IMPACT OF CLIMATE CHANGE ON SURFACE WATER RESOURCE AVAILABILITY:

A CASE STUDY IN WELMEL WATERSHED,GANALE-DAWA BASIN, SOUTH ETHIOPIA

MSc. THESIS

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JUN, 2018

HAWASSA

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A THESIS SUBMITTED TO FACULITY OF BIO-SYYSTEM AND WATER RESORCE ENGINEERING, HAWASSA UNIVERSITY INSTITUTE OF TECHNOLOGY, SCHOOL OF GRADUATE STUDIES

HAWASSA UNIVERSITY, HAWASSA, ETHIOPIA

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN WATER RESOURCE ENGINEERING (SPECIALIZATION: IRRIGATION AND DRAINAGE ENGINEERING)

JUN,2018

ACKNOWLEDGEMENT

First and foremost, thanks to the Almighty God for granting me His limitless care, love and blessings all along the way. I would like to express my greatest gratitude to the Ethiopia Ministry of Water, Irrigation and Electricity (MoWIE), for awarding me the scholarship. I would like to extend my thanks to Oromia Irrigation Development Authority as well Meda WalabuWereda Administration office for their contribution during the process of my scholarship award and for all their unlimited supports during my stay in the study site.

My sincere gratitude goes to my major advisor Dr. Shimelis Asseffa and my co-advisor Dr. Sirak Tekleab for all their regular advice and guidance from the starting until the completion of the work. I express my deepest appreciation for their encouragement and moral support throughout the study period. Last but not least, I would like to thank all my friends and family members back home who were spiritually with me, and gave me the strength to finalize my duties successfully. I am highly indebted to all my classmates and staff members of School of Water Resource Engineering for their ideal and technical supports and those who gave me their comments, ideas, shared love and happiness.

I am also thankful to the Ministry of Water irrigation and Electricity Hydrology and GIS departments and the National Meteorological Service Agency who werevery helpful and cooperative in providing me the necessary data.

Abbreviations and Acronyms

AOGCMs	Atmosphere-Ocean General Circulation Models
AR5	Fifth Assessment Report
ASTER	Advanced Space borne Thermal Emission and Reflection Radiometer
BCM	Billion Cubic Meter
DEM	Digital Elevation Model
GCM	General Circulation Model
GIS	Geographic Information System
GPS	Geographic Positioning System
HadCM3	Hadley Center Coupled Model, Version 3
HRU	Hydraulic Response Unit
IPCC	International Panel on Climate Change
ITCZ	Intertropical Convergence Zone
KM	Kilometer
LULC	Land use land cover
m.a.s.l	meters above sea level
MB	Model Bias
MoWIE	Ministry of Water, Irrigation and Electricity, Ethiopia
NSE	Nash-Sutcliff Efficiency
NMSA	National Meteorological Service Agency
PET	Potential Evapotranspiration
RCM	Regional Climate Model
SDSM	Statistical Downscaling Model
SRES	Special Report for Emission Scenario
SWAT	Soil and Water Assessment Tool
TGCIA	Task Group on Scenarios for Climate and Impact Assessment
SRTM	Shuttle Radar Topographic Mission
USDA	United State Department of Agriculture
UTM	Universal Transverse Mercatorcoordinates system

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ABSTRACT

Climate change, nowadays, has significant impact on the water resource system of an area. This study was conducted for Welmel watershed, Ganale-Dawa river basin, Ethiopia, using Soil and Water Analysis Tool(SWAT) hydrological model and General Circulation Model (GCM) aiming at estimating the impact of climate change on water availability of the study area. By making proper calibration, precipitation and temperature outputs of HadCM3 coupled atmosphere-ocean GCM model for A2a (medium to high) and B2a (Medium to low) SRES emission scenarios were downscaled using the Statistical Downscaling Model (SDSM). The downscaled minimum temperature shows an increasing trend in all future time horizons for both A2 and B2 scenarios. The average annual minimum temperature will be 0.3^0C change from baseline in 2020s (2014-2041).In2050s (2042-2069) of minimum temperature will be 0.65°C and also 0.63°C for A2 and B 2 scenario respectively. For the 2080s (2070-2099) periods the average annual minimum temperature will be increased by 1.3°C and 1.03°C for A2 and B2 scenario respectively.

The downscaled maximum temperature scenario, on the other hand indicates that for most months there will be an increasing trend for both A2 and B2 scenario. The projected temperature in 2020s indicates that maximum temperature will rise by 0.232°C. In 2050s the increment will be 0.527°C and 0.53°C for A2 and B2 scenario respectively. The future precipitation of the study area is expected to annual average increase by 11.90% for A2a and 11.67% for B2aemission scenarios. The actual evapotranspiration will also increase by 3.64% for A2a and 3.75% for B2a respectively.

The results obtained from this investigation indicate that there is significant variation in the seasonal and monthly flow. In the main rainy season (June-September) the runoff will be reduced by 12% in the 2080s. The result from synthetic (incremental) scenario also indicates that the catchment is sensitive to climate change. As much as 23% of the seasonal and annual runoff will be reduced if an increment of 2°C in temperature.

Key words Climate change, GCM, SWAT, SDSM

1: INTRODUCTION

1.1: BACKGROUND

Water is the most important natural resource required for the survival of all living species. As the available amount of water is limited and not uniformly distributed spatially and in relation to the population needs, proper management of water resources is essential to satisfy the current demands as well as to maintain sustainability water resources planning and management, in the manner of wisely use the existance water resources and done conservation structure to manage or conserve water resources. Now a days it is becoming difficult due to the conflicting demands from various stakeholders, increasing population, rapid urbanization, climate change shifts hydrologic cycle, the use of high-yielding but toxic chemicals in various land use activities, and increasing incidences of natural disasters (Yakob, 2009).

Climate change can cause significant impacts on water resources by changing the hydrological cycle. The change on temperature and precipitation components of the cycle can have a direct consequence on the evapotranspiration component quantity, and on quality and quantity of the runoff component. Consequently, the spatial and temporal availability of water resource, or in general the water balance, can be significantly affected, which clearly influences its impact on sectors like agriculture, industry and urban development, etc (Hailemariam, 1999).

Ethiopia is considered as the water tower of ''East Africa'' due to giving the available water resources to others country because of Ethiopia at higher altitude. The country has an estimated potential of 2.6BCM groundwater (Awulachew et al., 2007) and 111BCM surface water (Yazew, 2005) which indicates that there is ample amount of water with regard to its geographical positions. Ethiopia has 12 river basins and most of the basins are suitable both for Irrigation and hydropower developments. But the country was not using its water resource potential as needed for development (Awulachew et al., 2007).

However, this water potential has threatened by the climate change impact. Soliman-(2009 and Melesse-(2011) indicated that climate change in the Upper Blue Nile basin of Ethiopia would occur and would shift and reshape the annual and seasonal climate patterns and variation in rainfall, reduced reservoir yield and erratic rainfall. Similarly, Kebede et al., (2013) indicated that an increasing trend of annual maximum temperature and annual future rainfall with seasonal variations was observed in Baro-Akobo Basin and Nile Basin. Variations in frequency, distribution and intensity of rainfall are now a common phenomenon in the country. Furthermore, the country's economy is mainly dependent on rain-feed agriculture as a result people remains food insecure and the country is not possibly to achieve the millennium development goals in all sectors if it likely to continue. For proper planning, development and utilization of water resource projects, a good understanding and accurate estimation of the watershed water balance is a basic issue.

This can be achieved by properly studying the response of a basin for a given quantity of rainfall falling on the upstream area. A good estimation of the transformation of rainfall in to the different forms of water resource need an adequate and properly recorded historical data, such as stream flow and rainfall gauging stations. The provision of such recording instruments and stations at every proper site is capital intensive and difficult especially for developing countries like Ethiopia. Despite the fact that the impact of climate change is forecasted at the global scale, the type and magnitude of the impact at a catchment scale is not investigated in most part of the world. Therefore it is necessary to study the effect of climate change at this scale in order to take the effect into account by the policy and decision makers when planning water resources management.

There is no any studies in and around Welmel catchment on this title, but in the basin Calibration and validation of SWAT model land estimation of water balance components of Shaya mountainous(A.A Shawul,2013) and others are not done on this title.This research aims at estimating the impact of climate change on water balance components like surface runoff and evapotranspiration over Welmel watershed which is a tributary of Ganale-Dawa basin catchment using SWAT (Soil and Water Assessment Tool) hydrological model. Besides, the research assesses the climate change impact on the catchment hydrological response using GCM climate models.

1.2: PROBLEM STATEMENT

Despite the fact that the impact of climate change is forecasted at the global, and also at others Ethiopian parts, the impact at this catchment scale was not well investigated. Therefore it is necessary to study the effect of climate change at this scale in order to take the effect into account by the policy and decision makers when planning surface water resources management in Welmel watershed.

1.3: OBJECTIVE

1.3.1: GENERAL OBJECTIVE

The general objective of this research is to analyze the available amount of surface water resources for future climate scenarios in the sub-basin. The study may helps to understand and optimize available and limited water resources utilization strategies under the changing climate.

1.3.2: SPECIFIC OBJECTIVE

- ❖ To downscale course resolutions of climate model output.
- ❖ To evaluate climate scenario data for maximum temperature, minimum temperature and precipitation based on a General Circulation Model and a Statistical DownScaling Model for Welmel catchment;
- ❖ To investigate the possible hydrological impact of climate change in watershed based on the downscaled precipitation and temperature scenarios data from the observed data.
- ❖ To quantify possible impacts of the climate change on the surface water resources availability of the watershed.

1.4: SIGNIFICANCE OF THE STUDY

Based on future trend of maximum and minimum temperature recommendation given on future water balance of the watershed for better decision making and to indicate the measurement should taken in the catchment.

1.5: SCOPE OF THE STUDY

The study focused on the estimation of impact of temperature and precipitation parameters change on surface runoff and evapotranspiration water balance components in Welmel watershed by using data such as temperature and precipitation.

2: LITERATURE REVIEW

2.1: Climate model

The Earth's climate is governed by the interaction between many processes in the atmosphere, ocean, land surface and cryosphere. The interactions are complex and extensive so that quantitative predictions of the impact on the climate of greenhouse gas increase cannot be made through simple intuitive reasoning. For this reason, computer models have been developed which try to mathematically simulate the climate system, including the interaction between the system components (Dibike & Coulibaly, 2004). For climate simulation, the major components of the climate system that must be represented in sub models are atmosphere, ocean, land surface, cryosphere and biosphere, along with the processes that go on within and between them.

The mathematical models used to simulate the present climate and project future climate with forcing by greenhouse gases and aerosols are generally referred to as GCMs (General Circulation Models). General Circulation Models in which the atmosphere and ocean components have been coupled are also known as Atmosphere-Ocean General Circulation Models (AOGCMs).

Currently, the resolution of the atmospheric part of a typical model is about 250 km in the horizontal and about 1 km in the vertical above the boundary layer. The resolution of a typical ocean model is about 200 to 400 m in the vertical, with a horizontal resolution of about 125 to 250 km. Many physical processes, such as those related to clouds or ocean convection, take place at much smaller spatial scales than the model grid and therefore cannot be modeled and resolved explicitly. Their average effects are approximately included in a simple way by taking advantage of physically based relationships with the larger-scale variables through the techniques of parameterizations (Houghton, 2001).

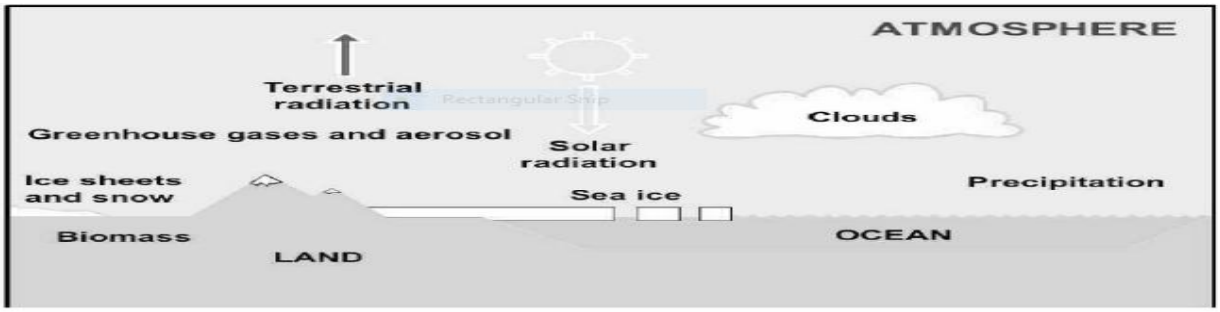


Figure 2.1: Schematic diagram of the processes and interaction in the global climate system (based on Hadley Centre for Climate Prediction and Research)(Abdo,2007)

2.1.1: THE CLIMATOLOGICAL BASELINE

In order to have a basis for assessing future impacts of climate change, it is necessary to obtain a quantitative description of the changes expected. However, before considering future climate it is important to characterize the present-day or recent climate in a region-often referred to as the climatological baseline. This baseline period is needed to define the observed climate with which climate change information is usually combined to create a climatic scenario. When using climate model results for scenario construction, the baseline serves as the reference period from which the modelled future change in climate is calculated (Houghton, 2001). The choice of baseline period has often been governed by availability of the required climate data. The baseline period is usually selected according to the following criteria (Carter, 2007):

- representative of the present-day or recent average climate in the study region;
- of a sufficient duration to encompass a range of climatic variations, including number of significant weather anomalies (e.g. severe droughts or cool seasons);
- covering a period for which data on all major climatological variables are abundant, adequately distributed over space and readily available;
- Including data of sufficiently high quality for use in evaluating impacts.

2.1.2: CLIMATE CHANGE

Climate change, now a day, is an overwhelming global issue. Everything, living or nonliving in one or another way relates with the subject of climate change. The main symptoms of global warming are increase in temperature of the atmosphere, oceans, and landmasses of planet earth. At present earth appears to be facing a rapid warming, which mostly believed as results of human-induced activities. The chief cause of this warming is thought to be the burning of fossil fuels, such as coal, oil, and natural gas from which greenhouse gases are released into the atmosphere (IPCC, 2013).Global warming is caused by a collective evident that, it is due to a distinct anthropogenic influence (Bates et al., 2008; Casper, 2010; IPCC, 2013).

Even though the natural hazards are contributing to the climate change, human-induced climate changes are tremendously higher and complex. Since the 1990s the Intergovernmental Panel for Climate Change (IPCC, 1990, 1996, 2001, 2007 and 2013) released different climate change related assessment reports. These reports have forced policy makers to take action on the climate change that threatens the earth. Meanwhile, based on the new evidence of climate change from different independent scientific analyses, from observations of the climate system, pale climate archives, theoretical studies of climate processes and simulations using climate models, the IPCC has released a new assessment report. As a result, the Working Gro up I of the IPCC's released its Fifth Assessment Report (AR5) outlined and has projected the climate change that could be occurred on the globe during the twenty first century.

Therefore, according to IPCCs Fifth Assessment Report (IPCC, 2013), warming of the climate system is unequivocal, and since the 1950s, many of the observed changes are unprecedented over decades to millennia. The atmosphere and ocean have warmed, the amounts of snow and ice have diminished, sea level has risen, and the concentrations of greenhouse gases have increased. Moreover, each of the last three decades has been successively warmer at the Earth's surface than any preceding decade since 1850.,the period 1983–2012 In the Northern Hemisphere was the warmest 30-year period of the last 1400 years. Ocean warming dominates the increase in energy stored in the climate system, accounting for more than 90% of the energy accumulated between 1971 and 2010. The rate of sea level rise since the middle ninetieth century has been larger than the mean rate during the previous two millennia. Over the period 1901 to 2010, global mean sea level has risen by 0.19m.

The Special Report for Emission Scenarios (SRES) are climate change projections developed by IPCC starting from 1990s (IPCC-TGICA, 2007; IPCC, 2013). These scenarios are due to emissions from greenhouse gases, aerosol precursor which produces global warming. The emission scenarios were developed based on population, economy, technology, energy and land use as deriving forces. According to IPCC, (IPCC-TGICA, 2007; IPCC, 2013) the emission scenarios are categorized in to four families based on their unique characteristics for the twenty first century.

A1 Scenario: Globalization

This family is characterized by very rapid economic growth with new and efficient technology use and global population will peaks in middle century and declines afterwards. There is convergence among regions capacity building, increase in social and cultural interactions. The A1 scenario family develops into three groups that describe alternative directions of technological change in the energy system. These are: Fossil intensive (A1FI) that emphasis on fossil fuels, Non - fossil energy sources (A1T), or balance across all energy sources (A1B).

A2 Scenario: Regionalization

The storyline and scenario describes a very heterogeneous world with a self-reliance and preservation of local identities. It is characterized by continuously increasing population and regionally oriented economic development.

B1 Scenario: Globalization, sustainability and equity globalized and extensive (sustainable development). It has similar trends of global population increment with A1 storylines. The scenario is characterized with rapid changes in economic structures towards a service and information economy and resource-efficient technologies.

B2 Scenario: Regionalization, sustainability and equity regional, extensive (mixed green bag). This scenario family describes the world emphasizes on local solutions to economic, social, and environmental sustainability. Global population increases at a rate lower than A2 storylines with intermediate levels of economic development. It has less rapid and more fragmented change in technology than A1 and B1 scenarios. These emission scenarios are used to indicate future likely impacts of climate change ranged from the relatively less effect of climate change to the very worst effect of climate change conditions that would possibly appear in the future.

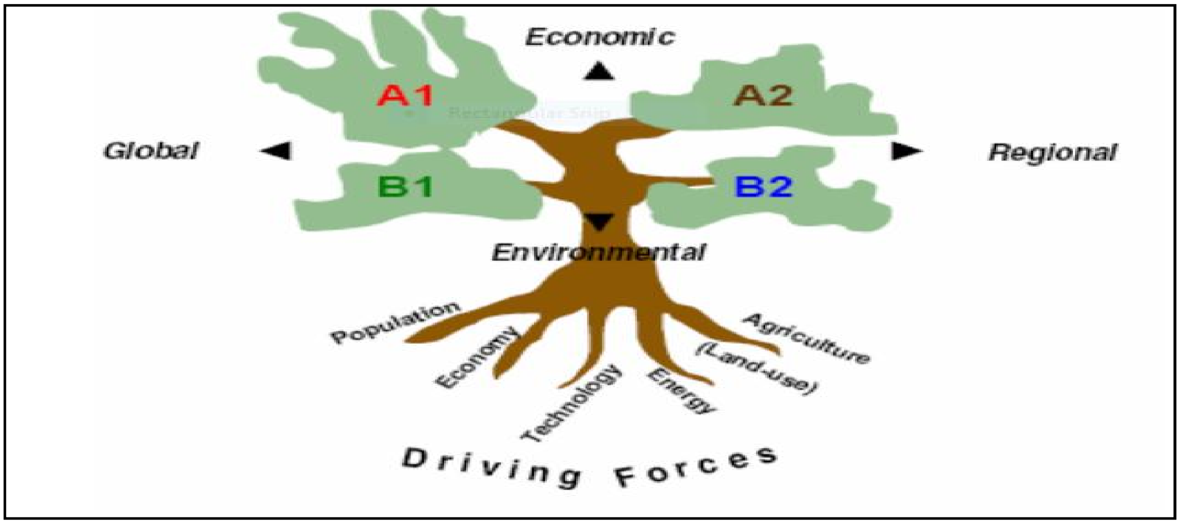


Figure 2.2: The Four IPCC SRES Scenario Storyline (IPCC-TGICA, 2007)

2.1.3: Impacts of Climate Change on Water Resources Availability

The hydrologic cycle is highly sensitive to climate change because the components of the hydrologic cycle are vulnerable to changing climate. Findings of the IPCC (2013), strongly suggests that climate change has the potential to deteriorate the water resources availability, water quality and water supplies. Being the most potable water for mankind, if groundwater severely affected by the climate change, it goes to threaten the survival of life on earth.In many countries of the world the use of water resources for public water supply constitutes important potable water. However, many factors affect future surface water and groundwater resources as changes in precipitation and temperature regimes, coastal flooding, urbanization, land use changes and changes in cropping system (Holman, 2006). Similarly, Herrera-Pantoja and Hiscock (2008) concluded that future climate may present a decrease in potential water resources that will increase stress on local and regional water resources. As a result attention to the water resources remains inevitable to overcome the problem with some solutions.

Many studies have been conducted to investigate the impact of climate change in water resources, stream flow and land use/land cover changes in the upper Blue Nile of Ethiopia. In the upper Blue Nile of Ethiopia, climate change has observed to shift the time of rainfall patterns and of the groundwater recharge and temperature has observed increasing trends in the mean annual, rainy and dry seasons (Tekleab et al., 2013). These changes contributed tremendous effects on the water potentials in Ethiopia.

Therefore, water is a vital resource and awareness needs to be raised on its vulnerability to overexploitation, pollution and most importantly, climate change (Nyenje and Batelaan, 2009). The change in climate and weather conditions in the atmosphere and hydrosphere leads to changes in precipitation patterns and this leads to changes in hydrologic cycle and finally causes changes in catchment hydrologic response. As surface and groundwater recharge has direct relationships with rainfall, the more rainfall rains the more water run on surface and infiltrates the soil to the groundwater and hence the more water stored in the water table.

2.1.4: Climate Models and their Application

Models are physical or mathematical simplifications of natural systems used for analyzing physical data. Model also describes equations of physical systems and techniques that provide a means for quantitative explorations or predictions that will help in decisions making. Projections of changes in the climate system are made using a hierarchy of climate models ranging from simple climate models, to models of intermediate complexity, to comprehensive climate models and Earth System Models (IPCC, 2013). Moss et al., (2010) described climate models as there are a wide variety and complexity of models which are numerical representations of the earth's natural systems used to study how climate responds to changes in natural and human-induced perturbations.

