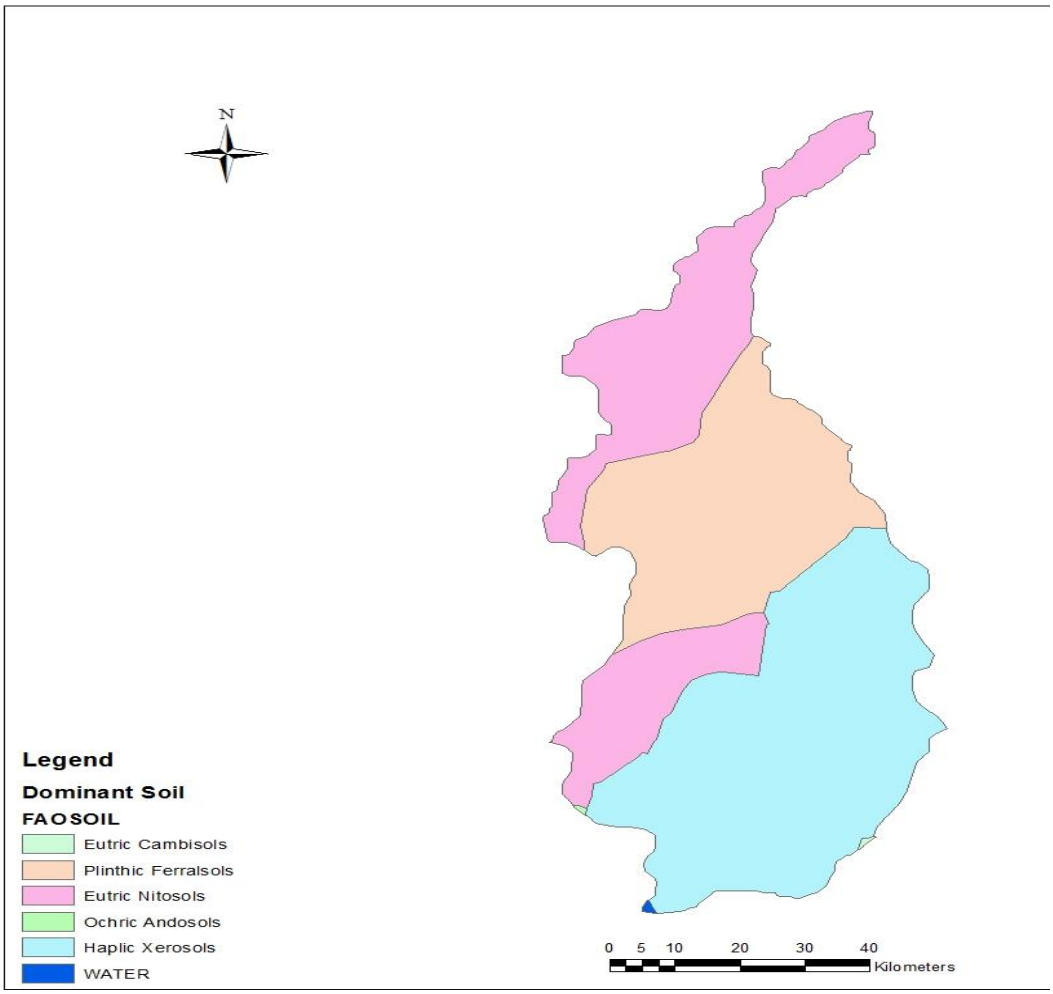


Figure 3-3: The map showing the dominant soil classes in the Bilate River Watershed.

Land Use and farming system

The distribution of land-use systems, in the BRW, is linked to the prevailing climatic gradient and anthropogenic land use activities. Two main agricultural systems can be distinguished within the BRW. The land use system in the Western Ethiopian Highlands is dominated by small-scale subsistence agriculture while the Rift Valley has several different systems such as pasture and commercial farms. The northern part of the Rift valley is used for large-scale maize farming, which operates commercially; also, the private farmers in this area have larger fields. In the semi-arid part of the Rift Valley, vegetation is generally less dense than in the western highlands of the watershed, and trees only grow in riparian areas. Towards the south, the communal lands are predominantly utilized by pastoralists for extensive livestock production, mainly cattle. A few irrigated mechanized farms are found near the mouth of Bilate River around Bilate Tena (Dimtu), of which the state owned tobacco farm is the major one.

Land use data with 500 x 500 m spatial resolutions were obtained from the Ministry of Agriculture (MoA) which is derived from FAO 98 land use classification for Ethiopia and further reclassification was performed in the model used for simulation of hydrological processes. The land cover in the BRW is predominated by different types of agricultural land (87%), grass and rangeland 0.8%and the remaining mixed land cover, including plantation forest, shrub land and wetland, accounts for about12.2%.The forests are transformed to croplands and/or grazing areas. The change from forests to crop and pasture land is directly related to increasing human population especially in the rural areas.

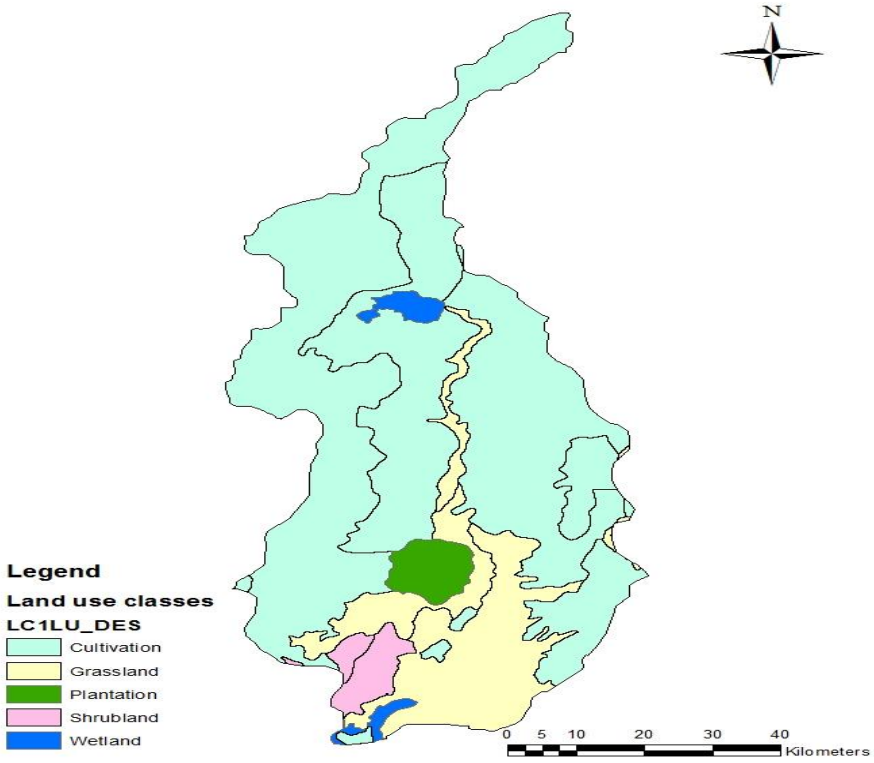


Figure 3-4: Map showing the land use land cover in the BRW

3.1.3 Hydro-meteorological characteristics of the BRW

Rainfall in the BRW shows high spatial variability. The illustration of spatial variation in annual precipitation is shown in the contour map in Figure 3.5. The mean annual rainfall at the stations with complete records was summarized and then spatial interpolation was performed over the entire watershed. Ordinary Kriging interpolation with exponential variogram show the spatial variation of rainfall The mean annual rainfall in the BRW ranges between 721 and 1353mm which shows large spatial variability with a maximum rainfall as large as 1.87 times the minimum rainfall. Areas that belong to part of the Western Ethiopian Highlands show higher rainfall on an annual basis while the part of the watershed that belongs to the Ethiopian Rift Valley shows lower rainfall.

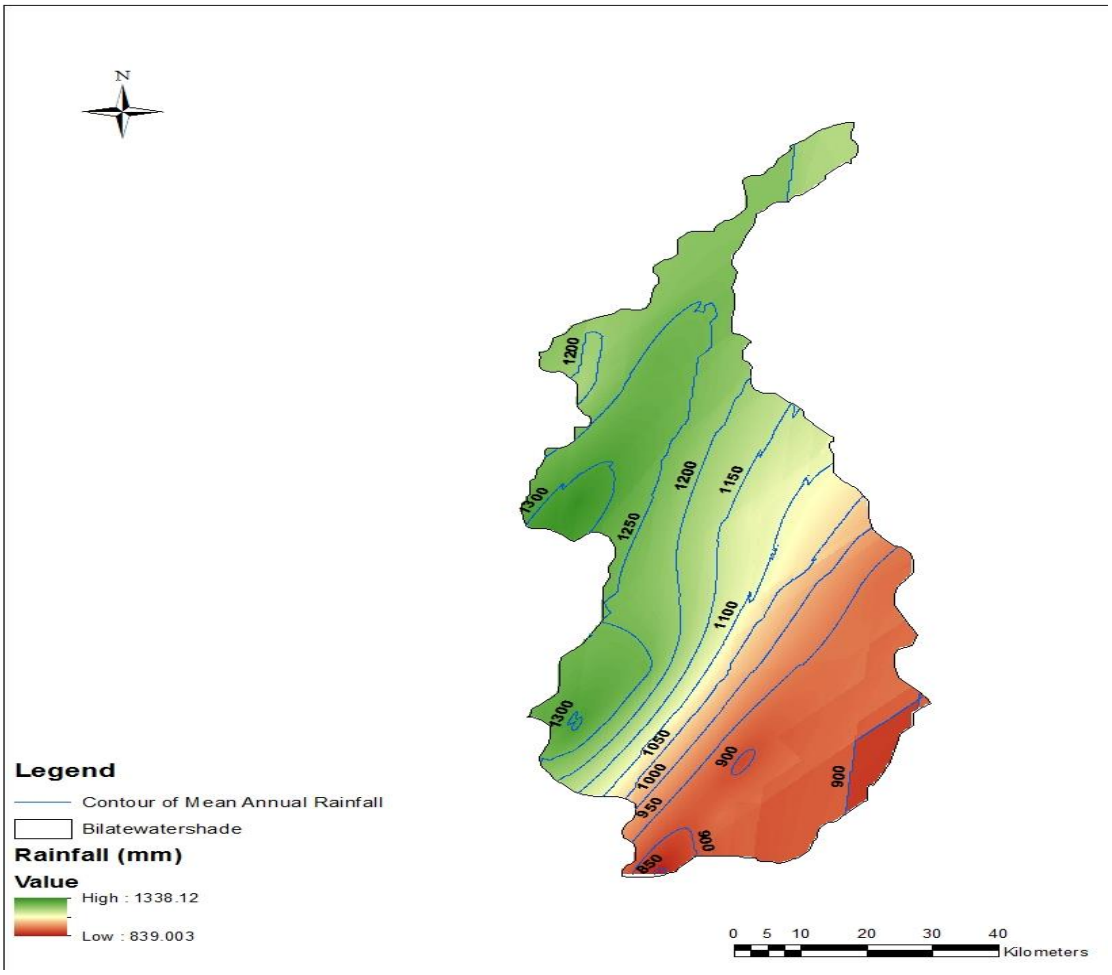


Figure 3-5: Contour map of mean annual rainfall of BRW

3.2 Data source and analyses

3.2.1 Rainfall

There are more than 18 rainfall observation stations in and around the Bilate River watershed (Fig 3.6). Time series rainfall data of these stations was obtained from the National Meteorological Agency (NMA) of Ethiopia. For the time period Jan/01/1984 to Dec/31/2013 rainfall stations with an amount of daily data above 75% were selected. From the available stations, only 11 stations satisfied the criteria. The selected stations with their mean annual value and the percent of daily missing rainfall data for the 30 years period under study are summarized in Table 3-1.

Table 3-1: Selected rainfall stations in the Bilate River Watershed (BRW) for the years1984-2013

S.N	Station Name	Easting (m)	Northing (m)	Altitude (m)	Missing daily %	Mean Annual Rainfall (mm)
1	Alaba Kulito	399982.7	808180.6	1772	0.74	1025
2	Angacha	373864.6	811557.1	2317	17.82	1223
3	Bilate	398710.0	753578.3	1361	6.03	781
4	Boditi	384561.1	768748.2	2043	1.97	1154
5	Durame	384070.2	795991.4	2000	5.16	1031
6	Fonko	386177.6	844881.6	2246	9.17	1093
7	Hosana	373561.7	836620.6	2307	3.74	1100
8	Imdiber	382787.9	897533.5	2082	8.19	1068
9	Mayo kote	373280.0	761280.2	2121	22.29	1173
10	Shone	384327.0	773908.4	1959	1.72	1353
11	Wulbareg	402990.4	855255.7	1992	3.69	1131

Some of the stations are located outside the boundary of the study area selected for hydrological simulation but still the area is located within the same hydro-meteorological setting, thus the stations that satisfy the criteria were used to fill the missing data by interpolation technique.

The appropriate daily rainfall, minimum and maximum temperature data was arranged by the day of a year (DOY) entry format. Data quality control was done by careful inspection of the completeness, and the spatial and temporal consistence of the records in the study area. The missing values of daily data were calculated and simulated by using **INSTAT +v.3.36** first and second order Markov-chain simulation models (Stern et al., 2006). A Markov-based random model was established to generate simulated time series of daily precipitation, and the simulated statistic parameters demonstrated good consistency with their observational equivalents (Yuguo et al., 2010).

The inbuilt Markov chain model of InStat software performs the simulation of the missing data in two steps. First, it determines the probability of dry and wet weather from the input weather data of the recorded dates, the model depicts rainfall or no rainfall dates. If there is rainfall, then it comes to the second step which is simulating the precipitation amounts.

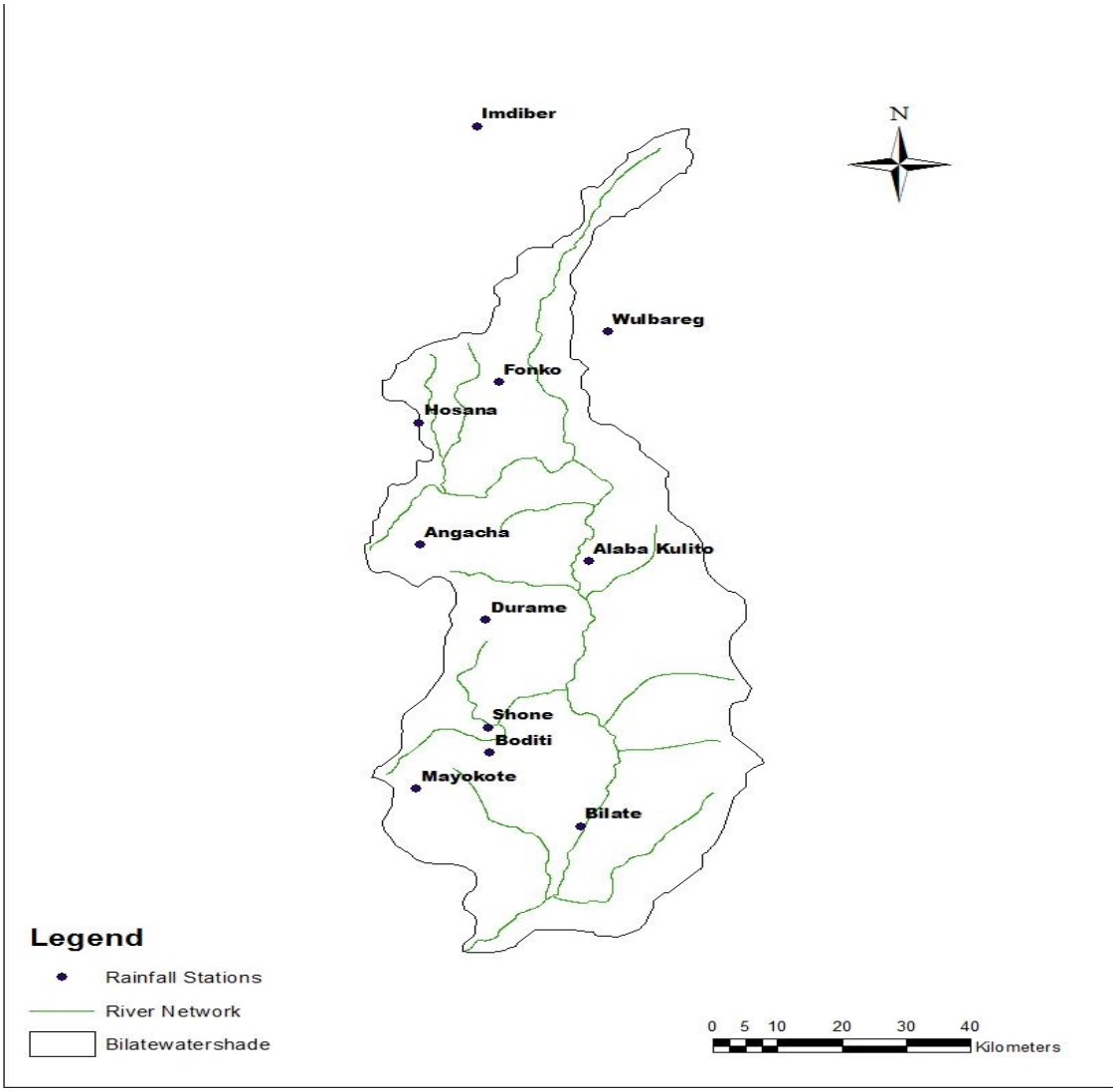


Figure 3-6: Location of rainfall and temperature gauging stations in the BRW

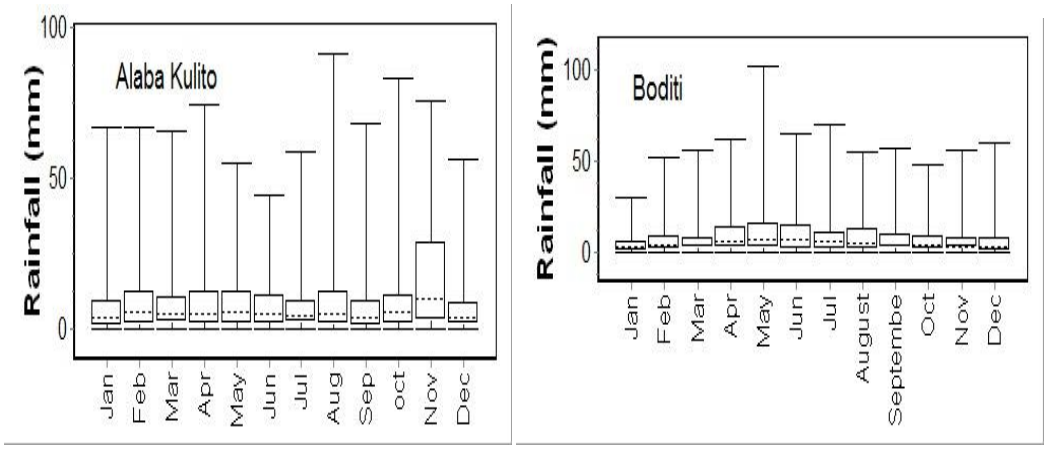
Some features of the observed daily rainfall at five selected stations in the BRW are shown in Figure 3.7. These stations were chosen based on their completeness, which have time series data of more than 95% for the period January 1984 to December 2013 and they all are located within BRW.

The box plots shown in Figure 3.7 were built for the rainy days of the corresponding months; these consider only days with rainfall amount of more than zero. This was done because if days with zero rainfall amounts are included, almost all the quartiles of the box plot will become zero except for the higher quartiles. As we can see from the legend of the box plot, the top horizontal line of the box plot indicates the 90% quartile while

the bottom horizontal line indicates the 10% quartile. The edges of the box represents the inter quartile range (IQR) which is the difference between the 75% quartile from the top and the 25% quartile from the bottom. The median line is represented by the broken horizontal line inside the box. In all box plots the median value is closer to the 25% quartile than to the 75% quartile, which shows the skewed distribution of the rainfall.

3.2.2 Temperature data

Compared to rainfall data, there is small amount of time series data for minimum and maximum temperatures (T_{min} and T_{max}) in the watershed due to the large number of stations that have many missing values and uneven spatial and temporal distributions. There are 18 gauging stations in and around the BRW. However, only a few stations have a data record for acceptable limit of time series for minimum and maximum daily temperature. From the 18 gauging stations of the NMA, only six of them have recorded data above 70%. The summary of the stations and their daily data availability is shown in Table 3.2 and their spatial distribution is shown in Figure 3.6 along with the rainfall gauging stations.



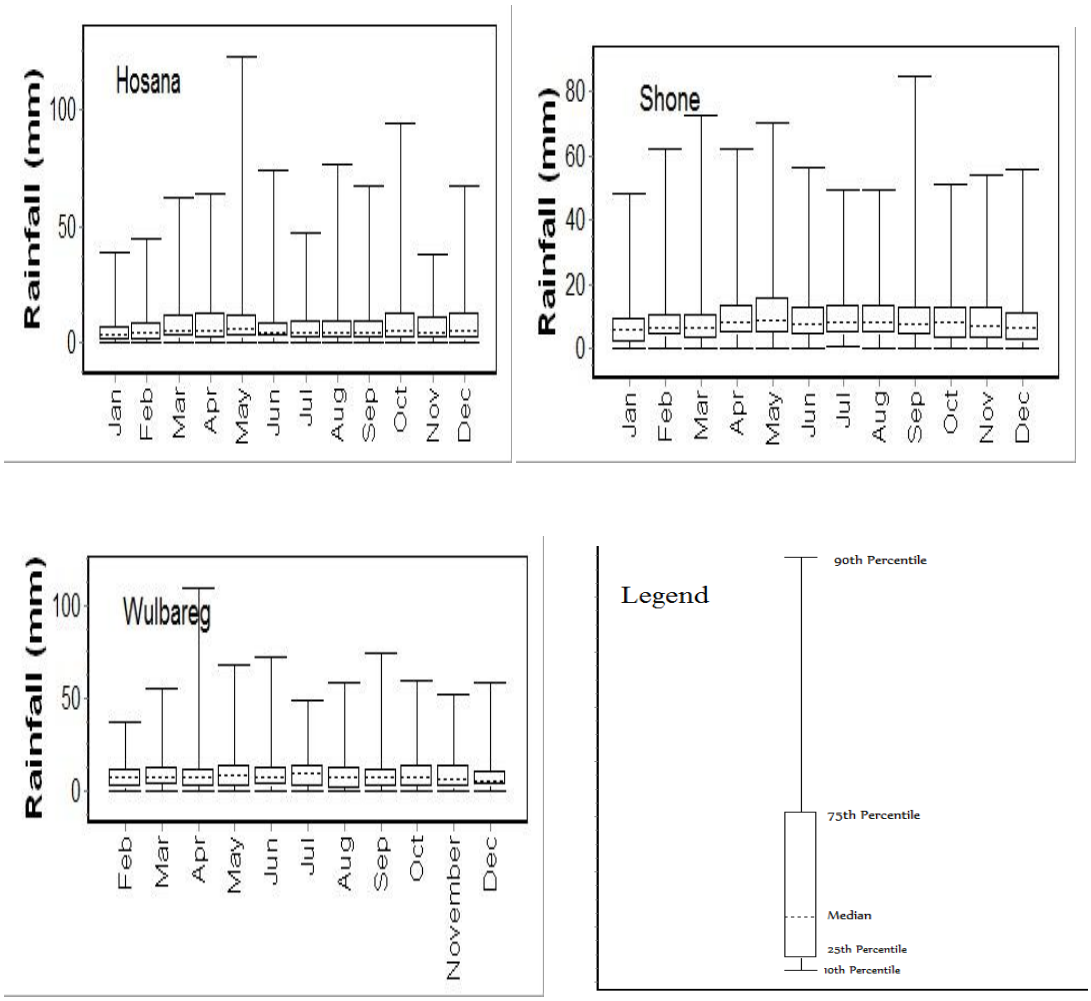


Figure 3-7: Box plots of the daily rainfall at five selected stations in the BRW

Table 3-2: Selected daily temperature (T_{min} and T_{max}) observation stations in BRW for the years1984-2013

S.No	Station Name	Easting (m)	Northing (m)	Altitude (m)	Missing daily %
1	Alaba Kulito	399982.7	808180.6	1772	6.36
2	Angacha	373864.6	811557.1	2317	23.20
3	Bilate	398710.0	753578.3	1361	15.03
4	Boditi	384561.1	768748.2	2043	2.43
5	Hosana	373561.7	836620.6	2307	20.38
6	Wulbareg	402990.4	855255.7	1992	11.48

The inter-annual surface temperature analysis in the BRW is made by using time series data of five stations for the period of Jan/01/1984 to Dec/31/2031. The five stations were selected based on the completeness of data record. These stations are Alaba Kulito, Angacha, Bilate, Hosana and Wulbareg.

The inter-annual variability of daily maximum temperature is shown in figure 3.8 with the 95% confidence of the mean values. The pattern of daily maximum temperature is more or less the same in all the stations, where the highest values of the daily maximum temperature are observed in February and March which is the dry period of the area, with the exception of Wulbareg station. The lowest value of maximum temperature is recorded in months of July and August.

Figure 3.9 shows the inter-annual variability of the daily minimum temperature averaged over each month. Unlike the daily maximum temperature, it is not easy to draw a trend of daily minimum temperature for the selected stations. Relatively, Hosana station shows the smallest minimum temperature value in average, whereas Bilate shows the highest value.

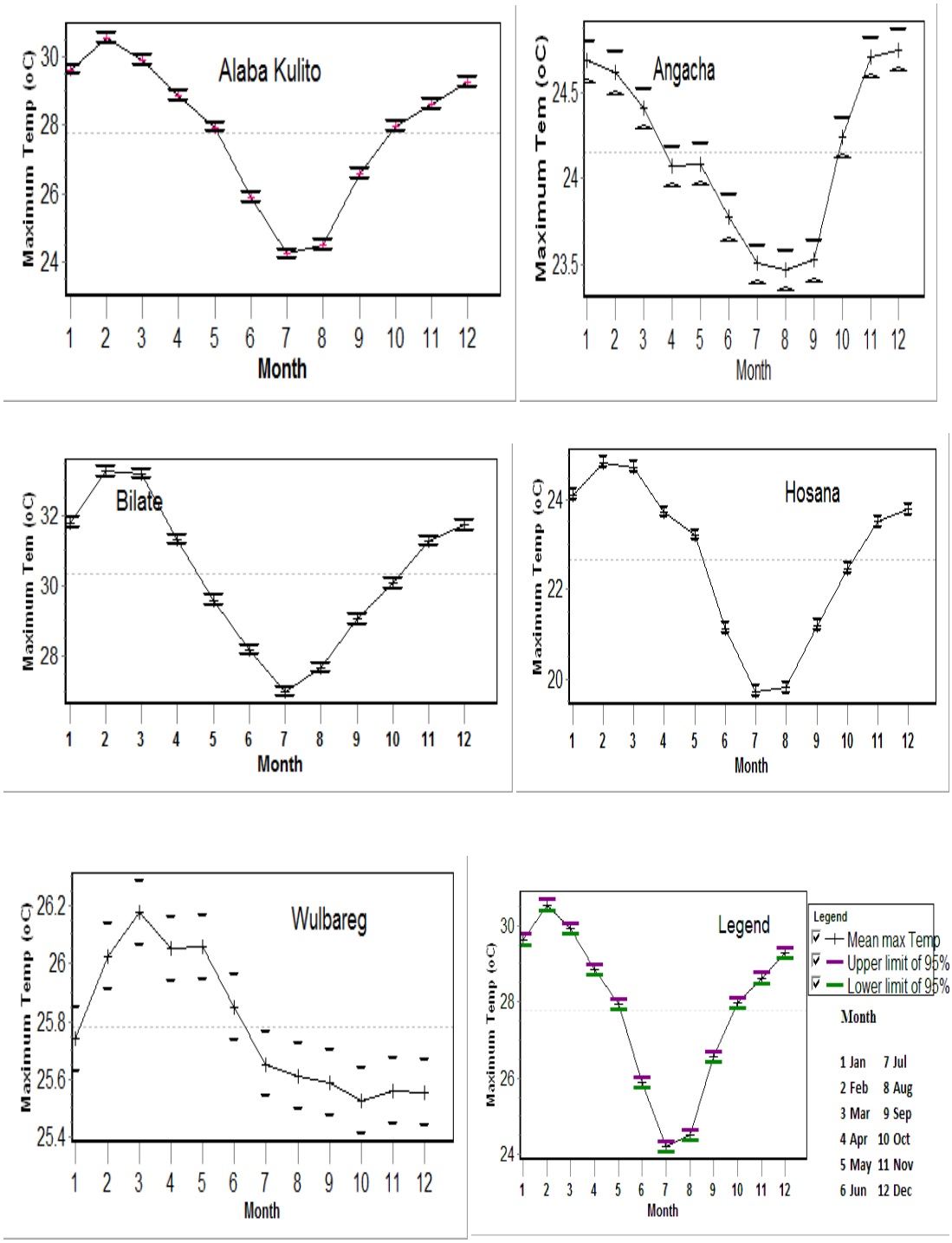


Figure 3-8: Inter-annual variability of daily maximum temperature at selected stations. 95% confidence interval of the mean values are also depicted

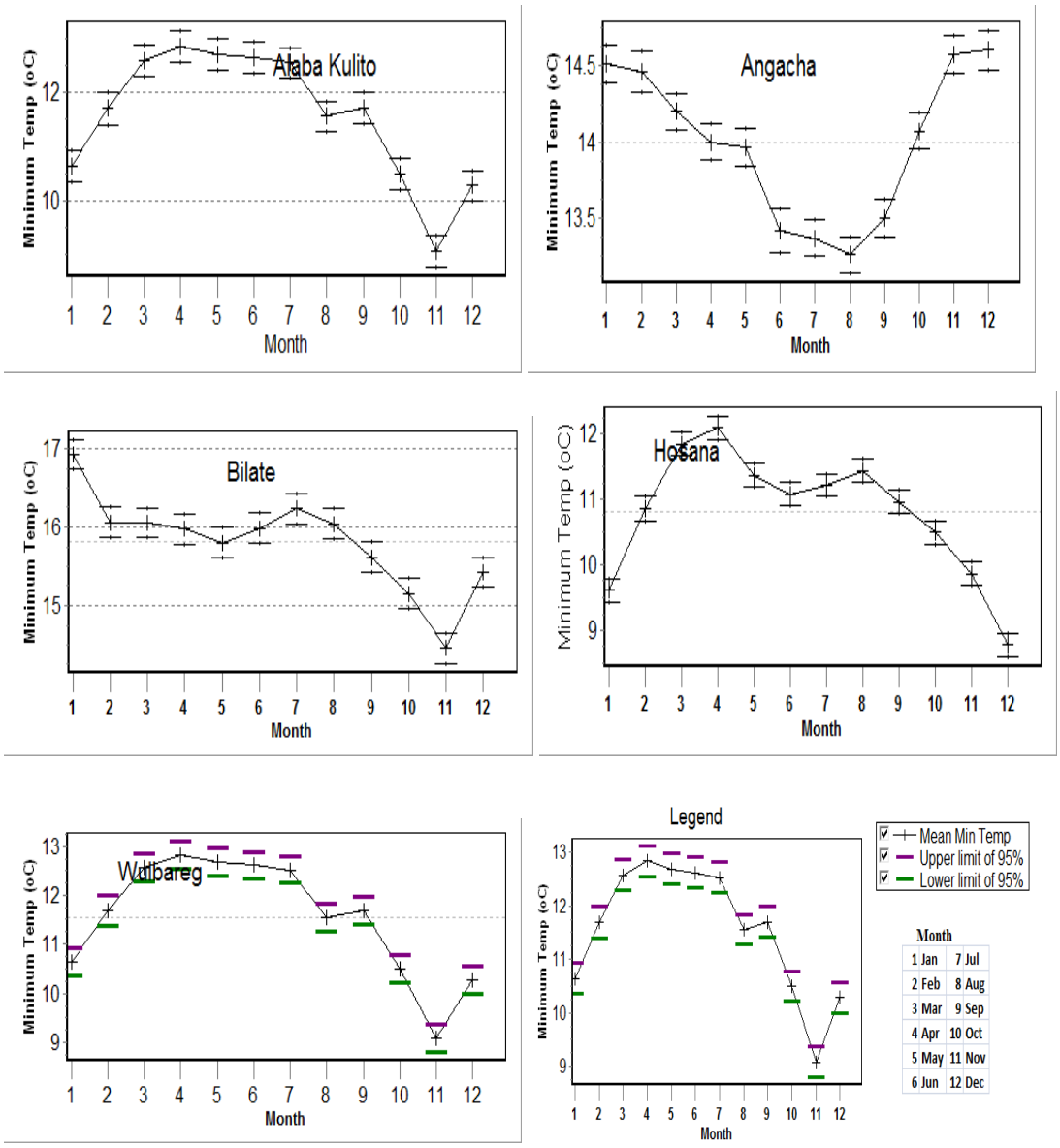


Figure 3-9: Inter-annual variability of daily minimum temperature at selected stations. 95% confidence interval of the mean values are also depicted

These show the dependence of temperature on elevation as these two stations are on the highest and lowest levels respectively leaving the watershed with the Adiabatic Lapse Rate which varies from 0.52 to 0.80°C drop per 100 m increase in altitude.

