JIMMA UNIVERSITY

JIMMA INSTITUTE OF TECHNOLOGY

SCHOOL OF POST GRADUATE STUDIES

FACULTY OF CIVIL AND ENVIRONMENTAL ENGINEERING

HYDROLOGY AND HYDRAULIC ENGINEERING CHAIR

CLIMATE CHANGE IMPACT ON STREAM FLOW (A CASE OF KATAR CATCHMENT, RIFT VALLEY BASIN, ETHIOPIA)

By: Safi Hussein

A thesis submitted to Hydrology and Hydraulic Engineering Chair, Jimma Institute of Technology, Jimma University in Partial fulfilment of the requirements for the Degree of Masters of Science in Hydraulic Engineering.

March, 2021

Jimma, Ethiopia

JIMMA UNIVERSITY
JIMMA INSTITUTE OF TECHNOLOGY
SCHOOL OF POST GRADUATE STUDIES
FACULTY OF CIVIL AND ENVIRONMENTAL ENGINEERING
HYDRAULIC ENGINEERING PROGRAM

CLIMATE CHANGE IMPACT ON STREAM FLOW (A CASE OF KATAR CATCHMENT, RIFT VALLEY BASIN, ETHIOPIA)

By: Safi Hussein

A thesis submitted to Hydrology and Hydraulic Engineering Chair, Jimma Institute of Technology, Jimma University in Partial fulfilment of the requirements for the Degree of Masters of Science in Hydraulic Engineering.

Advisor: Dr.Ing.Tamene Adugna (PhD)
Co-Advisor: Mr. Fayera Gudu (Assis. Prof)

March, 2021
Jimma, Ethiopia

STATEMENT OF THE AUTHOR

I, the undersigned, declare that the thesis entitled, “Climate Change Impact on Stream flow (A Case of Katar Catchment, Rift Valley Basin, Ethiopia)” is my own work, and that all the sources I have used or quoted have been indicated or acknowledged by means of completed references.

Safi Hussein Feto	________________	___/____/_________
Name of student	Signature	Date

DECLARATION

This is to certify that this thesis entitled "Climate Change Impact on Stream flow (A Case of Katar Catchment, Rift Valley Basin, Ethiopia)," accepted in partial fulfillment of the requirements for the award of the Degree of Master of Science in Hydraulic Engineering by the School of Post Graduate Studies, Jimma University through Jimma Institute of Technology, done by: Mr. Safi Hussein is a genuine work carried out by him under my guidance. The matter embodied in this thesis work has not been submitted earlier for the award of any degree or diploma.

The assistance and help received during the course of this investigation have been duly acknowledged. Therefore, I recommend that it can be accepted as fulfilling the research thesis requirements.

Dr. Ing. Tamene Adugna	________________	___/____/_________
Advisor	Signature	Date
Mr. Fayera Gudu (Assis. Prof)	________________	___/_____/________
Co-Advisor	Signature	Date

APPROVAL

As a member of the board of examiners of the MSc. Thesis open defense examination, we certify that we have read, evaluated the thesis prepared by: Mr. Safi Hussein entitled “Climate Change Impact on Stream Flow (A Case of Katar Catchment, Rift Valley Basin, Ethiopia)”.
We recommended that the thesis be accepted as fulfilling the thesis requirement for the degree of Master of Science in Hydraulic Engineering.

Members of Examining Board

Dr. Adane Abebe	________________	____/______/______
External Examiner	Signature	Date
Mr. Wandimagegn Taye (MSc.)	________________	____/______/______
Internal Examiner	Signature	Date
Mr. Nasir Gabi (MSc.)	________________	____/_____/_______
Chair Person	Signature	Date

ACKNOWLEDGEMENT

First and for the most praise be unto the Almighty God Who gave me all the courage and power throughout my achievements. Next, I would like to express great and heartfelt gratitude to my advisor Dr. Ing.Tamene Adugna and Co-advisor Mr. Fayera Gudu for their guidance and showing me a direction from proposal writing to the final study period of the research. I have no words to express my deepest gratitude to my mother Jamila Edo because she has been encouraging and supporting me throughout my research work.