These climate models help to project future likely impacts of climate change in the planetary system. Hydrologic cycle is one among others that is highly influenced by climate change as a result of effects on the atmospheric and rainfall patterns. Consequently, there are improvements on the climate models in time and space in predicting future climate change impacts that may occur. According to IPCC (2013) Climate models have improved since the fourth assessment report for future prediction and for studying preceding climatic situations. In the climate system models are known to reproduce observed continental and local scale atmospheric patterns and trends over many decades.

2.1.5: HadCM3/GCM Climate Model

Climate models, both global and regional, are the primary tools that aid in our understanding of the many processes that govern the climate system (Jeremy et al., 2007). Climate is one of the most challenging geophysical systems to simulate because of the number of interacting components and the wide range of time and spatial scales of relevant processes and their complexity (Laprise , 2008).

Global climate models also known as general circulation models (GCMs) are the most complex of climate models, since they attempt to represent the main components of the climate system in three dimensions. Many researchers agree that GCMs are the vital resource used to perform climate change experiments globally, regionally and fine scale up to point climate pattern from which climate change scenarios are derived; However, GCMs have main drawbacks because of their course resolution. Most of the time they lack producing of current climate trend including the most important statistical parameters like mean and variance.

GCMs depict the climate using a three dimensional grid over the globe, typically having a horizontal resolution of between 250 and 600 km, 10 to 20 vertical layers in the atmosphere and sometimes as many as 30 layers in the oceans. Their resolution is thus quite coarse relative to the scale of exposure units in most impact assessments. Moreover; many physical processes, such as those related to clouds, also occur at smaller scales and cannot be properly modeled. Instead, their known properties must be averaged over the larger scale in a technique known as parameterization. This is one source of uncertainty in GCM-based simulations of future climate (IPCC-TGICA 2007).

Few years ago, GCMs only included a representation of the atmosphere, the land surface, sometimes the ocean circulation, and a very simplified version of the sea ice. Nowadays, GCMs take more and more components into account, and many new models are now included such as sophisticated models of the sea ice, the carbon cycle, ice sheet dynamics and even atmospheric chemistry (Goosse . et al., 2013).

HadCM3 is a coupled atmosphere-ocean GCM developed at the Hadley Centre of the United Kingdom’s National Meteorological Service that studies climate variability and change. It includes a complex model of land surface processes, including 23 land cover classifications; four layers of soil where temperature, freezing, and melting are tracked; and a detailed evapotranspiration function that depends on temperature, vapor pressure, vegetation type, and ambient carbon dioxide concentrations (Palmer et al., 2004).

The atmospheric component of the model has 19 levels with a horizontal resolution of 2.5^0 latitude by 3.75^0 longitude, which produces a global grid of 96 x 73 cells. This is equivalent to a surface resolution of about 417 km x 278 km at the equator, reducing to 295 km x 278 km at 45^0latitude. The oceanic component of the model has 20 levels with a horizontal resolution of 1.25^0 latitude by 1.25^0longitude. HadCM3 has been run for over a thousand years, showing little drift in its surface climate. Its predictions for temperature change are average; and for precipitation increase are below average (IPCC, 2001).

The HadCM3 GCM output data can be downscaled to the local level data using latitudinal locations of a target site. Hence, the HadCM3 outputs can be used for studies in Ethiopia. Due to this, Kebede et al., (2013) has used this HadCM3 climate model to model climate system in Baro-Akobo river basin of Ethiopia and revealed successful work. Zeray, (2006) also used the GCM climate model to assess climate change impact on water resource potential in Lake Zeway of Awash river basin, Ethiopia. Based on this, for this study HadCM3 GCM was used as a source of large scale data for the determination of future climate change projections and likely water resources impacts by downscaling these large scale HadCM3 GCM outputs in to the basin of interest.

2.1.6: Climate Data Downscaling Approach

Downscaling of climate scenarios refers to a process of taking global information on climate response to changing atmospheric composition, and translating it to a finer spatial scale that is more significant in the context of local and regional impacts. There is software available today for downscaling of General Circulation Model (GCM) and Regional Climate Model (RCM) datasets and makes ready to use for future climate change predictions. According to Wilby et al., (2004) and Wilby and Dawson, (2007), there are two general approaches used in downscaling regional climatemodels: Dynamical and Statistical downscaling approaches

Dynamical downscaling approach is a method of extracting local scale information by developing and using regional climate models (RCMs) with the coarse general circulation models (GCM) data used as boundary condition. It simulates climate processes over the region of locality or basin with a high resolution regional climate model. Dynamical downscaling involves the nesting of a higher resolution Regional Climate Model RCM) within a coarser resolution the GCM. RCMs have been developed that as it can attain horizontal resolution finer and finer as compared to GCMs resolution. The advantage of dynamical downscaling method is that a regional climate model can simulate local fine scale feedback processes which are not verified with statistical methods. Performance of this downscaling is, however, highly dependent on the quality data input.

Statistical downscaling approach, assures development of statistical relationships between local climate variables (predictands) and large scale climate variables (predictors) (Wilby etal., 2004). It also provides an application of predictands-predictor relationships to the output of GCM and RCM experiments to simulate local climate characteristics. The most common method of statistical downscaling is when predictands are simulated as a function of predictors. This kind of downscaling is useful especially for impact assessment modeling studies for reproducing different climatic statistics at basin or local level. Therefore, statistical downscaling models are often used as a decision support tool to know whether or not the historical climate data available and the downscaled climate data have relationships through calibration and validation of the models.

According to Wilby et al., (2004), Xuetal.,(2005),Wilby and Dawson (2007), and Kebede et al., (2014) the statistical downscaling model provides a consistent estimates of temperature extremes and precipitations in seasonal and site level, is easily computational, can easily be crafted and used for specific uses, direct regional incorporations of observational records, and uses basic standard statistical procedures. Therefore in this study, the Statistical Downscaling Model (SDSM) was used to downscale future climate change scenarios, which was obtained from the output of General climate model in the watershed. Results of the SDSM were used as input to analyze the impact of climate change to water resources potentials.

2.2: HYDROLOGICAL MODELS

Hydrologic models are simplified and conceptual representations of a part of the hydrologic cycle. They are primarily used for hydrologic prediction and for understanding hydrologic processes. According to (Lenhart et al, 2002), models are used to establish a baseline when data is not available and to estimate long term impacts that are not easy to calculate. Hydrological model are classified in different aspects. These classification methods can be defined as short term and long term, small scale and large scale, forecasting and predictive, physical and mathematical, continuous and discrete, descriptive and conceptual, lumped and distributed, deterministic and stochastic.

Classifications are generally based on the method of representations of the hydrological models. Physical based models are based on our understanding of the physics of the hydrological process. Generally, physical based models are used to simulate wide range of complex process. Depending on the character of the result obtained, model are classified as stochastic, if one or more of the variables in a mathematical model are regarded as random variables having distributions in probability and deterministic, when all the variables are considered to be free from random variation (Lenhart et al, 2002).

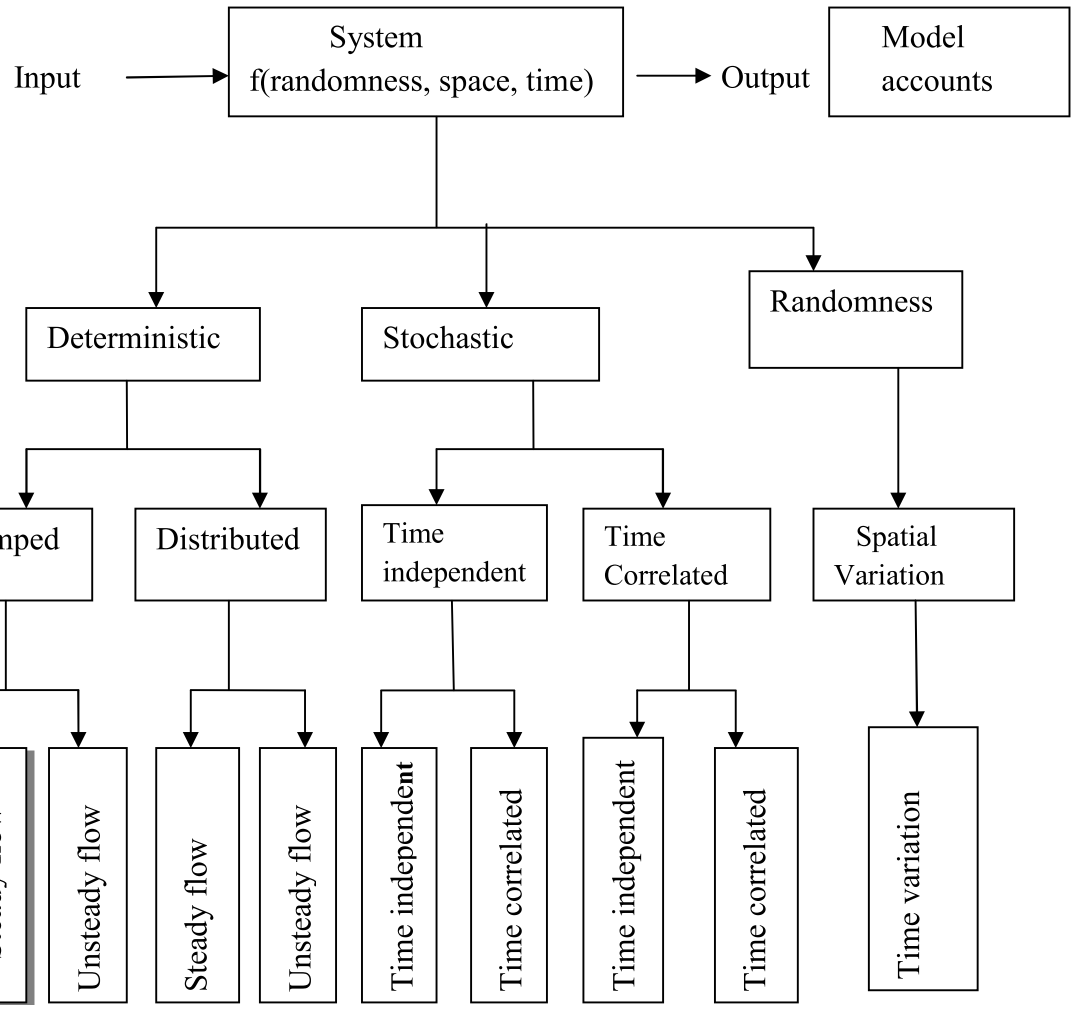


Figure 2.3: Hydrological Model Types and Classification (Lenhart et al, 2002)

Without going into too much detail, deterministic hydrologic models can be classified into three main categories (Cunderlik 2003).

1. Lumped Models: - parameters of lumped hydrologic models do not vary spatially within the basin and thus, basin response is evaluated only at the outlet, without explicitly accounting for the response of individual sub-basins. The impact of spatial variability of model parameters is evaluated by using certain procedures for calculating effective values for the entire basin. The most commonly employed procedure is an area weighted average (Haan et al., 2002).

2. Semi-distributed Models: - parameters of semi-distributed (simplified distributed) models are partially allowed to vary in space by dividing the basin into a number of smaller sub-basins.

3. Distributed Models: - parameters of distributed models are fully allowed to vary in space at a resolution usually chosen by the user. Distributed modeling approach attempts to incorporate data concerning the spatial distribution of parameter variations together with computational algorithms to evaluate the influence of this distribution on simulated precipitation-runoff behavior. Distributed models generally require large amounts of data for parameterization in each grid cell. However, the governing physical processes are modeled in detail, and they can provide the highest degree of accuracy if properly applied.

2.2.1: Hydrological Model Selection Criteria

There are various criteria which can be used for choosing the right hydrological model for a specific problem. These criteria are always project dependent, since every project has its own specific requirements and needs. Further, some criteria are also user-dependent (and therefore subjective). Among the various project-dependent selection criteria, there are four common, fundamental ones that must be always answered (Cunderlik, 2003):

- Model outputs important to the project and therefore to be estimated by the model (Does the model predict the variables required by the project such as long-term sequence of flow?)
- Hydrologic processes that need to be modeled to estimate the desired outputs adequately (Is the model capable of simulating single-event or continuous processes?)
- Availability of input data (Can all the inputs required by the model be provided within the time and cost constraints of the project?)
- Price (Does the investment appear to be worthwhile for the objectives of the project?).

2.2.2: Use of hydrological modeling in climate change impact studies

The choices of a model for a particular case study depend on many factors, the purpose of the study and model availability being the dominant ones. For detailed assessment of surface flow, conceptual models were applied in many parts of the world. Booij,(2005) discusses the advantages of conceptual models for climate change study as a nice compromise between the need for simplicity on one hand and the need for a firm physical basis on the other hand.

One of the more frequently used conceptual model for climate change impact study is the SWAT model. The SWAT model is widely used in Nordic countries as a tool to assess the climate change effects. Climate change impact on runoff and hydropower in the Nordic countries have been studied by using the SWAT models (Xu, 1999). Booij,(2005) applied the SWAT model to assess the impact of climate change on river flooding on Meuse River in the Netherlands. Dibike and Coulibaly,(2005) applied the SWAT model to study the hydrological impact of climate change in the Saguenay watershed in Canada.

In conclusion, the SWAT model is selected for this study because of the following reason:

1. The input data requirement is moderate;
2. The model simulates the major hydrological process in the catchments;
3. The model was tested for the impact of climate change on hydrological study in different parts of the world and
4. The availability of the model

2.2.2.1 General Description of Swat Model

SWAT (Soil Water Assessment Tool) is a widely-used semi-distributed, physically based and computationally efficient hydrological model which allows the simulation of a number of different physical and hydrological processes occurring across a watershed and, in particular, the stream flow as the ultimate basin characteristic [Neitsch et al., 2013]. Input to SWAT is geographic information on the basin and its shallow subsurface, like topography, soil and land-use, subsurface parameters and weather data, driving the dynamic hydrological processes. Output of the model is primarily discharge of the major basin stream and/or its tributaries, as well as other water budget components of the basin.

In recent years, SWAT model has gained international acceptance as a robust interdisciplinary watershed modeling. SWAT is currently applied worldwide and considered as a versatile model that can be used to integrate multiple environmental processes, which support more effective watershed management and the development of better informed policy decision (Gassman et al., 2007). The review of SWAT model applicability to Ethiopian situations at relatively larger watersheds (Dilnesaw, 2006; Setegn, 2010) indicated that the model is capable of simulating hydrological processes with a reasonable accuracy. In SWAT, a watershed is divided into multiple sub-watersheds, which are then further subdivided into hydrologic response units (HRUs) that consist of homogeneous land use, management, and soil characteristics (Neitsch et al., 2005).

2.3: Sensitivity Analysis, calibration and validation of hydrological models

2.3.1 Parameters Sensitivity Analysis

The steps to select sensitive parameters is 1st by using full flow data Sensitive parameters are identify, then the most sensitive parameters use for calibration. Analysis is a technique of identifying the responsiveness of different parameters involving in the simulation of a hydrological process. A hydrological model like SWAT, which involves a wide range of data and parameters in the simulation process, calibration is quite a cumbersome task. Sensitivity analysis is a method of minimizing the number of parameters to be used in the calibration step by making use of the most sensitive parameters largely controlling the behavior of the simulated process. Sensitivity is expressed by a dimensionless index I, which is calculated as the ratio between the relative change of model output and the relative change of a parameter (Ma et al., 2000).

2.3.2: Calibration

Calibration is tuning of model parameters based on checking results against observations to ensure the same response over time. This involves comparing the model results with that of the historic data recorded stream flows. In this process, model parameters varied until recorded flow patterns are accurately simulated. Hydrological Models calibration like SWAT run can be divided in to several steps. Among these Water balance and stream flow generation are the most important part. Refsgaard and Storm (1996) distinguished three types of calibration methods: the manual trial-and-error method, automatic or numerical parameter optimization method; and a combination of both methods. Manual calibration is the most common and especially recommended in cases where a good graphical representation is strongly demanded for the application of more complicated models. However, it is very cumbersome, time consuming, and requires experience. Automatic calibration makes use of a numerical algorithm in the optimization of numerical objective functions. The method undertakes a large number of iterations until it find the best parameters. The third method makes use of combination of the above two techniques regardless of which comes first. For this study, one of the water balance component, stream flow, was used for calibration

2.3.3: Validation

Using independent discharge data, models are validated and the goodness of fit is quantified by using the model bias (MB). coefficient of determination (R^2) and Nash-Sutcliff efficiency (NSE) between the observations and the final best simulations. (Van Rompaey et al., 2001).

2.3.4: Model performance assessment

Statistical measures provide quantitative estimates for the goodness of fit between observed and predicted values, and are used as indicators of the extent at which model predictions match observation (Liu and De Smedt 2004). the model bias (MB), Coefficient of determination (R^2 and Nash-Sutcliff efficiency (NSE) are those which measures model performance (Cao et al. 2006).

3: MATERIALS AND METHODS

3.1: DESCRIPTION OF THE STUDY AREA

3.1.1: LOCATION

Welmel watershed is found in south-eastern part of Ethiopia in Genale-Dawa basin as shown in (Figure 3.1). The catchment is situated between $6^{o}0'$ to $6^{0}60'$ N latitude $39^{0}20'$E and $39^{0}50'$E longitudes. The River originates from the Bale mountains located at elevation of 4261m a.m.s.l. (as extracted from SRTM) and drains to the Southeastern part of the country. It covers a total drainage area of 1170.8km^{2}. The average areal annual rainfall distribution is 887 mm and the maximum and minimum temperature of the watershed area is about 31^{0}C and 14^{0}C, respectively.

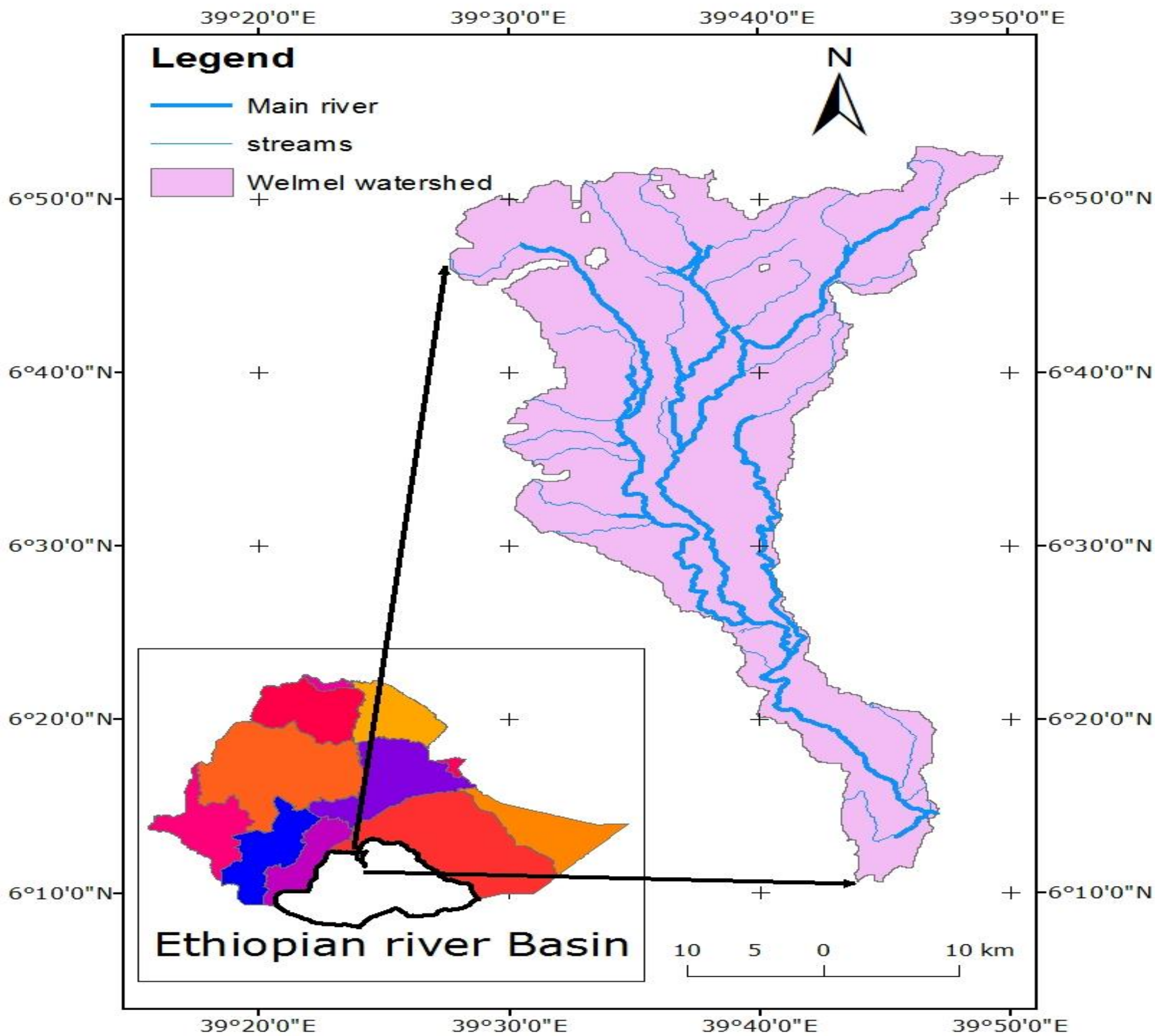


Figure 3.1: Location of Welmel catchment

3.1.2: TOPOGRAPHY

The elevation of catchment varies from1041 to 4261m a..s.l. The higher elevation ranges are located at the North corner while the remaining area is relatively uniform. (Figure 3.2) shows the elevation categories in the catchment. A 30 m grid Shuttle Radar Topography Mission (SRTM) digital elevation model was obtained from http://srtm.csi.cgiar.org which was used for all subsequent terrain analysis.