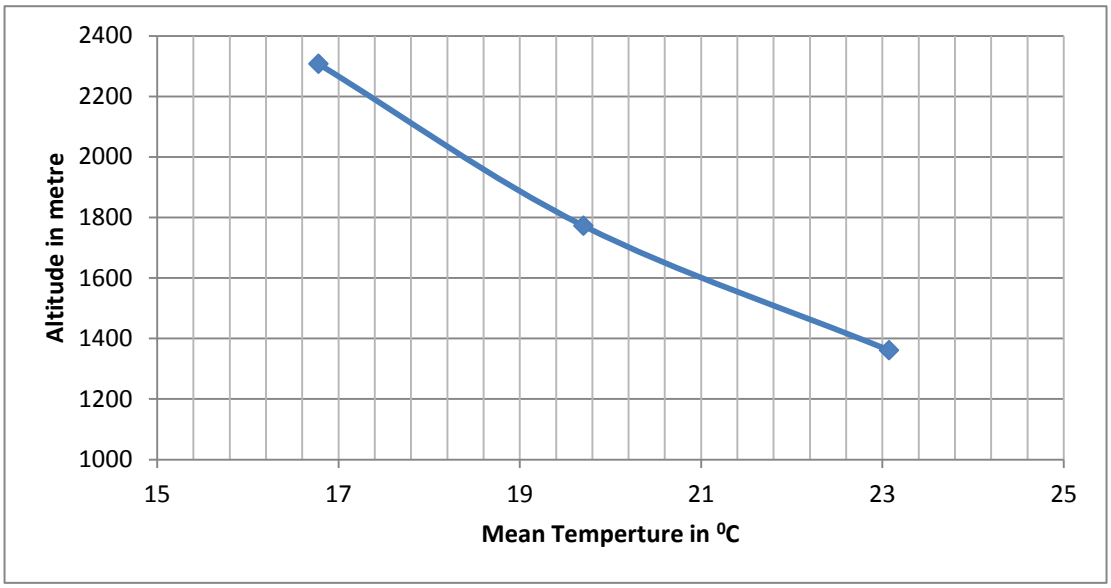
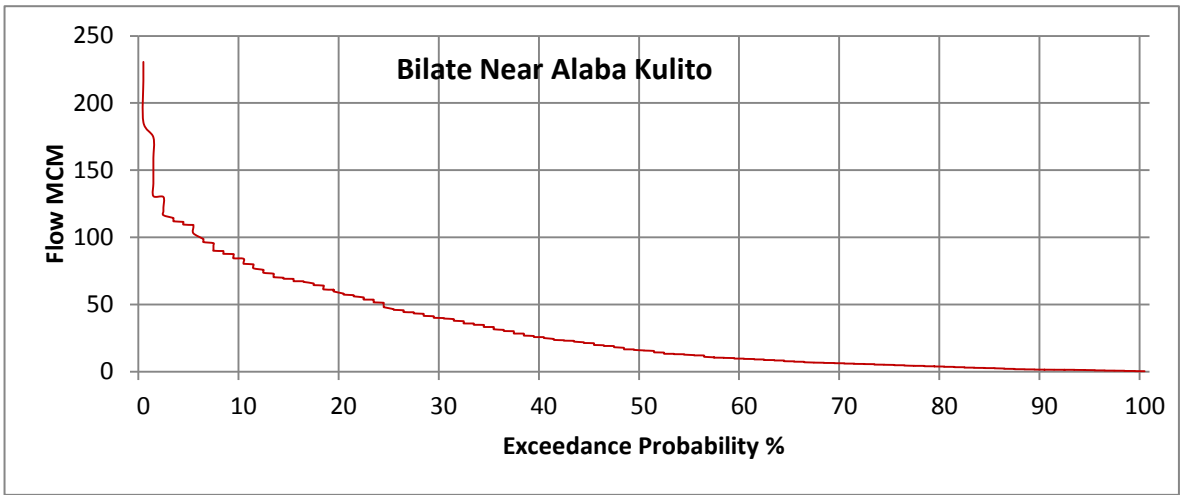


Figure 3-10: Altitude and temperature relation in Bilate River Watershed

3.2.3 River flow rate data

The river flow data from the gauging stations near Alaba Kulito and at Bilate Tena were used. Both of the gauging stations are located along the course of the main Bilate River and the station near Alaba Kulito is in the middle of the watershed while the station in Bilate Tena is located in the downstream (Figure 3.10). The gauging station near Alaba Kulito has, relatively, a long record of time series data compared to the other one (record period 1980-2013).

Figure 3.11 also shows the frequency of average daily flow for the recorded period at both gauging stations along the BRW. Without considering the length of the time series, figure 3.11 shows that the maximum daily flow at both gauging stations is above 100 meter cube per minute (m^3m^{-1}) and the minimum daily flow rate is below 1 m^3m^{-1}. From the data set, the maximum daily flow record of Bilate River near Alaba Kulito is 230 m^3m^{-1} and recorded in August, 2006, while the maximum daily flow rate was record of Bilate at Bilate Tena (Dimtu) is 374 m^3m^{-1} and it was recorded in August 1986.



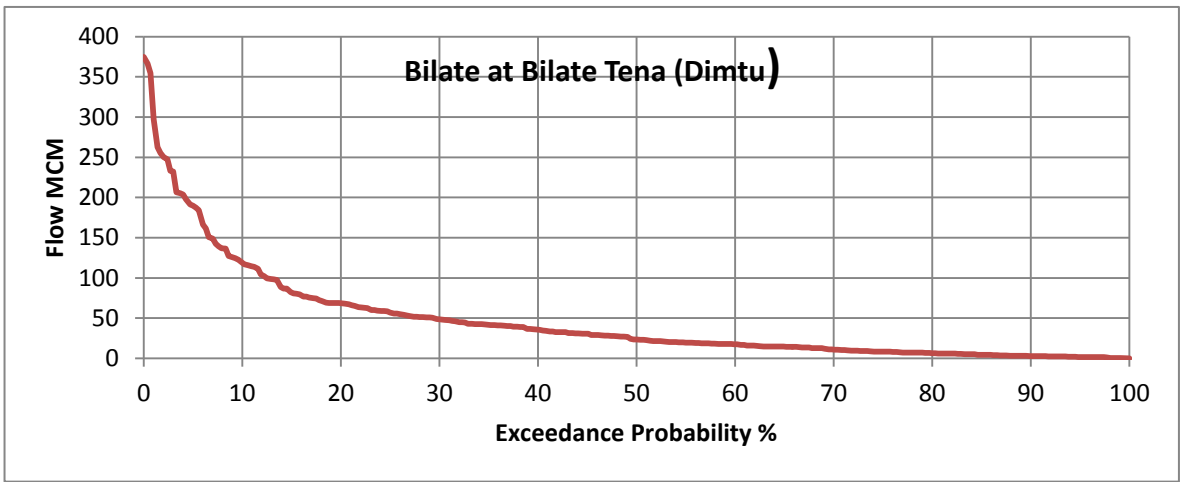


Figure 3-11: Flow gauging stations with their respective flow rate

The daily maximum and minimum flow near Alaba Kulito is shown in figure 3.12.Both the maximum and minimum flow shows an increasing trend of 1.17MCM and 0.01MCM respectively. The trend in the flow has similarity with the rainfall characteristics in the BRW which shows the erratic variability over the time period of 1984-2013.

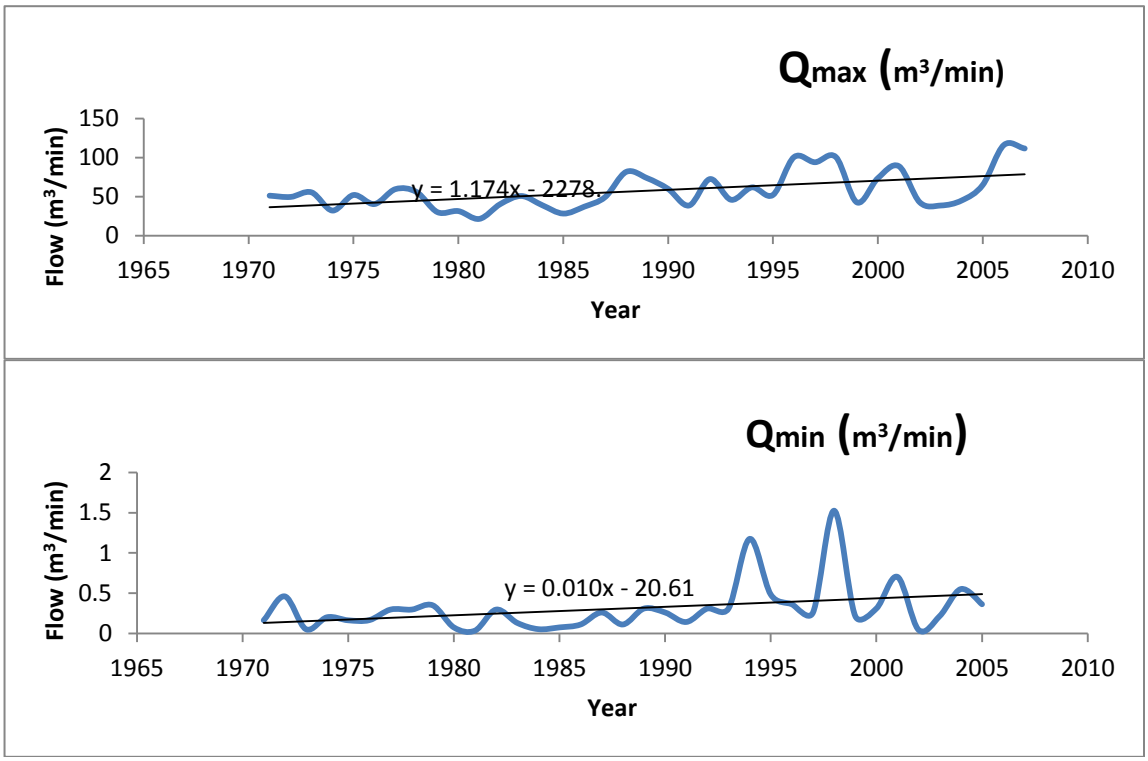


Figure 3-12: Daily maximum and minimum flows in the wet and dry seasons near Alaba Kulito gauging station

The river flow data for the period of 1990-1996 was obtained from the gauging stations near Alaba Kulito and this data was considered for calibration, while the daily flow data for the period of 1997-2002 was used for model validation. The gauge station near Bilate Tena has very intermittent data only used for description of the characteristics of the flow rate, but was not used for calibration and validation purpose.

3.2.4 The digital elevation model

The digital elevation model (DEM), daily precipitation and daily temperature, soil characteristics, land use and the river flow data are known to be the main data needed for the simulation of the SWAT model. Digital Elevation Model (DEM) with 30m resolution is acquired from the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). The DEM shown in Figure 3.13 is used for derivation of spatial parameters for the hydrological model. The topography of the BRW varies from

lowlands of altitude 1,146 metres above sea level (m.a.s.l.) near Lake Abaya to the highlands with a peak elevation of 3,393 m.a.s.l. towards the northern realm of the watershed. Stream characteristics (channel slope, length and width) and catchment characteristics (slope gradient, slope length, stream network) were derived from the DEM by using the Arc SWAT automatic watershed delineation tool.

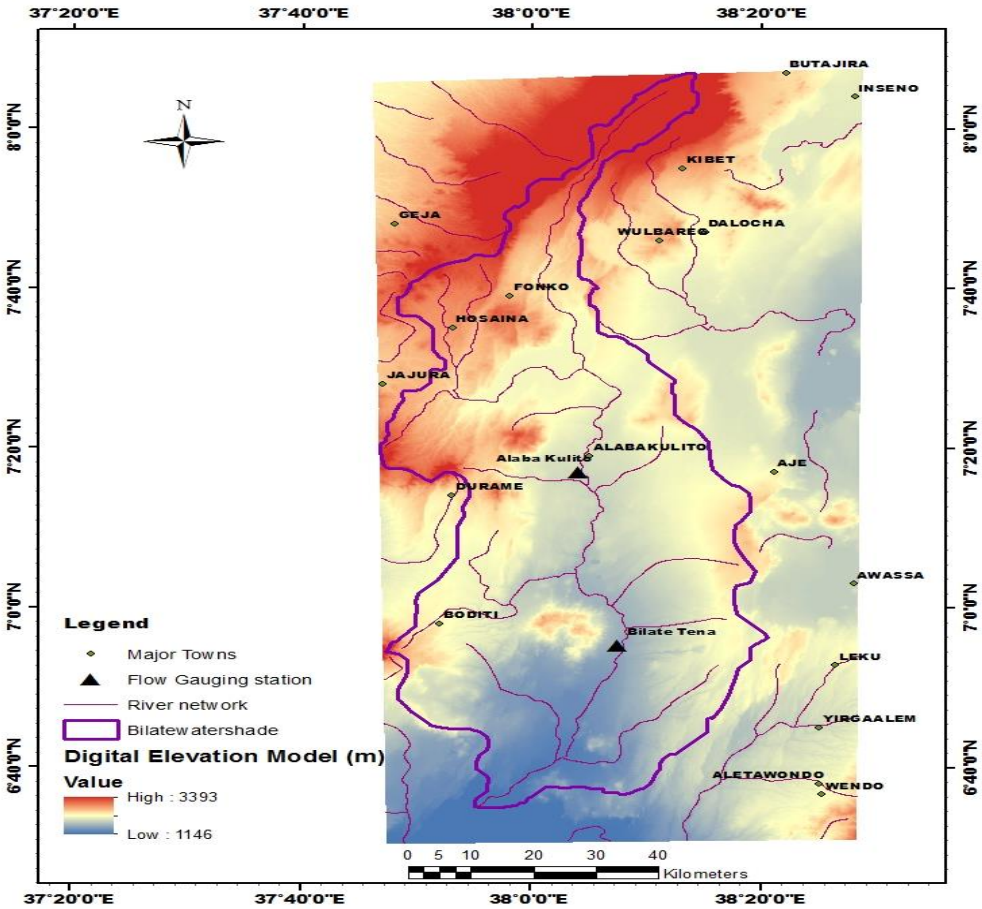


Figure 3-13: The Digital Elevation Model (DEM) map of BRW

3.2.5 The soil data

The soil data used in this research was obtained from the Food and Agriculture Organization of the United Nations data base (FAO, 2003). Accordingly, the average soil depths in the study area are between 1.00 and 2.00m and the dominant soil types are Eutric Nitosols, Plinthic Ferralsols, Eutric Cambisols, Ochric Andosols and Haplic Xerosols.

3.2.6 The land use land cover data

The land use land cover data with 500 x 500m spatial resolutions was obtained from the Ministry of Agriculture (MoA) which is derived from FAO 98 land use classification for Ethiopia. Further reclassification of the land use was performed in the model used for simulation of the hydrological processes. The land cover in the BRW is predominated by different types of agricultural land (87%), grass and rangeland 0.8%and the remaining is mixed land cover including plantation forest and shrub land. Wetland accounts for about12.2%.

3.3 Methods

3.3.1 Analyses of climate variability

Rainfall data of daily records for 30 years (1984-2013) of three weather stations were used for these analyses. Hosana, Alaba Kulito and Bilate weather stations were selected to represent the upper watershed, the mid watershed and the lower watershed respectively. The selection was also based on the completeness of the daily data and the stations reside totally inside the watershed. Seasonal rainfall variability was analysed for onset, end date and length of growing period (LGP). Other statistical parameters such as the mean, standard deviations and coefficient of variations were also determined.

To determine the onset, end date and LGP the definition from Stern et al. (2006) was used. By this definition, a day with an accumulated rainfall amount of 20mm in three consecutive days and not followed by greater than nine days of dry spell length within 30 days from the planting day is defined as the onset date.

The end of the growing season is determined by the amount of water which is stored in the soil and accessible to the crop after the rain stops. For this study the end of the rainy season was defined as any day when the soil water reaches zero with the assumption of a fixed average evapotranspiration of 5mm per day and 80mm/metre of soil water holding capacity (Stern et al., 2006; Hoefsloot, 2009). By using this definition the built-in Instat statistical software version 3.36 was used for the analysis and on the LGP was determined by taking the difference between the end date and the onset. The count of wet and dry days was made with the 3mm rainfall threshold for the agricultural water management purpose (Abiy et al., 2014).

The coefficient of variance (CV) statistics were used to test the level of mean variations of seasonal rainfall. CV is defined as the ratio of standard deviation to mean in percent, where mean and standard deviation are estimated from rainfall data.

$$CV = \frac{S.d}{\bar{X}} * 100 \quad \text{----------} \quad 3.1$$

$$\bar{X} = \sum_{i=0}^{n} \frac{x_i}{n} \ , \quad S.d = \sqrt{\frac{1}{n-1}} \sum_{i-1}^{n} (x_i - \bar{X})^2$$

Where: CV= Coefficient of variation
S.d = Standard deviation

$\bar{X}$=Mean of rainfall (mm)

Xi = Annual rainfall

n = Number of rainfall data

NMSA, (1996) Used CV to classify degree of variability of rainfall as less when (CV<20%), moderate when (CV from 20-30%) and highly variable for values of (CV>30%).

To describe annual rainfall variability, the Van-Rooy (1965) rainfall anomaly index (RAI), which has been modified to account for non-normality, was calculated as follows:

I, for positive anomalies

$$RAI = \frac{1}{3}\left[\frac{RF - M_{RF}}{M_{H10} - M_{RF}}\right] \quad \text{----------} \quad 3.2$$

II, for negative anomalies

$$RAI = -\frac{1}{3}\left[\frac{RF - M_{RF}}{M_{L10} - M_{RF}}\right] \quad \text{----------} \quad 3.3$$

Where: RAI stands for the annual rainfall anomaly index, RF is the actual rainfall for a given year, M_{RF} is mean for the total length of record; M_{H10} is the mean of the 10 highest values of rainfall on record, and $M_{L10}$is the mean of the 10 lowest values of rainfall on record. The RAI of Van Rooy has been shown to be a very effective index to compute seasonal variability for both positive and negative anomalies (Tilahun, 2006; Kisaka et al., 2015).

$$PCI = 100X\left[\frac{\sum Pi^2}{(\sum P_i)^2}\right] \text{----------} \quad 3.5$$

Where: Pi is the rainfall amount of the ith month, and $\sum Pi$ is Summation over the 12 months.

PCI values of less than 10 indicate uniform monthly distribution of rainfall, PCI values between 11 and 20 shows high concentration and values more than 21 shows a very high concentration in the distribution of rainfall (Taye and Zewdu, 2012).

The FAO-56 reference ET (ETo) approach (Allen et al., 1998) was used to determine the amount of evapotranspiration in the study area because it would provide the best estimate of ET under various climatic conditions (Suleiman et al., 2008). The ETo calculator software version 3.1 (Dirk Raes, 2009) which is known to use the FAO Penman–Monteith equation (FAO-56) was used to calculate the reference ET.

$$ETo = \frac{0.408\,\Delta(Rn - G) + \gamma\frac{900}{T+273}\mu_2\,(e_s - e_a)}{\Delta + \gamma(1 + 0.34\,\mu_2)} \text{----------} \; 3.6$$

where $\mathbf{R_n}$ is the net radiation (MJ m^2/day), **G** the soil heat flux (MJ m^2/day), **T** the mean daily air temp (°C), u_2 the mean daily wind speed at 2m height (m/s), e_s - e_a the saturation vapour pressure deficit (kPa), Δ the slope of the vapour pressure–temperature curve (kPa /°C), and $\gamma$the psychometric constant (kPa/ °C).

Aridity index (AI) was computed by using the UNESCO aridity index (Rodier, 1985) as follows:

$$\mathrm{AI} = \frac{\mathrm{P}}{\mathrm{ET_o}} \text{----------} \quad 3.7$$

Where P is the mean annual rainfall and ETo is the mean annual reference crop evapotranspiration. UNESCO adopted a classification for degrees of aridity as follows: AI < 0.05 is hyper-arid zone, 0.05 <AI < 0.20 is an arid zone, 0.20 <AI < 0.50 is a semi-arid zone, 0.5 <AI< 0.65 is a dry sub-humid zone and AI > 0.65 is humid (Rodier, 1985).

3.3.2 Statistical downscaling and future climate change scenarios

Instrumental records of daily rainfall, maximum temperatures and minimum temperatures for a period of 30 years (1980-2010) were used as a standard for baseline climate input for the Delta method Statistical Downscaling of Agricultural Model Intercomparison and Improvement Project (AgMIP) tool to produce climate scenarios. The historical records of rainfall and maximum and minimum temperature recorded in three weather stations within the Bilate Watershed during the last 30 years was obtained from the National Meteorological Agency.

The wind speed and relative humidity at the time of maximum temperature on a daily basis was retrieved from the AgMIP climate forcing dataset based on the NASA Modern-Era Retrospective Analysis for Research and Applications (MERRA).These datasets are stored at 0.25°×0.25° horizontal resolution (~25km), with global coverage and daily values from 1980-2010 in order to form a "current period" climatology (Ruane et al., 2015).

The data of 20 models (ACCESS1 -0, bcc-csm1-1, BNU-ESM, CanESM2, CCSM4, CESM1 -BGC, CSIRO-Mk3-6-0, GFDL-ESM2G, GFDL-ESM2M, HadGEM2-CC, HadGEM2-ES, inmcm4, IPSL-CM5A-LR, IPSL-CM5A-MR, MIROC5, MIROC-ESM, MPI-ESM-LR, MPI-ESM-MR, MRI-CGCM3, and NorESM1 -M) from the Coupled Model Intercomparison Project Phase 5 (CMIP5) ensemble and embedded in AgMIP protocol were provided by the AgMIP climate team from the NASA Goddard's online File Depot.

Downscaling and model description

The term 'statistical downscaling' typically comprises techniques that use empirical relationships between local-scale variables and large-scale atmospheric variables (Ekström et al., 2015). It creates empirical relationships between historical large-scale atmospheric and local climate characteristics. Once a relationship has been determined and validated, future large-scale atmospheric conditions projected by GCMs are used to predict future local climate characteristics (Von Storch et al., 2000; Fowler et al., 2007; Maraun et al., 2010; Trzaska and Schnarr, 2014).In situations where a low-cost, rapid assessment of highly localized climate change impacts is required, statistical downscaling (currently) represents the more promising option (Wilby et al., 2002).

The Delta method is a statistical downscaling procedure that is based on the sum of interpolated anomalies to high resolution monthly climate surfaces. The method produces a smoothed (interpolated) surface of changes in climates (deltas or anomalies) and then applies this interpolated surface to the baseline climate, taking into account the possible bias due to the difference in baselines (Ramirez-Villegas and Jarvis, 2010). In this study the Delta method analysis protocol of the Agricultural Intercomparison and Improvement Project (AgMIP) was used to project the future climate state in the farm lands of the Bilate Watershed (Rosenzweig et al., 2013).

AgMIP protocol is a well established method to create climate files for a large number of farm locations that are close to a central weather station where the historical climate series has been quality controlled (Rosenzweig et al., 2013; Ruane and Mutter, 2013; Nelson and Shively, 2014; Rosenzweig and Hillel, 2015). The method makes the

following two gross assumptions: first, “Changes in climates vary only over large distances (i.e. as large as GCM side cell size)” and, second, “Relationships between variables in the baseline ('current climates') are likely to be maintained towards the future”. But these assumptions might not hold true in heterogeneous landscapes, where topography and land use and land cover changes could cause local variations in anomalies (Ramirez-Villegas and Jarvis, 2010). To overcome the shortcomings in the assumptions the method was applied to three selected sites (Hosana, Alaba Kulito and Bilate) representing and covering relatively homogeneous areas in the upper, middle and lower courses of the watershed respectively.

Emission scenarios

The past climate variation since the industrial revolution is known to be highly driven by the changes in concentration of GHGs in the atmosphere, and thus to “predict” the climate of the future, it is necessary to estimate future changes in the GHG concentration as a result of continuous emission from fossil fuel burnings. And this is achieved by the development of scenarios for the emission of greenhouse gases, aerosols, various pollutants in the atmosphere, land use change, etc. (Goosse et al., 2010). Among the number of possible alternative futures, until the forth assessment report of the IPCC, the climate projections were based on the Special Report on Emission Scenarios (SRES) scenarios (IPCC, 2000). During the IPCC Fifth Assessment Report a new set of scenarios, the Representative Concentration Pathways (RCPs), was used for the new climate model simulations carried out under the framework of the Coupled Model Intercomparison Project Phase 5 (CMIP5) of the World Climate Research Programme (IPCC, 2013). A set of four RCPs were selected. RCP3-PD (peak and decline), the radiative forcing, peaks before 2100 at about 3 Wm^{-2} and then declines. RCP6.0 and RCP4.5 are characterised by a steady rise during the 21st century, up to a radiative forcing of about 6 and 4.5 Wm^{-2} respectively, and a stabilisation after 2100. Finally, the most extreme one, RCP8.5 displays a continuous rise in radiative forcing during the 21st century, leading to a value of about 8.5 W m^{-2} in 2100 (Goosse et al., 2010; van Vuuren et al., 2011; IPCC, 2013).

In this study climate change scenarios were generated for two Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5 using 20 GCMs from CMIP5 bias-corrected under three time slices, near-term (2010-2039), mid-century (2040-2069) and end-century (2071-2099). RCP 4.5 describes the medium stabilization scenario without overshoot pathway and RCP 8.5 describes rising radiative forcing pathway leading to very high emissions scenario (Van Vurren et al., 2011). In the analysis, both concentration pathways in three time slices were applied and the analysis was performed with the built in AgMIP Climate Scenario Generation Tools with R software environment.

Description of GCM's used

AgMIP protocols emphasize the use of multiple models because ensembles allow better characterization of the uncertainty associated with model outputs (Cheryl et al., 2014). So, the future climate scenarios are based upon the observed baseline climate and changes simulated by an ensemble of general circulation models (GCMs) from the Fifth Coupled Model Intercomparison Project (CMIP5). CMIP5 is meant to provide a framework for coordinated climate change experiments for the IPPC AR5 and beyond and it promotes a standard set of model simulations in order to provide projections of future climate change on two time scales, near term (out to about 2035) and long term till 2100.