I would like to acknowledge the Ministry of Water, Irrigation and Energy (MoWIE) particularly hydrology and GIS departments, and the Ethiopia Meteorological Service Agency for providing me the relevant data and information required free of payment.

And also, I would like to thank Jimma Institute of Technology and my sponsor Ministry of Water, Irrigation and Energy (MoWIE) for giving me the chance to attend the postgraduate program; without these organizations I will not achieve my dream. Last, but not least I would like to express my deep gratitude to all lecturers of Hydraulic Engineering program; they give me base line knowledge for the thesis work. I also glad to acknowledge my closely friends and colleagues who helped and supported me during the time of research work by knowledge, other advice and anyway.

.

ABSTRACT

Climate change significantly alters many hydrological conditions, which in turn affects the water resources and stream flow. The uncertainty of the availability of water resources will affect agricultural production and challenge socio-economic systems to feed the growing population. Therefore, this study was investigated to assess the potential impacts of climate change on streamflow of katar river catchment in Central Rift Valley basin, Ethiopia. Ensembles of coordinated regional climate downscaling experiment (CORDEX)-Africa under two Representative Concentration Pathways (RCP 4.5 and RCP 8.5) has been used to downscale the daily precipitation, daily maximum and minimum temperature of the study area. The observed meteorological variables and downscaled CORDEX Africa climatic data were corrected with distribution mapping (DM) method. The SWAT hydrological model was used to perform stream flow simulation. The trends of precipitations and temperatures in the basin were assessed by comparing the baseline Period (1986-2005) and future scenarios 2021-2040 (2030s) and the 2051-2070 (2060s). The trends of mean annual Precipitation were projected to decrease under RCP4.5 by 17.8% and 26% for the 2030s and the 2060s, respectively. Likewise, for RCP8.5, the average annual precipitation decreases were found to be 19% in the 2030s and 10% in the 2060s. The trends of monthly maximum temperatures were projected to increase under RCP4.5 from (+0.94°C to +1.68°C) and (+1.61°C to +3.32°C) While Under RCP8.5 that ranges from (+0.91°C to 1.93°C) and (+2.67°C to 4.00 °C) in both future periods of 2030s and 2060s respectively. Monthly minimum temperature increase ranges from (+1.14°C to +2.56°C) and (+1.72°C to +3.74°C) under RCP4.5 scenario while (+1.24°C to +2.21°C) and (+3.02°C to +5.03°C) under RCP8.5 in both future periods 2030s and 2060s respectively. The performance of SWAT model in simulating the stream flow was shown to be good with a coefficient of determination (R2) 0.66 and 0.65 and the Nash and Sutcliffe efficiency (NSE) of 0.65 and 0.62 for calibration and validation periods, respectively. The impacts of climate change on stream flow were assessed by comparing the baseline and future stream flow. The results obtained from this study indicates that the annual streamflow that is projected to decrease by 7.38 % and 33.49% under RCP4.5 in future periods of 2030s and 2060s respectively. For RCP8.5, projected to decrease by 19.44 % and 8.79% by the 2030s and the 2060s, respectively. Results from this study showed that the combined effects of decrease in precipitation and increase in temperature in the future period would decrease stream flow. Hence, it is strictly recommended that the adaptation measures such as watershed based integrated water resource management approach and constructing water harvesting structures to store excess water flowing during rainy season so as to use it for dry season.