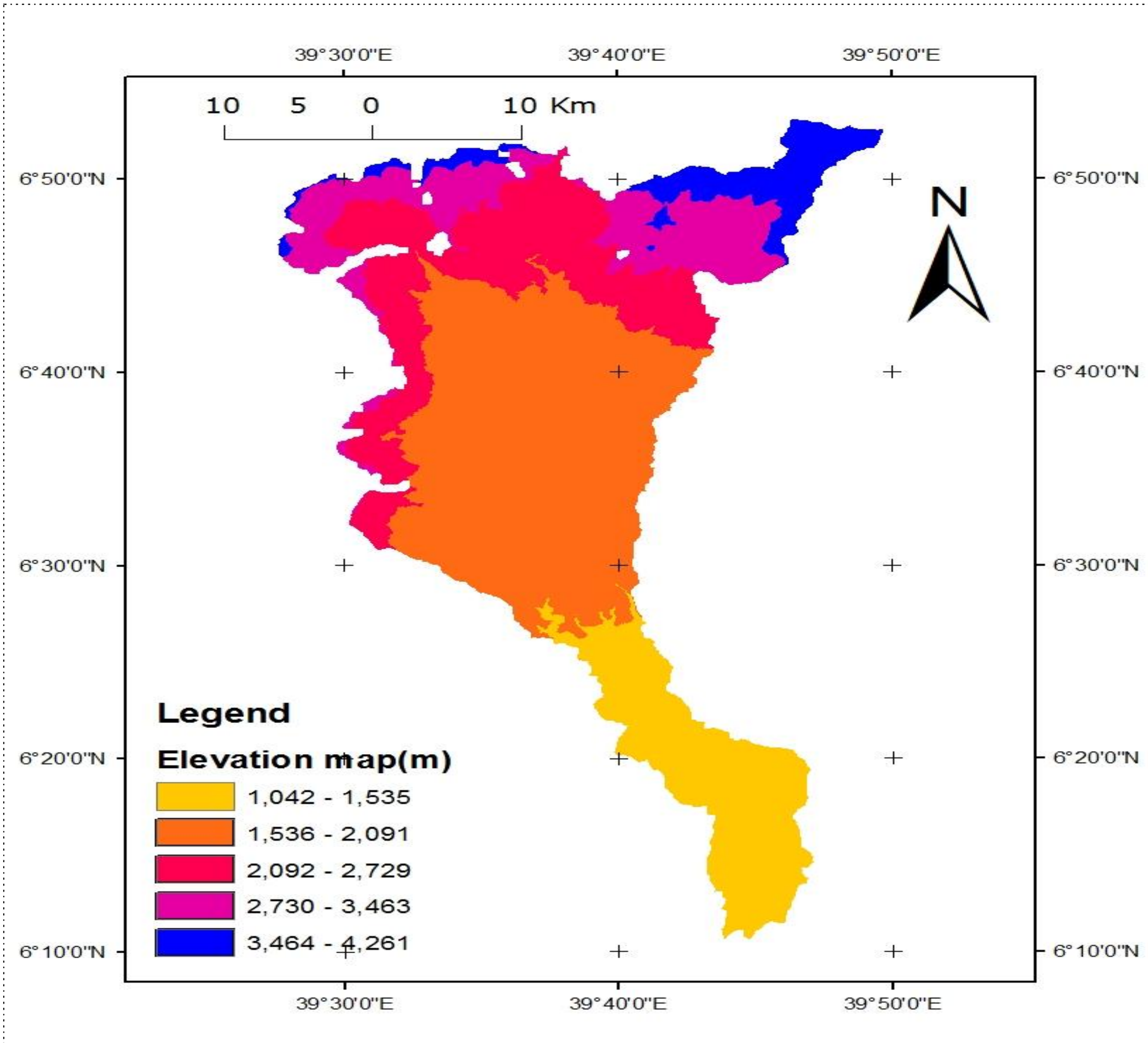


Figure 3.2: Elevation map of Welmel catchment(derived from SRTM 30 m digital elevation data)

A slope analysis was carried out for the catchment using the Arc GIS Spatial Analyst. From the slope map of the catchment area, around 42% of the catchment area falls in the slope range from 0-8% and 43% of the area falls in the slope range of 8-30%. The remaining 15% of the area has slope greater than 30% as shown in (Figure 3.3).9999% is when swat class is arranged to run,but nothing it is slope above 30%.The longest flow path of the river towards the outlet is 412 Km.

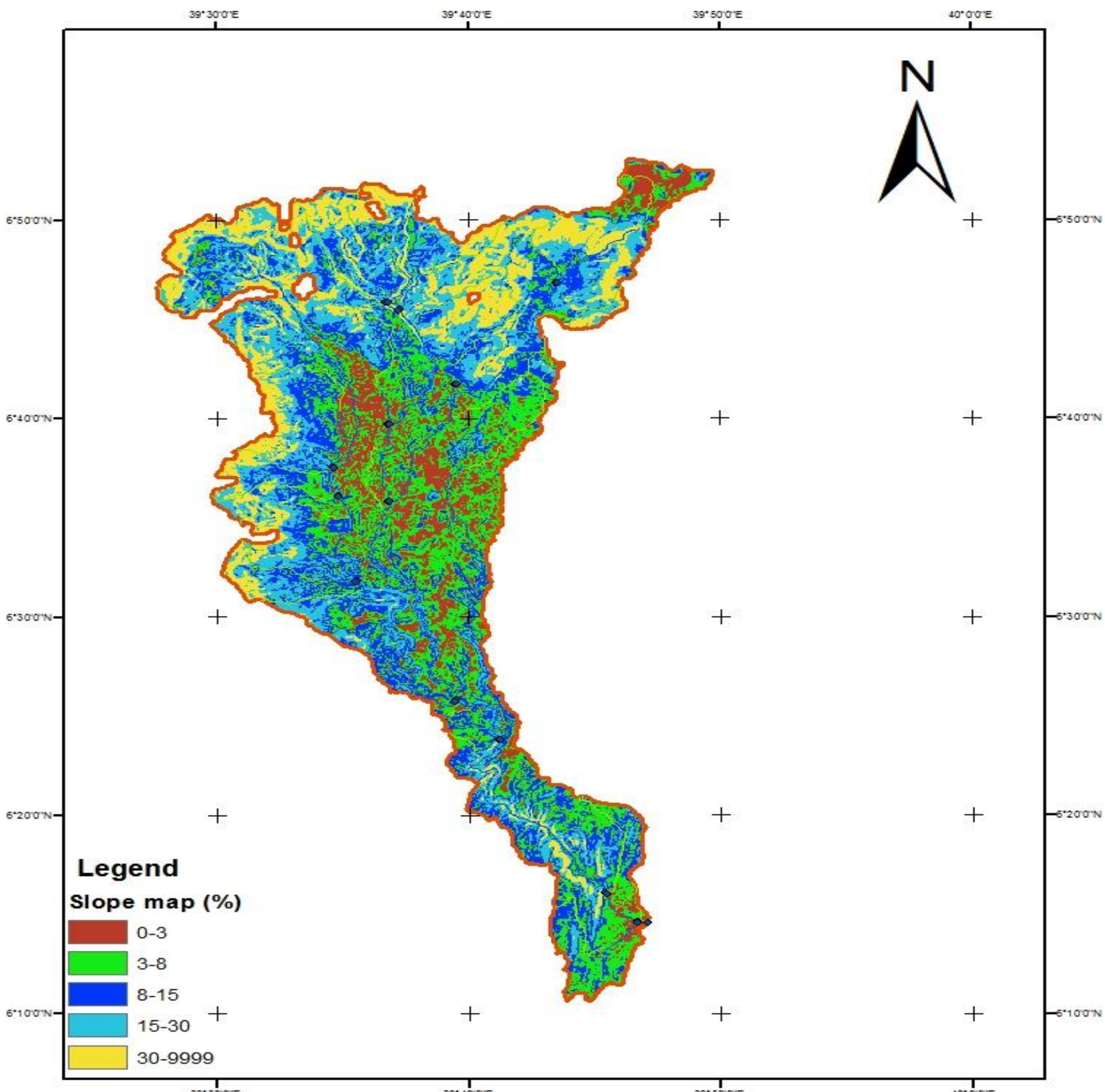


Figure 3.3: Slope map of Welmel catchment(derived from SRTM 30 m digital elevation data).

3.1.3: Climate

The climate of Ethiopia is mainly controlled by seasonal migration of Intertropical Convergence Zone (ITCZ) and its associated atmospheric circulation but the topography has also an effect on the local climate. The traditional climate classification of the country is based on altitude and temperature shows the presence of five climatic zones namely: Wurch (cold climate at more than 3000m altitude), Dega (temperate like climate-highland with 2500-3000m altitude), Woina Dega (warm 1500-2500m altitude), Kola (hot and arid type, less than 1500 m in altitude), and Berha (hot and hyper-arid type) climate [NMSA, 2001].

According to this classification, the study area falls in Dega and Woina Dega climate However, and part of study area at the North tips of the catchment falls in Wurch Zone.

The mean annual rainfall (1986-2013) of the stations as shown in(Figure 3.4) varies from around 780 mm (Negele) up to 1036 mm for Angetu which is just outside the catchment boundary. The mean annual rainfall (1986-2013) of Dello station which is located around near not in is 966mm.

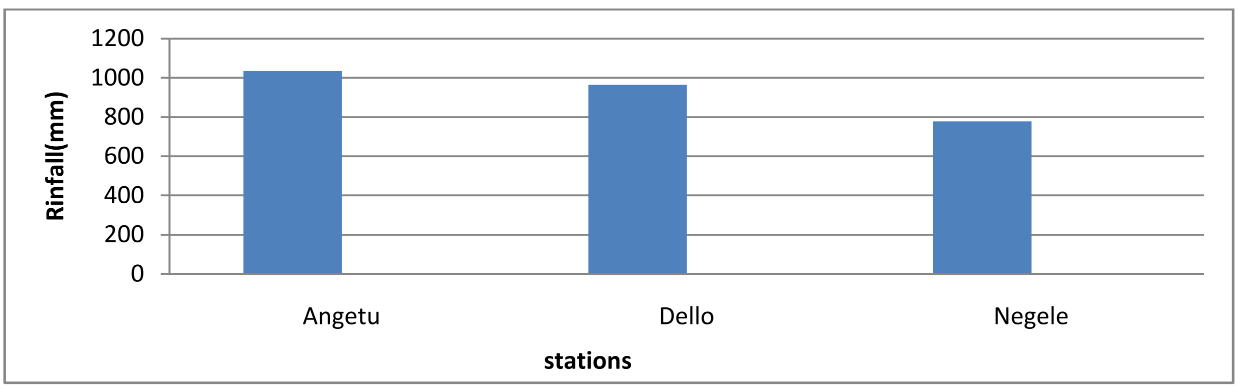


Figure 3.4: Mean annual rainfall from 1986-2013(Computed from Data from NMAS)

In the study area there is change in temperature i.e. there is variation between the daily maximum and minimum temperature. However, the seasonal variation of temperature is less compared to diurnal change. The mean monthly maximum and minimum temperature of Dello (1986-2013) at elevation of 1313 a.m.s.l (from NMA) varies from 27.09ºC to 31.08ºC and 14.14ºC to16.61ºC respectively. Generally speaking the months of January through March are the hottest month whereas the lowest temperatures occur during July and August as shown in (Figure 3.5).

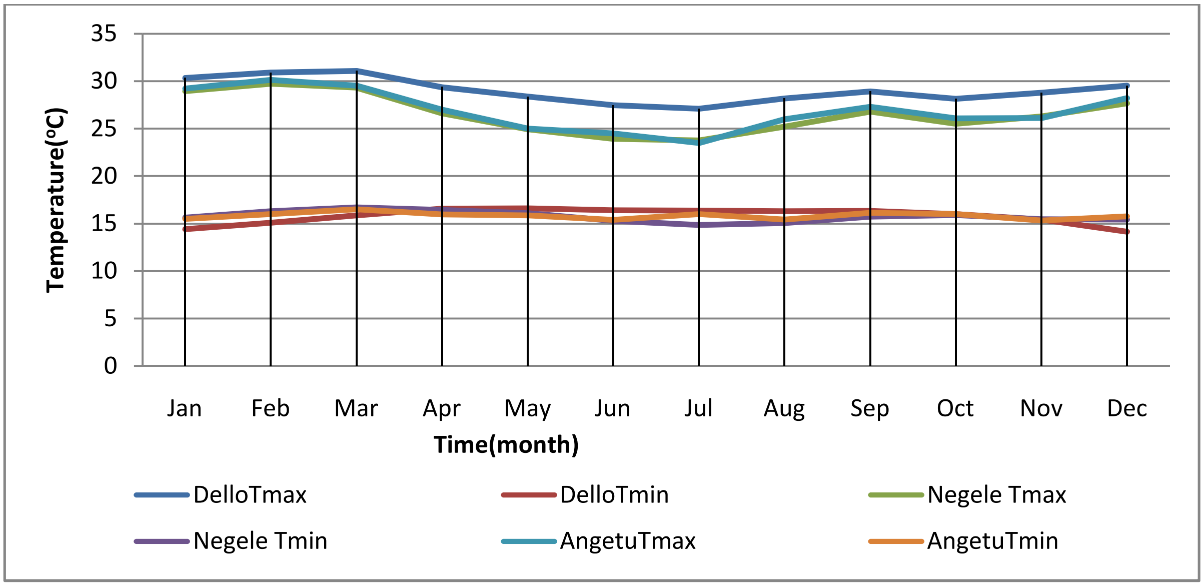


Figure 3.5: Mean monthly temperature of stations (1986-2013). (Computed from Data from NMAS)

3.1.4: Drainage Network

The source of the Welmel River is a spring that emerges from Bale Mountain on its way downstream, Tthe river also receives inflow from several streams. The total drainage area of the river is around 1170 km^2 and the longest flow path of river from source to the outlet of the catchment is around 412 km. There is one gauging stations in the catchment which has continuous records for a long period which is found Melka Amena town near the bridge of Welmel River on the road from Bale Robe to Negele Borena.

3.1.5: Soil of the study area

The soil of Welmel catchment is mostly covered by Luvisols with area coverage of around 522 km^2. Luvisol are generally fertile soils because of their mixed mineralogy, relatively high nutrient content and presence of weather able minerals. The forest mixed areas are mostly located on this type of the soil throughout the catchment [Tessema, 2006]. (See Figure 3.6) soil types of the study area (The description of the soil types is provided in (Appendix table.1)

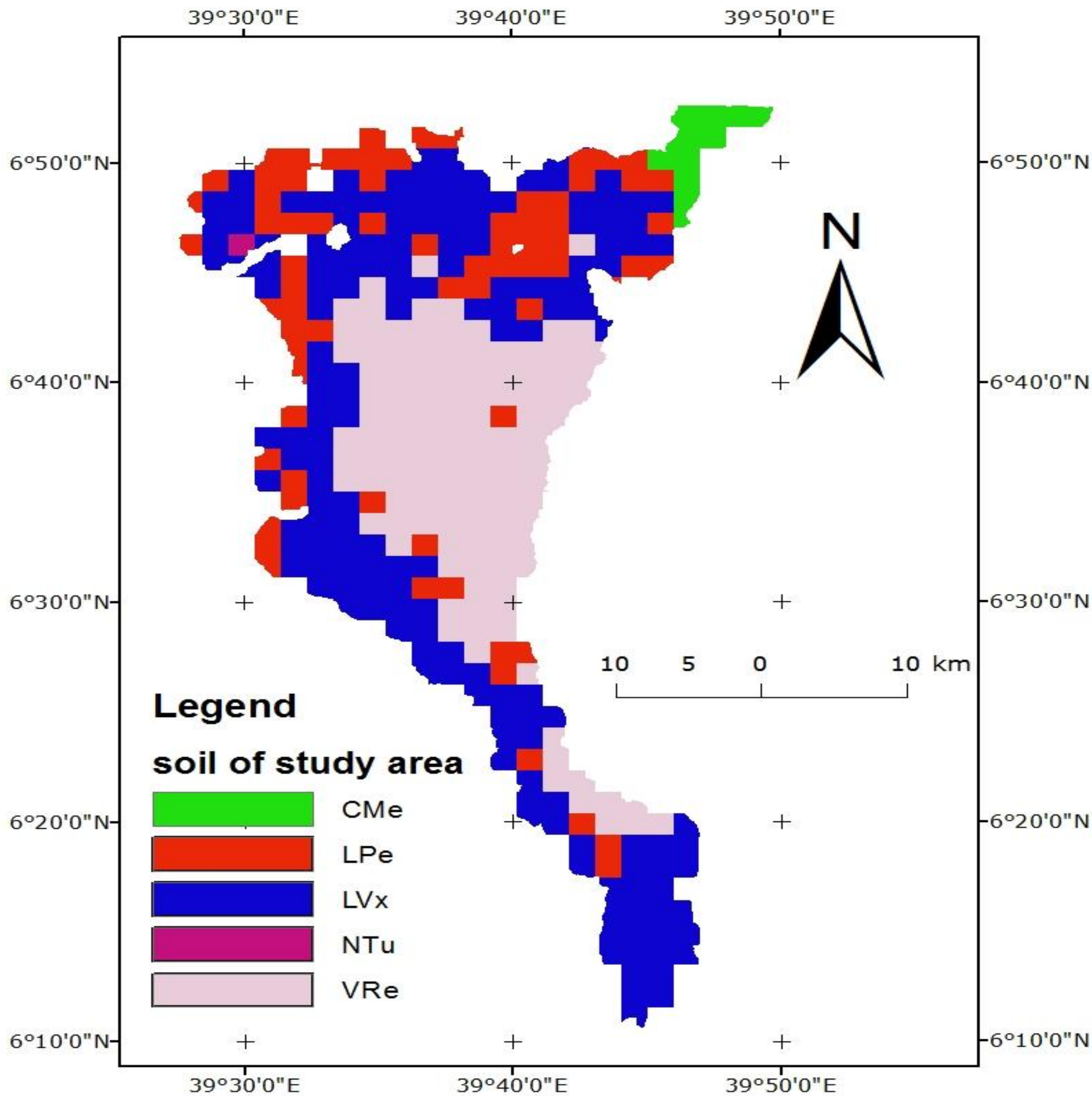


Figure 3.6: soil types of the study area (Source: Computed from Data from MoWIE))

3.1.6: LAND USE LAND COVER

By definition, land use refers to the modifications made on land by humans for the purpose of obtaining outputs in terms of products or benefits. On the other hand, land cover is the observed physical cover on the earth's surface as seen on the ground which includes vegetation (natural or planted), human constructions, water, ice, bare land and non-vegetated surfaces (Lesschen et al., 2005).The main land covers in the catchment are mixed high forest and range brush land. alfalfa, forest deciduous and agricultural others land use land cover.(See Figure 3.7) gives the complete overview of the land use land cover in the catchment (appendix table 2 lulc full name).

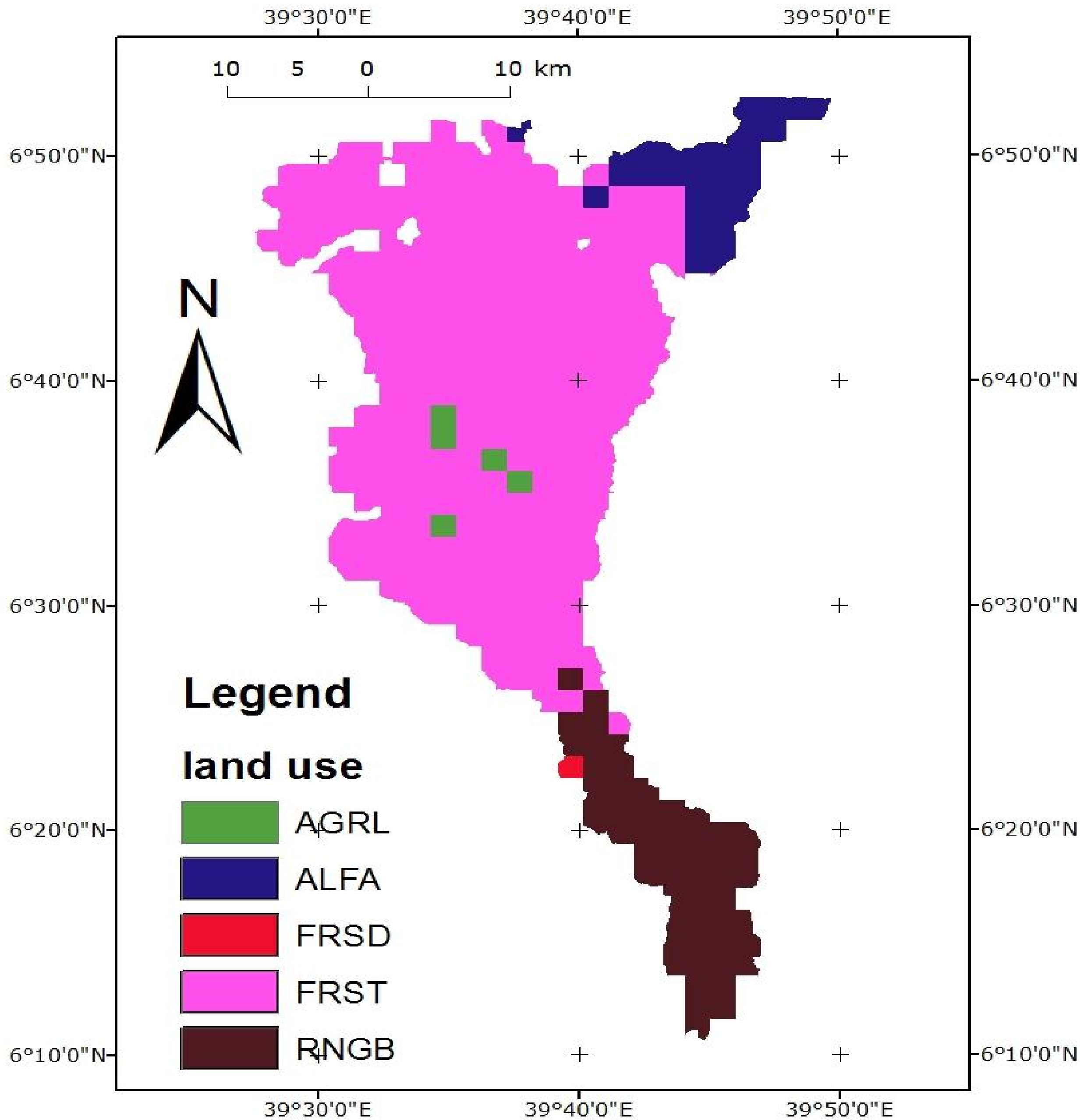


Figure 3.7: land cover of the study area (Computed Data from MoWIE,2014)

3.2: Data Sources

3.2.1: Meteorological data

Meteorological data was required for two purposes in this study. First the data was used as input to the SWAT model in hydrological model development. Second the data was used for downscaling the GCM data using Statistical Downscaling Model (SDSM).Based on these objectives, meteorological data was collected during the field survey from the Ethiopian National Meteorological Agency (NMSA) in Addis Ababa and Bale Robe office.