Table 3-3: List of the global climate models in CMIP5 used in the study

Model Name	**Modelling Centre (or Group)**	**Spatial Resolution (longitude*latitude)**
ACCESS1.0	Commonwealth Scientific and Industrial Research Organization (CSIRO) and Bureau of Meteorology (BOM), Australia	192*145
BCC-CSM1.1	Beijing Climate Centre, China Meteorological Administration	128*64
BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University	128*64
CanESM2	Canadian Centre for Climate Modelling and Analysis	128*64
CCSM4	National Centre for Atmospheric Research	288*192
CESM1(BGC)	Community Earth System Model Contributors	288*192

CSIRO-Mk3.6.0	Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre of Excellence	192*96
GFDL-ESM2G GFDL-ESM2M	NOAA Geophysical Fluid Dynamics Laboratory	144*90
HadGEM2-CC HadGEM2-ES	Met Office Hadley Centre	192*145
INM-CM4	Institute for Numerical Mathematics	180*120
IPSL-CM5A-LR IPSL-CM5A-MR	Institut Pierre-Simon Laplace	96*96 144*142
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies	128*64
MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology	256*128
MPI-ESM-MR MPI-ESM-LR	Max-Planck-Institut für Meteorologie (Max Planck Institute for Meteorology)	192*96
MRI-CGCM3	Meteorological Research Institute	320*160
NorESM1-M	Norwegian Climate Centre	144*96

3.3.3 Modelling the Response of the watershed to climate change scenarios

Model setup, calibration and validation

The model setup is performed following four major steps: (i) watershed delineation and derivation of sub-basin characteristics, (ii) hydrological response unit definition, (iii) model run and parameter sensitivity analysis, and (iv) calibration and validation of the model (Fiseha, 2013). The input data like soil maps, land use and hydro-meteorological data for the basins was prepared and, during the watershed delineation, the spatial datasets that include DEM, land use and soil maps were projected to the same coordinate system of zone 37 in Universal Transverse Mercator (UTM 37N), and the delineator in the ArcSWAT follows the steepest slope paths to define the stream networks.

The HRU definition was performed based on the soil, land cover and slope. In addition to the soil and land use data described above, five classes of slope were considered; these were 0-5%, 5-10%, 10-15%, 15-20% and ≥20%. The threshold values for multiple HRU definition were 10% for land use, 20% for soil and 5% for slope of every sub-basin area. Overall there were 285 HRUs defined in the watershed within 31 sub-basins. The model was then run by using weather data inputs from seven stations for precipitation and three stations for temperature. The simulation was run first for the calibration period of 1987 to 1996 using the first three years as a warm up period. After the results of the first simulation were found, the sensitivity analysis and calibration of the parameters was based on the parasol calibration algorithm. Manually tuning the sensitive parameters finally resulted in ranked outputs that show how the catchment behaves under the given conditions.

The top ten sensitive parameters were considered for further use in the model calibration and validation processes. The SWAT model performance was evaluated using statistical analyses to compare reliability and quality of simulated discharge against the observed data. The statistical approaches used in this study are the coefficient of determination (R^2), Nash–Sutcliffe coefficient (NSE) and percent bias (PB) (Nash and Sutcliffe, 1970; Gupta et al., 1999; Tan et al., 2014).

$$R^2 = \left(\frac{\sum_{i=0}^{n}(O-\bar{O})(P-\bar{P})}{\left[\sum_{i=0}^{n}(O-\bar{O})^2 \sum_{i=0}^{n}(O-\bar{P})^2\right]^{0.5}}\right)^2 \qquad (3.8)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O-P)^2}{\sum_{i=1}^{n}(O-\bar{O})^2} \qquad (3.9)$$

$$PB = \frac{\sum|O-P|}{\sum O}(100) \qquad (3.10)$$

Where O and P are observed and simulated stream flow, respectively; n is the number of measured stream flow. Both the R^2 and NSE ranges from 0 to 1 with higher value indicating good agreement between the model and the observation. The PB measures the tendency of the simulated flows to be larger or smaller than their observed counterparts; the optimal value is 0.0, where positive values indicate a tendency to overestimation,

and negative values indicate a tendency to underestimation. SWAT modelling performance is categorized as satisfactory if NSE > 0.5 and PB < ±25. Alaba station monthly stream flows from 1990 to 1996 and 1997 to 2002 were used for stream flow calibration and validation respectively (Nash and Sutcliffe, 1970; Gupta et al., 1999).

Climate change scenarios and climate projection models

During the IPCC Fifth Assessment Report a new set of scenarios, the Representative Concentration Pathways (RCPs), was used for the new climate model simulations carried out under the framework of the Coupled Model Intercomparison Project Phase 5 (CMIP5) of the World Climate Research Programme (IPCC, 2013). In this study climate change scenarios were generated for two Representative Concentration Pathways (RCPs): RCP 4.5 and RCP 8.5 using 20 GCMs from CMIP5 bias-corrected under three time slices, near-term (2010-2039), mid-century (2040-2069) and end-century (2071-2099).

Data of the twenty GCMs (table 3.3) from the Coupled Model Intercomparison Project Phase 5 (CMIP5) were provided by the AgMIP climate team from the NASA Goddard's online File Depot. Based on their underlying assumption and complexity, these GCMs can project a wide range of future climatic conditions (Sah and Zeleke, 2015). So far different studies have used outputs from a single GSM for impact studies (Smith et al., 2009) or outputs from several GSMs individually (Setegn et al., 2010) but multi model ensemble simulations are known to provide more reliable information than that of a single model output (IPCC, 2007). In this study, ensemble mean outputs of the twenty GCMs (ensemble_20) were used.

The capacity of climate models in CMIP5 to represent a certain aspect of present climate has been studied by Ramirez-Villegas et al.(2013) for the East Africa region. So, using ensemble mean outputs of these GCMs will help us to find the combination of GCMs that underestimate, overestimate and accurately capture annual data (Dessu and Melese, 2013).

In addition to the ensemble mean outputs of the twenty GCMs, the climate uncertainty assessment used in this study includes 25 climate scenarios developed for climate impact and uncertainty analysis based on the modified QUEST-GSI methodology (Todd et al., 2011; Tan et al., 2014). According to Tan et al., (2014) some of the points considered while modifying the QUEST-GSI methodology are (1) the HadCM3 GCM is replaced by CMIP5 GCM ensemble of 20 GCMs (under RCP 4.5 and 8.5), (2) prescribed increases in global mean temperature (1–6 ^{0}C) using ensemble_20 (3) six GCM structures from different countries and institutions (ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM, NorESM1-M) under RCP 4.5 (4) prescribed warming of 2 ^{0}C using ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM and NorESM1-M.

The resolution of GCMs varies from 96km*96 km to 320 km*160 km which is coarse and needs to be downscaled before applying them to assess the impact of climate change on regional scale. Statistical downscaling involves developing a relationship between the large and local scales using historical data and then applying this relationship to adjust independent large-scale data down to the local scale (Kirchmeier et al., 2014). Statistical downscaling methods are typically as effective as and less expensive than dynamical downscaling and especially useful for temporal downscaling (Brown et al., 2008). In this study the Delta method analysis protocol of the Agricultural Intercomparison and Improvement Project (AgMIP) was used to project the future climate state in the farm lands of Bilate Watershed (Rosenzweig et al., 2013). The downscaled GCM simulations provided meteorological data, for input to the hydrologic model, on a daily time step.

Table 3-4: Climate scenarios for SWAT input (Ensemble_20 is the average of twenty GCMs)

ID	Model	Scenario	Period	Detail
1	ensemble_20	4.5	2010-2039	Hydrological impact assessment
2	ensemble_20	4.5	2040-2069	
3	ensemble_20	4.5	2071-2099	
4	ensemble_20	8.5	2010-2039	
5	ensemble_20	8.5	2040-2069	
6	ensemble_20	8.5	2071-2099	
7	ensemble_20	4.5/+1^{0}C	2010-2039	Prescribed temperature increase

8	ensemble_20	4.5/+2^{0}C	2010-2039	
9	ensemble_20	4.5/+3^{0}C	2010-2039	
10	ensemble_20	4.5/+4^{0}C	2010-2039	
11	ensemble_20	4.5/+5^{0}C	2010-2039	
12	ensemble_20	4.5/+6^{0}C	2010-2039	
13	ACCESS1.0	4.5	2010-2039	GCM structure
14	BCC-CSM1.1	4.5	2010-2039	
15	CanESM2	4.5	2010-2039	
16	CCSM4	4.5	2010-2039	
17	MIROC-ESM	4.5	2010-2039	
18	NorESM1-M	4.5	2010-2039	
19	ACCESS1.0	4.5/+2^{0}C	2010-2039	2 ^{0}C increase in average global temperature
20	BCC-CSM1.1	4.5/+2^{0}C	2010-2039	
21	CanESM2	4.5/+2^{0}C	2010-2039	
22	CCSM4	4.5/+2^{0}C	2010-2039	
23	MIROC-ESM	4.5/+2^{0}C	2010-2039	
24	NorESM1-M	4.5/+2^{0}C	2010-2039	
25	Observed dataset	Baseline	1980-2009	Control run

3.3.4 Local Perceptions and Adaptation to Climate Variability

The study kebeles (the lowest administrative unit in Ethiopia) come from three districts representing the upper, middle and lower parts of the Bilate River Watershed and are known to practice irrigation in the watershed. The first study site is Bilwanja Kebele of Hulbareg Woreda in the Silite Zone near the Hulbareg town with a mean annual rainfall of 1131mm from the upper part of the watershed. The second study site is Alemtena Kebele in Halaba Special Woreda near Alaba Kulito town with mean annual rainfall of 1025mm representing the middle course of the watershed, and the third study site is Bilate Charcho Kebele in Duguna Fango Woreda of Wolaita Zone near Bilate Tena with a mean annual rainfall of 781mm representing the lower course of the watershed.

Sampling and data collection

A multi stage sampling technique was used to select the study kebeles and sample households in the watershed. First the Bilate River watershed was selected as the overall study area. In the second stage, three districts representing the upper, middle and lower

course of the watershed and one kebele within each district was also purposely selected to include villages which practice irrigation and whose community are aware of the dynamics of the hydrology in the watershed. From these sampled kebeles based the methods used by Israel (2009) 270 households were selected proportionally.

The survey was conducted between December 2013 and January 2014. An interview schedule was used to collect information from all sample farming households, making use of a structured and validated questionnaire to Understand Agricultural Household Adaptation to Climate Change prepared by Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) project with slight modifications. Pre-testing of the questionnaire was performed to avoid missing any important information.

Table 3-5: The study zone district (Woreda) and Kebele

Zone/Woreda	Kebele	Total No. of HH	No. of HH Interviewed
Silite Zone/ Hulbareg	Bilwanja	1030	95
Halaba Special Woreda	Alem Tena	506	86
Wolaita Zone/Duguna Fango	Bilate Charcho	735	89

The study examined, first, whether smallholder farmers in the Bilate watershed perceived climate change and then whether they have tried to adapt to the perceived climate change in their agricultural activities and, finally, it modelled the factors influencing their choice of adaptation methods.

To find out whether farmers in the watershed perceived climate change, a sample of farm households were asked if they have observed variation in the climatic parameters and descriptive statistics were used to assess the perception of farmers on climate change and the different adaptation methods adopted by them.

Smallholder farmers are known to use adaptation methods when the perceived that the net benefit of their agricultural productivity is significantly greater than the productivity without using it. That means the decision of whether or not to use any adaptation option

could fall under the general framework of utility and profit maximization (Deressa et al., 2008; Gbetibouo, 2009; Deressa et al., 2011).

The multinomial logit (MNL) model was used to model climate change adaptation behaviour of farmers by making use of discrete dependent variables with multiple choices. In context, multinomial estimation exhibits superior ability to predict discrete choices (Bezu et al., 2009). It is computationally simple (Hadgu et al., 2015) and the same model was used for similar studies in Ethiopia (Deressa et al., 2009; Tessema et al., 2013; Legese et al., 2014) for cases in which respondents are restricted to select only one adaptation option from different adaptation measures. During the survey, it was found that several adaptation options were used simultaneously by a single respondent. This behaviour made the use of MNL modelling inappropriate by violating the assumption of mutually exclusiveness and failing to fit into the test for their independence of irrelevant alternatives (IIA).

Binary logit model specification was adopted to examine factors influencing the climate change adaptation behaviour of farmers involving dummy dependent variables with binary choices. Consider (Y_{ij}^*) a latent variable equal to the benefit expected from the adoption of a given adaptation measure:

$$Y_{ij=}^* \ \alpha + \sum \beta_k X_k + \varepsilon_{Y_{ij}^*} \qquad (3.11)$$

Where $Y_{ij}^*$is a latentent binary variable with subscripts *i* showing the household adapted to climate change and *j* showing six different adaptation measures, α stands for the model intercept, β_k is the vector of the binary regression coefficient, X_k is the vector of exogenous explanatory variable that influences the farmer's choice of a particular adaptation option and *k* in the subscript shows specific explanatory variables and , $\varepsilon_{Y_{ij}^*} \cong \mathrm{N}(0, \alpha^2)$ is the error term which is normally distributed.

One cannot directly observe the latent variable(Y_{ij}^*). All one can see is

$$Y_{ij} = \begin{cases} 1 \ \ if \ Y_{ij}^* \ > 0 \\ 0 \ \ if \ Y_{ij}^* \ \leq 0, \end{cases} \qquad (3.12)$$

Where Y_{ij} is observed variable showing the household *i* will use adaptation option *j* ($Y_{ij} = 1$) if the perceived benefit from option *j* is greater than zero ($Y_{ij}^{*} > 0$), otherwise household *i* will not use adaptation measure *j* if the perceived benefit from it is equal to or less than Zero ($Y_{ij}^{*} \leq 0$) (Abid et al., 2015).

Therefore, we can interpret the above equation (3.12) in terms of the observed binary variable Y_{ij} as follows:

$$\Pr(Y_{ij} = 1) = Y_{ij} = G(X_k \beta_k) \qquad (3.13)$$

Where G (.) takes the specific binomial distribution (Fernihough, 2011; Abid et al., 2015).

The parameter estimates of the binary logit model provide only the direction of the effect of the independent variables on the dependent variable. They do not show the magnitude of change and probabilities. Therefore, to quantify the results we need to find the marginal effects (Y'_{ij}) by differentiating equation (3.13) with respect to the explanatory variables to provide the marginal effects of the explanatory variables that describe the effect of a unit change in explanatory variables on the probability of dependent variable.

$$Y'_{ij} = \Pr(Y_{ij} = 1) * (1 - \Pr(Y_{ij} = 1))\beta_k \qquad (3.1\ 4)$$

Chapter 4 : Result and Discussion

4.1 Temporal and Spatial Variability of Rainfall and Evapotranspiration in the Bilate River Watershed, Southern Ethiopia

4.1.1 Trend of annual and seasonal rainfall

The statistical trend results for the time series of rainfall observed at three stations as presented in table 4.1 below shows a non-significant trend at 95% confidence level in all the stations. The variability in rainfall in the watershed can be shown by the trend of the annual rainfall with a non-significant; but declining trend in Hosana station (-3.43 mm/yr; p=0.12) to an increasing trend in Bilate station (4.76 mm/yr; p=0.90). As depicted in Table 4.13, there is a decreasing trend during *Belg* season in the Hosana area (p=0.05). In Alaba Kulito and Bilate area there is an increasing trend both in the *Belg* and *Kiremit* seasons, which are known to be the wettest parts of the year in the area.

Table 4-1: Total annual and seasonal precipitation trends of three selected stations

Stations	Mean (mm)	SD (mm)	Slope (mm/yr)	Significance (P value)
Seasons				
		Hosana		
Annual	1100.2	128.20	-3.43	0.12
Bega	120.25	51.38	-0.64	0.28
Belg	407.71	95.98	-4.00	0.05
Kiremt	572.28	67.37	1.20	0.68
5 years mean	1042.86	183.14		0.50
10 years mean	1064.34	147.35		0.30
15 years mean	1086.95	133.03		0.12
		Alaba Kulito		
Annual	1069.96	156.55	0.35	0.60
Bega	173.6	71.76	-1.36	0.11
Belg	391.83	88.08	1.49	0.85
Kiremt	505.19	86.14	0.22	0.70
5 years mean	1123.92	170.83		0.89
10 years mean	1086.16	141.93		0.86
15 years mean	1066.69	136.33		0.88
		Bilate		
Annual	785.11	133.45	4.76	0.90
Bega	168.13	47.62	1.01	0.85
Belg	289.4	60.48	0.04	0.41
Kiremt	327.57	91.31	3.71	0.96
5 years mean	907.84	229.70		0.59
10 years mean	823.52	190.74		0.95
15 years mean	816	165.37		0.81

Figure 4.1 shows high temporal anomaly in rainfall between 1984 and 2013, that none of the stations experienced persistent near average rainfall with RAI=0. In Bilate, the wettest year recorded in 2000 (RAI=+5) and in 2010 (RAI=+4). In Alaba Kulito the highest positive anomalies were recorded in 1984 (RAI=+6), 1998 (RAI=+4) and 2012 (RAI=+5). The three wettest years at Hosana were 1984 (RAI=+8), 2007 (RAI=+4) and 2011 (RAI=+5). Hosana station has more number of years (seven out of 30 years) with an average annual rainfall amount (RAI=0) and the three driest years in Hosana were recorded in 1990 (RAI=-5), 2010 (RAI=-4) and 2012 (RAI=-5).

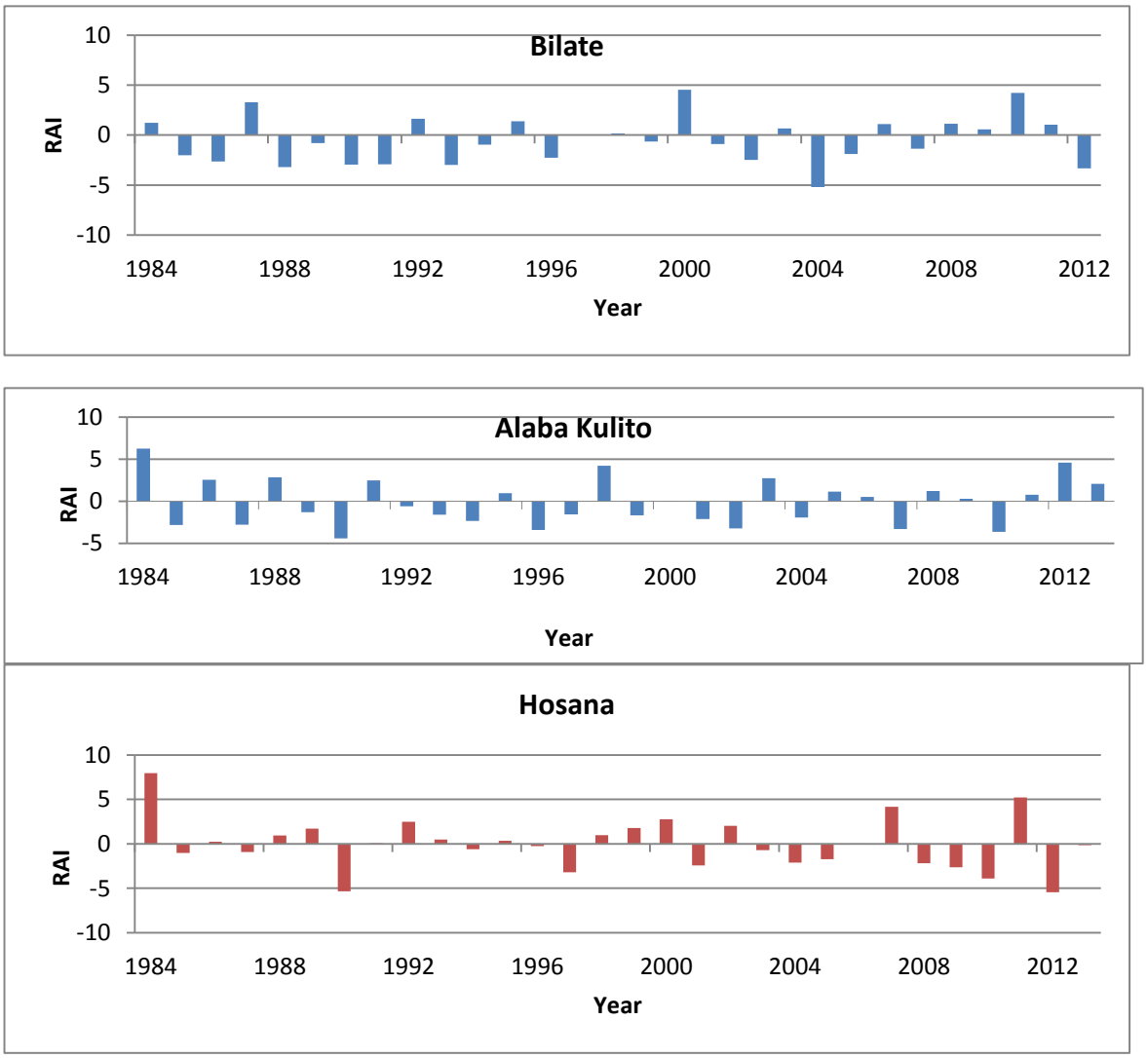


Figure 4-1: Rainfall anomaly index for the study period in three selected stations

A 30 year time-series analysis of the rainfall dataset (Table 4.1 and Figure 4.1) showed more frequent rainfall anomalies in the BRW. The results show that the BRW is characterised by periodic fluctuation of the dry and wet years. Even if it is not in consecutive years, Hosana station has seven out of 30 years with average annual rainfall amount (RAI=0), otherwise the results of the Rainfall Anomaly Index (RAI) depicted that in all the stations there is no persistent trend showing near average rainfall with RAI=0. Relatively, being an area having near average rainfall, Hosana area also experienced very dry years in 1990 (RAI=-5), 2010 (RAI=-4) and 2012 (RAI=-5). In contrast, Bilate area which is the driest of all stations, also experienced wettest years recorded in 2000 (RAI=+5) and in 2010 (RAI=+4). The variability in rainfall in the watershed can also be explained by the trend variation of the annual rainfall with decreasing trend in annual rainfall in Hosana with the average amount of decrease over the last 30 years being 3.43mm every year whereas the increasing trend in Bilate station is an average of 4.76mm rainfall every year. Clearly, the trend analysis results depend on the study period chosen. That means, if the time period were changed or extended, a different conclusion may be drawn. This result of increasing trend in rainfall in Bilate and declining trend in Hosana with all the anomalies shown in the watershed is in agreement with the previous studies of Abiy et al. (2014). Generally, the mean annual rainfall increases moving to the southwest and with an increasing elevation, ranging from 781mm at Bilate up to 1100mm at Hosana. This is also in agreement with Kassa (2015).

4.1.2 Monthly variations in rainfall amounts and number of rainy days

The results in Table 4.2 below showed that rainfall amounts received in the long rainy season (belg-kirmt) from March to September were highly variable in Alaba Kulito and Bilate all with CV > 0.3. The CV in rainfall amounts (CV-RA) is higher in the months of March and October in all the three stations. For Hosana, March (CV-RA = 0.44) and October (CV-RA = 0.56), for Alaba Kulito and Bilate both March (CV-RA = 0.47) and October (CV-RA = 0.47). Monthly variations in rainfall amounts are high and unpredictable in March (onset) and October (end) of rainy season. This significantly affects the cropping calendar in rain-fed agricultural productivity of the watershed.

Variability in number of rainy days (CV-RD) is also higher for the two mentioned months. For Hosana station March CV-RD=0.39 and Oct. CV-RD=0.53; in Alaba Kulito the CV-RD of March and October is 0.41 and 0.52 respectively. In Bilate station there has been the highest CV-RD in the months of June (CV-RD=0.42) and July (CV-RD = 0.41).

Table 4-2: Variability in monthly rainfall amount and number of rainy days during **long rainy season (belg-kirmt)/March to September**

	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct
Hosana								
RA (mm)	85.0	131.0	145.0	135.0	144.0	150.0	144.0	50.0
CV-RA	0.44	0.43	0.33	0.23	0.28	0.19	0.37	0.56
RD	8.0	10.0	12.0	11.0	13.0	14.0	12.0	4.0
CV-RD	0.39	0.39	0.22	0.21	0.23	0.18	0.29	0.53
Alaba Kulito								
RA (mm)	60.0	93.0	106.0	97.0	83.0	74.0	72.0	67.0
CV-RA	0.47	0.32	0.34	0.51	0.46	0.39	0.38	0.47
RD	7.0	9.0	9.0	9.0	9.0	12.0	9.0	5.0
CV-RD	0.41	0.34	0.24	0.33	0.29	0.25	0.26	0.52
Bilate								
RA (mm)	60.0	93.0	106.0	97.0	83.0	74.0	72.0	67.0
CV-RA	0.47	0.32	0.34	0.51	0.46	0.39	0.38	0.47
RD	6.0	8.0	9.0	8.0	7.0	7.0	7.0	7.0
CV-RD	0.39	0.32	0.3	0.42	0.41	0.3	0.34	0.36

There is high variability in the amount of rainfall in a given month and the number of raining days in that month in all the stations of the watershed. Bilate station is an exception to have the highest variation in the number of rainy days to have in months of June (CV-RD = 0.42) and July (CV-RD = 0.41), otherwise the highest CV-RD happened in March and October in other stations. The onset month (March) and end month (October) showed higher variability in rainfall amounts and the number of rainy days compared to mid seasonal months. This result shows that the main problem of the watershed was not the total amount of annual rainfall. The fluctuation of onset dates and end dates of the farming period or more specifically delay of the starting dates and early cessation of rain relative to the average dates of the past. Lower values of CV-RD shows

that the variation in rainy days is consistent compared to variations in the monthly rainfall amounts, onset and end of rainy season.

4.1.3 Variability of annual and seasonal rainfall amount

From Table 4.3, the recent 30 years mean annual rainfall of Hosana, Alaba Kulito and Bilate is found to be 1100 mm, 1070 mm and 785 mm with CV of 12%, 15% and 17% respectively. The mean *Kiremt* and *Belg* rainfall for Hosana is 572mm and 408mm with SD of 67 mm and 96 mm. The CV is higher for Hosana and Alaba Kulito in *belg* season than the annual. As the *belg* rainfall is very important, for crops like maize and sorghum which are known for their longer growing period, higher variability in the *belg* rainfall will hinder the agricultural production of the area.

As shown in Table 4.4 half of the year from April to September contributed 77% to the annual rainfall in Hosana station, for which *Belg* contributed 37% and *Kiremt* contributed 52%. The monthly contribution for January, February and March is 3%, 4% and 8% which is very low compared to August (14%). The annual rainfall CV in all stations is below 20% which is said to be less (NMSA, 1996) but the CV of *Belg* season, which is known to be main maize growing season for the area, is higher than the annual amount. Similarly at Alaba Kulito 36.64% of annual rainfall occurred in *Belg*, while 47.2% of the annual rainfall occurred in *Kiremt.* The Precipitation Concentration Index (PCI) is 11.05%, 10% and 9.67% in Hosana, Alaba Kulito and Bilate stations respectively.

Table 4-3: Annual and seasonal mean of rainfall (mm), standard deviation (mm), coefficient of variation (%) and Precipitation Concentration Index (PCI %)

	Annual			*Kiremt*			*Belg*			*Bega*			PCI
Station	Mean	CV	SD	Mean	CV	SD	Mean	CV	SD	Mean	CV	SD	%
Alaba Kulito	1070	15	157	505	17	86	392	22	88	173	41	71	10
Boditi	1197	14	173	556	20	109	455	24	108	185	28	53	10.38
Bilate	785	17	133	328	28	91	289	21	60	168	28	48	9.67
Hosana	1100	12	128	572	12	67	408	24	96	120	43	51	11.05
Wulbareg	1202	15	179	687	18	123	417	25	103	98	58	56	11.87

The Precipitation Concentration Index (PCI) of all the stations is near or above the threshold value of PCI=10% for uniform rainfall distribution throughout a year. March, April and May (MAM) contribute 33% of annual rainfall in the Bilate station which shows that MAM is relatively the main growing season in the lowland areas (NMSA, 1996).

Table 4-4: Mean monthly amount and percentage contribution of rainfall for selected stations

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Mean monthly rainfall (mm)												
Hosana	29	47	85	131	145	135	144	150	144	50	25	17
Alaba Kulito	36	52	93	118	128	118	118	150	120	74	37	26
Bilate	27	30	60	93	106	97	83	74	72	67	42	33
Percent contribution to annual %												
Hosana	3	4	8	12	13	12	13	14	13	5	2	2
Alaba Kulito	3	5	9	11	12	11	11	14	11	7	3	2
Bilate	3	4	8	12	14	12	11	9	9	8	5	4

4.1.4 Onset, end and length of growing period

The computation of onset, end and LGP was done by following the days of year (DOY) entry format for a year beginning in January and ending in December and using daily rainfall data of 30 (1984 -2013) years for three rainfall stations. The results in the table 4.5 showed that the average onset date of rainfall for Hosana is 94 $\pm$ 8 DOY (April 3), for Alaba Kulito 101$\pm$ 10 DOY (April 10) and for Bilate is 102 $\pm$ 11 DOY (April 11) with CV of 23%, 26% and 29% respectively. The average end dates of the rainy season in Hosana and Alaba Kulito are October 3 (277 $\pm$ 5 DOY) and September 25 (269 $\pm$ 7 DOY) with CV 5% and 7%. The main rainy season ends earlier in Bilate. It is on July 12 (194 $\pm$ 10 DOY) with CV 14%. The length of the growing period (LGP) in Hosana varies from 131 to 229 days with 30 years mean value of 183 $\pm$ 10 days, CV 14% and SD of 26 days. The result of LGP for Alaba Kulito varies from 87 days to 252 days with mean value of 168 days, CV 20% and SD of 34 days.

The box plot in figure 4.2 shows that the LGP is very variable in all the three stations, but it is highly variable (from 29-150 days) in Bilate station with CV of 38% and SD of

35 days. The upper and lower caps of the whiskers shows the maximum and the minimum values, the upper and lower sides of the box represent 75th and 25th percentile and the dot line inside the box indicates the median dates.