Keywords: Climate change, CORDEX-Africa, Katar catchment, SWAT.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST ABBREVIATIONS

CMIP5	Coupled Model Inter-comparison Project Phase 5
CORDEX	Coordinated Regional Downscaling Experiment
CUP	Calibration and Uncertainty Program
CRV	Central Rift Valley
DEM	Digital Elevation Model
EC-Earth	European community Earth-System Model
FAO	Food and Agriculture Organization of the United Nations
GCM	Global Circulation Model
GIS	Geographical Information System
IPCC	Intergovernmental Panel on Climate Change
LULC	Land Use Land cover
MoWIE	Ministry of water, Irrigation & Energy
NMSA	National Meteorological Service Agency
RCP	Representative Concentration pathway
RCM	Regional Climate Model
SRTM	Shuttle Radar Topography Mission
SUFI	Sequential Uncertainty Fitting
SWAT	Soil and Water Assessment Tool
SWATCUP	Soil and Water Assessment Tool Calibration and Uncertainty Program
UNFCCC	United Nations Framework Convention on Climate Change
USGS	United states Geology Survey

1. INTRODUCTION

1.1. Background

Climate change has the potential to impose pressures on water availability and accessibility as the occurrence of climatic extremes such as heat waves, drought, and change in rainfall pattern in reaction to global warming (IPCC, 2008). Numerous studies indicated that Climate change is expected to have significant impact on global temperatures and precipitation change (Mishra *et al.*, 2018; Kishiwa *et al.*, 2018). The intergovernmental panel on climate change (IPCC) climate projections show that temperature is expected to increase 0.3 to 1.7°C for the lowest and 2.6 to 4.8°C for the highest emission scenarios and precipitation is generally expected to increase in the tropical regions and at high latitudes but decrease in the subtropics during the 21st centuries. Average annual precipitation is expected to decrease by 2.55–7.97% for various representative concentration pathways (RCPs) by 2060s across central rift valley basin of Ethiopia (Gadissa *et al*., 2018). Any change of these variables alters hydrological cycle, which causes a severe impact on hydrological properties of river basin. Water resources in river systems have been changing under the impact of both climate variability of temperature and precipitation (Shitu & Berhanu, 2020). This in combination of the future climate change impact on reduction of the available water in the watershed causes a water stress within and around the Sub-basin. Such hydrologic changes will disturb almost every aspect of human welfare. Therefore, assessing the impact of climate change on hydrology of river is necessary to create awareness on the possible future risks of climate change in order to mitigate the impacts climate change on water resources. To compute the impacts of climate change on hydrology of the catchment, the outcomes of Global climate models (GCMs) together with hydrologic models are commonly used.

Hydrological simulation models are used to address the impact of climate change on the hydrology of a given watershed, including the effects of alternative best management practices and future climate change on stream flow. There are many criteria that are applied to select an appropriate hydrological model. Among many others, spatially and temporally distributed or semi-distributed hydrological models such as SWAT have important applications for discovering the relationships between the climate of the watershed and hydrological process (Mishra *et al*., 2018).

Global climate models (GCMs)/regional climate models (RCMs) downscaled data is used as an input to hydrologic models to simulate the corresponding future flow regime in the catchment. These models can provide reliable information regarding historical, current, and future climate trends over long periods (Smitha *et al*., 2017). Coordinated Regional Climate Downscaling Experiment (CORDEX) database contains several RCMs downscaled data, driven by GCMs projections, with different spatial resolutions much finer than those of the GCMs. However, these high-resolutions downscaled RCM simulations may not be directly used in hydrological model for hydrological impact assessment in watershed scale due to biases (Teutschbein & Seibert, 2012). These biases would be altered using different bias correction methods (Chen *et al*., 2013).

Recently, different studies had been conducted globally to investigate climate change impacts on hydrology of river basin using ensembles of high-resolution regional climate projections generated by Regional Climate Models (RCMs) within the Coordinated Regional Climate Downscaling Experiment-CORDEX Africa for the representative concentration pathways (RCPs) (Fentaw *et al.*, 2018; Kim *et al.*, 2014).

The IPCC suggest that developing countries like Ethiopia will be more susceptible to climate change because of their economic, climatic and geographic locations. Several studies approved that Ethiopia is vulnerable to climate change since the economy of the country mainly depends on agriculture, which is very sensitive to climate change (Gebre *et al.*, 2014; Setegn *et al.*, 2011). Rift valley basin is the important, intensively utilized and environmentally vulnerable basins in Ethiopia (Abraham, 2018; Legesse *et al.*, 2010).