There is spatial and temporal variation of rainfall in the study area. The two main rainfall season which accounts around 70-86% of the annual rainfall are from April to Jun and September to November. Small rains also occur sporadically during July. The monthly rainfall distributions of the study area indicate that March to May and September to November are the wettest month of the year which gets monthly rainfall amounts larger than 62mm to 236 mm (NMSA). (Figure 3.8) shows the Mean annual rainfall from 1986-2013

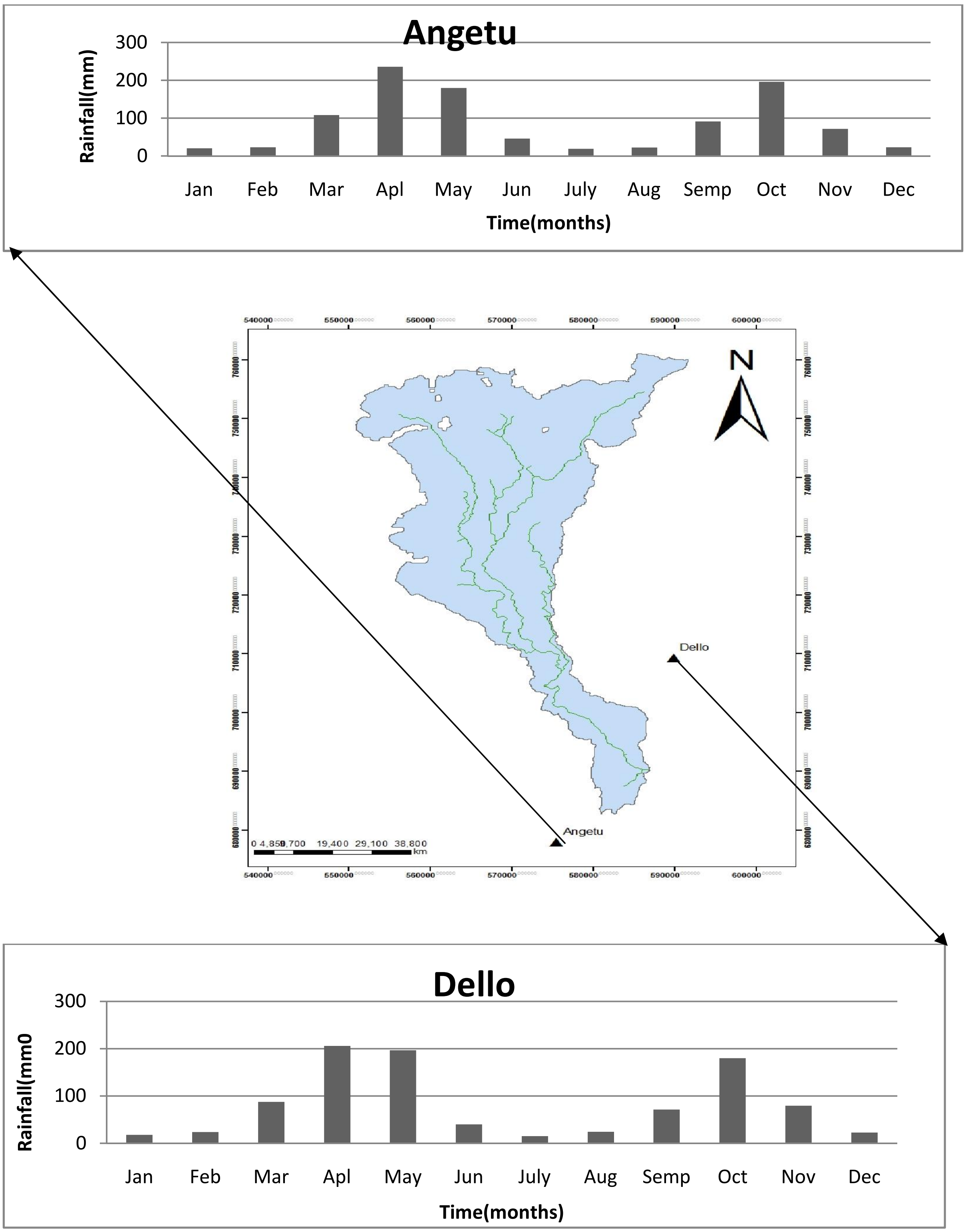


Figure 3.8: Mean monthly rainfall distribution (1986-2013) for stations in study area and location of meteorological station.(Computed from Data from NMAS)

The number of meteorological variables collected varies from station to station depending on the class of the stations that are grouped into three. The first group of stations contains only rainfall data. The second group includes maximum and minimum temperature in addition to rainfall data. There are also stations which contain variables like humidity, sunshine hours, and wind speed in addition to rainfall, maximum temperature and minimum temperature.(Table 3.1:) shows List of station name, location and meteorological variables

Table 3.1: List of station name, location and meteorological variables (Source: NMAS)

No	Station Name	Latitude (degree)	Longitude (degree)	Rainfall	Temp Max	Temp Min	Relative humidity	Wind speed	Sunshine hours
1	Dello	6.4167	39.8333	yes	yes	yes	yes	yes	yes
2	Negele	5.4167	39.5667	yes	yes	yes	yes	yes	yes
3	Angetu	6.1333	39.7	yes	yes	yes	No	No	No
4	Melka Amena	5.87	39.67	yes	No	No	No	No	No

The length of data collected also varies greatly from station to station. There are few stations which have long continuous records. The only station which has data for more than 25 years in the study area is Dello meteorological station for rainfall, maximum temperature and minimum temperature. For deriving statistical relationships between the predictand and predictor long period of records are required. Hence downscaling experiments have been executed based on Dello Mena meteorological data which fulfill all input requirements for SDSM.

3.2.2: Hydrological data

The stream flow of Welmel River was required for calibrating and validating the model. There are one main gauging station (Welmel at Melka Amena) inside the catchment which have continuous record for a relatively long period and therefore daily stream flow data (1999-2014) for these stations were collected during the field work from the Hydrology Department of Ministry of Water resources.

3.2.3: Spatial Data

Spatial data inputs for the models employed in this study such as land suse data including tabular and spatial land use information, digital elevation data soil data were gained from MoWIE of Ethiopia. The catchment was divided into different sub basins where the sub basin further divided in elevation and vegetation zones. Based on this, a digital elevation model of the catchment was prepared using Shuttle Radar Topography Mission (SRTM) with resolution of 30 m and the DEM was processed using DEM hydro processing to extract drainage area, drainage network and to divide the area into different sub basins and elevation zones.

3.2.4: Climate scenario data

Climate scenario data is required to quantify the relative change of climatic variables between the current and future time horizon which in turn is used as input to hydrological model for assessment of impacts on surface water. The climate scenario data used for statistical downscaling model (SDSM)was obtained from the Canadian Institute for climate studies website for model output of HadCM3. The predictor variables (see Table 3.2) are supplied on a grid by grid basis so that the data was downloaded from the nearest grid box i.e 11^{o}N to 33^{o}E of the study area.

3.2.5: Models and Other Materials

Arc Map 10.1, (used for grid map preparation), SWAT Extension2012 (used for water balance simulation),swat-cup(model calibration and validation) and SDSM V4.2.9 (used for downscaling large scale predictors to local scale predictands) were employed in this study.

3.3: Methods

During the estimation of the water balance components of the study area and assessment of climate change on water availability on the area, the following basic steps were followed.

3.3.1: FILLING MISSED DATA AND CHECKING DATA CONSISTENCY

Data was checked if there was missed data. The missed daily precipitation data were interpolated from the corresponding data available from nearby stations using normal ratio method. This approach enabled an estimation of missing rainfall data by weighting the observation at N gauges by their respective annual normal rainfall using the following equation (Singh, 1994).

$$P_x = \frac{N_x}{M}\left[\left[\frac{P_1}{N_1} + \frac{P_2}{N_2} + \frac{P_3}{N_3} + \cdots + \frac{P_m}{N_m}\right]\right] ------------------------ Eqn3.1$$

Where: Px= Daily precipitation of the target station. Nx= Average normal annual precipitation value for station X. $N1$, $N2$, $N3$…….. Nm= Average normal annual precipitation at the adjacent stations. $P1$,$P2$,$P3$, …...,Pm= Daily storm precipitation at the adjacent stations. m= is the number of stations sites.

The same procedure was applied for the estimation of the missed data of temperature. Whereas the stream flow is not missed data from 1999-2014 i.e. from recording station start or gage established. To check the data consistency of rainfall values from the rain gauge stations, double mass curve method was adopted to correct and adjust the reported rainfall values. Hence, the result indicated as the data are consistent (See Appendix Figure1).

3.3.2: ESTIMATION OF POTENTIAL EVAPOTRANSPIRATION

The model requires potential evapotranspiration as input. The evapotranspiration values are long-term monthly averages [SMHI, 2006]. There are a number of methods to estimate evapotranspiration. The methods vary based on climatic variables required for calculation. The temperature-based method uses only air temperature and sometimes day length; the radiation-based method uses net radiation and air temperature and some other formula like Penman requires a combination of the above including net radiation, air temperature, wind speed, and relative humidity. The FAO Penman-Monteith method is recommended as the sole ETo method for determining reference evapotranspiration when the standard meteorological variables including air temperature, relative humidity and sunshine hours are available (Allen et al., 1998).

$$\mathrm{ET_O} = \frac{0.48\Delta(R_n - G) + \gamma\frac{900}{T+273}U_2(e_s - e_n)}{\Delta + \gamma(1 + 0.34U_2)} \text{ ---------------------- Eqn3.2}$$

Where,

ETo= reference evapotranspiration (mm day-1)

R_n= net radiation at the crop surface (MJ m-2day-1)

G = soil heat flux density (MJ m-2day-1)

T = air temperature at 2 m height (°C)

u_2= wind speed at 2 m height (m s-1)

e_s= saturation vapour pressure (kPa)

e_a= actual vapour pressure (kPa)

e_s- e_n= saturation vapour pressure deficit (kPa)

Δ= slope vapour pressure curve (kPa °C-1)

γ = psychrometric constant (kPa °C-1)

Potential evapotranspiration for the study area was computed by FAO Penman-Monteith method for Dello station which contains the required meteorological variables.

The long term potential evapotranspiration from 1986-2013 was computed for the station to be used as input for the hydrological model.

3.3.3: Thiessen Polygon Map Preparation

To use the stations climatic data to the watershed modeling process in SWAT, a thiessen polygon grid map of precipitation was developed using Dello and Angetu meteorological stations. These stations were selected based on data availability and proximity to the Welmel watershed. Both stations are located outside but around the watershed. This map was prepared in the ArcGIS software to determine how much part of the watershed is covered by each of the meteorological stations (See Figure 3.9). The thiessen polygon method clearly identifies areal weight coverage of each meteorological station.

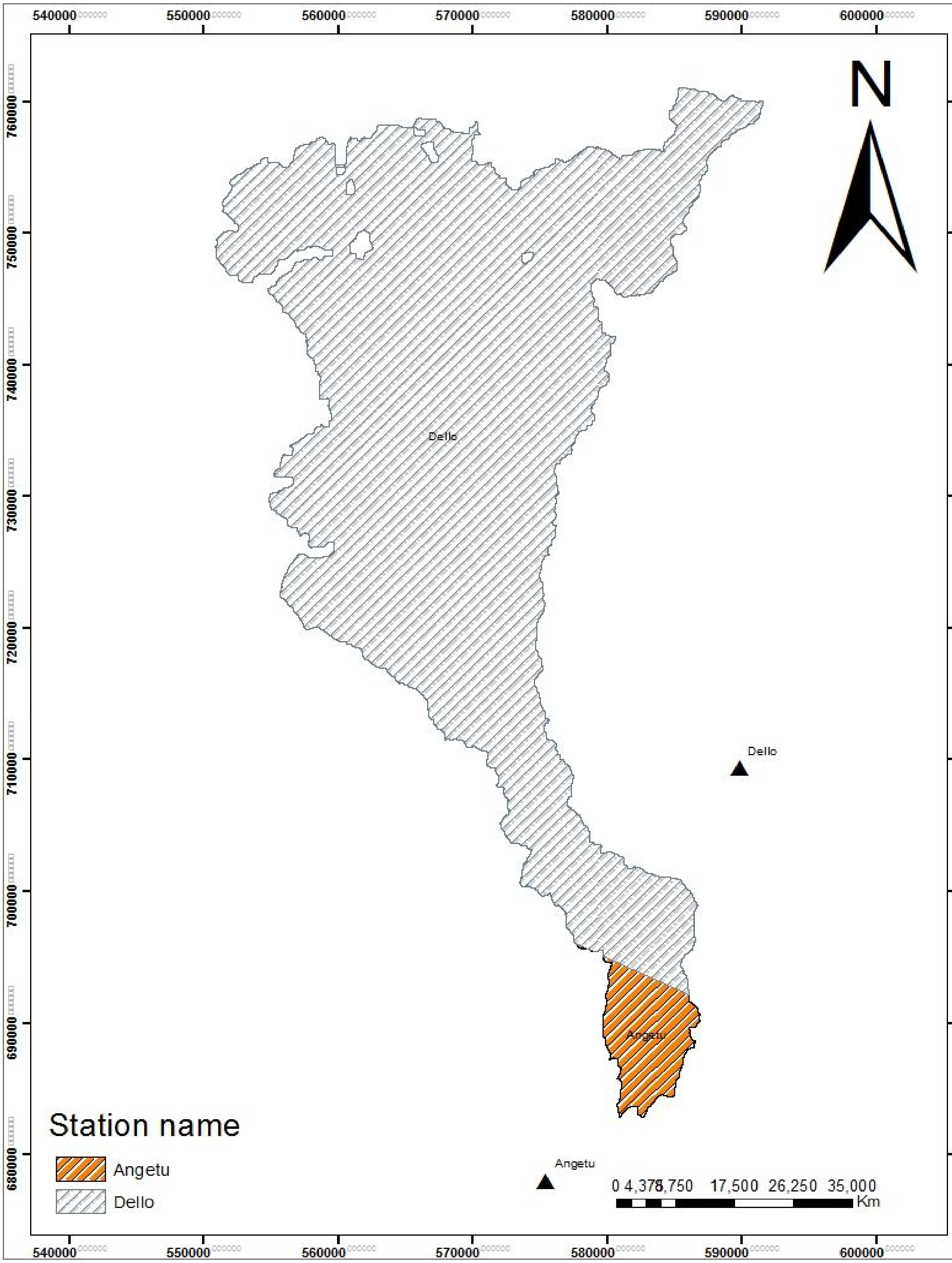


Figure 3.9: Grid Map of Meteorological Stations Thiessen Polygon

Accordingly, the areal coverage of Angetu meteorological station is 4.7% and Dallo 95.3% respectively. That means all almost the watershed falls into Dallo station.This areal classification helps to capture the grids for daily precipitation and evapotranspiration during the modeling process by SWAT. There is no others station which is found in the watershed, that is why proximity station is prefered.

3.4: SWAT- MODEL / BASIC CONCEPTS

The SWAT-hydrological compartments in a watershed consist of a land phase and a water-routing phase. The land phase of the hydrologic cycle controls the amount of water, sediment and pesticide loadings to the main channel in each sub-basin, whereas the routing phase of the hydrologic cycle shows the movement of water, sediment, nutrients, etc., through the channel network of the water of the watershed and then to the outlet (Neitsch et al., 2005).

The land phase of the hydrologic cycle is described by the transient water balance equation applied to water movement through the soil, namely:

$$SW_t = SW_o + \sum_{i=1}^{t}(R_{day,i} - Q_{sur,i} - E_{act,i} - W_{seep,i} - Q_{lat,i} - - - - - - - - - - - - Eqn3.3$$

Where:

SWt, final soil water content after t days (mm water),

SW_0, initial soil water content (mm water),

R_{day}, amount of precipitation on day i(mm water),

Qsurf, amount of surface runoff on day i(mm water),

Ea, amount of evapotranspiration on day i(mm water),

Wseep, amount of percolation and by pass flow exiting the soil profile bottom on day i(mm water),

Qgw, amount of return flow on day i(mm water)

t, time (days).

Surface runoff occurs, whenever the rate of water application to the ground surface exceeds the rate of infiltration, i.e. it is the excess water that cannot anymore infiltrate into the ground. Because of this process, the correct estimation of the infiltration is crucial for the subsequent evaluation of the surface runoff.

SWAT provides two infiltration methods for estimating the surface runoff volume component from HRUs, namely, the SCS-curve number (CN) method (SCS, 1972) or the Green & Ampt infiltration method (Green and Ampt, 1911). Whereas the CN-method uses daily rainfall rates, the Green & Ampt technique requires smaller time-steps to properly simulate the infiltration process. This discards the use of the latter method in the present study.

Here the surface runoff is modeled in SWAT using the SCS curve number method, i.e.

$$Q_{surf} = \frac{(R_{day} - I_a)^2}{R_{day} - I_a + S} ------------------------------ Eqn 3.4$$

Where:

Q_{surf}, accumulated runoff or rainfall excess (mm H20),

R_{day}, rainfall depth for the day (mm H20),

I_a, initial abstractions which includes surface storage, interception and infiltration,

Prior to runoff (mm H20), and which is usually taken as equal equal 0.2S, with

S ,retention parameter (mm H20).

The retention parameter S is defined by:

$$S = 25.4\left(\frac{1000}{CN} - 10\right) ---------------------------- Eqn 3.5$$

Where CN is the SCS-curve number, which ranges from 0 to 100, depending on the soil permeability, land use and the antecedent soil water conditions.

3.4.1: Preparation SWAT-model input

The model input requirements for the SWAT model are daily rainfall, temperature, and catchment characteristics of the area as shown in (Figure 3:10). SWAT-model input data is usually prepared in GIS- environment to alleviate the representation of the distributional geographic features of the watershed to be modeled. For this purpose, the Arc SWAT-GIS-software is available, which allows a relatively comfortable incorporation of all relevant hydrological components of the watershed. Among these, the most important ones are the watershed delineation using a digital elevation model (DEM), the soil and land use, the stream network, climate data and, last but not least, stream flow observations, which are the ultimate calibration target.

3.4.2:HadCM3/GCM Model Application

The main concern of this research is to estimate the impact of climate change on the local water availability in the watershed using climate data sets available from HadCM3 GCM output. In order to estimate the impact of climate change on water availability, a time series data at present and future scenarios were used. Observed data were collected from secondary data sources and based on boundary condition, predictor data from GCM outputs were downscaled using Statistical Downscaling Model (SDSM) for SRES emission scenarios (IPCC, 2013). In this study, all GCM simulations were driven from recent HadCM3 global coupled climate model simulations

3.4.3: General Approaches of the Study

In order to effectively implement the study, structural skeleton of the approach (input/output relationships) is likely shown in (Figure 3.10) below. It was designed to show how the parameters were interlinked each other in the flow of the system for estimating water resource and the climate change impact on water resources availability.