Table 4-5: Onset, end and length of growing period (LGP) in three selected stations

Station		Hosana	Alaba Kulito	Bilate
Onset	Max	127	158	158
	Min	51	53	43
	Mean	94	101	102
	CI	94 ± 8	101 ± 10	102 ± 11
	SD	22	26	29
	CV	0.23	0.26	0.29
End	Max	302	311	254
	Min	247	245	149
	Mean	277	269	194
	CI	277 ± 5	269 ± 7	194 ± 10
	SD	15	19	28
	CV	0.05	0.07	0.14
LGP	Max	229	252	150
	Min	131	87	29
	Mean	183	168	92
	CI	183 ± 10	168 ± 13	92 ± 13
	SD	26	34	35
	CV	0.14	0.2	0.38

Onset and end of rainy seasons measured in DOY, LGP measured in number of days, and CI stands for confidence interval.

Ethiopia is known to have three distinct seasons. The first is the *Belg* season (February, March, April and May) which is the main growing season for most of the long duration crops like maize and sorghum (NMSA, 1996; Abiye et al., 2014), the second is the *Kiremet* season (June, July, August and September) which is responsible for up to 57% of annual rainfall in the study area, and the third is the *Bega* season (October, November, December and January) which is usually a dry season known to be a non-growing season. From the above discussion it is clear that the long rainy season (*Belg - Kiremt*) runs from February to September and the computation of onset, end and LGP is done within these months by following the days of the year (DOY) entry format for a year beginning in January and ending in December and using daily rainfall data of 30 (1984-2013) years for three rainfall stations.

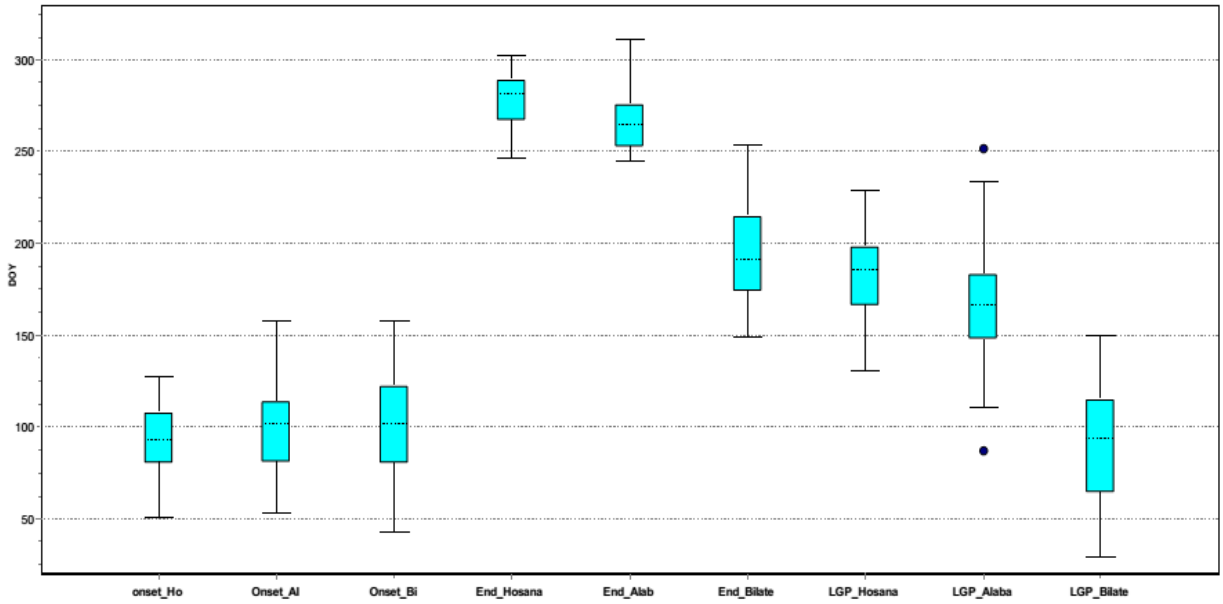


Figure 4-2: Box plot graph of onset, end and LGP in three stations

From Table 4.5, there is no big difference in the mean onset date of rainfall in the watershed, while the first and second week of April is the average onset date of rainfall in all the stations. But the average end date and so the LGP is different from station to station in the watershed. Based on the 30 years' results, the mean end date of the rainy season in Hosana, Alaba Kulito and Bilate station is October 3, September 25 and July 12 respectively, giving the stations a mean length of growing period of 183, 168 and 98 days respectively, and these results are in agreement with the findings of (Abiy et al., 2014). In the study it was revealed that variability in rainfall parameters like onset, length of growing period and end dates affects cropping calendar and agricultural production. This is because delay in onset of rainfall mean delay in planting of crops. Early end in rainfall mean that the crop yield will be affected because there will not have enough period for growing of crops.

4.1.5 Evapotranspiration

As shown in Figure 4.3, in Hosana station the mean monthly rainfall exceeded the evapotranspiration for the months from April to September and there is a water deficit in the area for the rest of the year.

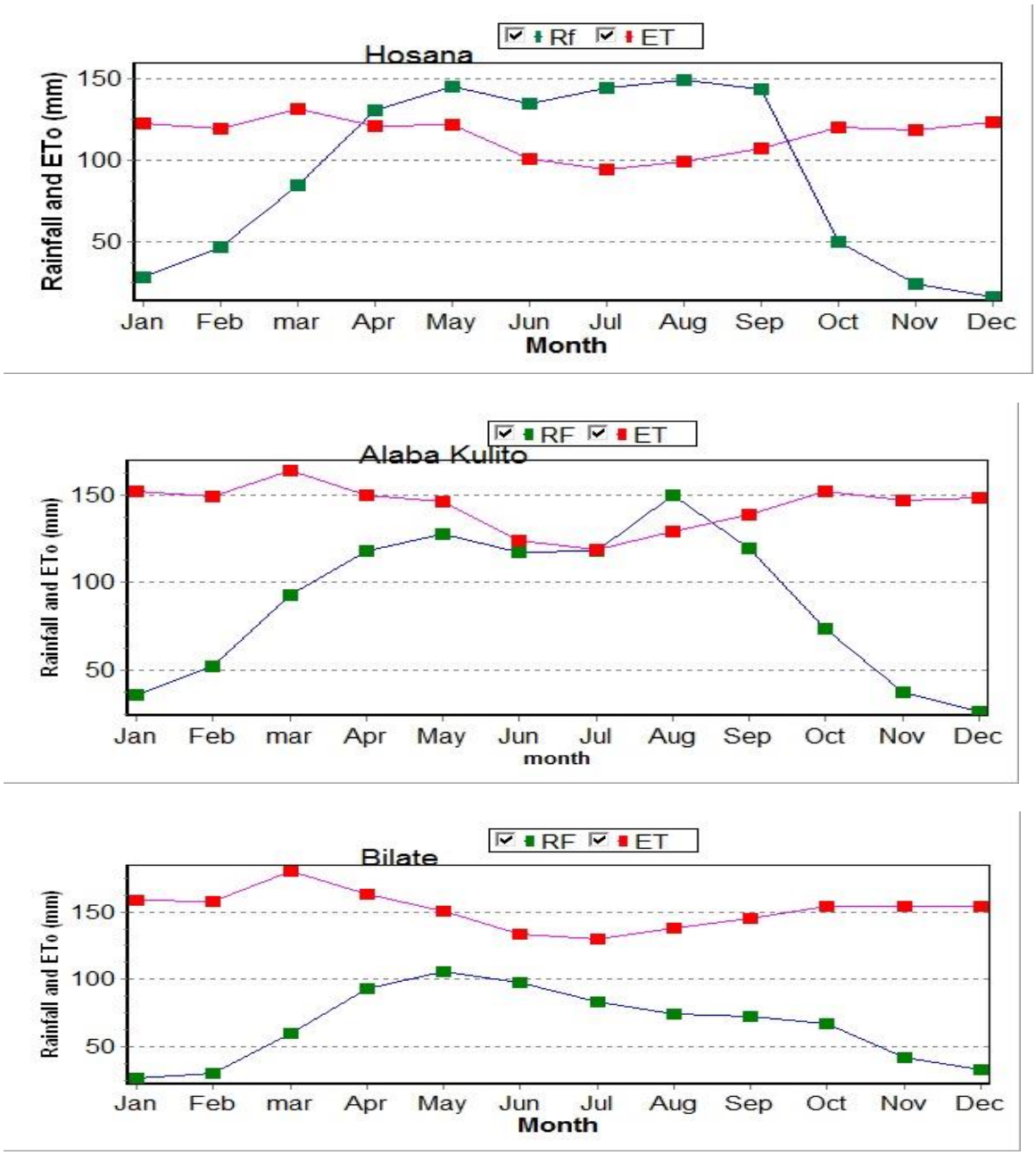


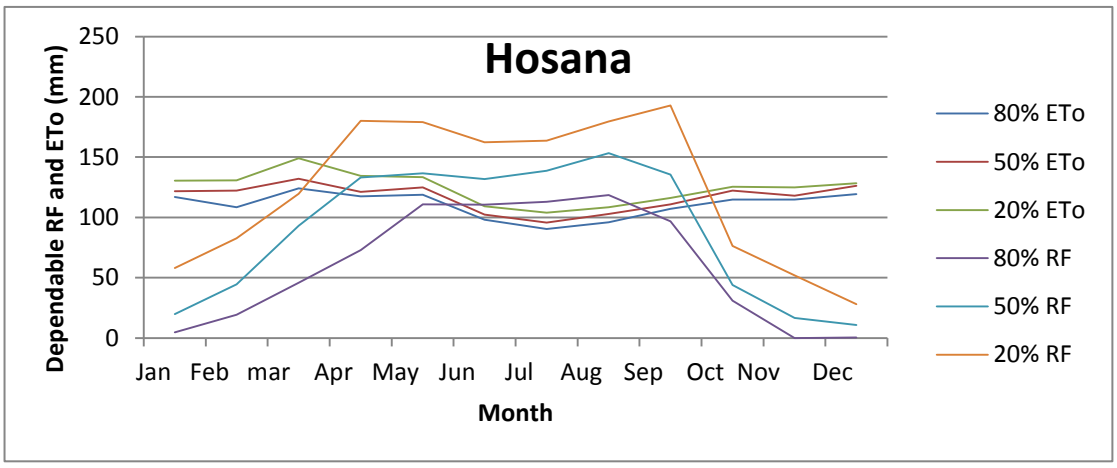
Figure 4-3: Comparison of monthly rainfall and reference crop evapotranspiration

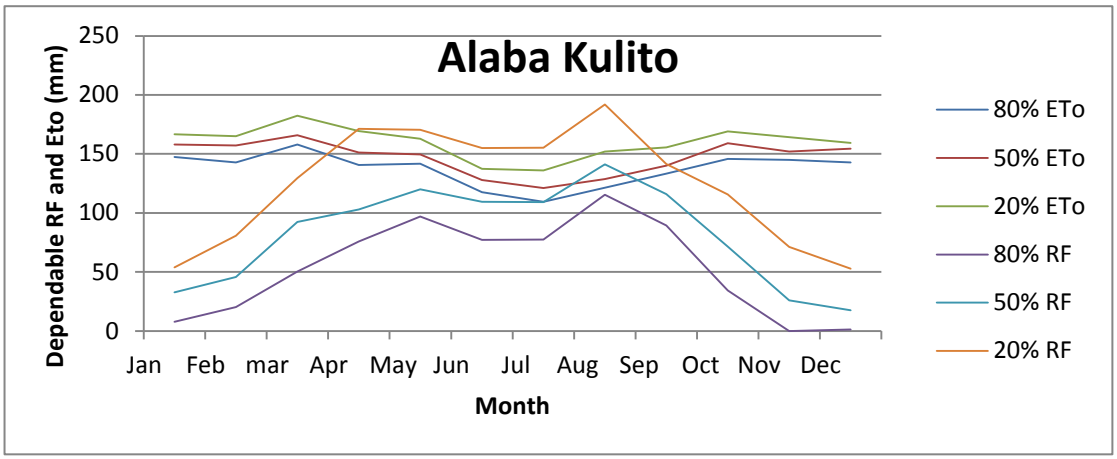
The relationship between 20%, 50%, and 80% exceedance levels of monthly rainfall total representing wet, normal and dry years respectively and the reference crop evapotranspiration of 20%, 50%, and 80% exceedance levels is shown in Fig 4.4 for three selected station. For Hosana station the rainfall total expected in a normal year is less than the reference crop evapotranspiration for half the months of a year. In a wet year (20% ETo) two more months with expected rainfall higher than the reference crop

evapotranspiration at 20%, 50% and 80% would make part of the growing season. Furthermore, the monthly 80% dependable reference crop evapotranspiration is in the range of ± 31mm of the monthly mean, which shows that there is a probability that the reference crop evapotranspiration exceeds the mean monthly rainfall leaving the area with a deficiency of crop water.

Similarly, in Alaba Kulito station in normal and dry years (50% and 20% RF) rainfall is less than the reference crop evapotranspiration throughout the year. In Bilate station only 20% RF in wet years exceeds the reference crop evapotranspiration in couple of months giving the area a slight chance of rain-fed agriculture with mean LGP less than 90 days.

For the entire stations monthly reference crop evapotranspiration was computed and compared with the monthly mean rainfall. This helps to determine the period with moisture deficit and times when the need for water from other sources is high and the farmers cannot depend only on rain for their agricultural production. As shown in Figure 4.3, in Hosana station the mean monthly rainfall exceeded the reference crop evapotranspiration for the months from April to September and there is water deficit in the area for the rest of the year. In Alaba Kulito, an area with 30 years' mean AI= 0.6 (dry sub-humid zone) the reference crop evapotranspiration values exceed the rainfall amount for most of the months except July and August.





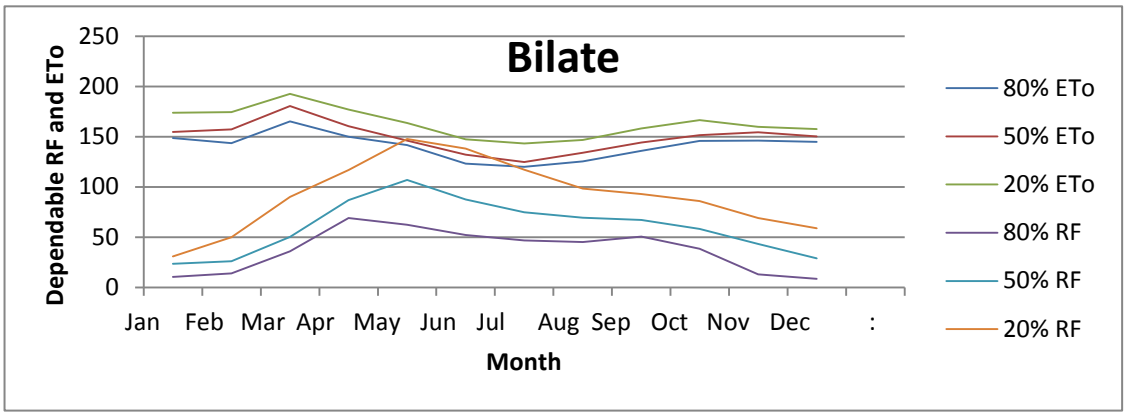


Figure 4-4: Monthly rainfall and reference crop evapotranspiration at three exceedance probability levels for selected three stations

As shown in Figure 4.3, in Bilate area, the evapotranspiration values exceed the rainfall amount for all of the months, showing that rain-fed agriculture is not feasible but only 20% RF in wet years exceeds the reference evapotranspiration (Figure 4.4) in a couple of months giving the area a slight chance of rain-fed agriculture with mean LGP less than 90 days; otherwise the area has rainfall below the threshold of rain-fed agriculture of 250mm (Aghajani, 2007). The Aridity Index (AI) of Bilate area for the last 30 years is 0.43, so that the area is classified as a semi-arid zone according to UNFCCC (Rodier, 1985).

4.1.6 Aridity Index

Hosana, with 30 years average Aridity Index (AI) of 0.8, is classified into humid zone even though there is water deficit for half of the year. In Alaba Kulito, an area with 30 years mean AI= 0.6 (dry sub-humid zone), the evapotranspiration values exceed the rainfall amount for most of the months except July and August. As shown in Figure 4.3, in Bilate area, the evapotranspiration values exceed the rainfall amount for all of the months, showing that rain fed agriculture is not feasible. The AI of Bilate area is 0.43, so that the area is classified as a semi-arid zone according to UNFCCC (Rodier, 1985).

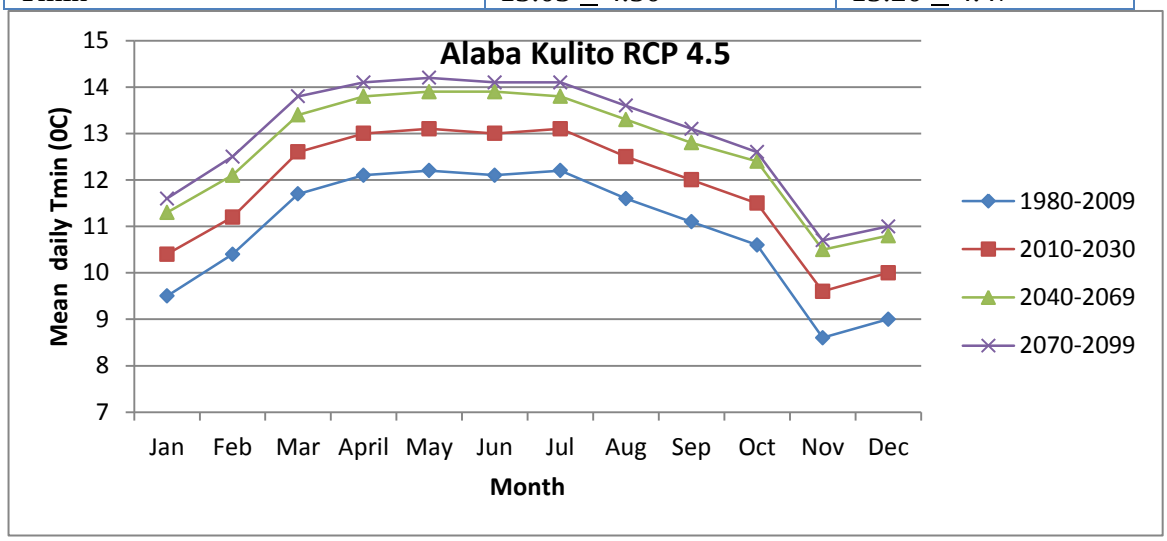
4.2 Statistical Downscaling (Delta Method) of Precipitation and Temperature in Bilate Watershed

4.2.1 Projected temperature

All the 20 models showed a similar trend in projected maximum and minimum temperature in both representative concentration pathways in the whole 21st century. The mean result of the ensemble of all 20 models is shown in Table 4.6. The downscaled results of minimum and maximum temperature at Alaba Kulito are shown in Figure 4.5 and Figure 4.6. Both scenarios show an increasing projection of minimum and maximum temperature where RCP 8.5 is slightly over the estimates, compared to RCP 4.5. The average maximum temperature (27.66 ^{0}C) of the base years (1980-2009) increases by 1.65 ^{0}C and 3.5^{0}C by the end of 21st century under RCP 4.5 and RCP 8.5 respectively. From the same statistics for data downscaled in both Representative Concentration Pathways the average minimum temperature (10.93) of the base year shows an increase of 2.1^{0}C and 4.27^{0}C for RCP 4.5 and RCP 8.5 respectively by 2100. This result of the increase in the minimum and maximum temperature is in agreement with the IPCC Fifth Assessment Report (Niang et al., 2014).

Table 4-6: Projected temperatures in Alaba Kulito area during 2030s, 2050's and 2080s

Analysis time slice	Projected temperature (°C)	
	RCP 4.5	RCP 8.5
Near time) (2030)		
Tmax	28.39 ± 2.75	28.43 ± 2.73
Tmin	11.89 ± 4.50	12.03 ± 4.50
Mid-century (2050)		
Tmax	29.09 ± 2.73	29.65 ± 2.70
Tmin	12.74 ± 4.49	13.48 ± 4.49
End-century (2080)		
Tmax	29.31 ± 2.69	31.16 ± 2.65
Tmin	13.03 ± 4.50	15.20 ± 4.47



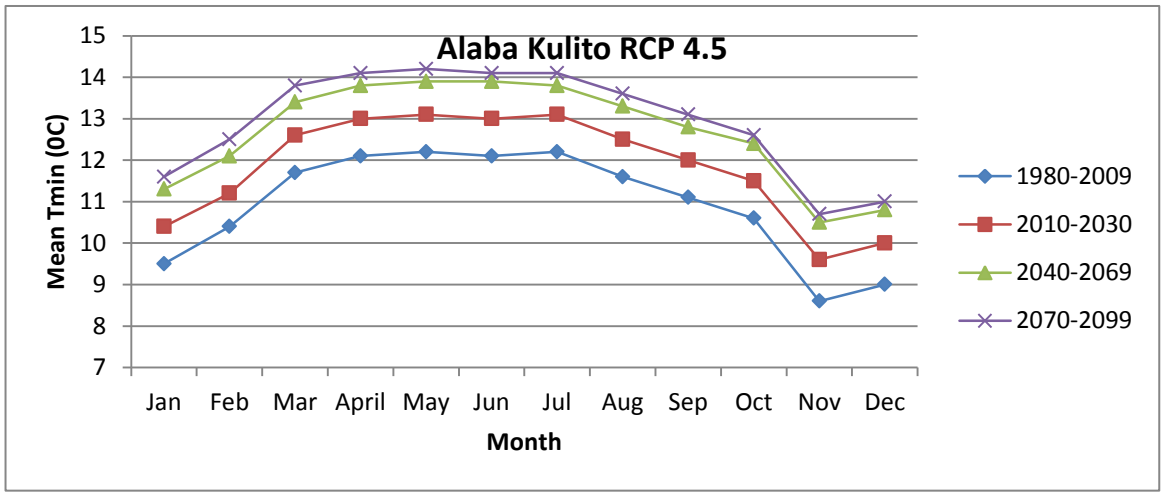
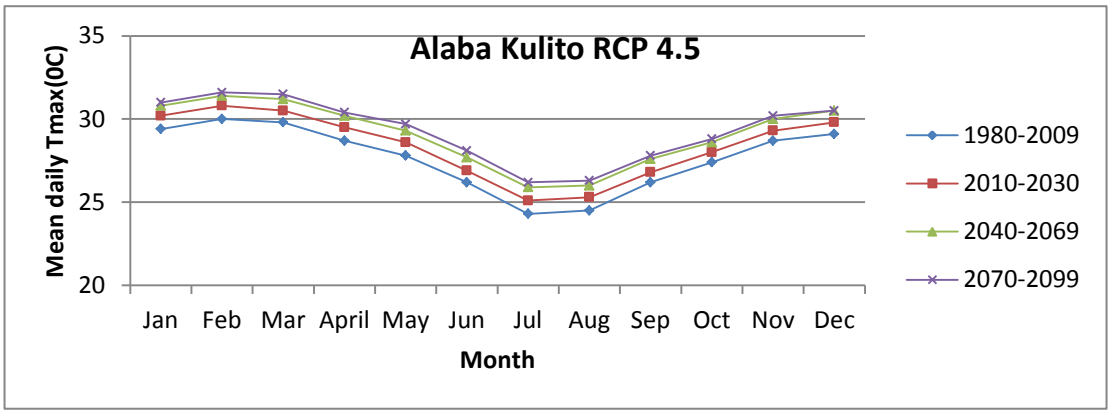


Figure 4-5: Trends of daily minimum temperature at Alaba Kulito under RCP 4.5 and RCP 8.5.



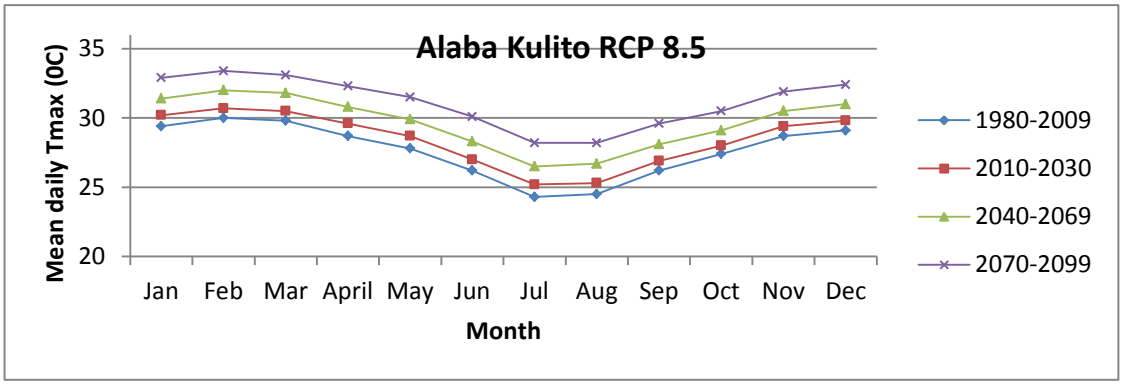


Figure 4-6: Trends of daily maximum temperature at Alaba Kulito under RCP 4.5 and RCP 8.5.

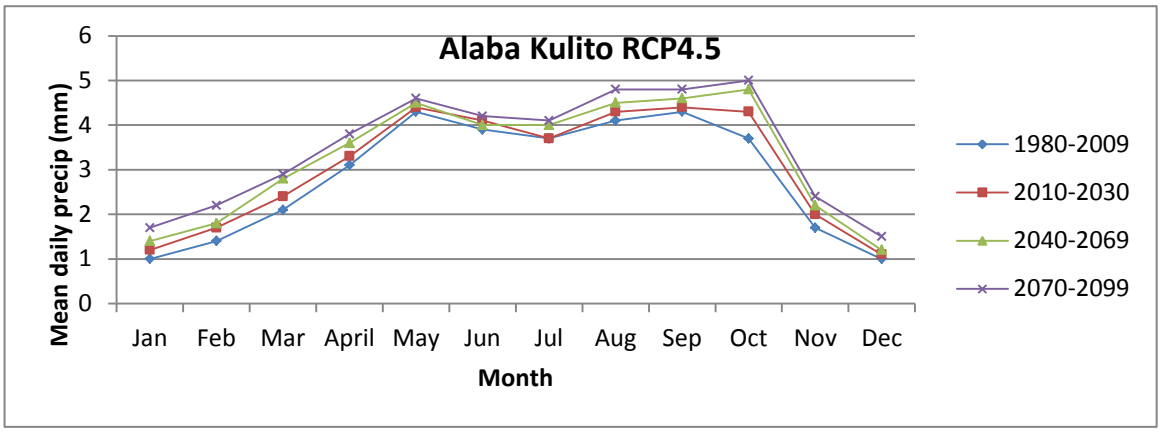
There will be consistency in the rising trend of minimum temperature under both RCP 4.5 and RCP 8.5 but with a sharper rise under RCP 8.5 leading to an increasing gap between the two emissions pathways. This can be explained by continued rising emission concentrations that the fifth assessment report (AR5) has shown will continue rising (RCP 4.5 near-term 423 ppm, mid-century 499 ppm and end-century 532 ppm) (Stocker et al., 2013). Progressive rise in maximum temperature under both Representative Concentration Pathways during the mid-century and a sluggish rise under RCP 4.5 in the end century will be experienced. The projected increase in both minimum and maximum temperature over the farm lands of the Bilate Watershed will end up in warming, attributed to be the direct effect of continued increase in carbon dioxide emissions during the 21st century, when the CO_2 concentration is projected to increase to above 650 ppm (IPCC, 2014). This is in close agreement with the findings that have shown that there will be a warming over East Africa (Waithaka et al., 2013).

The result of the projection of the mean ensemble of all 20 models shows rainfall variability within and between time-slices (Table 4.7). The high standard deviations of the results showed that spatial and temporal variability within and between locations in both scenarios will be expected. Hosana is the only area that will experience an overall rainfall decline under RCP 4.5 in near-term (Table 4.7), and a positive during mid-century (2040-2069) and end-century (2070-2099). Notably, under all time periods, projected total rainfall will be higher under the RCP 8.5 scenario (Table 4.7).

For the farm lands near Alaba Kulito, the mean ensemble of all 20 models showed a similar pattern of rainfall in all time periods (near term 2010-2039, mid-century 2040-2069 and end-century 2070-2099). The mean annual rainfall for the total projection period (2010-2099) will be 1202.97±184.9mm under RCP 4.5 and it will be 1252.52 ± 210.9mm under RCP 8.5 respectively. Except for a slight higher projection of rainfall under RCP 8.5, the trend in total rainfall projection under both scenarios is similar (Figure 4.7).