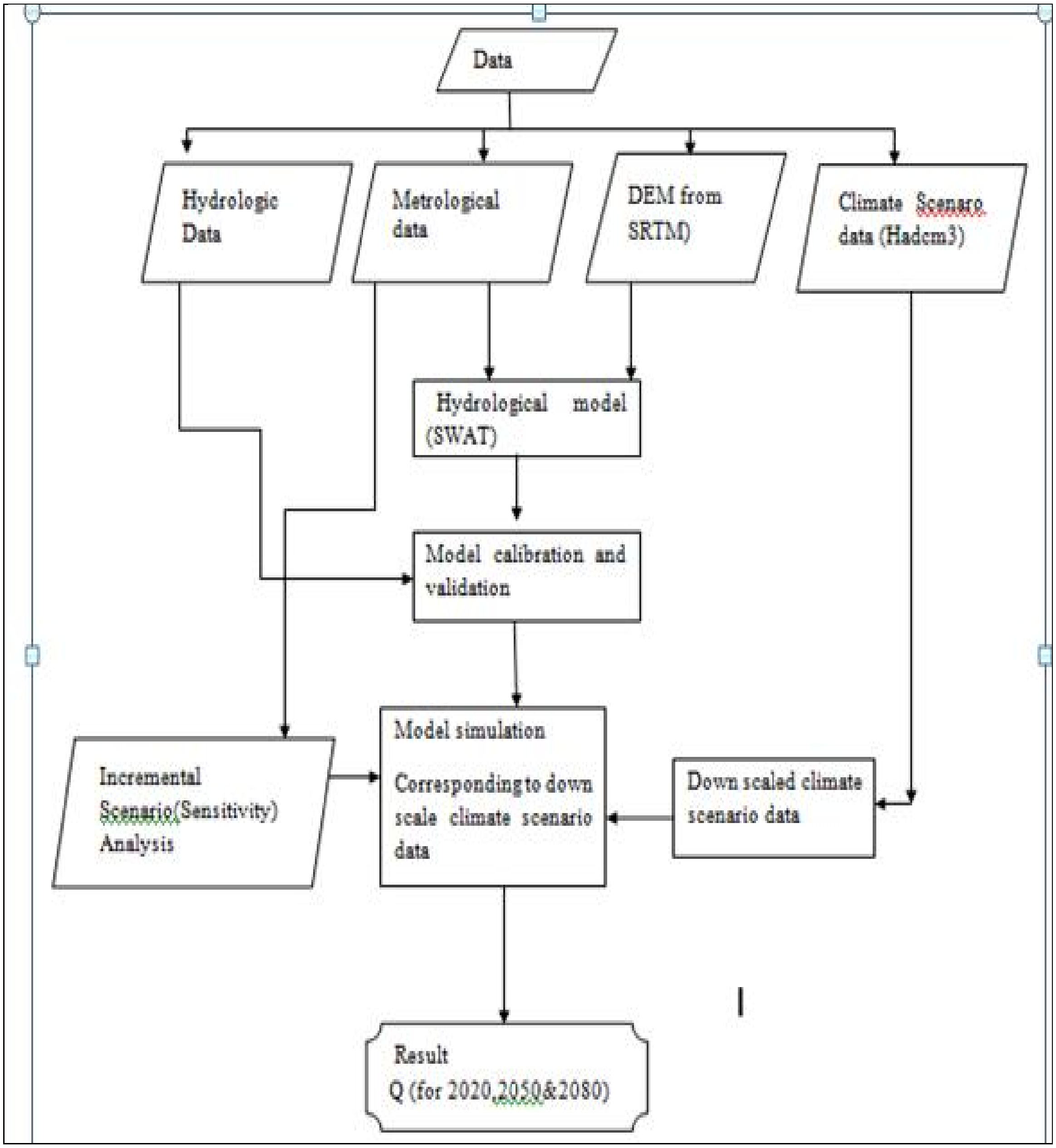


Figure 3.100: conceptual framework

3.4.4: SDSM MODEL INPUT DATA AND DOWNSCALING

The A2a and B2a SRES emission scenarios were selected for this study assuming the basin would experience such emission and socio economic scenarios in the future. In A2a and B2a experiments, A2 and B2 stands for medium to low and medium to high emission scenarios respectively. Letter 'a' refers to a different initial point of climate solution for ensemble members along the reference period.

These scenarios were downloaded from the Canadian Institute for Climate Studies (CICS) website http://www.cics.uvic.ca/scenarios/sdsm/select.cgi. Even though there was a possibility of selecting predictors from different available GCMs like HadCM3 and CGCM1, only the HadCM3 GCM has grid boxes representing the study area. CGCM1 model currently has not have predictor files for Africa Window but only for the North American Window. Hence, the data files downloaded were only for the HadCM3 model. The predictor variables of HadCM3 are provided on a grid box by grid box basis of size 2.5^{o} latitude x 3.75^{o} longitude. As the study area falls in between $6^{o}10$'N to $6^{o}60$'N latitude and $39^{o}24$'E to $39^{o}50$'E longitude, the nearest grid box for the HadCM3 model, which represents the study area was used. This box is represented by latitudinal box number of X=11 and longitudinal box number of Y=33 as shown in (Figure 3.11).The grid box data downloaded consist of three directories:

NCEP_1961-2001: this contains 41 years of 26 daily observed predictor data, derived from the NCEP reanalysis, normalized over the complete 1961-1990 period.

H3A2a_1961-2099: this contains 139 years of 26 daily GCM predictor data, derived from the HadCM3 A2a experiment, normalized over the 1961-1990 period.

H3B2a_1961-2099: this contains 139 years of 26 daily GCM predictor data, derived from the HadCM3 B2a experiment, normalized over the 1961-1990 period.

NCEP data are re-analysis data sets from the National Centre for Environmental Prediction, which were re–gridded to conform to the grid system of HadCM3. These were the data used in the model calibration and both the NCEP and HadCM3 data have daily predictor values of twenty six parameters as shown in (Table 3.2), which were used in the determination of the predictands. According to Wilby and Dawson (2004), the predictors selected with regard to each predictand should be physically and conceptually sensible, strongly and consistently correlated with it, and accurately modeled by GCMs.

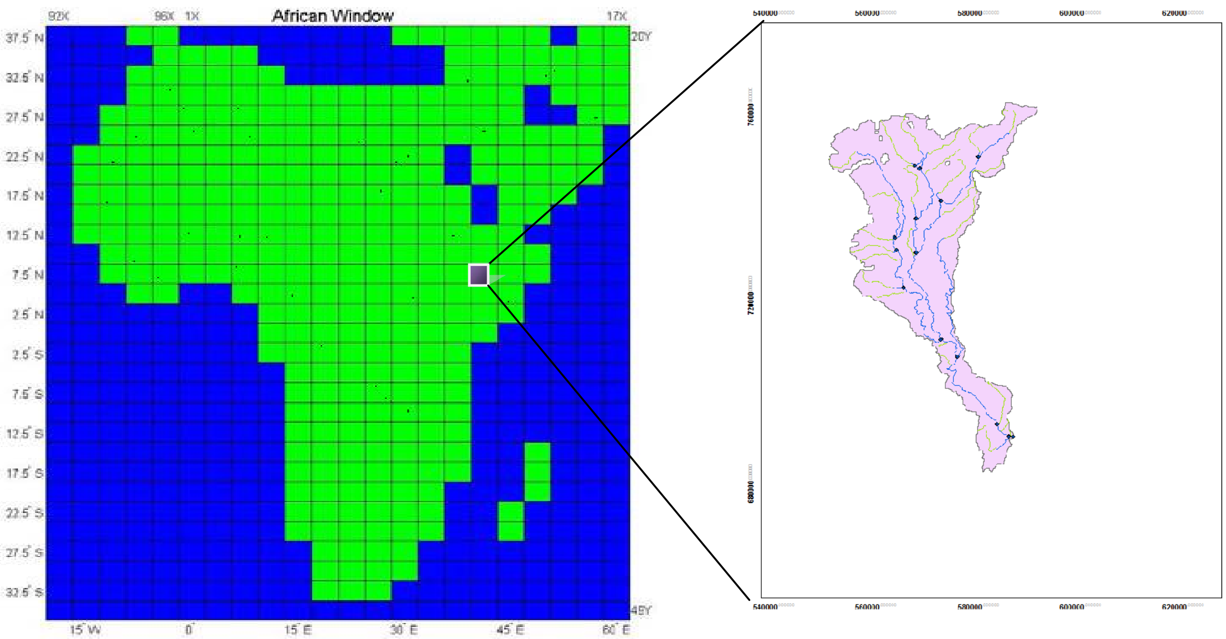


Figure 3.11: Africa Window from Which the Study Area Grid Box is Located

Observed daily data of precipitation, minimum and maximum temperature of the period from 1986 to 2013, collected from four stations namely Dello, Nagele, Angetu and Malka Amana stations, but Dello stations were used for downscaling global predictor to local scale. Because all stations a r e found in one grid cell of GCM/HadCM3 of 2.5° latitude by 3.75° longitude where the study area is located. Historical data of Precipitation, maximum and minimum temperature are available for the period (1986-2013) were used as a base line.(See Figure 3.11) shows the grid box predictors downscaled. The observed meteorological time series data of 1986 - 2000 were used for calibration and the data from 2001 - 2013 were used for validation of the Statistical Downscaling Model.

3.4.5: Statistical Downscaling Model (SDSM)

The Statistical Downscaling Model Version 4.2.9 was used for downscaling the large scale climate (Predictors) data to the local scale (predictands) data. SDSM is advantageous as it is easy to implement, and generation of the downscaled values involves observed historic daily data. The latter advantage ensures the maintenance of local spatial and temporal variability in generating realistic time series data. SDSM have additional tasks of data quality control and transformation, predictor variable pre-screening, automatic model calibration, basic diagnostic testing, statistical analysis and graphing of climate data. In the downscaling process, shown in Figure 3.10, with the bold boxes represents the main discrete processes of the SDSM model. The following sections discuss on the descriptions of the model processes separately (Wilby and Dawson, 2004).

One of the big advantages of SDSM, it enables the downscaling of climate change scenarios for individual sites at daily time scales and directly employs GCM output in the scenario construction processes. According to Mohammad S., 2006 SDSM is the most capable of reproducing various statistical characteristics of observed data in its downscaled results with95% confidence level, the ANN (artificial neural network) is the least capable in this respect, and the LARS-WG (long ashton research station weather generator) is in between SDSM and ANN. This means that the uncertainty associated with SDSM is small as compared to ANN and LARS-WG, because of this SDSM selected to downscaled large scale GCM output to Welmel watershad.

(I) Setting of the model parameter: For weather generation task, **Year Length** was set to the default "Calendar (366)" that allows 29 days in February every Leap years and used with observed data. For scenario generation, the year length was set to 360 since the HadCM3 has model years consisting of 360 days.

The **start and end date** for all input data were arranged as needed. **Missing Data Identifier**, the code assigned to identify missing data in all inputs, was set to default value **-999**. Whenever SDSM encounters this code the value will be skipped (e.g., during model **Allow Negative Values:** The default allows simulation of negative values by unconditional processes in the downscaling model (e.g., for temperature). Conditional processes (example, rainfall amounts) are unaffected by this button calibration, or calculation of summary statistics) but can generate a value during scenario generation.

For some conditional variables it is necessary to specify an event threshold. For example, when calibrating daily precipitation models, the parameter was set to 0.03 mm/day to treat trace rain days as dry days and **0** for temperature. **Default File Directory** that allows to select a default directory that is accessed by all screens when first searching for files.

II. Quality Control and Data Transformation: To come up with good model output, climatic input data were checked for missing and unrealistic values. The quality control function of SDSM also provides the minimum, maximum, and mean of the input data. All the input data were checked for missing data codes and data errors before the calibration process. Data transformation was not used in this model.

III. Screening the Downscaling Predictor Variables: The central concept behind any statistical downscaling method is the recognition of empirical relationships between the gridded predictors and single site Predictand. This is the most challenging part of the work due to the temporal and spatial variation of the explanatory power of each predictor (Wilby and Dawson, 2004). The selection was done at most care as the behavior of the climate scenario completely depends on the type of the predictors selected. Annual analysis period was used which provides the predictor-predictand relationship all along the months of the year. The significance level, which tests the predictor and predictand significance relationship, was set to be equal to the default value ($p<0.05$). Moreover, the process type that identifies the presence of an intermediate process in the predictor-predictand relationship was defined.

For daily temperature, since it is not regulated by an intermediate process, the unconditional process was selected. However, the conditional process was selected for daily precipitation because of its dependence on other intermediate process like on the occurrences of humidity, cloud cover, and/or wet-days. Several analyses were made till best predictor predictand correlations were found. Out of the group selected from the twenty six predictors , those predictors which have high explained variance were selected. The partial correlation analysis was done for the selected predictors to see the level of correlation with each other. This enables to drop the predictor which has very highly correlation with another predictor. Finally the potential usefulness of downscaling relationship was checked by scatter plotting.

Table 3.2: List of NCEP Predictor Variables (Wilby and De Smedt, 2004)

No.	Predictor variable	Predictor description	No.	Predictor variable	Predictor description
1	Mslpaf	Meansealevel pressure	14	p5zhaf	500 hpa divergence
2	p_faf	Surface air flow strength	15	p8_faf	850 hpa airflow strength
3	p_uaf	surface zonal velocity	16	p8_uaf	850 hpa zonal velocity
4	p_vaf	surface meridional velocity	17	p8_vaf	850 hpa meridional velocity
5	p_zaf	surface vorticity	18	p8_zaf	850 hpa vorticity
6	p_thaf	surfacewind direction	19	p850af	850 hpa geopotential height
7	p_zhaf	Surface divergence	20	p8thaf	850 hpa wind direction
8	p5_faf	500hpa air flowstrength	21	p8zhaf	850 hpa divergence
9	p5_uaf	500hpa zonal velocity	22	p500af	Relative humidity at 500 hpa
10	p5_vaf	500 hpa meridional velocity	23	p850af	Relative humidity at 850 hpa
11	p5_zaf	500 hpa vorticity	24	rhumaf	Near surface relative humidity
12	p500af	500 hpa geopotential height	25	shumaf	Surface specific humidity
13	p5thaf	500hpa wind direction	26	tempaf	Mean temperature at 2 m

IV. Selection of Potential Predictor Variable: This selection process involved the identification of appropriate predictor variables that have strong correlation with the predictand variable. Next use these empirical predictor-predictand relationships of the observed climate to downscale ensembles of the same local variables for the present and future climate. This is based on the assumption that the predictor-predictand relationships under the current condition will remain valid under future climate conditions too. The most relevant predictor variables were selected for each predictand through linear correlation analysis, partial correlation analysis and scatter plots between the predictors and the predictand variables Accordingly, the best correlated potential predictor variables were selected for minimum temperature, maximum temperature and precipitation for Dello meteorological stations as listed in (Table 3.3)

Table 3.3: Large scale predictor variables selected for SDSM for Delo metrological satiations

Predictand	Predictor	Symbol
Minimum temperature	Surface divergence 500hpa geopotential height 500 hpa divergence	p_zhaf p500af p5zhaf
Maximum temperature	mean sea level pressure 500 hpa geopotential height Relative humidity at 850 hpa	Mslpaf p500af p850af
Precipitation	500hpa geopotential height mean sea level pressure	p500af mslpaf

Table 3.4: Correlation matrix of the predictors

predictor	Partial r	P value
mslpaf	-0.111	0.000
p500af	-0.055	0.000
p850af	0.102	0.000
tempaf	0.149	0.000

Finally the scatter plot reveals that tempaf does not indicate a good relationship from the predictand (maximum temperature) and is therefore dropped from the list (See appendex Figure 2 scatterplot). Therefore the potential predictor variables for downscaling the maximum temperature become mslpaf, ncepp500, and p850af. Similar analysis was done for the other predictands and the result is shown in Table 3.4

V. Model Calibration:

This operation is normally carried out based on the selected predictor variables that use the NCEP data base of the selected grid box. The mathematical relation between a specific predictand and the selected predictor variables is estimated and the parameters of a multiple linear regression equation were determined. Setting was done based on the SDSM manual (Wilby and Dawson, 2004). Accordingly, the temporal resolution of the downscaling model was selected by choosing the model type as monthly. In Monthly models, model parameters are estimated for each month of the year. For this study, the calibration was done for the period of 1986-2000 for all stations at a monthly model type in order to see the monthly temporal variations. The unconditional and conditional processes were selected for temperature and precipitation values respectively.

From the advance setting the model transformation was set to ’none’ for temperature and ’fourth root’ for precipitation calibration. Stochastic conditional selection and ordinary least squares optimization algorithm were set. During the calibration of temperature, the inflation variation and bias correction values were set to the default value of 12.0 and 1.0 respectively.

VI. Weather Generator and Validation:

Weather Generator task of SDSM produces synthetic current daily weather data based on inputs of the observed time series data and the multiple linear regression parameters produced during the calibration step using the present large scale NCEP predictor data. Each time-serious-data of the observed climate variable is linked to the regression model weights to generate the synthetic time series data into a serious of ensembles. The results among the ensembles differ based on the relative significance of the deterministic and stochastic components of the regression models and mainly due to the stochastic component of the downscaling.

As indicated in the SDSM manual, larger differences can be observed in precipitation ensemble members than that of temperature. Because precipitation series display more “noise” arising from local factors but local temperature variables are largely determined by regional forcing. The result of the weather generator, obtained by averaging the twenty ensemble results, was used to validate the calibrated model using independent observed data not used during the calibration procedure and the synthesized artificial weather time series data representing the present condition. During weather generation, the data series from 1986-2000 were used for the calibration and from 2001-2013 was selected for validation process for station. The whole Climate Scenario generation is shown in(Figure 3.12)

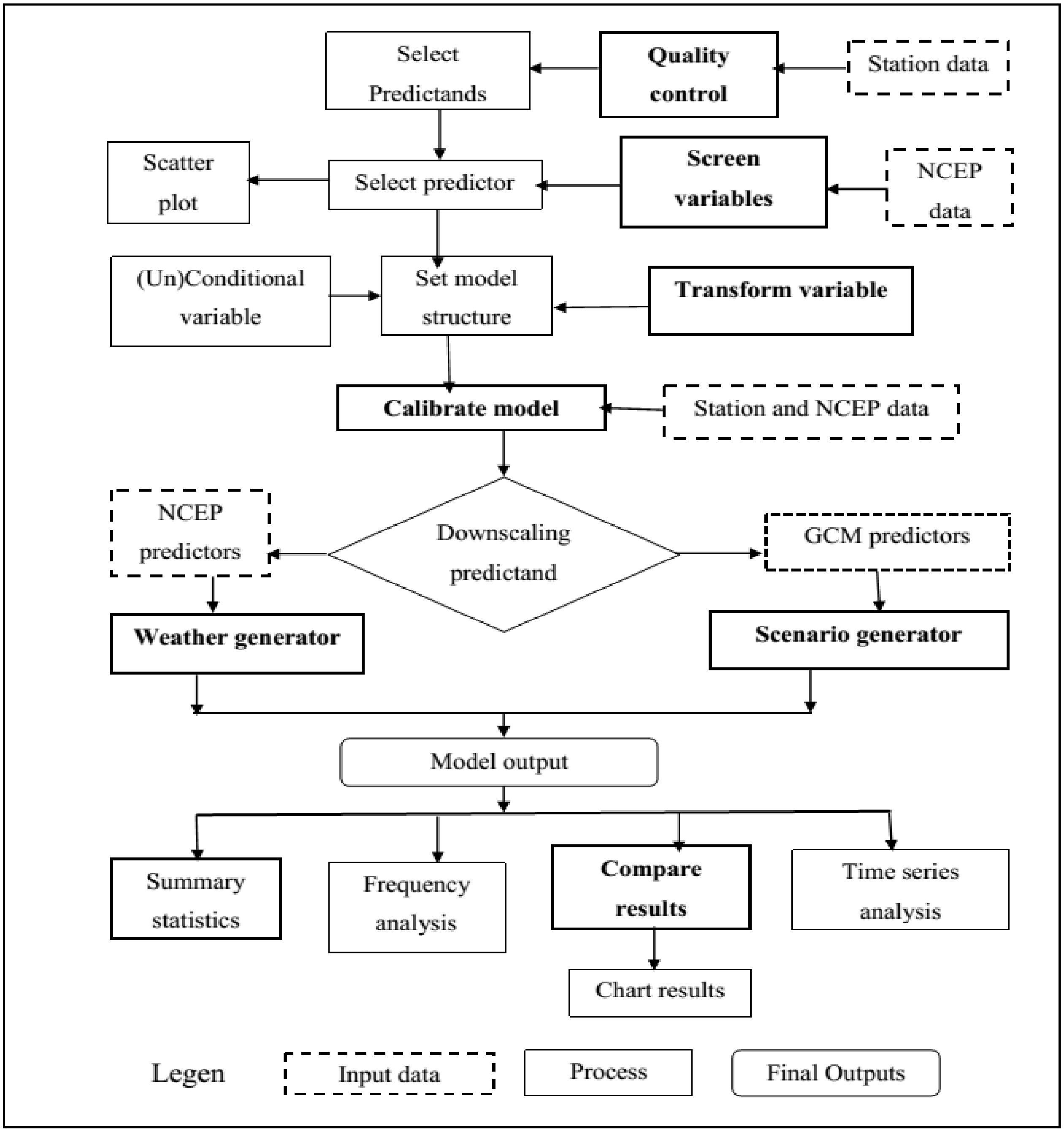


Figure 3.12: Climate Scenario generation (Dawson & Wilby, 2007)

(vii) Scenario Generator:

The scenario generation operation produces ensembles of synthetic daily weather series given the regression weight produced during the calibration process and the daily atmospheric predictor supplied by a GCM (either under the present or future greenhouse gas forcing). Twenty ensembles of synthetic daily time series were produced for the two emission scenarios (HadCM3A2a and HadCM3B2a) for a period of 139 years (1961 to 2099)(this is predictand input and SDSM predictors of model) . Finally the mean of twenty ensembles for the specified period is produced for the maximum and minimum temperature and precipitation. Precipitation downscaling is necessarily more complex than temperature because daily precipitation amounts at individual sites are relatively poorly resolved by the regional-scale predictors, and precipitation is a conditional process (i.e. both the occurrence and amount processes must be specified) (Dawson & Wilby, 2007).

3.4.6: ESTIMATION OF IMPACT OF CLIMATE CHANGE ON WATER BALANCES COMPONENTS SIMULATION.

These synthesized average out puts of the A2a and B2a emission scenario generations' data of the selected time horizons were used as input for the SWAT model during water balance components simulation. The base period water balance was simulated using the baseline observed and downscaled (A2a and B2a) precipitation and estimated evapotranspiration. From the future downscaled precipitation and estimated evapotranspiration for A2a and B2a scenarios, the time series data of three time horizons 2014 -2041 (2020s), 2042 -2069 (2050s) and 2070 – 2099 (2080s) were selected to make comparable with the baseline parameters. These values were, then, used as input for SWAT model to simulate the consecutive water balance of the watershed. The future (2020s, 2050s and 2080s) water balance components were then compared with the baseline water balance components to evaluate the impact of climate change on water availability for A2a and B2a scenarios occurred in the watershed.

3.5: SENSITIVITY ANALYSIS, CALIBRATION AND VALIDATION OF SWAT MODEL

After discharge and climate historical data were collected from the gauging station and meteorological stations respectively, different techniques were used for calibration and validation of the model. The data obtained during the first years of the data series were used for calibration and the remaining data series were used for validation.

The total period of data that was used in the model development was 15years (1999-2013). All the data for this period was used to select sensitive parameter. Then these years were divided in such a way that the data (2000-2008) was used for the calibration and the data (2009-2013) was used for validation. Calibration was done by swat-cup.

A) Sensitivity Analysis

Sensitivity analysis is a method of minimizing the number of parameters to be used in the calibration by making use of the most sensitive parameters control the behavior of the simulated process. Sensitivity is expressed by a dimensionless index, which is calculated as the ratio between the relative change of model output and the relative change of a parameter.

B) Model Performance Evaluation

Statistical measures provide quantitative estimates for the goodness of fit between observed and predicted values, and are used as indicators of the extent at which model predictions match observation (Liu and De Smedt 2004). The model performance was evaluated for both calibration and validation in different ways including visual comparison between observed and predicted parameter values or evaluation of peak flow rate and time to the peak (Gebremeskel et al, 2003).

The goodness of fit in the peak discharge and time to the peak can be evaluated by their relative absolute error and mean absolute error respectively. While other evaluation criteria, like model bias, model determination confidence, and the model efficiency, for the models were used.

1. Model Bias

Model bias is a relative mean difference between predicted and observed stream flows for a sufficiently large simulation sample, reflecting the ability of reproducing water balance. It is an important criterion for comparing whether a model is working well or not through measuring under or over prediction for a set of predictions systematically. Model bias (MB) value is given by the equation.

$$MB=\frac{\sum_{i=1}^{N} Q_{si}-Q_{oi}}{\sum_{i=1}^{N} Q_{oi}} \text{---------------------------------} Eqn3.6$$

Where MB= the model bias, Q_{si} and Q_{oi} are the simulated and observed stream flows at time step i (m^3/s) and N is the number of time steps over the simulation period. Model bias measures the systematic under or over prediction for a set of predictions. A lower MB value indicates a better fit, and the value 0.0 represents the perfect simulation of observed flow volume. Positive and negative values indicate over and under predictions respectively.

2. Model Confidence

Model confidence expressed by its determination coefficient is one of the important criteria in assessment of continuous model simulation. It is calculated as the rate of the sum of the squares of the deviations of the simulated and observed discharges from the average observed discharge.

$$R^2 = \frac{\sum_{i=1}^{N}(Q_{si} - \bar{Q}_o)^2}{\sum_{i=1}^{N}(Q_{oi} - \bar{Q}_o)^2} ----------------------------- Eqn3.7$$

Where R^2= the model determination coefficient, $\bar{Q}_o$= the mean observed stream flow over the simulation period. R^2 Represents the proportion of the variance in the observed discharges that are explained by the simulated discharges. Value varies between 0 and 1, with a value close to 1 indicating a high level of model confidence.

3. Nash-Sutcliffe Efficiency

(Nash and Sutcliffe, 1970) pointed out model evaluation criteria called Nash-Sutcliffe coefficient which is used so as to describe how well discharges were simulated by the model. This efficiency criterion is commonly used for model evaluation. The equation can be described as

$$NS= 1 - \frac{\sum_{i=1}^{N}(Q_{si} - Q_o)^2}{\sum_{i=1}^{N} Q_{oi} - \bar{Q}_o{}^2} ----------------------------- Eqn3.8$$

Where NS= the Nash-Sutcliffe efficiency used for evaluating the ability of reproducing the time evolution of stream flows or discharges. The NS value can range from a negative value to 1, with 1 indicating a perfect fit between the simulated and observed hydrographs (appendex table 3).

4: RESULTS AND DISCUSSION

4.1: THE HADCM3/GCM OUTPUT FOR THE BASELINE PERIOD

The downscaling experiment was conducted for minimum temperature, maximum temperature and precipitation based on the data from meteorological station which contain observed data for the specified period and the results are discussed in section below.

4.1.1:Minimum temperature

The monthly minimum temperature downscaled for A2 and B2 scenario in the baseline period is shown in Figure 4.1

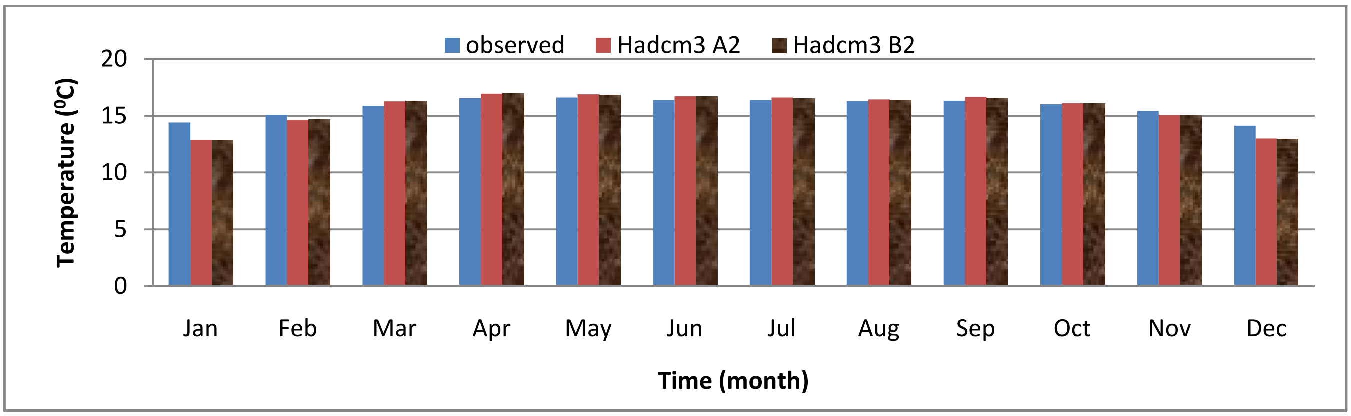


Figure 4.1: Observed and downscaled monthly mean minimum temperature for the baseline period (1986- 2013)

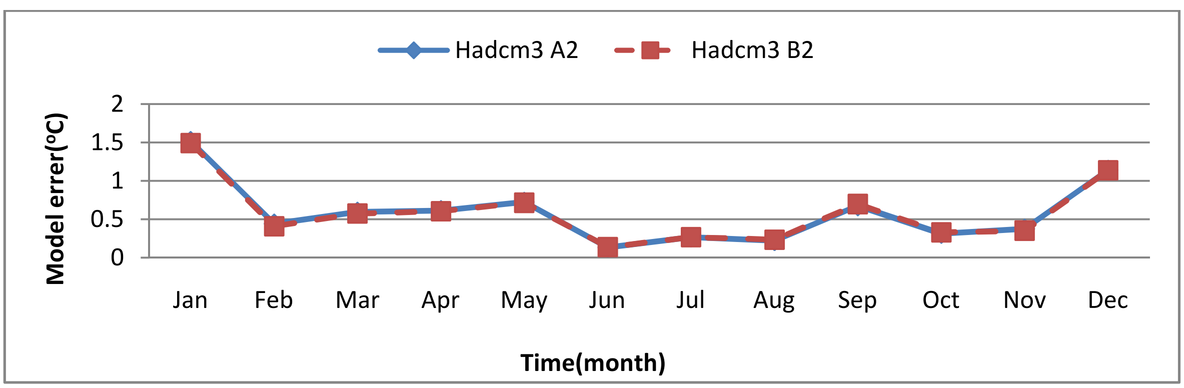


Figure 4.2: Absolute model error in estimate of monthly minimum temperature from observed period.

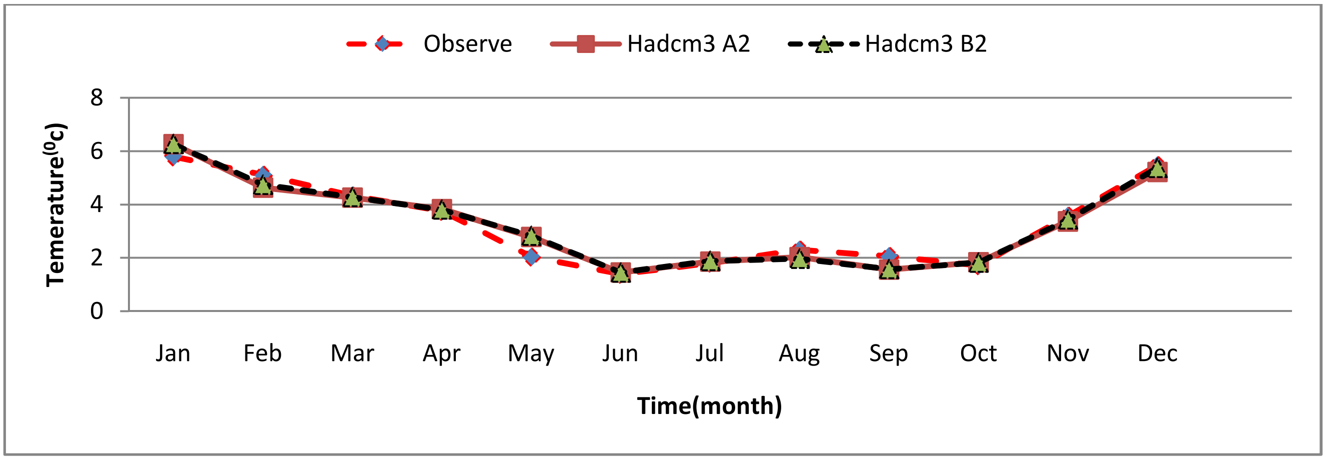


Figure 4.3: Variance of observed and downscaled monthly minimum temperature

As shown in Figure 4.2 and figure 4.3 show absolute model error and Variance of observed and downscaled respectively in estimate of monthly minimum temperature from observed period. Absolute model error is the difference of the two downscaled scenarios from observed data.

4.1.2: Maximum temperature

The monthly maximum temperature downscaled for A2 and B2 scenario in the baseline period is shown in Figure 4.4

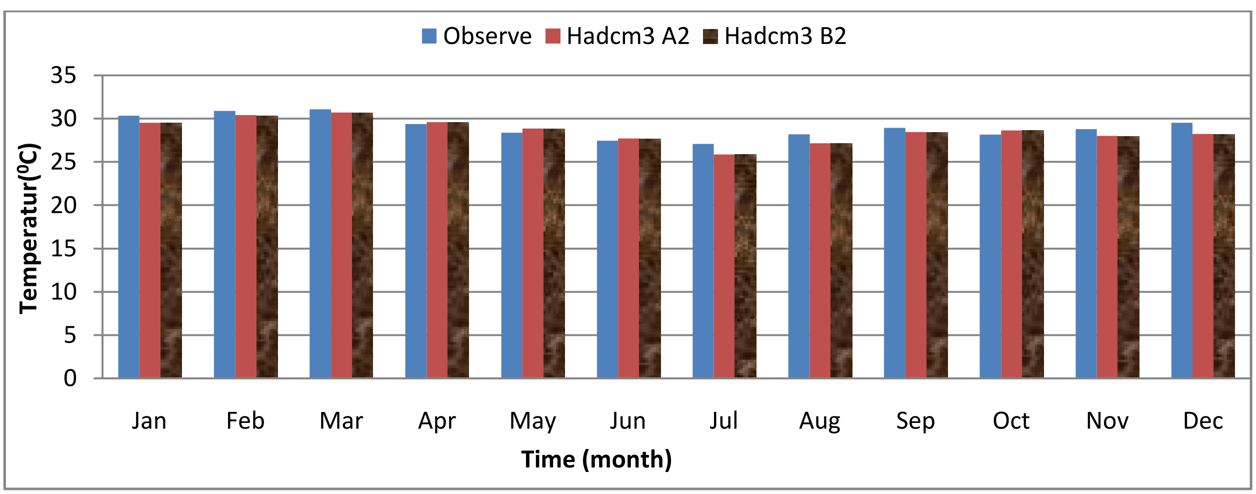


Figure 4.4: Observed and downscaled monthly mean maximum temperature for the baseline period (1986-2013)

The absolute model error in estimation of the mean maximum temperature is shown in (Figure 4.5).

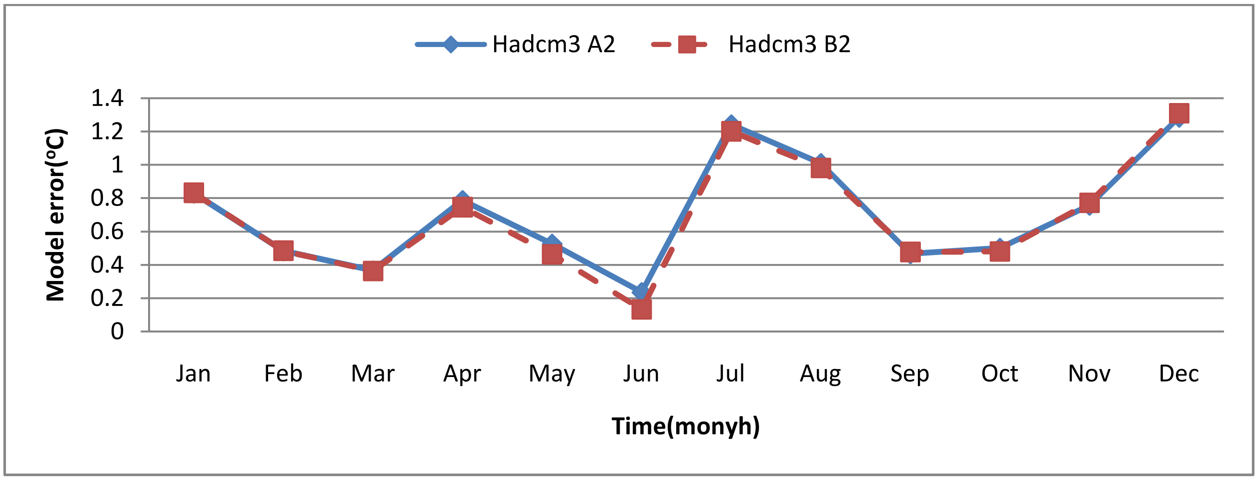


Figure 4.5: Absolute model error in estimate of monthly maximum temperature

The variability of monthly maximum temperature of observed values is well preserved in the downscaled value from January to April. From April to Aug the variance of observed value is slightly higher than the downscaled values because of uncertainty of model and less quality data but it is acceptable range as other researchers done, however variability of this is greater than others and the general trend of both observed and downscaled values shows a similar pattern.

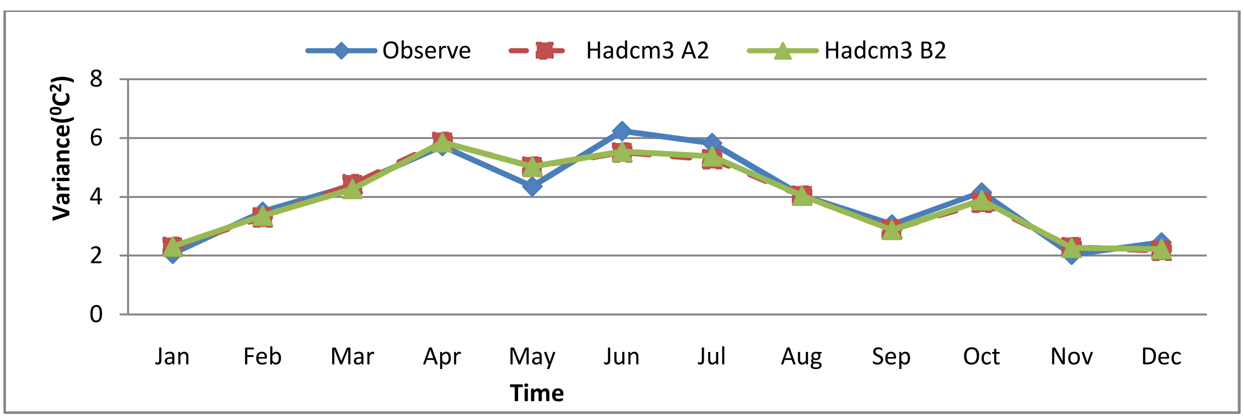


Figure 4.6 Variance of observed and downscaled monthly maximum temperature

4.1.3: PRECIPITATION

The monthly precipitation downscaled for the baseline period is shown in (Figure 4.7). The SDSM model performs in estimating the mean monthly precipitation in many months but there is a relatively large model error in rainy months like May, September and October. Variation is there in others months. The fact that precipitation downscaling is necessarily more problematic than temperature, because daily precipitation amounts at individual sites are relatively poorly resolved by regional-scale predictors.

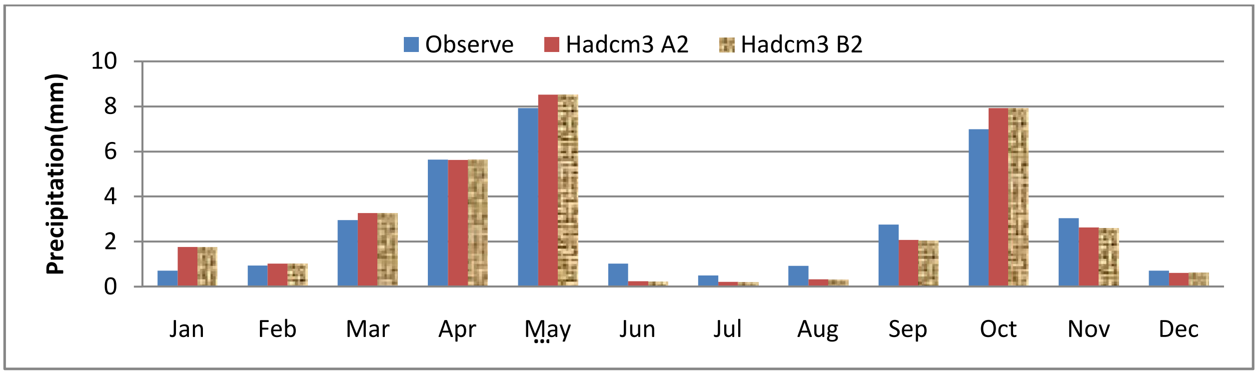


Figure 4.7:Mean daily observed and downscaled precipitation for the baseline period (1986-2013).

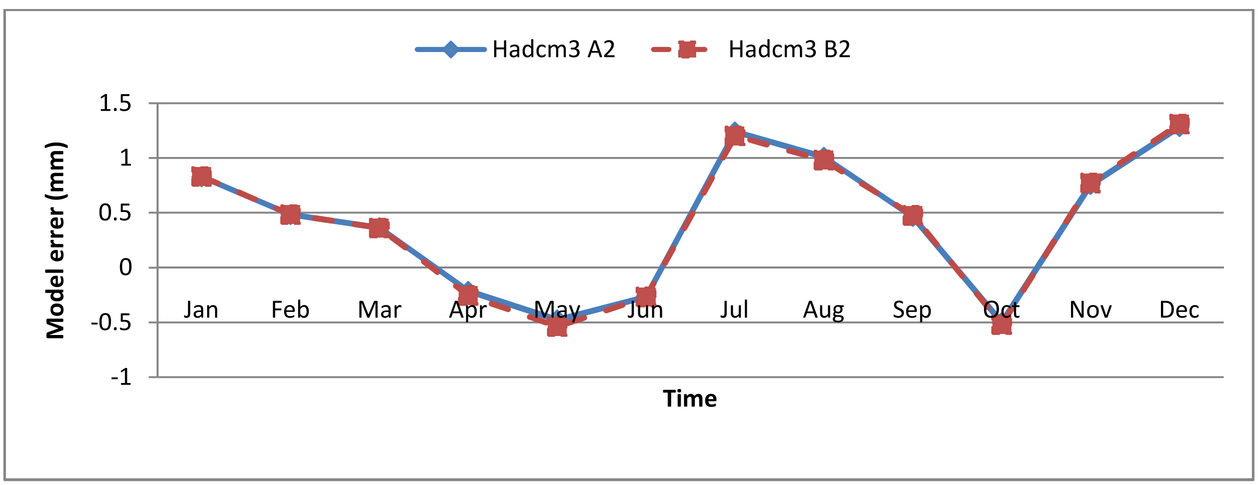


Figure 4.8: Absolute model error in estimates of the Mean daily precipitation

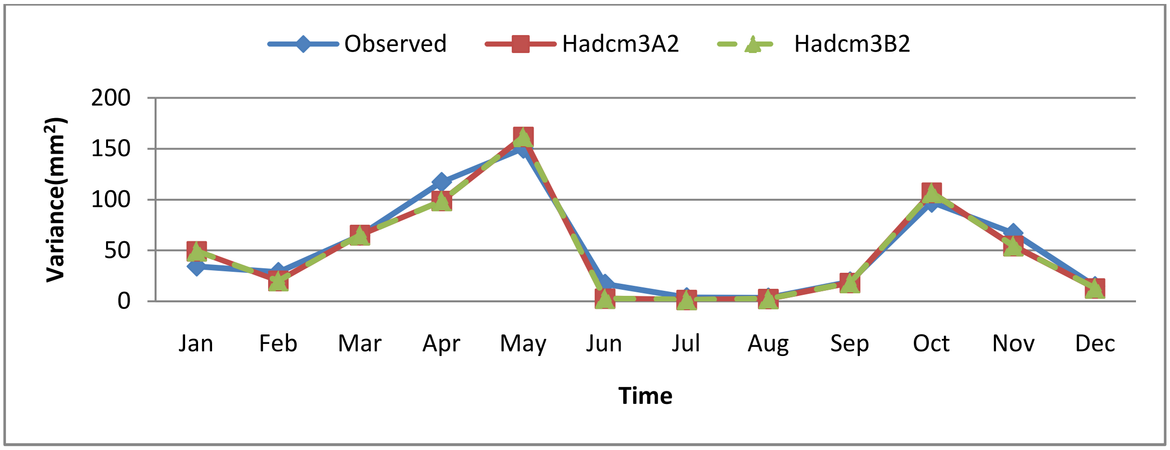


Figure 4.9: Variance of observed and downscaled monthly mean precipitation

The variability of observed and downscaled precipitation show that there is variation in months January April,June, October and November However, the variances of observed and downscaled precipitation have the same trend. Generally the variance of observed and downscaled precipitation exhibits a similar pattern i.e. an increase in variance of observed value which is also reflected in the downscaled precipitation and vice versa.(See Figure 4.9). The range is agree when related with other researchers (Abdo and Mulushewanigatu2013).