Table 4-7: Projected mean annual rainfall in farm lands of Bilate River Watershed

Analysis time slice	**Projected mean annual rainfall (mm)**	
	RCP 4.5	**RCP 8.5**
Near term (2010-2039)		
Alaba Kulito	1124.87 ± 161.60	1129.83 ±161.32
Bilate	827.37 ± 112.36	832.5 ± 113.15
Hosana	1081.09 ± 171.33	1078.52 ± 170.44
Mid-century (2040-2069)		
Alaba Kulito	1201.91± 174.57	1243.16 ± 182.30
Bilate	892.45 ± 123.29	923.61 ±131.37
Hosana	1136.43 ± 181.46	1160.97 ± 187.09
End-century (2070-2099)		
Alaba Kulito	1282.13 ± 188.40	1384.58 ± 208.52
Bilate	940.52 ± 134.65	1047.59 ± 151.56
Hosana	1179.32 ± 193.70	1265.08 ± 208.25



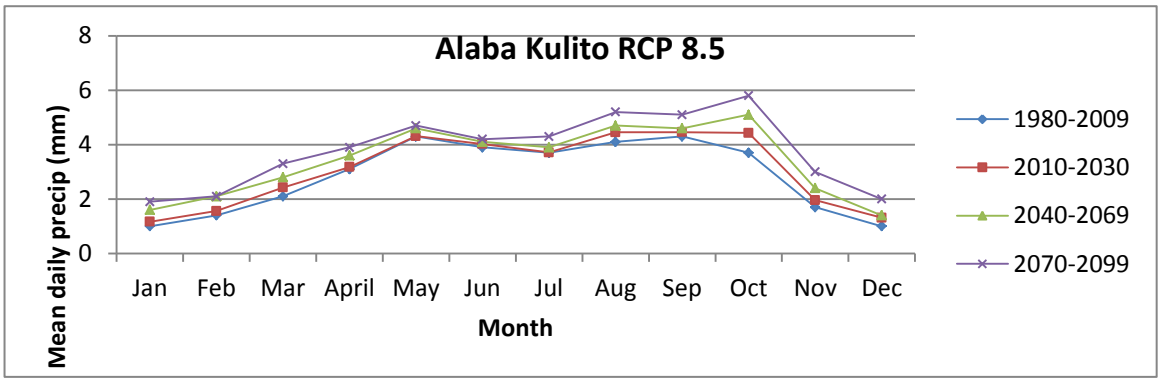


Figure 4-7: Monthly trends of precipitation at Alaba Kulito station under RCP 4.5 and RCP 8.5

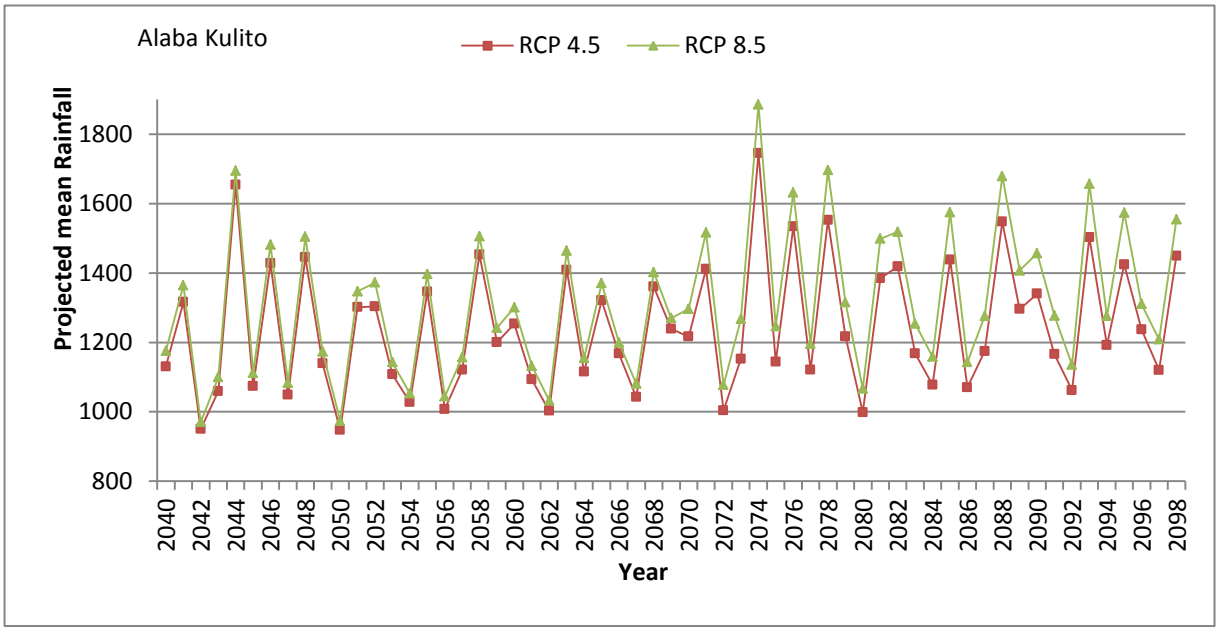


Figure 4-8: Projected mean annual rainfall total in Alaba Kulito (2040-2099)

The total annual rainfall for the watershed will progressively increase within and between the three periods (2010-2039, 2040-2069 and 2070-2099). This is in agreement with the IPCC Fifth Assessment Report (AR5) that explains CMIP5 projects likely increases in mean annual precipitation over areas of central and eastern Africa beginning in the mid-21st century for RCP8.5 and over eastern Africa by the end of the 21st century, that will have a wetter climate with more intense wet seasons and less severe droughts (Niang et al., 2014).

4.3 Response of the stream flow level of the Bilate watershed to climate model outputs

4.3.1 Model calibration, sensitivity analysis and validation

The sensitivity analysis was made using a built-in SWAT sensitivity analysis tool that uses the Latin Hypercube One-factor-at-a-Time (LH-OAT) global sensitivity analysis procedure (Van Griensven et al., 2006). The sensitivity of all parameters was analysed using average observed flow at Alaba Kulito gauging station and the optimisation procedure was then set to minimize the sum of squared error objective function.

Ranges of values used during the sensitivity analysis and the calibrated parameter value are shown in Table 6.3.The results show that the most sensitive parameters are those representing the surface run-off, evaporation, soil water, ground water and channel flow. The parameters governing the hydrological processes in the basin in the order of their sensitivity rank are SCS runoff curve number for moisture condition II (CN2), soil evaporation compensation factor (ESCO), available soil water capacity (Sol_Awc), threshold water level in the shallow aquifer for return flow to occur (Gwqmn), effective hydraulic conductivity in main channel alluvium (Ch_K2), base flow recession constant (Alpha_Bf), Manning's roughness coefficient for main channel (Ch_N2), surface runoff lag coefficient (Surlag), groundwater delay time (Gw_Delay) and aquifer percolation coefficient (Rchrg_Dp).

Calibration of the parameters was immediately followed after the sensitivity analysis. Stream flow at the Alaba Kulito gauge station was calibrated by auto-calibration and

manual procedures for the period of 1990-1996. The model efficiency measures for initial monthly default simulation are the coefficient of determination (R^2), Nash–Sutcliffe coefficient (NSE) and percent bias (PB) were 0.78, 0.45 and 42.39 respectively which shows low performance of the model by the default parameter values. Thus, model parameter adjustments were undertaken for a realistic hydrologic simulation and the key hydrologic parameters shown in Table 4.8 were adjusted until the simulated flow was nearly equal to the observed flow during the calibration processes. The statistical results show that the model predicted the stream flow at the Alaba Kulito gauge station reasonably (R^2=0.79; NSF=0.78; PB=0.56).

Table 4-8: Hydrologic parameters included in SWAT sensitivity analysis for the Bilate River Watershed

Parameter	Description	Model Process	Rank	Variation Range	Fitted Value
CN2	SCS runoff curve number for moisture condition II	Runoff	1	**-25 - +25**	20[c]
ESCO	Soil evaporation compensation factor	Evaporation	2	0-1	1[a]
Sol_Awc	Available soil water capacity	Soil water	3	-25 - +25	15[c]
Gwqmn	Threshold water level in the shallow aquifer for return flow to occur (mm)	Groundwater	4	0-1000	258[a]
Ch_K2	Effective hydraulic conductivity in main channel alluvium (mm h^{-1})	Channel flow	5	0-150	31[a]
Alpha_Bf	Base flow recession constant (days)	Groundwater	6	0-1	0.09[a]
Ch_N2	Manning's roughness coefficient for main channel	Channel flow	7	0-1	0.43[a]
Surlag	Surface runoff lag coefficient	Runoff	8	0-12	9.64[a]
Gw_Delay	Groundwater delay time	Groundwater	9	0-10	6.45a
Rchrg_Dp	Aquifer percolation coefficient	Groundwater	10	0-1	0.49[b]

a=default values are replaced by this value (absolute change); b= default values are multiplied by one plus this value (relative change); c=default values are increased by this value (absolute change)

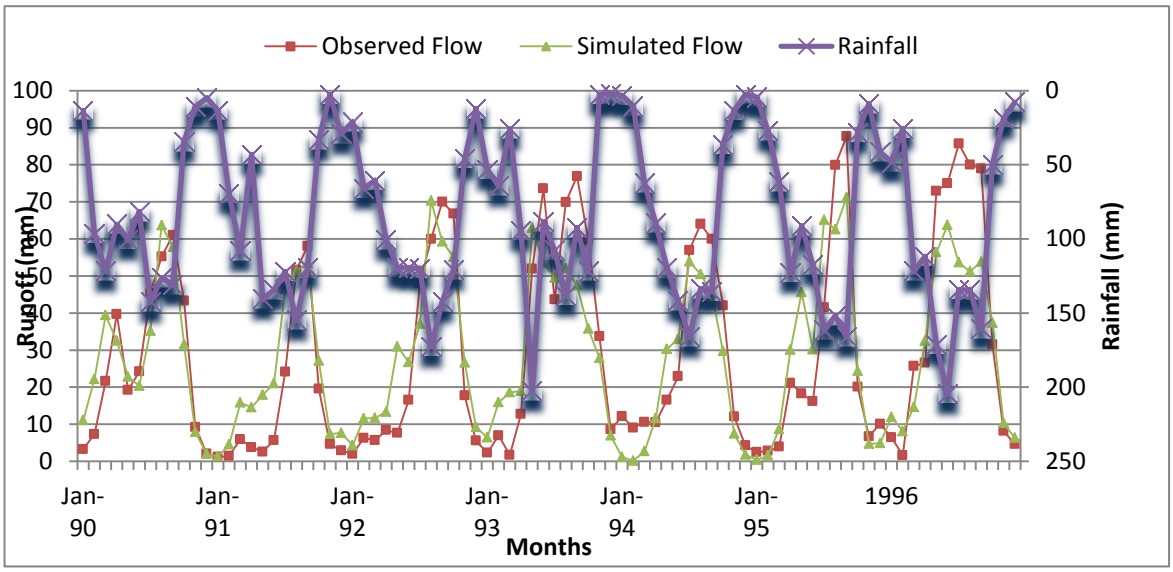


Figure 4-9: Manual calibration results for monthly flow at Alaba Kulito (1990 -1996)

Figure 4.9 shows hydrograph comparisons for the Bilate River Watershed at the Alaba Kulito gauging station during simulation periods (1 January 1990 to 31 December 1996) to measure how the calibrated model predicts stream flows against the observed flows. Overall, the calibrated flows match observed flows well, but the magnitude of peaks during the summer (June–August) is somewhat different from the observed flow in particular years, such as July 1993, 1995 and 1996 (Figure 4.9).

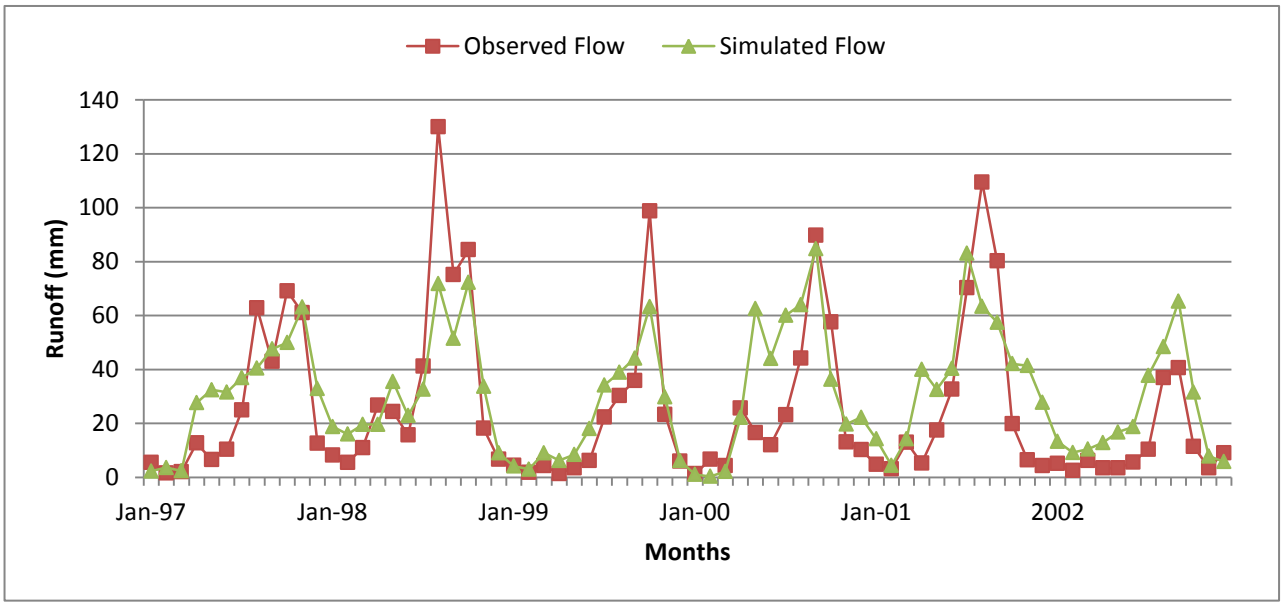


Figure 4-10: Simulated versus observed flow during validation period

In the validation process, the model was operated with input parameters set during the calibration process without any change. An independent six year (1997–2002) input data was used and it was found that the model has strong predictive capability (R^2=0.64; NSF=0.60; PB=-21.7). Statistical model efficiency criteria fulfilled the requirement of R^2>0.6 and NSE >0.5 which is recommended by the SWAT developer (Nash and Sutcliffe, 1970; Santhi et al., 2001) and the PB < ±25 suggested by Gupta et al. (1999). The model validation results for monthly flow (Fig. 4.10) indicated generally a good fit between measured and simulated output and this showed the model parameters are representing the processes occurring in the watershed to the best of their ability to predict watershed response for various climate scenarios.

4.3.2 Climate change impact on stream flow

To evaluate the influences of climate change on the monthly stream flow in the Bilate river basin during the coming decades, a simulation for 2020, 2050 and 2080 was done by the calibrated SWAT model under different climate scenarios (RCP 4.5 and RCP 8.5). A baseline scenario, assumed to reflect current conditions, was executed prior to performing scenario simulations and the simulated baseline annual stream flow (ID 25) with the amount of 28.55 m^3s^{-1} was used as the reference frame to show the amount of change in the stream flow under different climate scenarios. Table 4.9 shows the results of the ensemble_20 annual stream flow changes as well as the results of the other developed climate scenarios for Alaba Kulito station. The annual stream flow increased progressively throughout the century for all time periods under both RCP scenarios. The increases under RCP 8.5 scenario are larger compared to RCP 4.5 scenarios, approximately 42.42% during the 2080s period. The lowest stream flow change occurred under RCP 8.6 with an increase of 10.3% for the 2020s period. Under RCP 4.5 scenario, the annual stream flow is expected to increase by 10.9, 16.12 and 23.48% for the 2020s, 2050s and 2080s periods respectively.

The low flows (Q95) highly and progressively increased by 7.82%, 10.48% and 35.7% for RCP 8.5 scenario for the 2020s, 2050s and2080s respectively. While the low flow under RCP 4.5 will increase very slightly (1.66% and 1.79%) for 2020s and

2050s but it will increase at 18.88% for the 2080s. The high flows (Q5) slightly decreased for RCP 4.6 (-2.87 to -4%) and dramatically increased for RCP 8.5 (20.67%) for the 2080s. Results for the Bilate River Watershed pointed to a positive change of annual stream flow throughout the century by the ensemble of 20 GCMs which is driven by the projected increase in precipitation and shows that water resources of the Bilate River will be satisfactory until the end of the century provided the local consumption rates of the 1990s remain in place.

Table 4-9: Stream flow simulation changes against the base period simulation for different climate scenarios

ID	Mean monthly stream flow (m^3/s /%)	Monthly Q95 (m^3/s /%)	Monthly Q5 (m^3/s /%)
1	31.66/10.9	7.86/1.66	61.09/-4
2	33.15/16.12	7.87/1.79	60.64/-4.71
3	35.25/23.48	9.19/18.88	61.81/-2.87
4	31.5/10.34	8.33/7.82	62.48/-1.83
5	34.38/20.43	8.54/10.48	63.84/0.31
6	40.66/42.42	10.49/35.7	76.79/20.67
7	30.73/7.65	7.31/-5.44	56.53/-11.18
8	31.53/10.45	8.07/4.37	59.72/-6.16
9	32.07/12.33	8.66/12.09	61.04/-4.09
10	32.53/13.95	8.79/13.72	61.92/-2.7
11	31.58/10.63	8.27/7.05	58.97/-7.34
12	31.75/11.2	8.52/10.23	59.2/-6.98
13	28.98/1.52	8.63/11.59	53.87/-15.35
14	30.78/7.83	6.65/-13.94	57.89/-9.04
15	29.86/4.59	6.22/-19.5	55.95/-12.08
16	29.5/3.34	7.8/0.9	53.82/-15
17	29.93/4.83	7.29/-5.73	53.9/-15.31
18	26.78/-6.18	5.77/-25.32	52.31/-17.81
19	28.62/0.25	8.17/5.66	51.6/-18.92
20	30.25/5.98	6.55/-15.22	56.06/-11.91
21	34.3/20.16	6.04/-21.87	65.33/2.65
22	29.06/1.81	7.72/-0.18	52.33/-17.77
23	28.78/0.81	7.06/-8.62	50.49/-20.66
24	26.46/-7.29	5.79/-25.14	50.65/-20.41
25	28.55	7.73	63.64

Increases in stream flow are also projected for each month (Figure 4.11) with exceptions in the months of July and August where there will be a decrease of stream flow in the watershed. The largest projected monthly increases in stream flow will be in December (5.67, 5.98, 7.94 m^3/s for the RCP 4.5 and 6.06, 8.04 and 14.25 m^3/s for the RCP 8.5) in the 2020s, 2050s and 2080s respectively; and this month is known to be the driest and coldest month of the years, while the largest possible monthly decrease in stream flow will occur in the month of July (-10.21, -9.92, -9.98 m^3/s for the RCP 4.5 and -11.25, -

10.42 and -7.34 m^3/s for the RCP 8.5) in 2020s, 2050s and 2080s respectively, and the month of July is the wet season.

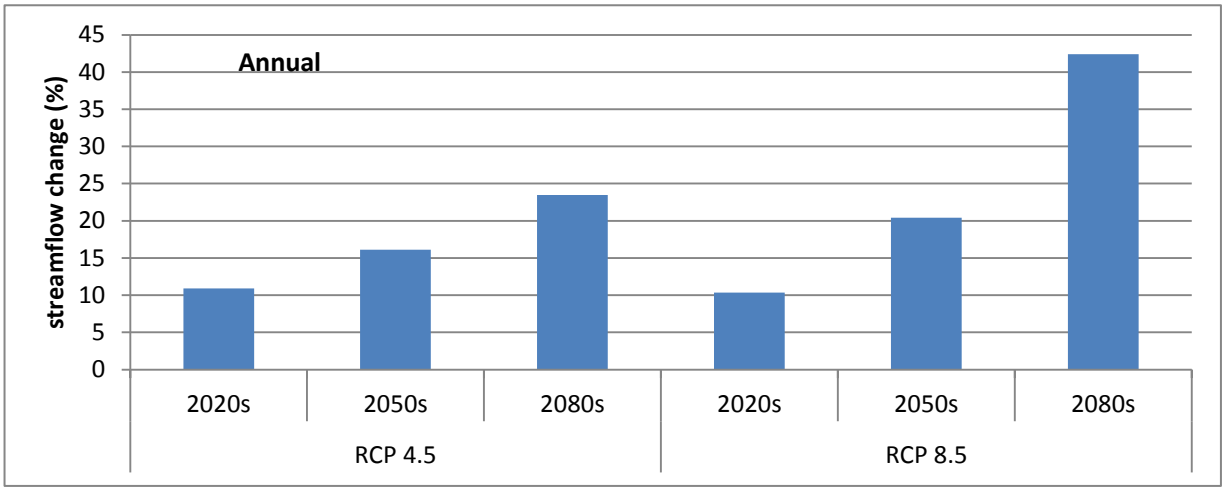


Figure 4-11: Annual stream flow changes at Alaba Kulito station of Ensemble_20 under RCP 4.5 and RCP 8.5 for the periods of 2020s, 2050s and 2080s

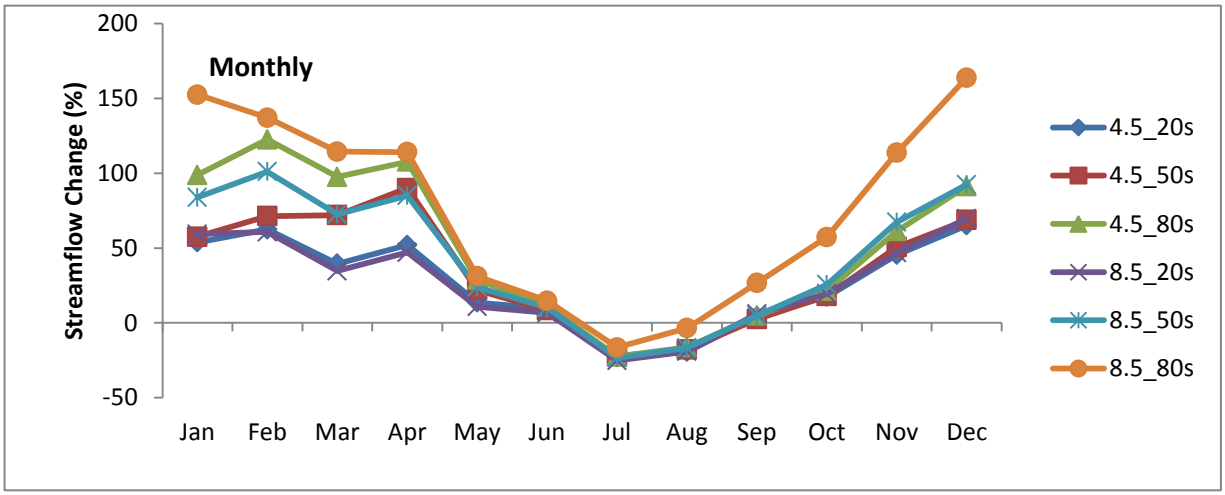


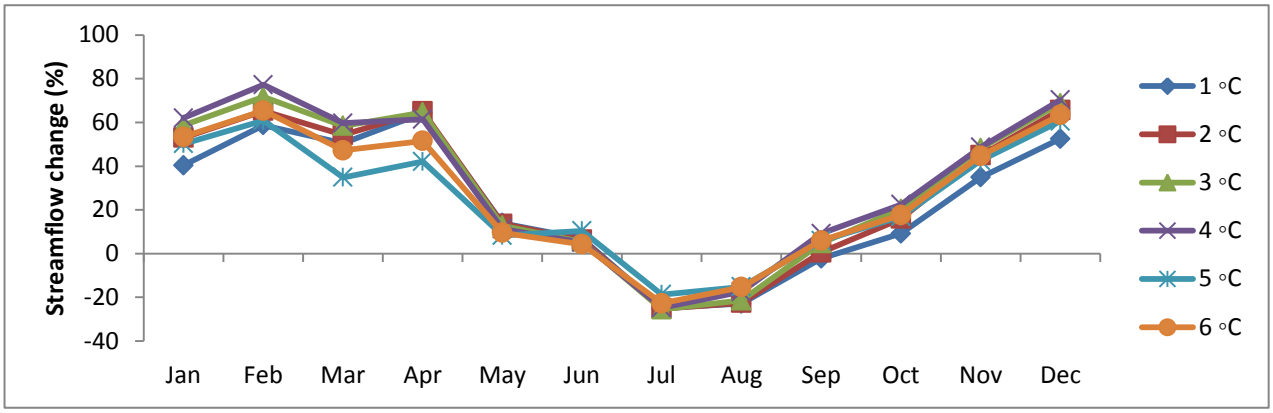
Figure 4-12: Monthly stream flow changes at Alaba Kulito station of Ensemble_20 under RCP 4.5 and RCP 8.5 for the periods of 2020s, 2050s and 2080s

4.3.3 Climate impact uncertainty assessment

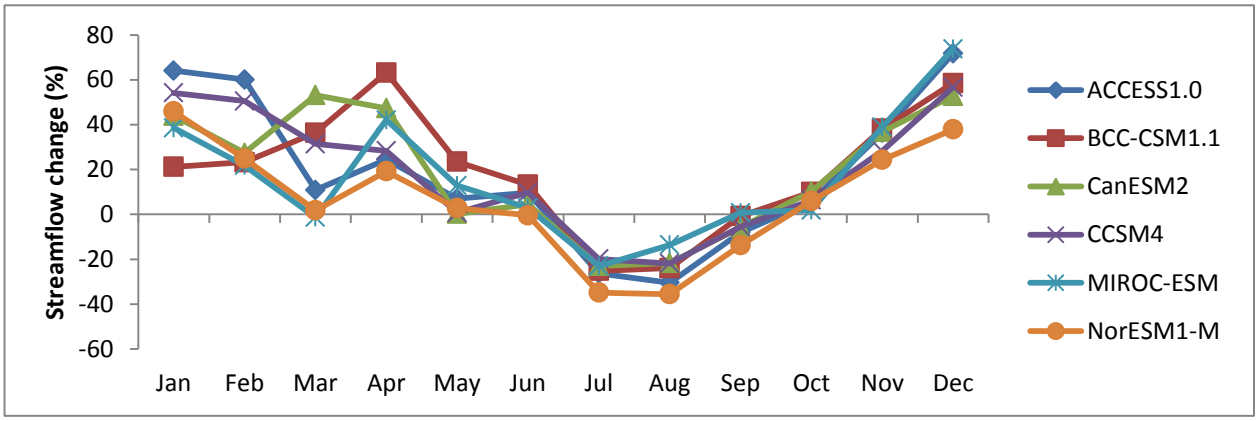
Figure 4.12 shows the projected changes in annual river discharge by the Ensemble of 20 CMIP 5 GCMs for three future time periods under two RCPs. An increase in annual river flow compared with the baseline is projected under all six scenarios. The magnitude of increase for annual river discharge ranges from 10.34% to 42.42%. The

projected increases in monthly discharge under all six scenarios mostly may be associated with decreases in the rainy season and increases in the dry season (Fig. 4.13).

(a)



(b)



(c)

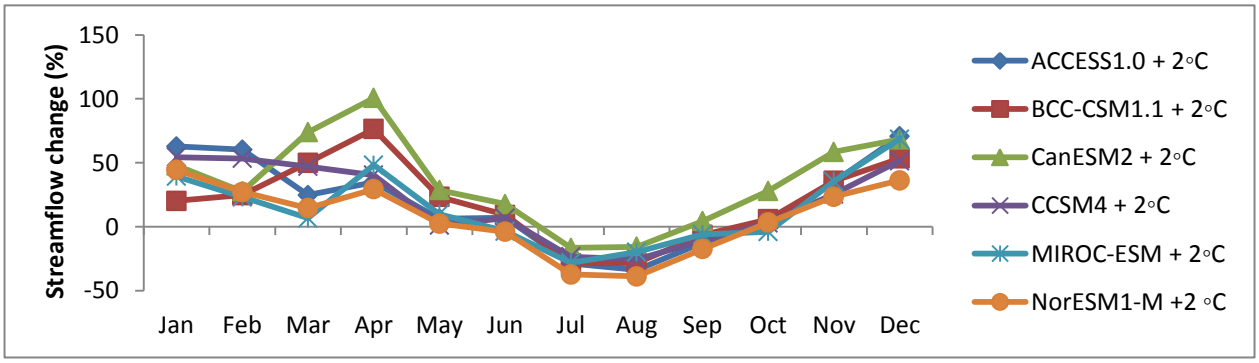


Figure 4-13: Changes in monthly discharge against the baseline at Alaba Kulito station for climate scenarios: (a) Prescribed temperature of 1-6^{0}c, (b) GCM structure, and (c) 2 ^{0}C increase in temperature

For prescribed temperature increase of 1-6^{0}C scenarios, mean annual river discharge does not show a linear decrease as it does in other watersheds in other studies (Tan et al., 2014; Khoi and Han, 2015) showing that the local temperature increments have less effect on the hydrology of the Bilate River Basin. Similar observations have been reported for other river basins in the East Africa region (Dessu and Melese, 2013). Figure 4.13 (a) Shows the changes in monthly discharge for all the six scenarios of prescribed temperature increase. The monthly river discharge in the wet season of the area (June-September) decreases from -2.23% in September for the 1°C scenario to -25.52% in July for the 3°C scenario and monthly discharge in the dry season (October-May) increases dramatically from 9.13% in October for the 1°C scenario to 77.23% in February for the 4°C scenario. Uncertainty in projected monthly stream flow for prescribed temperature scenarios varies from -24.97 to 64.24% for the 1^{0}C scenario to the range of -22.71 to 65.35% for the 6 ^{0}C scenario.

Five of the six GCMs (ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM) under RCP 4.5 for 2020s show that annual stream flow will increase compared to the baseline, except for the NorESM1-M, which shows a change of -6.18% in annual stream flow. The six GCMs (ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM, NorESM1-M) selected to see the uncertainties related to GCMs suggest that the river flow will change by small amounts of −6.18% to 7.83% change compared with the baseline. Projected changes in mean annual river discharge under the prescribed increase in mean temperature of 2°C shows a similar trend of increase for the five GCMs (ACCESS1.0, BCC-CSM1.1, CanESM2, CCSM4, MIROC-ESM) and a decrease of simulated stream flow for NorESM1-M. It was observed that the simulated run-off in the Bilate River depended on the projected amount of rainfall and the GCM structure selected to simulate the future climate and less dependent on the local temperature increment.

Figures 4.13 (b) and (c) show that the projected increases and decreases of monthly stream flow changes for selected GCM structures and an increase of 2°C on top of the downscaled temperature output of the selected GCM. The results show stream flow

changes are evenly distributed throughout the year for both the causes. Uncertainty in the Q5 ranges from -17.81% to -9.04% for GCM structures and from -20.66% to 2.65% for GCM plus 2°C scenarios. This results show that there will be a decrease in the high flows in the 2020s. Uncertainty in Q95 ranges from -25.32% to 11.59% for GCM structures. As shown in Figure 6.6 (b) ACCESS1.0 shows the largest variation (-30.39% to 71.6 7%) and CanESM2 shows the smallest variation (-23% to 52.8 %) at monthly scale.