4.2: THE GCM FOR FUTURE SCENARIO

I) Minimum temperature

The downscaled minimum temperature shows an increasing trend in all future time horizons for both A2 and B2 scenarios. The average annual minimum temperature may be 0.3°C change from baseline in 2020s. In 2050s the increment will be 0.65°C and also 0.63°C for A2 and B2 scenario respectively. For the 2080s periods the average annual minimum temperature will be increased by 1.3^{0}C and 1.03°C for A2 and B2 scenario respectively.

The increment for A2 scenario is greater than B2 scenario because A2 scenario represents a medium high scenario which produces more Co_2 concentration than the B2 scenario which represents a medium low scenario. The relative change of monthly minimum temperature varies from month to month. The minimum relative change of temperature is observed in October where the minimum temperature may be expected to increased by 0.13 °C and 0.09 °C in 2080s for A2 and B2 scenario respectively where as the maximum change of temperature is observed in

January where the minimum temperature is increased by 4.25 ^{o}C and 3.3 ^{o}C for A2 and B2 scenario respectively (See Figure 4.10 and Figure 4.11).

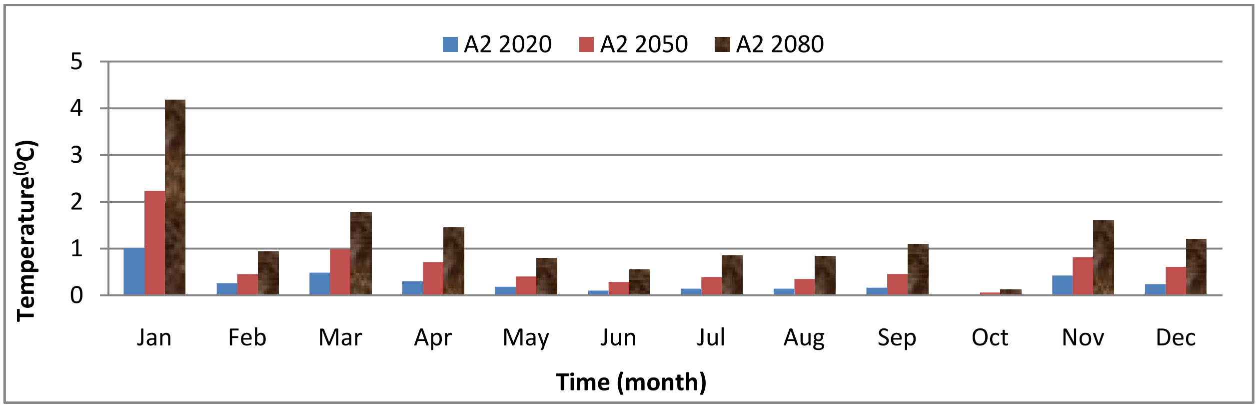


Figure 4.10: Change of downscaled monthly minimum temperature from the baseline period for HadCM3A2a

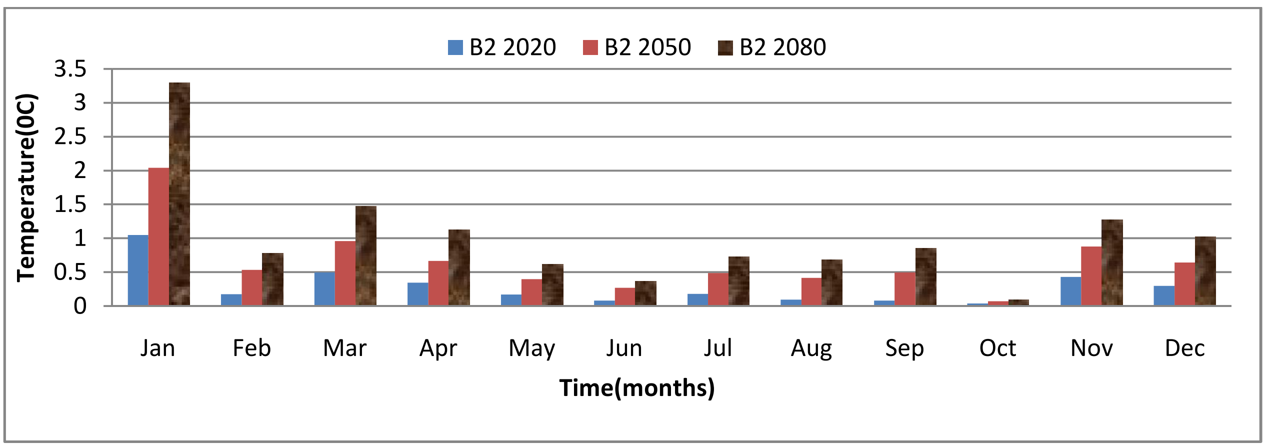


Figure 4.11: Change of downscaled monthly minimum temperature from the baseline period for HadCM3B2a

II) Maximum temperature

The downscaled maximum temperature scenario indicates that for most months there will be an increasing trend for both A2 and B2 scenario. The projected temperature in 2020s indicates that maximum temperature will rise by 0.232^{o}C. In 2050s the increment will be 0.53^{o}C and 0.53^{o}C for A2 and B2 scenario respectively. In 2080s the annual maximum temperature will be increased by 1.082^{o}C and 0.85^{o}C for A2 and B2 scenario respectively. The increment in maximum temperature is less than the minimum temperature. The relative increment of maximum temperature from the baseline period for both scenarios in future time horizon are shown in the (See Figures 4.12 and 4.13). The projected minimum and maximum temperature in all future time horizons is within the range projected by (IPCC, 2007) which indicate that the average temperature will be rises by 0.23^{o}C-4.25^{o}C towards the end of this century.

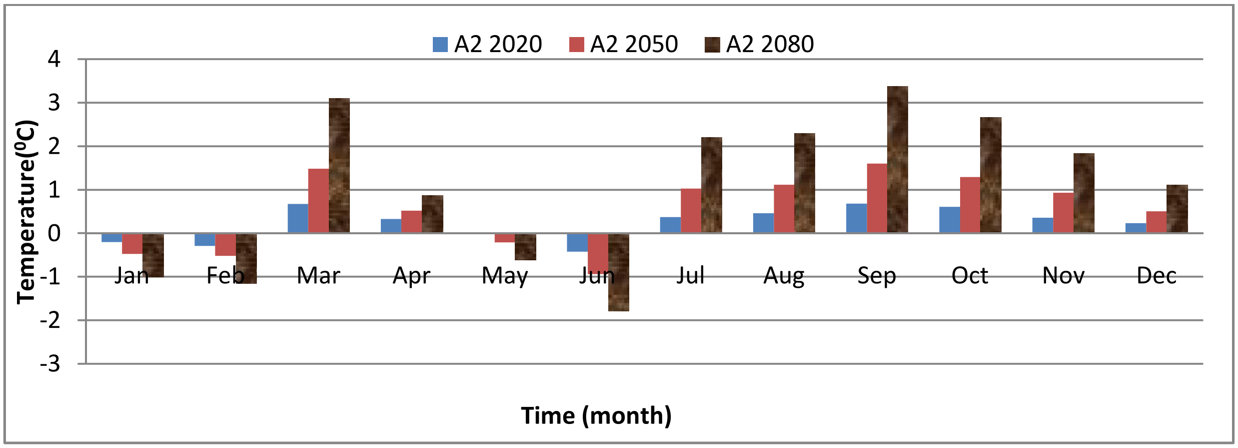


Figure 4.12: Change in monthly maximum temperature between the baseline period and future for HadCM3A2a

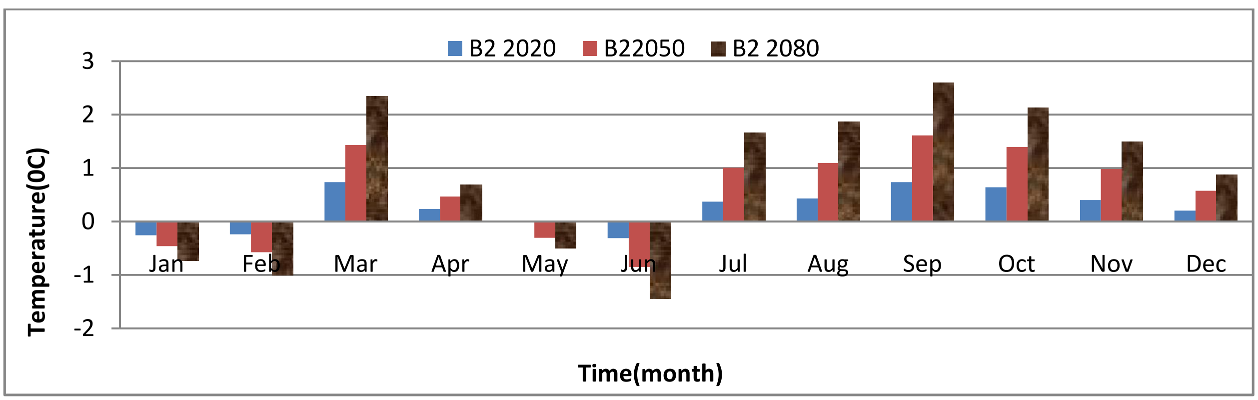


Figure 4.13: Change in monthly maximum temperature between the baseline period and future for HadCM3B2a

III) Precipitation

Projection of rainfall did not manifest a systematic increase or decrease in all future time horizon unlike that of maximum and minimum temperature which exhibits an increasing trend for both A2 and B2 scenario in all future time horizon. The rainfall amount generally shows a decreasing trend in the beginning of rainy season (March and April) and shows increasing trend towards the

the rainy reason (May and October) for both A2 & B2 scenario in all future time horizon for both bimodal season. This is due to GCMs usually generate an estimate of the average rainfall over a large grid square for the GCM time step, but they fail to take into account localized temporal and spatial variations in rainfall which, on a smaller scale, can produce highly significant result variations (Calder, 2005).

The second reason is there is an intermediate process between regional forcing and local weather (e.g., local precipitation amounts depend on wet–/dry–day occurrence, which in turn depend on regional–scale predictors such as humidity and atmospheric pressure, this results to variation (Wilby and Dawson 2004). The third reason is precipitation varies based on topography but GCM considers the pixel or grid value as an average therefore, due to this all reasons precipitation shows both an increase trend value as well as underestimation trend in a few months. This result agrees with East Africa report IPCC Projected Climate Change (Hulme et al., 2001; IPCC, 2001).

The rainfall will experience a decrease of 33.87% and 25.4% in April from the baseline period by 2080s for A2 and B2 scenario respectively where as the rainfall increase by 21% and 19% in October by 2080s for A2 and B2 scenario respectively. The rainfall will indicate a reduction in March, April and November from the baseline period both for A2 andB2 scenario in all future time horizons.

The mean annual rainfall variation is not significant compared to the monthly variation. The mean annual rainfall will indicate a slight increase rainy monthly in 2020s ,2050s and 2080s (Figure 4.14).

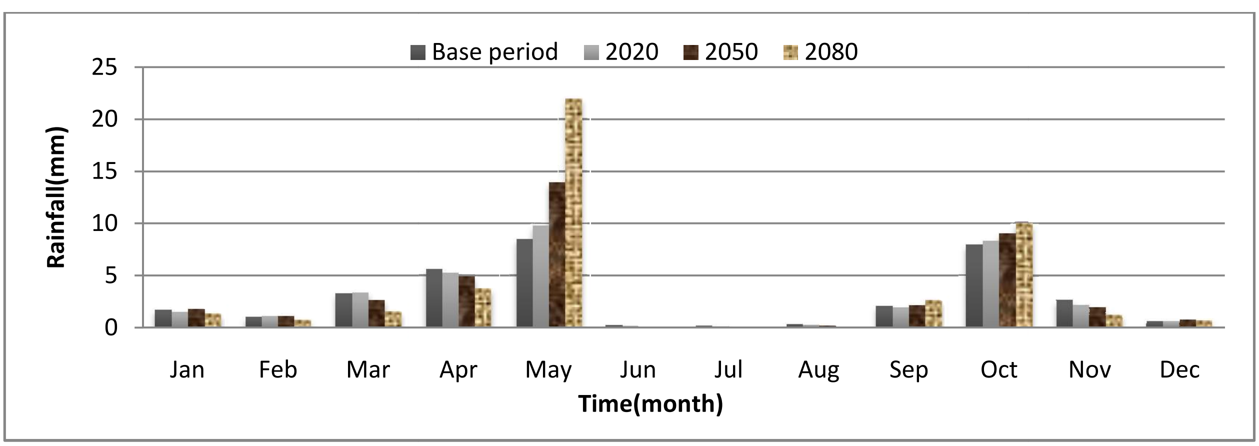


Figure 4.14: Mean daily precipitation downscaled from HadCM3A2a

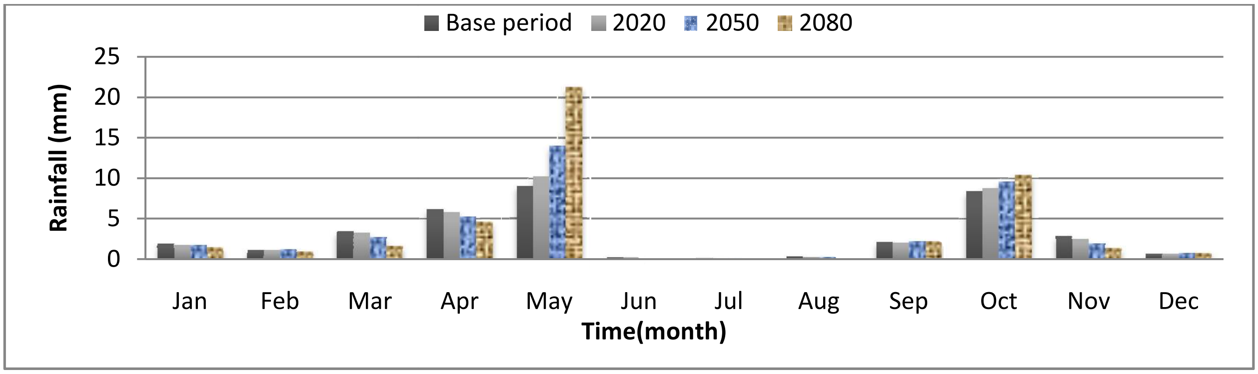


Figure 4.15: Mean daily precipitation downscaled from HadCM3B2a

4.3:SWAT MODEL CALIBRATION AND VALIDATION

Table 4.1: List of optimum parameter set in calibration

Symbol	Parameter description	Range Value	Calibration Value
R__CN2	SCS runoff curve number	-0.25-0.25	0.027
R_OV_N	Manning's "n" value for overland flow	0.01-30	11.21
R__CANMX	Maximum canopy storage.	0-100	27
R_REVAPMN	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)	0-500	231
R_FFCB	Initial soil water storage expressed as a fraction of field capacity water content.	0-1	0.32
R_SLSUBBSN	Average slope length	10-150	87
GW_DELAY	Groundwater delay (days).	0-500	121

The observed and simulated hydrograph using the above optimum parameter is shown in (Figure 4.16). The objective functions which were used to evaluate the model performance are summarized in (See Table 4.2). As it is indicated in the table, the Nash and Sutcliffe efficiency criterion which was commonly considered as the main model performance indicator in the

SWAT model is equal to 0.62. Generally the model performance in terms of replicating the observed hydrograph can be considered as satisfactory for the specific purpose of this study.

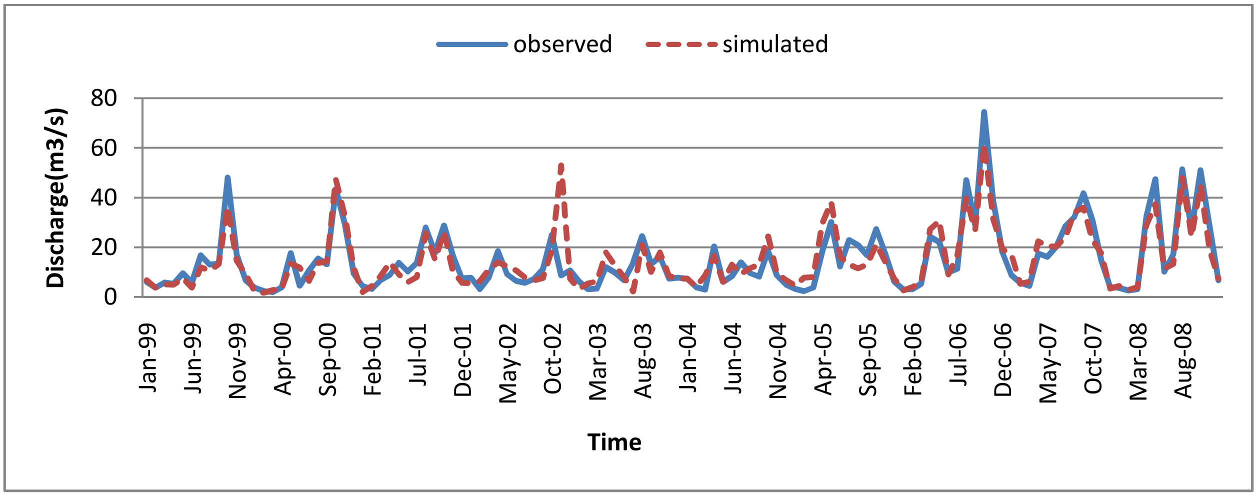


Figure 4.16: Observed and simulated mean monthly hydrograph during calibration period

The model was also validated against an independent data set which is not used during the calibration by using the same parameter as it was used in the calibration. The model performs reasonably well in simulating the discharge during validation period. The Nash and Sutcliffe efficiency and model determination confidence during the validation period are 0.60 and 0.56 respectively which could be taken as satisfactory.

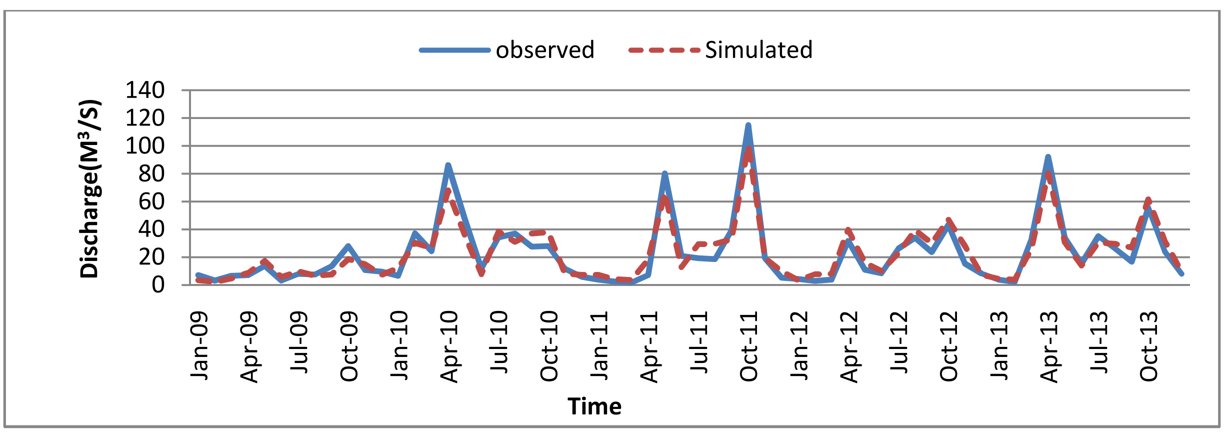


Figure 4.17: Observed and simulated mean monthly hydrograph during validation period

The calculated model bias (MB), coefficient of determination (R^2) and Nash- Sutcliffe efficiency (NS) showed the performance of the model in estimating flow is acceptable. Based on this, the calculated values of these model performance criteria have shown very close to their satisfactory fit values (Table 4.2).So far, the hydrograph (Figure 4.16) of the model evaluation criteria of the observed and simulated discharges have showed the model has well calibrated. This ensures that model can then be used to simulate future water balance change in the watershed.

Table 4.2: Calibration and Validation Periods Model Performance Evaluation Results

Evaluating criteria	Symbol	calibration value	validation value	Acceptable value
Model Bias(%)	MB	17	18.25	0-20
Coefficientof Determination	R2	0.58	0.56	0.50-1.0
Nash & Sutcliffe efficiency	NS	0.62	0.60	0.50-1.0

4.4: IMPACT OF CLIMATE CHANGE ON FUTURE WATER AVAILABILITY

The ultimate objective of the downscaling is to generate an estimate of meteorological variables corresponding to a given scenario of the future climate so that these meteorological variables will be used as a basis for hydrological impact assessment. Therefore, after calibrating the hydrological models with the historical record, the next step is the simulation of river flows in the catchment using the downscaled precipitation and temperature.

The simulated baseline (1986–2013) and future periods (2020s, 2050s, and 2080s) precipitation and surface runoff water balance components of bothA2a and B2aemission scenarios were illustrated in Table 4.3. These components were analyzed and presented in annual average basis. Hence, list of the main water balance components were provided and their future changes were analyzed based on the A2a and B2a emission scenarios.

From the simulated result of the SWAT model, the future precipitation of the study area is expected to averagely increase by 11.90% for A2a and 11.67% for B2aemission scenarios. This result is consistent with the climatic projections produced by SDSM model for the station in this study. The actual evapotranspiration will also increase by 3.64% for A2a and 3.75% for B2a which showed similar projections as precipitation and temperature. This indicates as temperature and precipitation increase, actual evapotranspiration will also increase with similar trend in the time horizons keeping other conditions constant.

Generally, the precipitation and actual evapotranspiration produced for both scenarios will increase with higher change for B2a than A2a emission scenario. This result is consistent

with findings of (Nyenje and Batelaan, 2009) which indicated these components will increase in the future. Hence, risk of annual flooding is limited in the watershed due to decreased amount of surface runoff in the future.

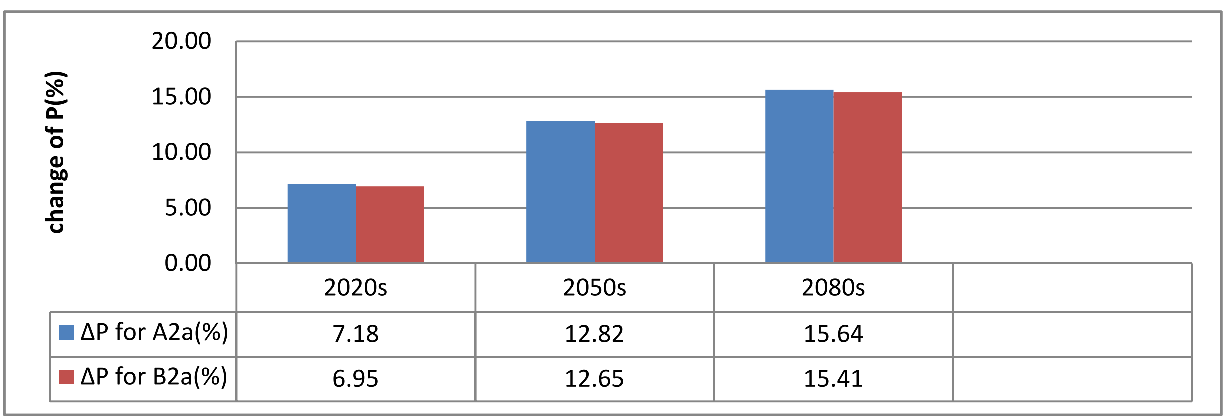
Averagely the surface runoff decrement in the future from the reference period is expected to be 12.4% for A2a and 12.29% for B2a SRES emission scenarios .It can be concluded that the future hydrological water balance changes will happen in the watershed for the emission scenarios considered in this study. The precipitation and actual evapotranspiration will show positive increment. The surface runoff, however, will decrease due to the coverage of the watershed as data land use land cover of 2014 indicate it, 78% is covered by high mixed forest and this follows high interception existence , increase groundwater flow discharge and increase actual evapotranspiration. The increment of actual evapotranspiration inforce to have high infiltration rate, which minimizes the surface runoff.

Table 4.3: Baseline and Future Period Mean Annual P, ET and SR for A2a and B2a Scenarios.

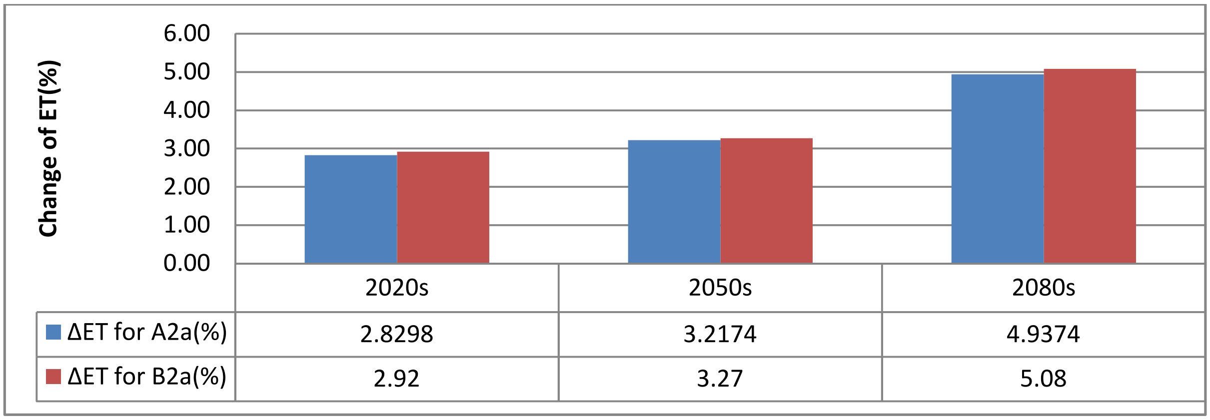
Description	A2a				B2a		
	period	P	ET_{actual}	SR	P	ET_{actual}	SR
Observed (mm)	baseline	886.4	678.5	102.56	886.4	678.5	102.56
Simulated (mm)	2020s	950	697.7	93.04	948	698.3	93.04
	2050s	1000	700.33	90.56	998.5	700.7	90.5
	2080s	1025	712	86.22	1023	713	86.32
Change (mm)	2020s	63.6	19.2	-9.52	61.6	19.8	-9.52
	2050s	113.6	21.83	-12	112.1	22.2	-12.06
	2080s	138.6	33.5	-16.34	136.6	34.5	-16.24
Change (%)	2020s	7.18	2.8	-9.52	6.95	2.92	-9.28
	2050s	12.82	3.22	-11.70	12.65	3.27	-11.76
	2080s	15.64	4.9	-15.93	15.41	5.08	-15.83

(-) indicate decrement

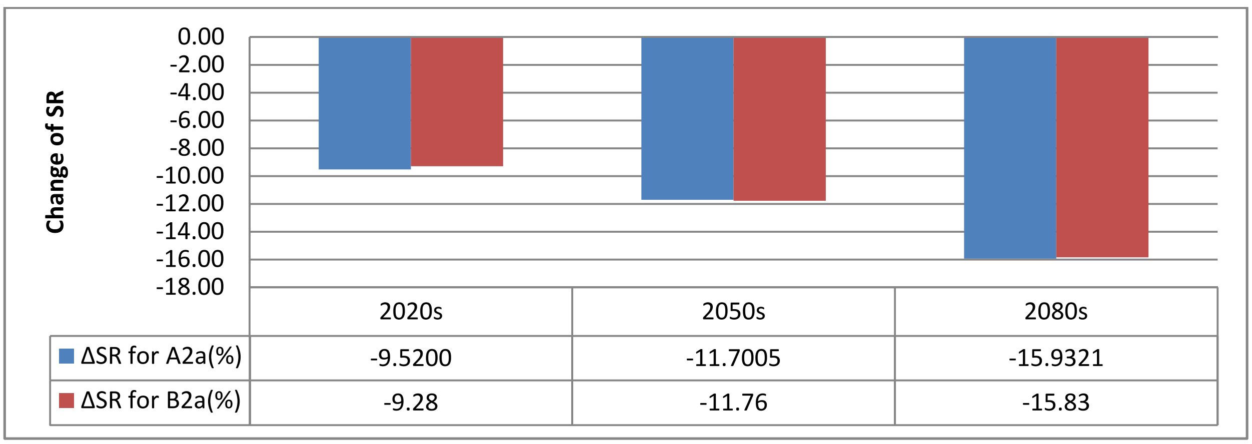
P = Precipitation, ET = Actual evapotranspiration, SR = Surface runoff



(a)



(b)



(c)

Figure 4.18: Change in (a) P, (b) ET, and (c) SR for A2a & B2a for Future Time Horizons.

5: CONCLUSIONS AND RECOMMENDATIONS

5.1: CONCLUSIONS

The overall objective of this thesis work was to estimate the impact of climate change on local surface water availability in Welmel watershed. Based on data availability and proximity to the watershed, Dallo and Angetu, stations were used from the available meteorological stations. To investigate the future climate change impacts, Dallo meteorological stations, a statistical downscaling model (SDSM) was employed to downscale the large scale GCM outputs to local scale parameters. Hence, available data of (1986-2000) and (2001-2013) of the selected stations were used separately for model calibration and validation processes respectively. Using SDSM model, precipitation, minimum and maximum temperature projections were investigated by taking large scale climatic data from HadCM3 GCM outputs.

The results from the statistical downscaling model indicate that both the minimum and maximum temperature show an increasing trend inall future time horizons for both A2 and B2 scenarios. The maximum change of minimum temperature is observed in the month of January where it may be increased by 4.25 ^{0}C and 3.3 ^{0}C for A2 and B2 scenario respectively towards the end of this century. The maximum temperature may also be increased by 1.082^{o}C and 0.85^{o}C for A2 and B2 scenario respectively within the same time period.

The result of downscaled precipitation reveals that precipitation does not manifest a systematic increase or decrease in all future time horizons for both A2 and B2 scenarios unlike that of minimum and maximum temperature. The rainfall amount generally shows a decreasing trend in the beginning of rainy season (March and April) and shows increasing trend towards the the rainy reason (May and October) for both A2 & B2 scenario in all future time horizon. The rainfall may experience a decrease of 33.87% and 25.4% in April from the baseline period by 2080s for A2 and B2 scenario respectively where as the rainfall increase by 21% and 19% in October by 2080s for A2 and B2 scenario respectively.

The result of hydrological model calibration and validation indicates that the SWAT model simulates the runoff considerably good for the study area. The model performance criterion which is used to evaluate the model result indicates that the Nash and Sutcliffe efficiency criteria (NS) are 0.62 and 0.60 during calibration and validation period respectively.

An investigation of the available water potentials at present and future time was quantified by water balance components determination model. The main concern is to investigate the present (1986-2013) and future three time horizons (2020s, 2050s and 2080s) water resource potential of Welmel watershed. The future change in water resource potentials was investigated after downscaling future rainfall and temperature obtained from HadCM3 GCM model.

Due to the effect of climate change, precipitation and actual evapotranspiration may averagely increase by 11.90% and 11.67% for A2a and 3.64% and 3.75% for B2ascenarios respectively. But surface runoff will decrease by12.4% for A2a and 12.29% for B2a emission scenarios.

5.2: RECOMMENDATIONS

- Since precipitation and temperature show positive increment in the three periods (2020s, 2050s and 2080s) people have to be aware of it and take actions as per necessary.
- The surface water resources potentially available in Welmel watershed are useful for irrigation use, livestock consumption and potable water for the resident people. Wise uses of these water resources have paramount importance.
- The model simulation considered only future climate change scenarios assuming all other conditions constant. But change in land use scenarios, soil, management activities and other climate variables will also contribute to surface runoff variability. Therefore, it is better if consider these changes for future climate change predictions.
- Policy and technical measures should be taken to avoid or reduce the negative effect of climate change on the natural environment and also the adaptation options for minimizing the impact of climate change consequences should be developed.

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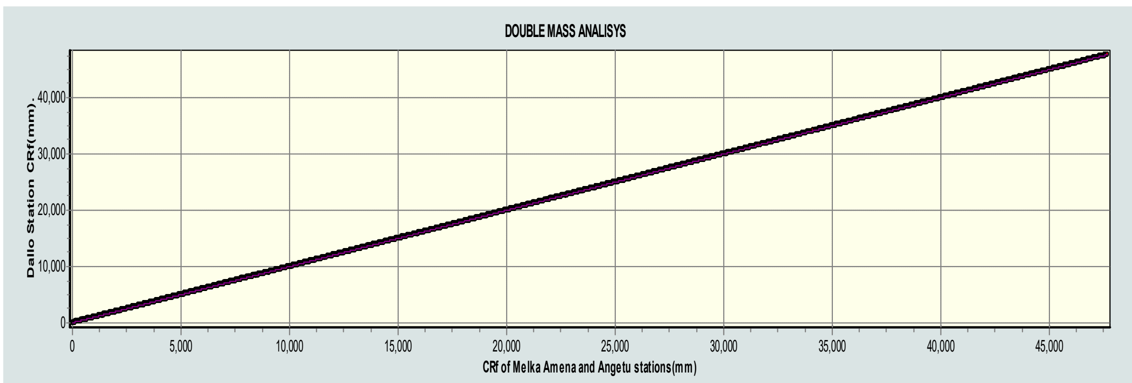
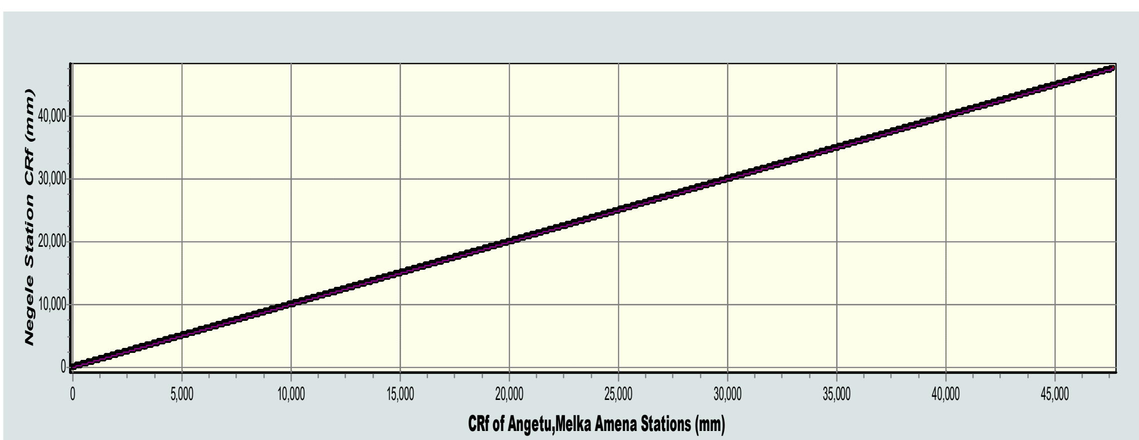
APPENDIX

A) APPENDIX FIGURES

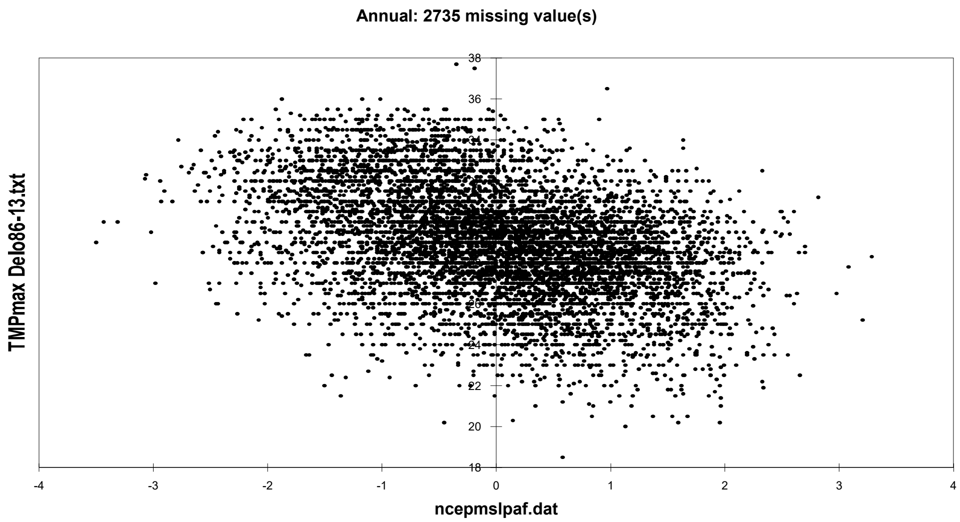


(a) Double Mass Curve of Dallo station



(b) Double Mass Curve of Negele Station, CRF = Cumulative Rainfall.

Appendix Figure1. Double Mass Curve of Precipitation of Dallo and Negele**.**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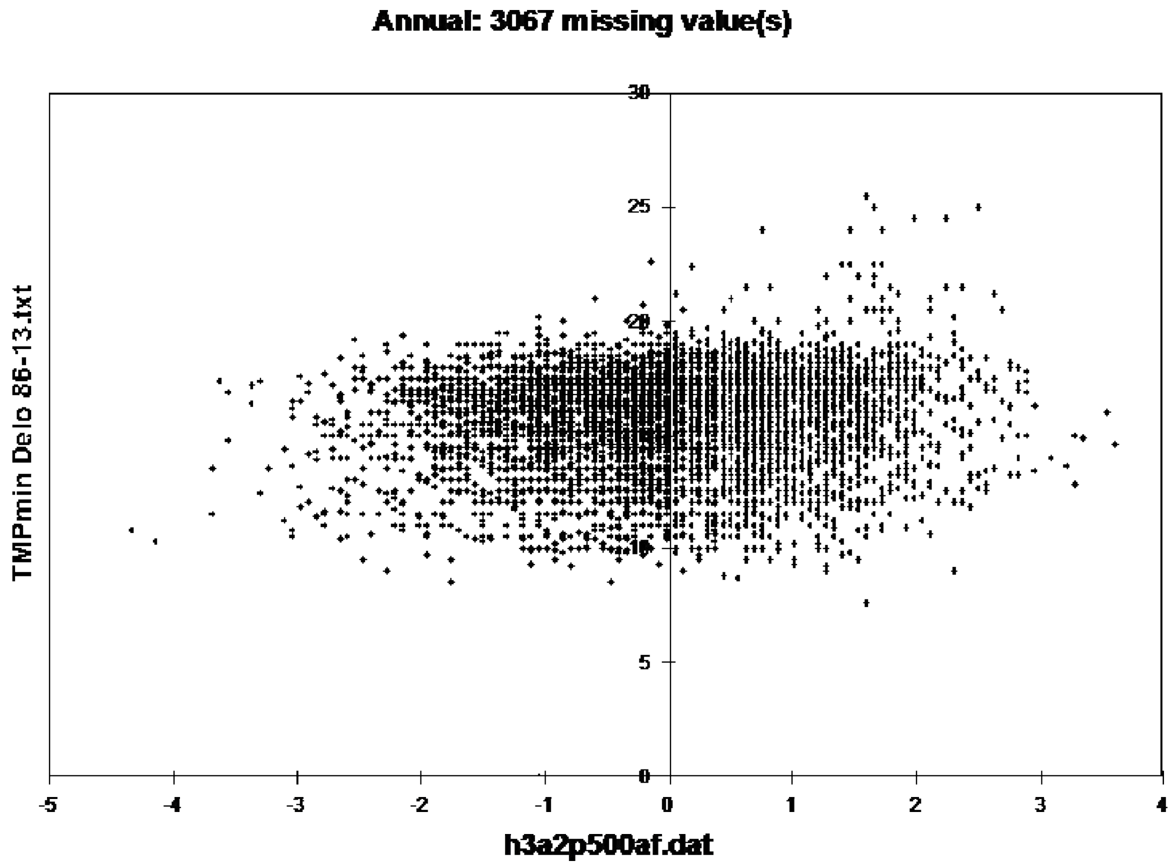
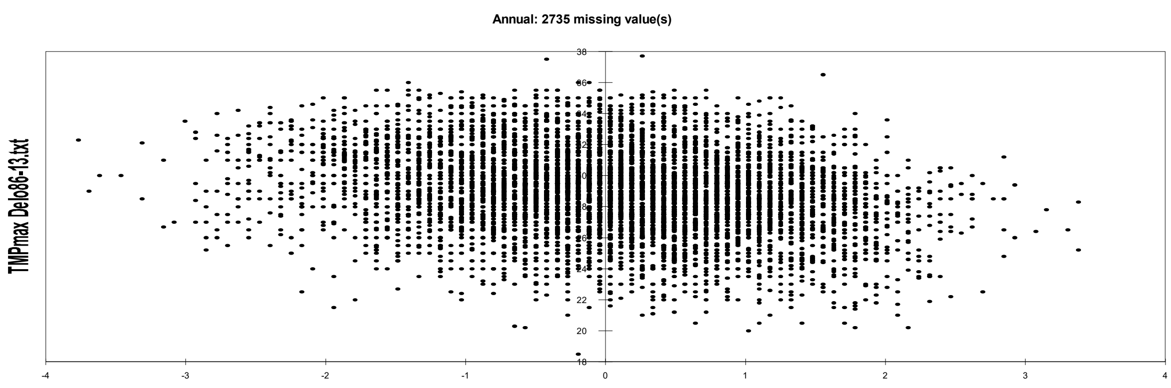
4





Appendix figure2 scatter plot Tmax predictors

B) APPENDIX TABLES.

Rowid	VALUE	COUNT	soil type name	SWAT_CODE
0	5	129	Eutric Vertisols	VRe
1	6	180	Chromic Luvisols	LVx
2	7	14	EutricCambsols	CMe
3	9	79	Eutric Leptosols	LPe
4	10	1	Rhodic Niosols	NTu

Appendix Table 1. Watershed Soil Classification

VALUE	Rowid	COUNT	LCLU_DEFINATION	SWAT_CODE
1	0	5	Cultivation	AGRL
2	1	1	Woodland	FRSD
4	2	54	Shrubland	RNGB
5	3	296	Natural Forest	FRST
7	4	47	Afro-alpine	ALFA

Appendix Table 2. Watershed Land Use Classification

Performance rating	RSR	NSE	PBIAS (%)
Very good	$0.00 \leq RSR \leq 0.50$	$0.75 < NSE \leq 1.00$	$PBIAS \leq \pm 1.00$
Good	$0.50 < RSR \leq 0.60$	$0.65 < NSE \leq 0.75$	$\pm 10 \leq PBIAS < \pm 15$
Satisfactory	$0.60 < RSR \leq 0.70$	$0.50 \leq NSE \leq 0.65$	$\pm 15 \leq PBIAS < \pm 25$
Unsatisfactory	$RSR > 0.70$	$NSE < 0.50$	$PBIAS \geq \pm 25$

Appendix Table 3. Model performance ratings based on the range of values for RSE, NSE and PBIAS for monthly stream flow.