4.4 Local Perceptions and Adaptation to Climate Variability and Change in the Bilate River Watershed

4.4.1 Model variables

Dependent Variables (Adaptation Options)

A wide variety of actions taken by an individual farmers, communities and organizations to prepare for, or respond to climate change impacts have been identified as adaptation options by the climate change research community. The adaptation options in the Bilate Watershed were identified by asking the farming households about their perception of the climate change and measures they take to offset the negative impacts of the changes (Figure 4.14). Some other adaptation options like planting shade trees, changing from crop to livestock, migrating to another area and renting out their land holding were assumed to be part of the adaptation options but they were ignored after the interview schedule because they were not reported in the responses of the farm households or were perceived as community level mitigation measures.

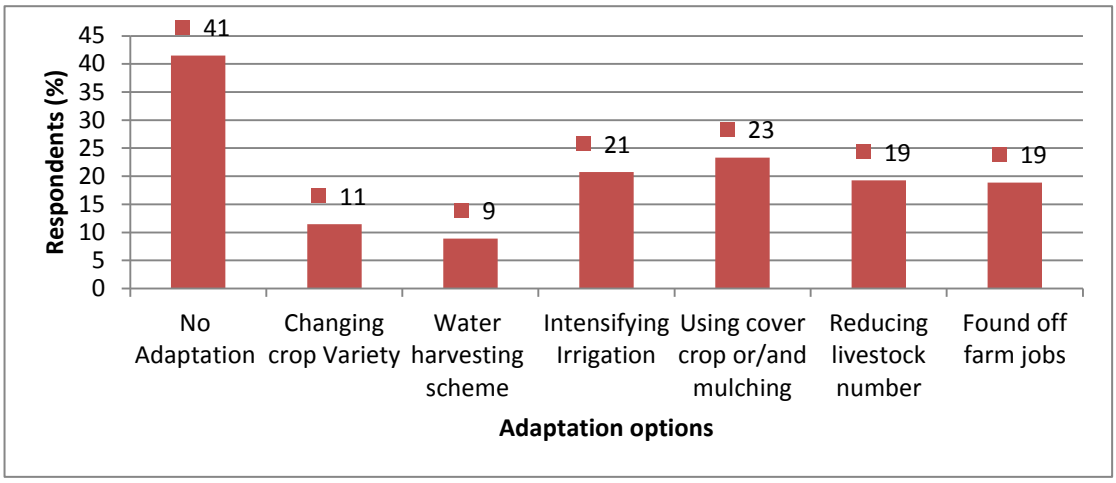


Figure 4-14: Farmers' adaptation options in the Bilate Watershed

The use of cover crop and mulching mainly to conserve moisture and intensification of irrigation are two main adaptation methods reported to be used by farmers of the Bilate watershed whereas changing crop varieties and building water harvesting schemes are the least used methods. About 42% of the farming households participating in the interview schedule reported that their families used none of the adaptation methods.

Independent Variables

Farmers' choices of adaptation strategies are determined by a range of household socio-economic characteristics, institutional factors and their agro-ecological setting. Hypothesized factors are discussed below and the description of the expected effect of each of these variables is presented in table 4.10.

Age

In literatures, the age of farmers has been discussed to influence their decision to adopt new technologies both positively and negatively (Gbegeh and Akubuilo, 2013). Some studies in Ethiopia showed that the age of the household head as a measure of farming experience affects positively the farmers' adaptation options (Deressa et al., 2009; Hadgu et al., 2015), while other researchers concluded that older farmers are less likely to be flexible than younger farmers and thus have a lesser likelihood of adopting new technologies (Adesina and Baidu-Forson, 1995). The study of Shiferaw and Holden (1998) in Ethiopia shows that there is a negative relation between age and adoption of

improved soil conservation practices. Here it is expected that households with older heads are more likely to adapt to climate change.

Gender

Gbetibouo (2009) argues that the effects of gender on climate change adoption decisions are location-specific. In many parts of Africa women have fewer capabilities and resources than men; this in turn weakens their capacity to embrace labour-intensive agricultural innovations (Gbegeh and Akubuilo, 2013). In Ethiopia women-headed households are expected to be less likely to adapt due to their limited access to land, information, inputs and institutions as a result of traditional social barriers (Wilson and Getnet, 2011; Tessema et al., 2013). There are some other studies with results contrary to the above argument which shows that women-headed households are more likely to take up climate change adaptation methods (Nhemachena and Hassan, 2007). Thus, adaptation methods are assumed to be context specific.

Educational level

There is a positive relationship between the education level of the household head and the adoption of the household new technology (Asfaw et al., 2015) and the years of formal education of the farmers was positively related to adaptation to climate change (Shongwe, 2014). This shows that farmers with higher levels of education are more likely to adapt better to climate change (Obayelu, 2014). Here also it is assumed that farmers with higher levels of education are more likely to adapt better to climate change.

Household size

There are two categories of views for the influence of household size on climate change adaptation (Deressa et al., 2008). The first category argues that households with a larger number are more likely to adopt an agricultural technology and use the execss labour more intensively because they have fewer labour shortages at peak times (Croppenstedt et al., 2003), while the second category argues that larger households are less likely to adapt to climate change than the smaller households (Ndambiri et al., 2012). Here it is

hypothesized that households with larger family size have higher probability of adapting to climate change.

Wealth

Owning land, livestock and a farm and nonfarm income are known to represent household wealth in rural areas and also influence the adaptation options of households (Tessema et al., 2013). Shortage of land is seen to be a barrier to climate change adaptation (Bryan et al., 2009). Higher income and livestock ownership are seen as facilitators of climate change adaptations in literature (Tessema et al., 2013) because wealthier farmers are advantageous in adaptation (Foster and Rosenzweig, 2010). So all land size, income level and livestock ownership are hypothesized to have a positive relation with adaptation to climate change.

Extension and climate information

Many of the decisions made by farmers are affected by weather and climate but there is lack of reliable information that can help them consider these decisions (Clarkson et al., 2014). As discussed in Deressa et al. (2008) extension on crop and livestock production and information on climate are among the information required to make decisions on climate change adaptation. Extension services are claimed to encourage adaptation to climate change by raising farmers' awareness of the issue (Nhemachena and Hassan, 2007). Therefore, here also both the access to extension services and access to information on climate are expected to positively influence adaptation.

Agro-ecological zone

The agro-ecological setting of farmers is expected to influence their adaptation to climate change (Legese et al., 2014). In Ethiopia there are three traditional agro-ecological zones, the *kolla* (lowland) characterized by hotter and drier climate, the *woinadega* (middle land) and *dega* (highland) are wetter and cooler (Deressa et al., 2009;Tessema et al., 2013). Deressa et al. (2009) also explain that farmers in drier and hotter climate are more likely to respond to climate change. The study sites in this research are located in the *Woinadega* and the *Kola* areas and farmers residing in the

Kola area are hypothesized to adapt to climate change more than the farmers of the *Woinadega* area.

Table 4-10: Description of the independent variables

Explanatory Variables	**Mean**	**S.D**	**Description**
Age of the household head	39.49	8.55	Continuous
Gender of the household head	0.76	0.43	Dummy takes the value of 1 if male and zero otherwise
Educational level of household head	5.48	3.22	Continuous (number of formal schooling years)
Family size of household	6.33	1.95	Continuous
Average annual total income of the household	9728.63	4633.72	Continuous
Access to extension services	0.85	0.36	Dummy takes value of 1 if there is access and otherwise zero
Access to climate information	0.50	0.50	Dummy takes value of 1 if there is access and otherwise zero
Local agro-ecology (mid-land)	0.67	0.47	Dummy takes value of 1 if kola and Zero otherwise
Farm size in hectare	1.30	0.84	Continuous
Livestock ownership	0.95	0.22	Dummy takes value of 1 if own cattle and otherwise zero

4.4.2 Hypothesis testing for model significance

A logistic regression model is very useful under two circumstances: first, given a set of values of the independent variables, we wish to estimate the probability that the event of interest will occur and, second, to evaluate the influence each independent variable has upon the response (Domínguez-Almendros et al., 2011). There are various methods to measure the appropriateness of fit of logistic models under these circumstances. So, to test the overall significance of models, the global null hypothesis approach which tests the hypothesis that all the regression coefficient β's = 0 versus the alternative that at least one is not zero was used.

In logistic regression, a likelihood ratio chi-square test (Stata calls this LR chi2) is used and it is computed by contrasting a model which has no independent variables (i.e. has the constant only) with a model that does (Williams, 2015). The test statistics is

distributed χ2 with degrees of freedom equal to the difference between the number of variables in the model with predictors and intercept-only model (Abid et al., 2015).

In our case, it can be seen that (Table 4.11) χ2 for all adaptation values holds positive sign between 58 and 118 with the p values associated with it are all less than 0.001. On the base of test statistics the null hypothesis that states all the regression coefficient β's = 0 can be rejected and the alternative hypothesis that at least one is not zero can be accepted, so it can be concluded that our models with predictors fit significantly better than the intercept-only model.

The goodness of fit of all adaptation models is determined by the measure of pseudo-R^2. The results of pseudo-R2 ranged from 0.26 to 0.56 showing the better fit of the models in adaptation to climate change. The classification matrices in logistic regression serve to evaluate the accuracy of the model. The overall percentage of accurate predictions for the models varies between 82% and 92% which shows only a few cases are classified incorrectly and all the models selected for this study can fairly estimate the factors affecting the use of different adaptation methods in the study area.

Table 4-11: Model significance test and predictive power

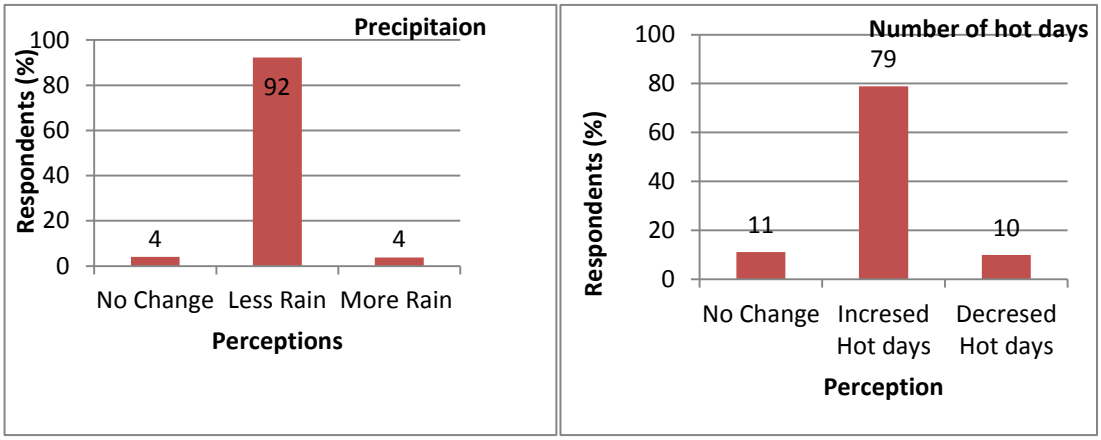
Models	χ2 (chi-squared)	df	p level	-2 Log likelihood	AIC	Model Correctness (%)	Nagelkerke pseudo-R2
Changing crop variety	58.35	10	0	134.14	154.14	86.9	0.38
Water harvesting scheme	69.50	10	0	121.12	141.11	92.2	0.31
Intensifying irrigation	118.99	10	0	156.68	178.68	89.3	0.56
Using cover crop or/and mulching	81.15	10	0	212.22	234.22	85.6	0.39
Reducing livestock number	71.65	10	0	192.93	214.93	83.0	0.37
Found off farm jobs	74.21	10	0	214.17	236.17	82.2	0.26

df- degrees of freedom , p-level shows the statistical significance to reject the null hypothesis (Ho)
AIC (Akaike information criterion) measures relative quality of statistical model

4.4.3 Farm level perception of climate change

In order to adapt to climate change, farmers must first perceive that changes are taking place (Bryan et al., 2009). Adger et al. (2009) discussed that farmers' perception of long-term changes in climate is a crucial pre-indicator of the climate change adaptation. Therefore, sample farm households were asked whether or not they perceived changes in long term climate indicators in their vicinity.

The results of the study shows that (Figure 4.15) the majority of farmers perceived a decrease in the amount of annual rainfall (92%) while only 4% of the farmers felt an increase in annual rainfall while the remaining 4% said they did not notice any change in the amount of the rainfall in their area. Seventy nine percent of the farmers felt an increase in the number of hot days while 11% and 10% of the remaining farmers did not feel any change and those who felt a decrease in the number of hot days respectively. The sample households were not asked about their feelings about the change of mean temperature because the area under investigation is known to be within high range of daily temperature and it would thus not be easy to perceive the mean change in daily temperature for farmers.



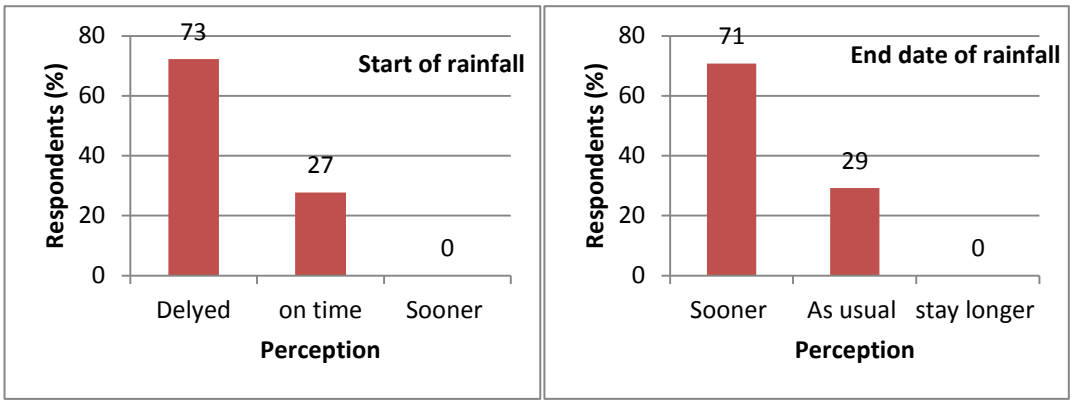


Figure 4-15: Farmers perceptions on seasonality of important climate variables in Bilate River Watershed

The onset and end date of rainfall in a given year are determinants of the length of the growing period for an area (Stern et al., 2006; Abiy et al., 2014). The farming household's perception on these climatic events is crucial to counteract to the changes from the norms. Seventy three percent of the farmers perceived that the onset of rainfall in the area in the last five years is delayed, 27% said it is starting on time and no one has perceived it to begin earlier than usual. Seventy one percent of the responding farmers also perceived that rainfall in the area ends sooner than usual. So, most of the farmers perceived that in recent years rainfall starts late and ends soon so that leaves them with a shorter growing period.

4.4.4 Farm level constraints to adaptation

Long term deviation of climatic variables from the norm was perceived by 92% of the sample farmers. Only 58% of the sample households who perceived that climate is changing have actually made an adaptation practice at household level. The farmers who did not use any adaptation methods have mentioned five main constraints (Figure 4.16), which are: knowledge gap in the form of lack of information (23%), financial constraints (16%), shortage of labour (21%), shortage of land size (21%) and water scarcity in the irrigation channels (19%).

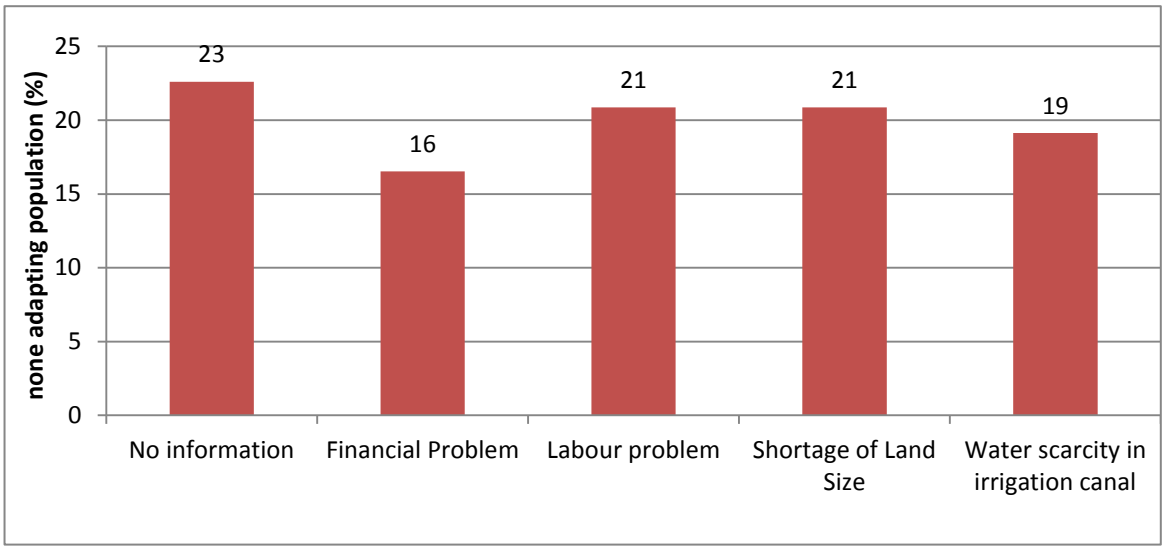


Figure 4-16: Constraints to adaptation to climate change in the study area

The knowledge gap in the form of lack of information is mainly attributed to the educational level of the head of the household. The results of the cross tabulation of educational level of the household heads with their responses of adaptations for a shift in temperature or rainfall shows that 88.5% of the farmers who had ten years and above of formal schooling made adaptations, while 85.2% of farmers who did not attended any level of formal education did not make adaptations.

4.4.5 Determinants of farmers' choice of adaptation methods

The logistic regression models for the adaptation strategies were used to quantify the impact of independent variables affecting the choice of adaptation methods by the sample farming households. The coefficients of the logistic regression (Table 4.12) provide only the direction of the effect of the independent variable on the response variables but do not show the actual magnitude of change and probability. Therefore, the marginal effect from the logistic regression model (Table 4.13) was computed and presented to show the expected change in the probability of a given choice in adaptation measure being made with respect to a unit of change in an independent variable.

Table 4-12: Parameter estimates of the logistic regression model for climate change adaptation at farm level

Explanatory Variables	Changing crop variety	Water harvesting scheme	Intensifying irrigation	Using cover crop or/and mulching	Reducing livestock number	Found off farm jobs
Age of the household head	-0.0693**	-0.06974**	-0.24169*	-0.09026*	-0.1152137*	-0.014342
Gender of the household head	-0.0959	0.301735	0.17167	-0.78114	-0.4600129	0.3057538
Educational level of household head	0.2476*	0.074736	0.33413*	-0.0451	0.1371988**	0.1354289**
Family size of household	-0.1634	-0.08552	0.23174**	0.0752	-0.0768305	-0.080697
Average annual total income	0.0000	-0.000344*	0.00005	-0.0001278*	-0.0002944*	0.0000276
Access to extension services	1.4226	0.514987	1.08566	-0.1902725	1.245076	0.6463725
Access to climate information	-1.4354*	0.788514	-0.96229**	1.651216*	-0.5327847	-0.3868611
Local agro-ecology *Kola*	-1.7476*	-0.417091	-0.58346	2.671329*	0.7797067**	-0.6721689
Farm size in hectares	0.6678**	-0.267969	1.30393*	-0.0564182	1.780417*	-1.698609*
Livestock ownership	0.4646	2.458837	1.07656	1.081059	1.708569**	0.6750463
Constant	-5.5165**	-18.2407	4.2613**	-3.8419**	3.145837	-2.5157

*,** shows significance at 1and 5% probability levels respectively

Table 4-13: Marginal effects of the binary logistic models of farm level climate change adaptation

Explanatory variables	Changing crop variety	Water harvesting scheme	Intensifying irrigation	Using cover crop or/and mulching	Reducing livestock number	Found off farm jobs
Age of the household head	-0.00307	-0.00205	-0.01260	-0.0111942	-0.0099	-0.00155
Gender of the household head	-0.00434	0.008252	0.00860	-0.1118589	-0.0438	0.03517
Educational level of household head	0.01095	0.002196	0.01742	-0.0055962	0.0118	0.01466
Family size of household	-0.00723	-0.00251	0.01208	0.0093289	-0.0066	-0.0087
Average annual total income	-1.30E-06	-0.00001	2.73E-06	-0.0000158	-0.00003	2.98E-06
Access to Extension services	0.04259	0.01289	0.041706	-0.024728	0.07737	0.0592
Access to climate information	-0.06718	0.02372	-0.05133	0.2108997	-0.0460	-0.0419
Local agro-ecology *Kola*	-0.10908	-0.01317	-0.03352	0.2628968	0.06096	-0.0796
Farm size in hectare	0.02955	-0.00787	0.06798	-0.0069969	0.15317	-0.18383
Livestock ownership	0.0249	0.03125	0.03755	0.0947675	0.08260	0.05817

Age of the household head

Contrary to the expectations and findings in other research in Ethiopia, the age of the household head is negatively associated with major adaptation strategies prevailing in the area at the 5% level of significance. The average marginal effect computed shows that sample households with a one more year older head would return the decline in the probability of intensified irrigation at the 1% significance level by 1.26% and for other adaptation strategies the decrease in the probability at the 5% significance level is extremely low with effects varying from 0.11% to 1.1%. The finding of this research is in agreement with arguments of Adesina and Baidu-Forson (1995) which state that older farmers are less likely to be flexible than younger farmers and thus have a lesser likelihood of adopting new technologies, and in Ethiopia there is a negative relation between age and some adoption strategies to climate variability (Shiferaw and Holden, 1998).

Gender of the household head

There is a positive coefficient of the gender of the household head for building a water harvesting scheme, intensifying irrigation and getting an off-farm job. This indicates a positive relationship between male headed households and the probability of using these adaptation measures (Table 4.12) even if it is not significant at the 1and 5% significance levels. But the negative coefficient of the gender for using mulching and reducing the number of livestock shows these adaptation fevered by female household heads.

Educational level of household head

The years of formal education of the farmers was positively related to adaptation to climate change (Shongwe, 2014). According to results in Table 4.12 the highly significant coefficient of education of the household head to major adaptation strategies shows that the probability of adapting to climate change increases with the formal years of schooling. A unit increase in number of years of formal schooling would result in a 1% and 1.7% increase in the probability of changing crop variety and intensifying irrigation respectively at 1% significance level (Table4.13). Similarly, the marginal values of

education are positive for reducing livestock number and getting off-farm jobs as adaptation to climate change.

Family size of household

Our results indicate that family size of the household is found to positively relate at the 5% significance level to intensifying irrigation. But this variable is not found to determine the other adaptation strategies at up to 10% significance. Even though it is less significant, the household size is negatively related to the rest of the adaptation measures and this is in agreement with the argument that larger households are less likely to adapt to climate change than the smaller households (Ndambiri et al., 2012).

Income

Regardless of the expectations, it is found that households with overall income are negatively and without fail associated with using a water harvesting scheme, using cover crop or mulching and reducing the number of livestock. The computed marginal effect for all strategies is almost zero. This finding is in contradiction to prior researches explaining that wealthier farmers are advantageous in adaptation (Foster and Rosenzweig, 2010).

Access to extension services

Extension services on crop and livestock production are known to be an encouraging factor to adaptation to climate change (Nhemachena and Hassan, 2007). In the current study also the direction of change is positively related to the adaptation methods explained except for mulching where it is negatively related (Table 4.12). But the relation was not significant at all levels.

Access to climate information

Access to climate information mainly in the form of seasonal forecast has mixed direction of relation for the adaptation strategies mainly used in the study area. It has a significant and positive impact on using cover plants and mulching as adaptation mechanisms, thus households with access to climate information use this method 21%

more often than the households that are not using it at the 1% significance level. But the result in table 4.12 also shows that access to climate information is negatively and significantly related to changing crop variety and intensifying irrigation.

Local agro-ecology

According to Deressa et al. (2009) farmers in drier and hotter climates are more likely to respond to climate change. In this research also farmers residing in the lowland (*Kola)* area are hypothesized to adapt more to climate change than the farmers of the midland (*Woinadega)* by using all types of adaptation strategies. But the results are not consistent for all types of adaptation strategies. Peoples living in the *Kola* area use mulching and cover crop 26% more times than people living in the *Woinadega* and this is reliable at 1% level of significance. From Tables 4.12 and 4.13 we can see that people in the *kola* area are 10% less likely to opt for changing crops as a mechanism of climate change adaptation.

Farm size

Owning land is known to represent household wealth in rural areas (Tessema et al., 2013). From the results in Table 4.12 we can see that land area has positive impacts on changing crop variety, intensifying irrigation and reducing livestock number. One unit of change in the land area changes the probability of changing crop variety and intensifying irrigation by 2.9% and 6.7% respectively at 5% and 1% significance levels. This finding is in agreement with other research in Africa that states shortage of land is seen to be a barrier in climate change adaptation (Bryan et al., 2009).

Livestock ownership

Livestock ownership is not found to significantly determine any of the adaptation methods in the study area but the direction of the relationship is positive for all the adaptation options thus making the finding consistent with other researches that report livestock ownership as a facilitator of climate change adaptations (Tessema et al., 2013).

Chapter 5 : Conclusions and Recommendations

5.1 Conclusions

The threat of climate change in Ethiopia is mainly in the areas of agriculture and water resources. Reasonable estimates of climate change impacts on agriculture require integrated use of climate, hydrologic, and economic models. Rainfall is the major climatic parameter that needs to be analysed for its statistical characteristics in order to conduct successful rain-fed agriculture, while evapotranspiration is another factor that can be estimated from other climatic parameters. In this study analysis of rainfall variability including the onset, end and length of growing period with the number of raining days and over-all statistical parameters was analysed. The reference evapotranspiration (ETo) was also determined from other directly measured climatic variables and compared with the annual and seasonal rainfall trend as this is the determining factor of planning and management of water resources and agricultural practices. The result showed that there was a considerable spatial variation of rainfall and temperature over Bilate watershed. The annual total rainfall of the watershed varies from a little over 780mm in Bilate station to over 1350 mm in Shone station. From the different rainfall features considered in the study, onset and end dates of rainfall and so the length of growing period was also found to considerably variable. The main climatic problem of all the stations for their rain-fed agriculture is a pseudo onset of the rain, days with limited amounts of rainfall that are followed by dry spell of more than nine days within a month period. From the comparison of rainfall and evapotranspiration mean values for the last 30 years, it has been seen that the areas in the upper and mid part of the watershed experience a water deficit from six to nine months of the year, while the area in the lower part of the watershed experiences moisture deficit throughout the year which necessities supplementing the rain-fed agriculture with other sources of water for irrigation.

In this study historical datasets from National Meteorological Agency of Ethiopia were used to perform statistical downscaling in the Bilate Watershed by the Delta method using the AgMIP Climate Scenario Generation Tool with R. Four time slices were selected: base-period (1980-2009), near-term (2010-2039), mid-century (2040-2069) and end-century (2070-2099). The results from the Delta method statistical downscaling model are in agreement with the IPCC's prediction over the Eastern Africa in its Fifth Assessment Report (FAR). This study has showed that projected rainfall will progressively increase in total under the two projected scenarios (RCP 4.5 and RCP 8.5) within the time slices and across the whole projection period. The study revealed that spatio-temporal rainfall variability will continue in the watershed with total rainfall remaining higher in areas that are currently historically getting higher rainfall compared to the downstream areas that historically have lower rainfall records. All temperature regimes under both RCP 4.5 and RCP 8.5 will be expected to increase during the course of the 21st century. The results of the future climate scenario generation reveal conformity with findings of some research work in the Eastern Africa in particular and the global context in general.

This study applied the SWAT model to assess the sensitivity of the Bilate River stream flow to individual and combined changes in temperature and rainfall with 25 different scenarios. The climate scenarios were generated from an ensemble of twenty GCMs from the Coupled Model Intercomparison Project Phase 5 (CMIP5) under RCP 4.5 and 8.5 scenarios for the 2020s, 2050s and 2080s period. The results of calibration and validation of the SWAT model show that the model can be a reliable tool for hydrology cycle simulation in the Bilate River Watershed. Based on the different climatic scenarios, the simulation results indicated a range of possible hydrologic futures; mostly an increase in annual river flow compared with the baseline is projected under all scenarios. The magnitude of increase for annual river discharge ranges from 10.34% to 42.42 %.

The most up-to-date climate change impact and uncertainties on stream flow changes were assessed based on the modified QUEST-GSI methodology with four major elements: (1) RCP emission scenarios, (2) prescribed increase of annual temperature of 1–6^{0}C, (3) GCM structure, and (4) prescribed increase of temperature of 2^{0}C. The

analysis of the results of the simulations shows that uncertainties of the simulated run-off in the Bilate River depended on the projected amount of rainfall embedded in the GCM structures selected to simulate the future climate and were less dependent on the local temperature increment. The ensemble of GCMs used in this study is only the simple mean of GCM structure outputs which could be improved by applying weights to GCMs based on their performance in projection of historical climate variables, and also more climate scenarios should be developed in the future to better understand the range and quantify the impact of climate change on stream flow.

The research was conducted in three *kebeles* in Bilate Watershed (BRW) where 270 farm households were randomly selected for the study. The binary logit model specification was adopted to examine factors influencing the climate change adaptation behaviour of farmers involving dummy dependent variables with binary choices. Hypothesis testing for model significance was made to measure the appropriateness of fit of logistic models and all the models selected for the study were seen to fairly estimate the factors affecting the use of different adaptation methods in the study area. Even if the majority of farmers (over 92%) perceived that climate was changing in one or the other form, only 58% of the sample households were actually making an adaptation at household level by using different methods. Those who did not use any of the adaptation methods explained their real and perceived constraints for farm level adaptation to climate change. The knowledge gap in the form of lack of information, shortage of labour and shortage of minimal land size are the three most explained constraints to climate change as explained by responding household heads. The results further showed that age and educational level of the household head, farm size and the income level of the household are household characteristics that significantly affect the choice of adaptation options, while access to climate information in the form of seasonal forecasts and local agro ecology are other factors that determined the selection of adaptation methods by the farming households in the study area. Contrary to the expectations and findings of other research, explanatory variables like sex of the household head and access to extension services on crop and livestock production were not found to determine the adaptation methods in the study area significantly.

5.2 Recommendations

The main climatic problem of all the stations for their rain-fed agriculture is a pseudo onset of the rain during the growing season, which is explained as days with limited amount of rainfall that is followed by dry spell of more than nine days within a month. This implies that farmers should have regular information on current issues of climatic variables and adaptation options in the area, which can be achieved through the strengthening of the extension services and disseminating farm-level adaptation measures and other relevant climate information to farmers.

Much of the area in the lower part of the watershed experiences moisture deficit throughout the year which necessities supplementing the rain-fed agriculture with other sources of water for irrigation, especially to compensate the times of pseudo start of rainfall. Besides the statistical parameters like the mean, standard deviation, coefficient of variation and the seasonal rainfall variability which explained the average onset, end date and length of growing period which were determined in this study, the impact of large-scale climate anomalies, such as El Niño Southern Oscillation (ENSO) on the main growing period (*Belg* and *Kiremt* seasons) of the Bilate River watershed needs to be addressed by further research.

The ensemble of GCMs used in this study is only the simple mean of GCM structure outputs which could be improved by applying weights to GCMs based on their performance in the projection of historical climate variables, and also more climate scenarios should be developed in the future to better understand the range and quantify the impact of climate change on stream flow, and further study is required to determine how systematic differences between GCM structure outputs and the observed data are related with consideration to specific models.

The SWAT model inputs like the land use and the soil data used in this research were obtained from the Food and Agriculture Organization of the United Nations data base. The model simulation of hydrological processes considers that these biophysical scenarios of the watershed remain as that of 1990s; which is not a perfect premises for the

model to predict future stream flow scenario and can be improved by looking other methods to determine future land use and land cover.

A wide variety of actions taken by individual farmers, communities and organizations to prepare for, or respond to, climate change impacts have been identified as adaptation options by the climate change research community. Some adaptation options like planting trees, changing crop varieties, and other physical watershed management practices were assumed to be part of the adaptation options but were ignored after the interview schedule because they were not reported in the responses of the farm households nor were perceived as community level mitigation measures. So, further studies on adaptation options have to consider community level adaptations and responses to climate change impacts.

References

Abid, M., Scheffran, J., Schneider, U. A., and Ashfaq, M. 2015. Farmers' perceptions of and adaptation strategies to climate change and their determinants: The case of Punjab Province, Pakistan. *Earth Syst. Dynamics*, 6, pp.225-43. doi:10.5194/esd-6-225-2015.

Abiy G., Quraishi, S., Girma, M. 2014. Analysis of seasonal rainfall variability for agricultural water resource management in southern region, Ethiopia. *Journal of Natural Science Research*, 4(11), pp. 56-79.

Adams, R.M., Rosenzweig, C., Peart, R.M., Ritchie, J.T., McCarl, B.A., Glyer, J.D., Curry, R.B., Jones, J.W., Boote, K.J. and Allen, L.H. Jr., 1990. Global climate change and U.S. agriculture. *Nature*, **345**, pp. 219-224

Adesina, A.A. and Jojo Baidu-Forson 1995. Farmers' perceptions and adoption of new agricultural technology: Evidence from analysis in Burkina Faso and Guinea, West Africa. *Agricultural Economics 13*(13), pp.1-9.

Adger, W.N., Dessai, S., Goulden, M., Lorenzoni, I., Nelson, D.R., Naess, L.O., Wolf, J. and Wreford, A. 2009. Are there social limits to adaptation to climate change? *Climate Change*, 93, pp.335-54.

African Development Bank (AfDB), Asian Development Bank (ADB), Department for International Development, United Kingdom (DFID) 2003. *Poverty and climate change, reducing the vulnerability of the poor through adaptation.* Washington, DC.: The World Bank.

Aghajani, G.H. 2007. Agronomical analysis of the characteristics of the precipitation (case study: Sazevar, Iran). *Pakistani Journal of Biological Science*, 10(8), pp.1353-1358.

Agricultural Transformation Agency (ATA) 2014. *Transforming Agriculture in Ethiopia (2013/2014).* Annual Report. Addis Ababa: ATA.

Akter, S. and Bennett, J.W. 2009. *Household perceptions of climate change and preferences for mitigation action: The case of the Carbon Pollution Reduction Scheme in Australia*. Research Reports 94819. Environmental Economics Research Hub.

Alemayehu, A. S., Alamirew, T., Melesse, A.M. and Chakma, S. (2015). Climate Change Impact on the Hydrology of Weyb River Watershed, Bale Mountainous Area, Ethiopia. In Melesse, A.M. and Abtew, W. (Eds.). *Landscape Dynamics, Soils and Hydrological Processes in Varied Climates*. Springer Cham Heidelberg New York Dordrecht London. Springer International Publishing Switzerland. (pp. 587-613)

Alemseged T. Haile, Tom Rientjes, Ambro Gieske, and Mekonnen Gebremichael 2009. Rainfall Variability over Mountainous and Adjacent Lake Areas: The Case of Lake Tana Basin at the Source of the Blue Nile River. *Journal of Applied Meteorology Climatology*, 48(8), pp.1696–717.

Allen, R.G., Periera, L.S., Raes, D. and Smith, M. 1998.*Crop evapo-transpiration: Guidelines for computing crop requirements.* Irrigation and Drainage Paper 56. Rome, Italy: FAO.

Amundsen H., Berglund F. and Westskog, H. 2010. Overcoming barriers to climate change adaptation – a question of multilevel governance? *Environment and Planning C: Government and Policy* , 28(2), pp.276–89.

Anandhi, A., Srinivas, V.V., Nanjundiah, R.S., and Kumar, D.N. 2008. Downscaling precipitation to river basin in India for IPCC SRES scenarios using support vector machine. *International Journal of Climatology*, 28, pp.401-420.

Andrew D. Foster and Mark R. Rosenzweig 2010. Microeconomics of technology adoption. Centre discussion paper No. 984. Economic growth centre.

Arnell, N.W. and Liv, C. 2001. Hydrology and water resources. In, McCarthy, J.J., Canziani, O.F., Leary, N.A., Dokken, D.J. and White, K.S. (eds.) *Climate Change 2001: Impacts, Adaptation and Vulnerability.* Cambridge, UK, Cambridge University Press, 191-233.

Arnold, J.G. and Fohrer, N. 2005. SWAT2000: Current capabilities and research opportunities in applied watershed modelling. *Hydrological Process*, 19, pp.563–72.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R. 1998. Large area hydrologic modeling and assessment: Part I. Model development. *Journal of American Water Resources Assoc.*, 34(1), pp.73–89.

Asfaw, S., Federica Di Battista and Leslie Lipper 2015. *Food Security Impact of Agricultural Technology Adoption under Climate Change: Micro-evidence from Niger*. Rome, Italy: Agricultural Development Economics Division (ESA) Food and Agriculture Organisation of the United Nations (FAO).

Asha latha, K. V., Munisamy Gopinath, and Bhat, A.R.S. (2012). Impact of Climate Change on Rainfed Agriculture in India: A Case Study of Dharwad. *International Journal of Environmental Science and Development, 3*(4), pp. 368-371.

Bauer, A., Judith Feichtinger and Reinhard Steurer, 2012. The Governance of Climate Change Adaptation in 10 OECD Countries: Challenges and Approaches. *Journal of Environmental Policy and Planning*, pp. 279-304.

Belaineh Legese, Yared Ayele and Woldeamlak Bewket, 2014. Smallholder Farmers Perceptions and Adaptation to Climate Variability and Climate Change in Doba District, West Hararghe, Ethiopia. *Asian Journal Of Emprical Research*, 3(3), pp.251-65.

Betrie G.D., Mohamed Y.A., van Griensven A., Srinivasan R., 2011. Sediment management modelling in the Blue Nile Basin using SWAT model. *Hydrology and Earth System Sciences*, 15, pp.807–818.

Bezabh, T., Tewodros Tadesse, Henok Shiferaw and Amdom Gebremedhin, 2015. Role of Rural Institutions in Determining Farmers Adaptation to Climate Change: The case of Kilte-Awlaelo District, Northern Ethiopia. *International Journal of Multidisciplinary and Current Research*, 3(1), pp.479-485.

Bezu S., Holden B. and Barrett C., 2009. Activity Choice in Rural Non-farm Employment (RNFE): Survival versus accumulativestrategy. In *8th Nordic Conference in Development Economics*. Oscarsborg, Drobak, Norway.

Bhattacharjee, P.S., and Benjamin F. Zaitchik, 2015. Perspectives on CMIP5 model performance in the Nile River headwaters regions. *International Journal of climatology*, 35(14), pp. 4262-4275. DOI: 10.1002/joc.4284.

Blunden, J., Arndt, D. S. and Baringer, M. O., Eds., 2011. State of the Climate in 2010. *Bulletin of the American Meteorological Society*, 92(6), pp.S1–S266.

Braganza, K., Karoly, D.J., Hirst, A.C., Mann, M.E., Stott, P., Stouffer R.J. and Tett, S.F.B., 2003. Simple indices of climate variability and change: Part I- variability and correlation structure. *Climate dynamics*, 20(6), pp.491 - 502.

Branstator, G. and Selten, F., 2009. Modes of Variability and Climate Change. *Journal of Climate*, 22, pp.2639-2658.

Brown, C., Greene, A., Block, P. and Giannini, A., 2008. Review of downscaling methodologies for Africa climate applications. IRI Technical Report 08-05: IRI Downscaling Report. Columbia University.

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., and Herrero, M., 2013. Adapting agriculture to climate change in Kenya:Household strategies and determinant. *Journal of Environmental Mangement*, 114, pp. 26–35.

Bryan, E., Temesgen T. Deressa, Glwadys A. Gbetibouo, and Claudia Ringler, 2009. Adaptation to climate change in Ethiopia and South Africa: Options and constraints. *Environmental Science and Policy*, 12(4), pp.413-26.

Burnash R.J. C., Ferral R. L. and McGuire R.A. 1973. *A General Streamflow Simulation System - Conceptual Modeling for Digital Computers*. Sacramento, CA: Report by the Joliet Federal State River Forecasts Center.

Butcher, J., Johnson, T., Nover, D. and Sarkar, S., 2014. Incorporating the effects of increased atmospheric CO2 in watershed model projections of climate change impacts. *Journal of Hydrology, 513*, pp.322–34.

Chandrasiri, W.A.C.K., 2013. Farmers' perception and adaptation to climate change: a case study in vulnerable areas of kurunagala district. Annals of Sri Lanka Department of Agriculture 2013. Peradeniya, Sri Lanka: Socio Economics and Planning Centre, Department ofAgriculture.

Chaubey, I., Cotter, A.S., Costello, T.A. and Soerens, T.S., 2005. Effect of DEM data resolution on SWAT output uncertainty. *Hydrological Processes*, 19, pp. 621–628.

Chen, C., Greene, A.M., Robertson, A.W., Baethgen, W.E., and Eamus, D. 2013. Scenario development for estimating potential climate change impacts on crop production in the North China Plain. *International journal of climatology*, 33(15), pp. 3124–3140.

Chen, J., Brissette, F.P. and Leconte, R. 2012. Coupling statistical and dynamical methods for spatial downscaling of precipitation. *Climatic Change*, 114, PP. 509–526

Cheng, C.S., Qian Li, Guilong Li, Heather Auld, 2012. Possible Impacts of Climate Change on Daily Streamflow and Extremes at Local Scale in Ontario, Canada. Part II:Future Projection. *Atmospheric and Climate Sciences*, 2, pp. 427-440.

Christensen, O. B., Christensen, J. H., Machenhauer, B. and Botzet, M. 1998. Very high-resolution climate simulations over Scandinavia - Present climate. *Journal of Climate*, 11, pp.3204–29.

Clarkson, G., Dorward, P., Kaur, H. and Tall, A. 2014. *New capacity to produce and communicate climate information services built in Tanzania*. [Online] Global Framework for Climate Services Available at: HYPERLINK "http://www.gfcs-climate.org/node/641" http://www.gfcs-climate.org/node/641.

Cook, K.H., and Vizy, E.K. 2012. Impact of climate change on mid-21st century growing seasons in Africa. *Climate Dynamics*, 39, pp. 2937-2955.

Cook, K. H. and Vizy, E.K. 2013. Projected Changes in East African Rainy Seasons. *Journal of Climate*, 26, pp. 5931- 5948.

Coulibaly, P., Dibike,Y.B. and Anctil, F. 2005. Downscaling Precipitation and Temperature with Temporal Neural Networks. *Journal of Hydrometeorology*, 6, pp. 483–496.

Crawford N.H. and Linsley R.S. 1966. *Digital Simulation in Hydrology: The Stanford Watershed Model IV*. Technical Report No. 39. Palo Alto, CA.: Department of Civil Engineering, Stanford University.

Croppenstedt, A., Mulat Demeke and Meschi, M.M. 2003. Technology Adoption in the Presence of Constraints: The Case of Fertiliser Demand in Ethiopia. *Review of Development Economics*, 7(1), pp. 58-70.

CSA (Central Statistics Agency), 2005. *National Statistics (Abstract)*. Addis Ababa, Ethiopia: CSA.

CSA, 2013. *Population Projection of Ethiopia for All Regions At Wereda Level from 2014 – 2017.* Addis Ababa: Central Statistical Agency Federal Democratic Republic of Ethiopia Central Statistical Agency.

Curry, J., 2011. *Reasoning about climate uncertainty*. Atlanta, USA: Georgia Institute of Technology School of Earth and Atmospheric Sciences.

D'Onofrio, D., Palazzi, E., von Hardenberg, J., Provenzale, A. and Calmanti, S. 2013. Stochastic Rainfall Downscaling of Climate Models. *journal of hydrometeorology*, 15, pp. 830-843.

Daniel, E.B., Camp, J.V., LeBoeuf, E.J., Penrod, J.R., Abkowitz, M.D., and Dobbins, J.P. 2010. Watershed Modeling Using GIS Technology: A Critical Review. *Journal of Spatial Hydrology* , 10(2), pp. 13-28.

Daniel, E.B., Camp, J.V., LeBoeuf, E.J., Penrod, J.R., Dobbins J.P., and Abkowitz, M.D. 2011. Watershed Modeling and its Applications: A State of the Art Review. *The Open Hydrology Journal*, 5, pp. 26-50.

Dannevig, H., Rauken, T. and Hovelsrud, G. 2012. Implementing adaptation to climate change at the local level. *The International Journal of Justice and Sustainability*, 17(6-7), pp. 597-611.

Derbile, E.K., 2013. Reducing vulnerability of rain-fed agriculture to drought through indigenous Knowledge system in north-eastern Ghana. *International Journal of Climate Change Strat. Manage*, (5), pp. 71 - 94.

Deressa, T.T., Hassan, R.M., Ringler, C., Alemu, T. and Yesuf, M. 2009. Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, 19, pp.248–255.

Deressa, T., Hassan, R.M., Alemu, T., Yesuf, M. And Ringler, C. 2008. *Analysing the determinants of Farmers Choice of Adaptation Methods and Perception of Climate Change in the Nile Basin of Ethiopia*. IFPRI Discussion Paper 00798. Environment and Production Technology Division.

Deressa,T.T., Hassan, R.M. and Ringler, C. 2011. Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *Journal of Agricultural Science*, 149, pp. 23-31.

Dessu S.B. and Melesse A.M. , 2012. Modeling the rainfall-runoff process of the Mara River Basin using SWAT. *Hydrological Processes*, 26(26), pp. 4038-4049.

Dessu, S.B. and Melese, A.M, 2013. Impact and Uncertainties of climate change on the hydrology of the Mara River basin, Kenya/Tanzania. *Hydrological Process*, 27(20), pp. 2973-2986.

Dibike, Y.B., and Coulibaly, P., 2005. Hydrologic impact of climate change in the Saguenay watershed: comparison of downscaling methods and hydrologic models.. *Journal of Hydrology (Amsterdam)*, 307(1/4), pp.145-63.

Domínguez-Almendros, S., Benítez-Parejo, N. and Gonzalez-Ramirez A.R. 2011. Logistic regression models. *Allergol Immunopathol (Madr).*, 39(5), pp. 295-305.

Drexler, U.Z., Snyder, R.L., Spano, D.and Tha Paw U.K. 2004. A review of models and micrometeorological methods used to estimate wetland evapotranspiration. Hydrological processes, 18, pp. 2071–2101.

Easton, Z.M, Fuka, D.R, White, E.D, Collick, A.S, Biruk Ashagre, B., McCartney M., Awulachew S.B., Ahmed A.A., Steenhuis T.S. 2010. A multi basin SWAT model analysis of runoff and sedimentation in the Blue Nile, Ethiopia. *Hydrology and Earth System Sciences* , 14(10), pp.1827–1841.

Easton, Z.M., Fuka, D.R., Walter, M.T., Cowan, D.M, Schneiderman, E.M. and Steenhuis, T.S. 2008. Re- conceptualizing the soil and water assessment tool (SWAT) model to predict run off from variable source areas. *Journal of Hydrology*, 348, pp.279 – 291.

Ekström, M., Grose, M.R. and Whetton, P.H. 2015. An appraisal of downscaling methods used in climate change research. Climate Change, 6(3), pp. 301–319

Elisabeth Meze-Hausken, 2004. Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia. *Climate Research*, 27, pp.19–31.

El-Jabi, N., Turkkan, N., Caissie, D. 2013. Regional Climate Index for Floods and Droughts Using Canadian Climate Model (CGCM3.1). *American Journal of Climate Change*, 2, pp.106-115.

Erik-Jorgensen, S., Ni-Bin Chang and Fu-Liu Xu, 2014. Ecological Modelling and Engineering of Lakes and Wetlands. *Developments in Environmental Modelling 26*.

Ezenekwe, L.N., Ezemonye, M.N., and Emeribe, C.N. 2013. An appraisal of the characteristics of rainfall in kano. British Journal of Advance Academic Research. 2(1), pp 20-28

FAO (Food and Agriculture Organization), 2003. *The Digital Soil Map of the World*. Rome: Land and Water Development Division Food and Agricultural organization of United Nations.

Fernihough, A., 2011. *Simple logit and probit marginal effects in R*. Working paper series WP11/22: UCD centre for economic research University of Dublin. Dublin, Ireland.

Ficklin, D.L, Luo, Y., Luedeling, E., Zhang, M. 2009. Climate change sensitivity assessment of a highly agricultural watershed using SWAT. *Journal of Hydrology*, 374, pp.16–29.

Fiseha Behulu Muluneh, 2013. *Modelling the Hydrologic Behavior of the Upper Tiber River Basin under Climate Change Scenarios*. PhD Research Thesis. Roma, Italy: Universita degli Studi ROMA TRE.

Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S.C., Collins, W., Cox, P., Driouech, F., Emori, S., Eyring, V., Forest, C., Gleckler, P., Guilyardi, E., Jakob, C., Kattsov, V., Reason, C. and Rummukainen, M. 2013: Evaluation of Climate Models. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V. and Midgley, P.M. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Förch, G., and Althoff, I. 2009. *Water Balance Modelling in the Southern Ethiopian Rift Valley: The Example of the Bilate River Catchment*. Siegen, Germany: Universität Siegen, Centre for International Capacity Development Universität Siegen, Germany.

Ford J. 2008. Emerging trends in climate change policy: The role of adaptation. *International Public Policy Review, 3* (2), 5-16.

Fowler, H.J., Blenkinsop, S. and Tebaldi, C., 2007. Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology*, 27(12), pp. 1547-1578.

Fussel, H.M. 2007. Adapting planning for climate change; concepts, assessment approaches, and key lessons. *Sustainability Science*, 2(2), pp. 265–75.

Gao, G., Chen, D., Xu, C.Y and Simelton, E. 2007. Trend of estimated actual evapotranspiration over China during 1960–2002. *Journal of Geophysical Research*, 112 (D11120), pp.1-8.

Gassman, P.W., Reyes, M.R., Green, C.H., Arnold, J.G. 2007. The soil and water assessment tool: historical development, applications, and future research directions. *American Society of Agricultural and Biological Engineers*, 50(4), pp.1211–1250.

Gassman, P.W., Sadeghi, A.M. and Srinivasan, R. 2014. Applications of the SWAT Model Special Section:Overview and Insights. *Journal of Environmental Quality*, 43(1), pp.1-8.

Gbegeh, B.D. and Akubuilo C.J.C. 2013. Socioeconomic determinants of adoption of yam minisett by farmers in Rivers state, Nigeria. *Wudpecker Journal of Agricultural Research* , 2(1), pp. 033 - 038.

Gbetibouo, G.A. 2009. *Understanding Farmers' Perceptions and Adaptations to Climate Change and Variability*. IFPRI Discussion Paper 00849. Environment and Production Technology Division.

Girvetz, E.H., Maurer, E.P., Duffy, P., Ruesch, A., Thrasher, B., Zganjar, C. 2013. Making climate data relevant to decision making: The important details of Spatial and Temporal Downscaling, The World Bank.

Goosse H., Barriat, P.Y., Lefebvre, W., Loutre, M.F. and Zunz, V. 2010. Introduction to Climate dynamics and climate modeling. Online textbook available at http://www.climate.be/textbook.

Graham, L.P, Andreasson, J. and Carlsson, B.2007a. Assessing climate change impacts on hydrology from an ensemble of regional climate models, model scales and linking methods - a case study on Lule River basine. *Climate Change*, 81, pp. 293-307.

Green, M. and Weatherhead, E.K. 2014. A critical comparison of using a probabilistic weather generator versus a change factor approach; irrigation reservoir planning under climate change. *Journal of Water and Climate Change*, 5(1), pp.13 - 24.

Green,W.H. 2000. *Econometrics analysis*. 4th ed. New Jersey, Prentice Hall.

Greene, W.H. 2012. *Econometric Analysis*. 7th ed. New York University: Stern School of Business.

Gruza, G. and Rankova, E. 2004. Detection of changes in climate state, climate variability and climate extremity. *Meteorology and Hydrology*, 4, pp. 1-15.

Gupta, H.V., Sorooshian, S., and Yapo, P.O. 1999. Status of automatic calibration for hydrologic models: Comparison with multilevel expert calibration. *Journal of Hydrologic Engineering*, *4*(2), 135-143.

Hadgu, G., Tesfaye, K., Mamo, G. And Kassa, B. 2015. Farmers Climate change adaptation options and their determinants in Tigray Region, Northern Ethiopia. *African Journal of Agricultural research* , 10(9), pp. 956-964.

Hageback, J., Sundberg, J., Ostwald, M., Chen, D., Yun, X. and Knutsson, P. 2005. Climate variability and land-use change in Danangou Watershed, China—examples of small-scale farmers' adaptation. *Climatic Change* , 72, pp. 189–212.

Hagemann, S., Machenhauer, B., Jones, R., Christensen, O.B., De´que, M., Jacob, D. and Vidale, P.L. 2004. Evaluation of water and energy budgets in regional climate models applied over Europe. *Climate Dynamics*, 23, pp. 547–567.

Hashmi, M.Z., Shamseldin, A.Y. and Melville, B.W. 2009. Statistical downscaling of precipitation:state-of-the-ar t and application of bayesian multi-model approach for uncer tainty assessment. *Hydrology and Earth System Sciences Discussions*, 6, pp. 6535–6579.

Hession, S. L. and Moore, N. 2011: A spatial regression analysis of the influence of topography on monthly rainfall in east Africa. *International Journal of Climatology*, 31, pp. 1440–1456.

Hewitson, B.C. and Crane, R.G. 2006. Consensus between GCM climate change projections with empirical downscaling: Precipitation downscaling over South Africa. *International Journal of Climatology* , 26, pp. 1315–1337.

Hoefsloot, P. 2009. *LEAP (Livelihood Early Assessment Protection) Version 2.1 for Ethiopia.* User manual The Netherlands: By collaboration of FAO, World Bank and World Food Programme.

Houghton, J.T., Ding, Y., Griggs, D.J., Noguer, M., van der Linden, P.J., Dai, X., Maskell, K. and Johnson, C.A. (Eds.), 2001. *The Scientific Basis.Contributions of Working Group 1 to the Third Assessment Report of the Intergovernmental Panel on Climate Change.*. Cambridge, United Kingdom and New York, USA: Cambridge University Press.

Huizhi, L. And Jianwu, F. 2012. Seasonal and Interannual Variations of Evapotranspiration and Energy Exchange over Different Land Surfaces in a Semiarid Area of China. *Journal of Applied Meteorology and Climatology*, 51, pp.1875 - 1888.

Hussain, S. S. 2013. *Adaptation needs for Agriculture and Water resources in Khyber Pakhtunkhwa, Pakistan* . The Livelihoods Programme Hindukush. Islamabad : Intercooperation Pakistan.

Hydrologic Engineering Center (HEC-1), 1981. *Flood Hydrograph Package—User's Manual*. Davis, CA.: US Army Corps of Engineers.

IPCC, 2000. Emissions Scenarios. A Special Report of Working Group III of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge.

IPCC, 2000. *Special Report on Emission Scenarios (SRES): A special report of Working Group II of the intergovermental pannel on Climate Change.* Cambridge: Cambridge University Press.

IPCC, 2001. Climate Change 2001: Impacts, Adaptation and Vulnerability. *Contribution of Working Group II to the Third Assessment Report of the Intergovernmental Panel on Climate Change.*

IPCC, 2007. *Assessment of adaptation practices, options, constraints and capacity*. Cambridge, UK: Cambridge University Press.

IPCC , 2007. *Climate change 2007 the physical science basis*. Contribution of working group I to the fourth assessment report of the Intergovernmental Panel on Climate Change.. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

IPCC, 2013: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., Qin, D., Plattner, G.K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V.and Midgley, P.M., (Eds.).]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, 1535 pp.

IPCC, 2014: Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, Pachauri, R.K. and Meyer, L.A. (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Ishak, A.M., Bray, M., Remesan, R. and Han, D. 2010. Estimating reference evapotranspiration using numerical weather modelling. *Hydrological Processes*, 24, pp. 3490–3509

Ishaya, S. and Abaje, I.B., 2008. Indigenous people's perception on climate change and adaptation strategies in Jema'a local government area of Kaduna State, Nigeria. *Journal of Geography and Regional Planning* , 1(8), pp. 138-143.

Israel, G.D., 2009. *Determining Sample Size*. Agricultural Education and Communication Department. University of Florida, Gainesville.

Jayakrishnan, R., Srinivasan, R., Santhi, C., Arnold, J.G. 2005. Advances in the application of the SWAT model for water resources management. *Hydrological Processes* , 19(3), pp.749–762.

Jones, P.G., and Thornton, P.K. 2013. Generating downscaled weather data from a suite of climate models for agricultural modelling applications. *Agricultural Systems*, 114, pp.1–5.

Jouni Raisanen, 2007. How reliable are climate models? (Review Article). *Tellus*, 59A, pp. 2–29.

Juholaa, S., Haanpa, S. And Peltonen, L. 2012. Regional challenges of climate change adaptation in Finland: examining the ability to adapt in the absence of national level steering. *Local Environment: The International Journal of Justice and Sustainability*, 17, pp. 629–639.

Jurkovic, R.S. and Pasaric, Z. 2012. Spatial variability of annual precipitation using globally gridded data sets from 1951 to 2000. International Journal of Climatology, 33(3), pp. 690–698.

Kassa Fekadu, 2015. Ethiopian Seasonal Rainfall Variability and Prediction Using Canonical Correlation Analysis (CCA). *Earth Sciences*; 4(3), pp 112-119.

Khoi, D.N. and Hang, P.T.T. 2015. Uncertainty Assessment of Climate Change Impacts on Hydrology: A Case Study for the Central Highlands of Vietnam. *Managing Water Resources under Climate Uncertainty*. Springer International Publishing Switzerland. pp. 31-44.

Kim, J. and Hogue, T.S. 2008. Evaluation of a MODIS-Based potential evapotranspiration product at the Point Scale. *Journal of Hydrometeorology*, 9(3), pp.444 - 460.

Kim, S., Kwak, J., Kim, H.S., Kim,Y., Kang, N., Hong, S.J. and Lee, J. 2014. A Regionalization of Downscaled GCM Data Considering Geographical Features in a Mountainous Area. *Advances in Meteorology*, Volume 2014 (ID 473167), pp. 1-14

Kirchmeier, M.C., Lorenz, D.J. and Vimont, D.J. 2014. Statistical Downscaling of Daily Wind Speed Variations. *Journal of Applied Meteorology and Climatology*, 53, pp. 660 - 675.

Kisaka, M.O., Muna, M.M., Ngetich, F.K., Mugwe, N.,Mugendi, D. and Mairura, F. 2014. Rainfall Variability, Drought Characterization and Efficacy of Rainfall Data Reconstruction: Case of Eastern Kenya. *Advances in Meteorology*, 2015(ID 380404), pp. 1- 16.

Knutti, C. and Tebaldi, R. 2007.The use of the multimodal ensemble in probabilistic climate projections. Philosophical Transactions of the Royal Society (special issue on Probabilistic Climate Change Projections). *International Journal of Climatology*, 365, pp. 2053-2075.

Krysanova, V. And Whiteb, M. 2015. Advances in water resources assessment with SWAT—an overview. *Hydrological Sciences Journal*, 60(5), pp. 771-783.

Kucharik, C.J. and Serbin, S.P. 2008. Impacts of recent climate change on Wisconsin corn and soybean yield trends. *Environmental Research Letters, 3*(034003).

Tan, M.L., Ficklin, D.L., Ibrahim, A.L and Yusop, Z. 2014. Impacts and uncertainties of climate change on streamflow of the Johor River Basin, Malaysia using a CMIP5 General Circulation Model ensemble. *Journal of Water and Climate Change* , 5(4), pp. 676–695.

Leung, L.R, Qian.Y., Bian. X., Washington, W.M., Han. J., Roads, J.O. 2004. Mid-century ensemble regional climate change scenarios for the Western United States. *Climatic Change*, 62, pp.75–113.

Li, Y. and Smith, I. 2009. A Statistical Downscaling Model for Southern Australia Winter Rainfall. *Journal of Climate, 22*, 1142 - 1158.

Li, Y., Horton, R., Ren, T. And Chen, C. 2010. Investigating Time-Scale Effects on Reference Evapotranspiration from Epan Data in North China. *Journal of Applied Meteorology and Climatology*, 49, pp. 867-878.

Lindseth, G. 2005. Local level adaptation to climate change: Discursive strategies in the Norweigan context. *Journal of Environmental Policy and Planning* , 7(1), pp. 61–84.

Liu, W.B., Zhang, A.J., Wang, L., Fu, G.B., Chen, D., Liu, C.M. and Cai, T.J. 2014. Projecting streamflow in the Tangwang River basin (China) using a rainfall generator and two hydrological models. *Climate Research*, 62(2), pp. 79–97.

Lobell, D.B. and Burke, M.B. 2008. Why are agricultural impacts of climate change so uncertain? The importance of temperature relative to precipitation. *Environmental resource letter, 3* (034007).

Lobell, D.B. and Field, C.B. 2007. Global scale climate–crop yield relationships and the impacts of recent warming. *Environmental Research Letters*, 2 (014002).

Mango L.M., Melesse, A.M., McClain, M.E., Gann, D. and Setegn, S.G. 2011. Land use and climate change impacts on the hydrology of the upper Mara River Basin, Kenya: results of a modeling study to support better resource management. *Hydrology and Earth System Science*, 15, pp. 2245–2258.

Maraun, D., Wetterhall, F., Ireson, A.M., Chandler, R.E., Kendon, E.J., Widmann, M., Brienen, S., Rust, H.W., Sauter, J., Themel, M., Venema, V.K.C., Chun, K.P., Goodess, C.M., Jones, R.G., Onof, C., Vrac, M. and Thiele-Eich, I. 2010. Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user. *Reviews of Geophysics*, 48(3). pp. 1-38.

Martens, P., McEvoy, D. and Chang, C. 2009,. The climate change challenge: linking vulnerability, adaptation and mitigation. *Current opinion in Environmental Sustainability*, 1 , pp. 14–18.

McVicar, T.R., Li, L.T., Van Niel, T.G., Hutchinson, M.F., Mu, X.M., and Liu, Z.H. 2005. *Spatially distributing 21 years of monthly hydro-meteorological data in China: Spatio-temporal analysis of FAO-56 crop reference evapotranspiration and pan evaporation in the context of climate change.* CSIRO Land and Water Technical Report 8/05. Canberra, Australia. http://www.clw.csiro.au/publications/technical2005/tr8-05.pdf

Megan, C.K., Lorenz, D.J. and Vimont, D.J. 2014. Statistical Downscaling of Daily Wind Speed Variations. *Journal of Applied Meteorology and Climatology*, 53, pp. 660 - 675.

Mendelsohn, R. 2009. The Impact of Climate Change on Agriculture in Developing Countries. *Journal of Natural Resources Policy Research, 1* (1), 5-19.

Mertz, O., Halsnæs, K., Jørgen E. Olesen, J.E. and Rasmussen, K. 2009. Adaptation to Climate Change in Developing Countries. *Environmental Management* , 43, pp.743–752.

Mertz, O., Mbow, C., Reenberg, A. and Diioouf, A. 2009. Farmers' perceptions of climate change and agricultural adaptation strategies in rural Sahel. *Environmental Management*, 43, pp.804–816.

Middleton, N.J. and Thomas, D.S.G. 1997: World Atlas of Desertification (2nd ed.), Edward Arnold, London for United Nations Environment Programme, 182 pp.

Monzurul, M.A.H., Ghosh, B.C. and Islam, S.M.R. 2015. Climate Change and Rice Yield in Bangladesh: A Micro Regional Analysis of Time Series Data. *International Journal of Scientific and Research Publications,* 5(2), pp. 1-8.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D. and Veith, T.L. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *American Society of Agricultural and Biological Engineers*, 50(3), p. 885−900.

Morton, J.F. 2007. The impact of climate change on smallholder and subsistence agriculture. *Proceedings of the National Acadamy of Sciences of the United States of America* 104 (50), pp. 19680–19685.

Moss, R., Meehl, G., Lemos, M., Smith, J., Arnold, J., Arnott, J., Busalacchi, A. 2013. Hell and High Water: Practice-Relevant Adaptation Science. *Climate change Science (Policy Forum), 342* (No 6159), 696-698.

Mou, X., Xia, X., Gong, D., Liu, Q., Wu, Q. and Guo, J. 2014. Effects of changes in climatic variables on maize crop water requirements in Huang– Huai– Hai watersheds, China. *Journal of Water and Climate Change*, 5(2), pp.176 - 191.

Mulugojjam Taye and Ferede Zewdu, 2012. Spatio-temporal Variability and Trend of Rainfall and Temperature in Western Amhara: Ethiopia: A Gis approach. *Global Advanced Research Journal of Geography and Regional Planning*, 1(4), pp. 065-82.

Mulungu, D.M.M. and Munishi, S.E. 2007. Simiyu River catchment parameterization using SWAT model. *Physics and Chemistry of the Earth*, 32(15-18), pp. 1032–1039.

Narsimlu, B., Gosain, A.K., Chahar, B.R., Singh, S.K. and Srivastava, P.K. 2015. SWAT Model Calibration and Uncertainty Analysis for Streamflow Prediction in the Kunwari River Basin India, Using Sequential Uncertainty Fitting. *Environmental Process*, 2, pp.79-95.

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

Ndambiri, H.K., Ritho, C., Mbogoh, S.G., Ng'ang'a, S.I., Muiruri, E.J., Nyangweso, P.M., Kipsat, M.J., Ogada, J.O., Omboto, P.I., Kubowon, P.C. and Cherotwo, F.H, 2012. Assessment of Farmers' Adaptation to the Effects of Climate Change in Kenya: the Case of Kyuso District. *Journal of Economics and Sustainable Development* , 3(12), pp.52-60.

Neitsch, S.L., Arnold, J., Kiniry, J., Williams, J., King, K. 2005. *Soil and water assessment tool theoretical documentation version 2005*. Texas, USA: Grass land, soil and water reserch centere.

Nelson, G.C. and Shively, G.E. (2014): Modeling climate change and agriculture: an introduction to the special issue. *Agricultural Economics,* 45(1).

Ngigi, S.N. 2009. Water Resources Management Options for Smallholder Farming Systems in Sub-Saharan Africa. In *Climate Change Adaptation Strategies*. New York: The MDG Centre for East and Southern Africa of the Earth Institute at Columbia University.

Nhemachena, C. and Hassan, R. 2007. *Micro-Level Analysis of Farmers' Adaptation to Climate Change in Southern Africa*. IFPRI Discussion Paper 00714. Washington DC, USA: Environment and Production Technology Division International Food Policy Research Institute (IFPRI).

Niang, I., Ruppel, O.C., Abdrabo, M.A.,Essel, A., Lennard, C., Padgham, J. and Urquhart, P. 2014. *Africa. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability*. Part B: Regional Aspects. Contribution of Working GroupII to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge, United Kingdom and New York, USA: Cambridge University Press.

Nielsen, J. Ø. and Reenberg, A. 2010. Cultural barriers to climate change adaptation: A case study from Northern Burkina Faso. *Global Environmental Change* , 20, pp.142-152.

NMSA (National Meteorological Service Agency), 1996. Climate and Agro-climatic Resources of Ethiopia. Addis Ababa, Ethiopia: National Meteorological Service Agency.

Obayelu, O.A., Adepoju, A.O. and Idowu, T. 2014. Factors influencing farmers' choices of adaptation to climate change in Ekiti State, Nigeria. *Journal of Agriculture and Environment for International Development*, 108(1), pp.3-16.

Ojwang, G.O., Agatsiva, J. and Situma, C. 2010. *Analysis of Climate Change and Variability Risks in the Smallholder Sector.* Department of Resource Surveys and Remote Sensing (DRSRS) in collaboration with the Food and Agriculture Organization of the United Nations, Rome, Italy.

Olanrewaju, R.M. 2010. The Impact of Climate on Yam Production in Kwara State, Nigeria. *Environmental Issues*, 3(1), pp.30-34.

Paavola, J. and Adger, T.W. 2005. Analysis of Fair Adaptation to Climate Change. *Ecological Economics,* , 56(2006), pp. 594-609.

Parry, M.L., Canziani, O.F., Palutikof, J.P., van der Linden, P.J. and Hanson, C.E.(eds) , 2007. *Climate Change 2007: Impacts,Adaptation and Vulnerability.*. Working Group I Contribution to the Fourth Assessment Report of the IPCC. Cambridge University Press.

Penalbaa, O.C. and Vargasa, W.M. 2008. Variability of low monthly rainfall in La Plata Basin. *Meteorological Applications*, 15(3), pp. 313–323.

Pervez, M. S. and Henebry, G.M. 2015. Assessing the impacts of climate and land use and land cover change on the freshwater availability in the Brahmaputra River basin. *Journal of Hydrology: Regional Studies* , 3, pp.285–311.

Picketts, I.M., Curry, J. And Rapaport, E. 2012. Community Adaptation to Climate Change: Environmental Planners' Knowledge and Experiences in British Columbia, Canada. *Journal of Environmental Policy & Planning*, 14(2), pp. 119-137.

Pielke, R., Prins, G., Rayner, S., Sarewitz, D. 2007. Climate change 2007: lifting the taboo on adaptation. *Nature* , 445, pp. 597–598.

Pierce, D.W., Cayan, D.R. and Thrasher, B.L. 2014. Statistical Downscaling Using Localized Constructed Analogs (LOCA). Journal of Hydrometeorology, 15, pp. 2558 - 2585.

Porter, C.H., Villalobos, C., Holzworth, D., Nelson, R., White, J.W., Athanasiadis, I.N., Janssen, S., Ripoche, D., Cufi, J., Raes, D., Zhang, M., Knapen, R., Sahajpal, R., Boote, K. and Jones, J.W. 2014. Harmonization and translation of crop modeling data to ensure interoperability. *Environmental Modelling and Software*, 62, pp. 495-508.

Raes, D. 2009. *Evapotranspiration from a reference surface*: Land and Water Division Food and Agriculture Organization of the United Nations (FAO). Rome, Italy.

Raisanen, J. 2007. How reliable are climate models? (Review Article). *Tellus*, 59A, pp.2–29

Ramirez-Villegas J., and Jarvis, A. 2010. *Downscaling Global Circulation Model Outputs:* The Delta Method Decision and Policy Analysis Working Paper No. 1, 1-18. Cali, Colombia.: International Center for Tropical Agriculture (CIAT).

Ramirez-Villegas, J., Challinor, A.J, Thornton, P.K. and Jarvi, A. 2013. Implications of regional improvement in global climate models for agricultural impact research. *Environmental Research Letters*, 8(2), pp. 1-12.

Rockwood, D.M., Davis E.D. and Anderson J.A. 1972. *User Manual for COSSARR Model.*. US Army Engineering Division, North Pacific: Portland,OR.

Rodier, J.A. 1985. *Aspects of arid zone hydrology. In: Rodda J.C. (ed.).* Facets of Hydrology II. Wiley, pp. 205-247.

Rodriguez-Puebla, C., Encinas, A.H., Nieto, S. and Garmendia, J. 1998. Spatial and temporal patterns of annual precipitation variability over the Iberian Peninsula. *International Journal of Climatology*, 18, pp. 299–316.

Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P., Antle, J.M., Nelson, G.C., Porter, C., Janssen, S., Asseng, S., Basso, B., Ewert, F., Wallach, D., Baigorria, G. and Winter, J.M., 2013. The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies. *Agricultural and Forest Meteorology*, 170, pp.166-182.

Rosenzweig, C. and Hillel, D. 2015. The Agricultural Model Intercomparison and Improvement Project (AgMIP) Integrated Crop and Economic Assessments — Joint Publication with American Society of Agronomy, Crop Science Society of America, and Soil Science Society of America. ICP Series on Climate Change Impacts, Adaptation, and Mitigation: Volume 3

Rowhani, P., Lobell, D.B., Linderman, M., Ramankutty, N. 2011. Climate variability and crop production in Tanzania. *Agricultural and Forest Meteorology*, (151), pp. 449-460.

Ruane, A. and Mutter, C. 2013. Guide for Regional Integrated Assessments: Handbook of Methods and Procedures Version 5.0. The Agricultural Model Intercomparison and Improvement Project (AgMIP).

Ruane, A.C., Goldberg, R. and Chryssanthacopoulos, J. 2015. climate forcing datasets for agricultural modeling: Merged products for gap-filling and historical climate series estimation. *Agricultural and Forest Meteorology*, 200, pp. 233-248.

Ryu, J.H., Lee, J.H., Jeong, S., Park, S.K. and Han, K. 2011. The impacts of climate change on local hydrology and low flow frequency in the Geum River Basin, Korea. *Hydrological Proceses*, 25(22), pp. 3437–3447.

Sah, P.P. and Ketema Zeleke, 2015. Assessment of streamflow and catchment water balance sensitivity to climate change for the Yass River catchment in south eastern Australia. *Environmental Earth Sciences*, 73(10), pp. 6229–6242.

Santhi, C., Arnold, J.G., Williams, J.R., Dugas, W.A., Srinivasan, R. and Hauck, L.M. 2001. Validation of the SWAT model on a large river basin with point and nonpoint sources. *Journal of the American Water Resources Association*, 37(5), pp.1169–1188.

Semenza, J.C., Hall, D.E., Wilson, D.J., Bontempo, B.D., Sailor, D.J. and George, L.A. 2008. Public perception of climate change voluntary mitigation and barriers to behaviour change. *American Journal of Preventive Medicine*, 35(5), pp. 479–487.

Setegn, S.G., Srinivasan, R., Melesse, A.M, Dargahi, B. 2009. SWAT model application and prediction uncertainty analysis in the Lake Tana Basin, Ethiopia. *Hydrological Processes.*, 24(3), pp. 357–367.

Setegn, S.G. 2010. *Modeling hydrological and hydrodynamic processes in lake tana basin, ethiopia*. Doctoral Thesis. Stockholm, Sweden: KTH- Hydraulic Engineering Research Group Royal Institute of Technology (KTH).

Setegn, S.G, Rayner, D., Melesse, A.M., Dargahi, B., Srinivasan, R. 2010. Impact of Changing Climate on Water Resources Variability in the Lake Tana Basin, Ethiopia. *Water Resources Research*. 47(4), pp. 1-13.

Shi, T., Guan, D., Wang, A., Wu, J., Jin, C. and Han, S. 2008. Comparison of three models to estimate evapotranspiration for a temperate mixed forest. *Hydrological Processes*, 22(17), pp. 3431–3443.

Shiferaw, B. and Holden, S.T. 1998. Resource Degradation and Adoption of Land Conservation Technologies in the Ethiopian Highlands: A Case Study in Andit Tid, North Shewa. *Agricultural Economics* , 18, pp.233-247.

Shongwe, P. 2014. Factors Influencing the Choice of Climate ChangeAdaptation Strategies by Households: A Case of Mpolonjeni Area Development Programme (ADP) in Swaziland. *Journal of Agricultural Studies*, 2(2), pp. 86- 98.

Smit B. and Wandel J. 2006. Adaptation, adaptive capacity and vulnerability. *Global Environmental Change*, 16(3), pp. 282–292.

Smith, K., Boniecka, L., Bari M. and Charles, S. 2009. *The impact of climate change on rainfall and streamflow in the Denmark River catchment, Western Australia*: Department of Water.

Solomon, S., Qin, D., Manning, M., Alley, R.B., Berntsen, T., Bindoff, N.L., Chen, Z., Chidthaisong, A., Gregory, J.M., Hegerl, G.C., Heimann, M., Hewitson, B., Hoskins, B.J., Joos, F., Jouzel, J., Kattsov, V., Lohmann, U., Matsuno, T., Molina, M., Nicholls, N., Overpeck, J., Raga, G., Ramaswamy, V., Ren, J., Rusticucci, M., Somerville, R., Stocker, T.F., Whetton, P., Wood R.A. and Wratt, D. 2007: Technical Summary. In: Climate Change 2007: The Physical Science Basis. Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate

Change [Solomon, S., Qin, D., Manning, M., Chen, Z., Marquis, M., Averyt, K.B., Tignor, M. and Miller, H.L. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Song, C., Pei, T. and Zhou, C. 2014. The role of changing multi-scale temperature variability in extreme temperature events on the eastern and central Tibetan plateau 1960 - 2008. *International journal of climatology*,34(14), pp. 3683 – 3701.

Sridhar V. and Nayak, A. 2010. Implications of climate-driven variability and trends for the hydrologic assessment of the Reynolds Creek Experimental Watershed, Idaho. *Journal of Hydrology*, 385, pp.183–202.

Stern, R., Rijks, D., Dale, I. and Knock, J., 2006. *Instat Climatic Guide*. Reading, UK: Statistical Services Centre, Reading University.

Stocker, T.F., Qin, D., Plattner, G.-K., Alexander, L.V., Allen, S.K., Bindoff, N.L., Bréon, F.-M., Church, J.A., Cubasch, U., Emori, S., Forster, P., Friedlingstein, P., Gillett, N., Gregory, J.M., Hartmann, D.L., Jansen, E., Kirtman, B., Knutti, R., Krishna, Kumar, K., Lemke, P., Marotzke, J., Masson-Delmotte, V., Meehl, G.A., Mokhov, I.I., Piao, S., Ramaswamy, V., Randall, D., Rhein, M., Rojas, M., Sabine, C., Shindell, D., Talley, L.D., Vaughan D.G. and Xie, S.-P. 2013. *Technical summary. In Climate Change 2013: The Physical Science Basis.*. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. [Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V. and Midgley, P.M. (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 33–115.

Su, H., Mccabe, M.F. and Wood, E.F 2005. Modeling Evapotranspiration during SMACEX: Comparing Two Approaches for Local- and Regional-Scale Prediction. *Journal of hydrometeorology — special section*, 6, pp. 910- 922.

Sugawara, M., Ozaki, E., Wantanabe, I. and Katsuyama, Y. 1976. *Tank Model and its Application to Bird Creek, Wollombi Brook, Bihin River, Sanaga River, and Nam Mune.* Tokyo, Japan: Research Note of National Center for Disaster Prevention, Number 11.

Suleiman, A., Al-Bakri, J. Duqqah, M. and Crago, R. 2009: Intercomparison of Evapotranspiration Estimates at the Different Ecological Zones in Jordan. *Journal of Hydrometeorology*, **9**, 903–919.

Sumner, D.M. and Jacobs, J.M. 2005. Utility of Penman-Monteith, Priestley-Taylor, reference evapotranspiration, and pan evaporation methods to estimate pasture evapotranspiration. *Journal of Hydrology*, 308 (1-4), pp. 81–104.

Sun, L. and Wu, G. , 2001. Influence of land evapotranspiration on climate variations. *Science in China Series D: Earth Sciences*, 44 (9), pp. 838 - 846.

Swain, E., Stefanova, L. And Smith, T. 2014. Applying Downscaled Global Climate Model Data to a Hydrodynamic Surface-Water and Groundwater Model. *American Journal of Climate Change*, 3(1), pp.33-49.

Tao, F., Yokozawa, M., Liu, J., Zhang, Z. 2008. Climate–crop yield relationships at provincial scales in China and the impacts of recent climate trends. *Climate resources 38*, pp.83 -94.

Taylor, A.L., Dessai, S. and De Bruin, W.B. 2014. Public perception of climate risk and adaptation in the UK: A review of the literature. *Climate Risk Management, 4–5 (2014) 1–16.*

Taylor, K. E., Stouffer, R. J. and Meehl, G. A. , 2012. An overview of CMIP5 and the experiment design. *Bulletin of American Meteorol. Soc*, 93(4), pp.485-98.

Tenalem Ayenew, Molla Demlie and Stefan, W. 2008. Hydrogeological framework and occurrence of groundwater in the Ethiopian aquifers. *Journal of African Earth Sciences*, 52(3), pp. 97-113.

Tessema, Y.A., Aweke, C.S. and Endris, G.S. 2013. Understanding the process of adaptation to Climate Change by small-holder farmers: the case of east Hararge Zone, Ethiopia. *Agricultural and Food Economics*, 1(12). Pp. 1-13.

Thiemann, S., Schütt, B. and Förch, G. 2004. *Development and Application of a Soil Erosion Risk Model. The Case of the Bilate River Catchment Area, South Ethiopia*. Lake Abaya Research Symposium LARS 2004. Siegen, Germany: FWU Water Resources Publications Siegen University.

Thurlow, J., Zhu, T. and Diao, X. 2012. Current Climate Variability and Future Climate Change: Estimated Growth and Poverty Impacts for Zambia. *Review of Development Economics*, 16(3), pp. 394–411.

Tilahun, K., 2006. Analysis of rainfall climate and evapotranspiration in arid and semi-arid regions of Ethiopia using data over the last half a century. *Journal of Arid Environments*, 64, pp. 474 - 487.

Todd, M.C., Taylor, R.G., Osborn, T.J., Kingston, D.G., Arnell, N.W. and Gosling, S.N. 2011. Uncertainty in climate change impacts on basin-scale freshwater resources- preface to the special issue: the QUEST-GSI methodology and synthesis of results. *Hydrology and Earth System Sciences*, 15, pp.1035–1046.

Trenberth, K.E., Dai, A., Rasmussen, R.M. and Parsons, D.B 2003. The Changing Character of Precipitation. *Bulletin of American Meteorologica Socity.*, 84, pp.1205-1217.

Trzaska, S. and Schnarr, E. 2014. *A review of downscaling methods for climate change projections*. African and Latin American Resilience to Climate Change (ARCC). Burlington, Vermont USA: Center for International Earth Science Information Network (CIESIN).

Tsakiris, G., Pangalou, D. and Vangelis, H. 2007. Regional drought assessment based on the Reconnaissance Drought Index (RDI).. *Water Resources Management*, 21, pp. 821–833.

Tsidu, G.M. 2012: High-Resolution Monthly Rainfall Database for Ethiopia: Homogenization, Reconstruction, and Gridding. *Journal of Climate*, 25, pp. 8422–8443

Tubiello, F.N., Soussana, J.F. and Howden, S.M. 2007. Crop and pasture response to climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 104 (50), pp.19686–19690.

U.S. EPA (Environmental Protection Agency) 2013. *Watershed Modeling to Assess the Sensitivity of Streamflow, Nutrient, and Sediment Loads to Potential Climate Change and Urban Development in 20 U.S. Watersheds*. EPA/600/R-12/058F. Washington, DC: National Center for Environmental Assessment Office of Research and Development U.S. Environmental Protection Agency.

UNFCCC, 2007. Climate change: impacts, vulnerabilities and adaptation in developing countries. Climate Change Secretariat (UNFCCC). 68 pp. Bonn, Germany

UNDP, 2003. *Adaptation Policy Frameworks (APF) for Climate Change: Developing Strategies, Policies and Measures.*. [Online] Available at: http://www.undp.org/climatechange/adapt/apf.html.

UNDP, 2005. *Adaptation Policy Frameworks for Climate Change.Developing Strategies, Policies and Measures.*. Cambridge UK and New York NY: Cambridge University Press.

Van Aalsta, M.K., Cannonb, T. and Burtonc, I. 2008. Community level adaptation to climate change:The potential role of participatory community risk assessment. *Global Environmental Change*, 18, pp. 165 – 179.

Van Griensven, A., Meixner, T., Grunwald, S., Bishop, T., Diluzio, M., Srinivasan, R. 2006. A global sensitivity analysis tool for the parameters of multi-variable catchment models. *Journal of Hydrology* , 324, pp. 10-23.

Van Roosmalen, L., Christensen, J.H., Butts, M.B., Jensen, K.H., Refsgaard, J.C. 2010. An intercomparison of regional climate model data for hydrological impact studies in Denmark. *Journal of Hydrology*, 380, pp. 406–419.

Van Rooy, M.P. 1965. A rainfall anomaly index independent of time and space. *NOTOS*, 14, pp. 43 - 48.

Van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J. and Ros, S.K. 2011. The representative concentration pathways: an overview. *Climatic Change*, 109, pp.5-31.

Vernieuwe, H., Vandenberghe, S., De Baets, B. and Verhoest, N.E.C. 2015. A continuous rainfall model based on vine copulas, *Hydrology and Earth System Sciences*, 19, pp. 2685-2699. doi:10.5194/hess-19-2685-2015.

Vicente-serrano, S.M., Begueria, S. and Lopez-moreno, J.I. 2010. A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of climate*, 23, pp. 1696 - 1718.

Von Storch, H., Hewitson, B., Mearns, L. 2000. *Review of downscaling techniques. Regional Climate Development under Global Warming*. General Technical Report No. 4. Conference Proceedings. Torbjornrud, Norway.

Wagesho, N. 2014. Catchment dynamics and its impact on runoff generation: Coupling watershed modelling and statistical analysis to detect catchment responses. *International Journal of Water Resources and Environmental Engineering*, 6(2), pp. 73-87

Waithaka, M., Nelson, G.C., Thomas, T.S., and Kyotalimye, M. (Eds.) 2013. *East African Agriculture and Climate Change: A Comprehensive Analysis*: International Food Policy Research Institute. Washington DC.

Wani, S.P. and Garg, K.K 2009. *Watershed Management Concept and Principles.* International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Andhra Pradesh, India.

Wemmer T., 2004. *GIS-based comparative study of the sub-basins of the Abaya-Chamo Basin, Ethiopia.* MSc Thesis. Trier, Germany: University of Trier.

Werner, A., Bennett, K., Runnells, J., Lee, R. and Rodenhuis, D. 2007. *Preliminary Analysis of Climate Variability and Change in the Canadian Columbia River Basin: Focus on Water Resources Pacific Climate*. Pacific Climate Impacts Consortium. University of Victoria, Victoria.

Wheater, H., Sorooshian, S. and Sharma K.D. 2008. Modelling Hydrological Processes in Arid and Semi Arid Areas. *International hydrology series.* Cambridge UK.

White, E.D., Easton Z.M., Fuka D.R., Collick A.S., Adgo, E., McCartney M., Awulachew, S.B., Selassie, Y.G., Steenhuis, T.S. 2011. Development and application of a physically based landscape water balance in the SWAT model. *Hydrological Processes.*, 25(6), pp. 915–925.

Wi, S., Yang, Y.C.E., Steinschneider, S., Khalil, A. and Brown, C.M. 2015. Calibration approaches for distributed hydrologic models in poorly gaged basins: implication for streamflow projections under climate change. *Hydrology and Earth System Science*, 19, pp. 857–876.

Wilbanks, T.J. and Kates, R.W. 2010. Beyond Adapting to Climate Change: Embedding Adaptation in Responses to Multiple Threats and Stresses. *Annals of the Association of American Geographers*, 100(4), pp.719-728.

Wilby, R.L., Dawson, C.W. and Barrow, E. M., 2002. SDSM- a decision support tool for assessment of regional Climate change Impacts. *Environmental Modelling Softwars.* 17 (2), pp.147–159.

Williams, J.R. and Hann, R.W. 1973. *HYMO: Problem-Oriented Language for Hydrologic Modeling—User's Manual.*. USDA: ARS-S-9.

Williams, C.J.R. and Kniveton, D.R. (Eds.) 2011. African Climate and Climate Change: Physical, Social and Political Perspectives. *Advances in Global Change Research (43).*

Williams, R. 2015. *Logistic Regression, Part III: Hypothesis Testing, Comparisons to OLS*. Notre Dame, Nezerlands: University of Notre Dame.

Wilson, K. and Getnet, M. 2011. Investigating how development interventions increase community-level adaptive capacity inEthiopia. In the New Voices, Different Perspectives. In *Proceedings of the Africa Adapt Climate Change Symposium*. Addis Ababa, Ethiopia.

Winkler, H. 2005. Climate change and developing countries (Review Articles). *South African Journal of Science*, 101, pp. 355 - 364.

Wriedt, G., Van der Velde, M., Alberto Aloe, A. and Bouraoui, F. 2009. Estimating Irrigation water requirement in Europe. *Journal of Hydrology*, 373 (3-4), pp. 527–544.

Wu, K. and Johnston, C.A. 2008. Hydrologic c omparison between a f orested and a wetland/lake dominated watershed using SWAT. *Hydrological Process*, 22, pp.1431–1442.

Xu, C.Y. and Chen, D. 2005. Comparison of seven m odels f or estimation of evapotranspiration and groundwater recharge using lysimeter m easure ment data in Germany. *Hydrological processes*, 19, pp. 3717–3734.

Xu, C.-Y., and Singh, V.P. 2005. Evaluation of three complementary relationship evapotranspiration models by water balance approach to estimate actual regional evapotranspiration in different climatic regions. *Journal Hydrology*, 308(1-4), pp.105–121.

Ye, X., Zhang, Q. and Viney, N.R. 2011. The e ffect of soil data re solution on hydrological processes modelling in a large humid watershed. *Hydrological processes*, 25, pp.130–140.

Yuguo, D., Jinling, Z. and Zhihong, J. 2010: Experimental Simulations of Extreme Precipitation Based on the Multi-Status Markov Chain Model. *Journal of Meteorological Research*, 24(4): pp. 484-491