Katar catchment is located in central rift valley basin of Ethiopia is one notable example where information gaps exist regarding the impact of climate change on streamflow at a catchment level based on the Representative Concentration Pathways (RCP), even though the stream is a major tributary to Ziway lake. Therefore, this study applied a high-resolution RCM with RCP emission scenarios to quantify the impact of climate change on the stream flow of Katar catchment. This has been achieved through a method that combines the model outputs from CORDEX-Africa for the representative concentration pathways, RCPs and physical-based, semi-distributed hydrological models (SWAT) to simulate the hydrological processes. This can afford useful information for water resource managers to better understand the likely consequences of climate change on hydrological systems in the catchment level.

1.2. Statement of the problem

Possible changes in seasonal pattern of temperature and precipitation will lead to changes in the hydrological cycle, influencing the components of water balance of catchment in several ways such as the availability and distribution of water resources in space and time, stream flow, frequency of extreme events etc. Water resources problems worldwide in the future are found to become more complex due to climate change, population growth, regulatory requirements, project planning horizons, temporal and spatial scales, social and environmental considerations (Fikru, 2018). Climate change is expected to alter hydrologic processes thereby affecting key resources and processes including water supply, irrigation, infrastructure, aquatic habitat, and access (Animesh *et al*., 2012). The uncertainty of the availability of water resources will affect agricultural production, challenge socio-economic systems, and threaten environmental sustainability by increasing use of non-recyclable resources to feed the growing population (WaleWorqlul *et al*., 2018).

Ethiopia is an example of a country whose river basins are susceptible to changes in climate, and yet the country's poverty alleviation and economic growth strategy require effective water resources management for competing sectors and users (Taye *et al*., 2018). Rapid growth of agriculture, deforestation and urbanization within the Katar catchment of Rift valley basin, Ethiopia, as well as population growth is placing increasing demands on the basin's water resources. Therefore, assessing the impact of climate change on river flow is very important for sustainable planning and management of the water resources. In a basin known for high climate variability involving droughts and floods, climate change will likely intensify the existing challenges. Hence, this study seeks to address the impact of climate change on stream flow of katar catchment and understanding the general trends of the future climate variables such as Precipitation, Maximum Temperature and Minimum Temperature over the catchment. Accordingly, quantifying the potential impact of climate change on water availability is needed to plan how to adapt to these changes, and how to mitigate the changes for water resources.

1.3. Objectives

1.3.1. General Objective

The general objective of this research is to assess the potential impact of climate change on stream flow of katar catchment.

1.3.2. Specific Objectives:

i. To assess future trends of precipitation and temperature compared to the baseline period over the catchment.
ii. To evaluate the performance of SWAT model in simulating stream flow.
iii. To assess the impact of climate change (Precipitation and Temperature) on katar stream flow.

1.4. Research Questions

To assess and address the above-mentioned problems and objectives, a number of hypothetical questions can be formulated. Among those:

i. What are the trends of future precipitation and temperature over the catchment?
ii. How well can SWAT model simulate stream flow in the catchment?
iii. Is there a change on stream flow due to the change in precipitation and temperature?

1.5. Significance of the study

Climate change has significant impact on natural resources, socioeconomic and environmental systems. This study aims to identify the impact of climate change on stream flow of katar catchment. Understanding the types and impacts of climate change on stream flow of catchment is an essential indicator for resource base analysis, development of effective and appropriate response strategies for sustainable management of water resources in the country in general and at the study area in particular. Moreover, the study presents a method to quantify climate change and their impact on the hydrological regime. This was achieved through a method that combines the GCMs CORDEX-Africa Models/RCMs and the hydrological model (SWAT) to simulate the hydrological processes.

1.6. Scope of Study

The scope of this study is broad and attempts to indicate the impact of climate change on stream flow of katar catchment by using CORDEX-Africa output data from GCMs/ICHEC-EC-EARTH models with two representative concentration pathways (4.5 and 8.5) selecting one Regional model RACMO22T and Soil Water Assessment Tools (SWAT). CORDEX data analysis was done with one ensemble value (r1i1p1). The precipitation, maximum and minimum temperature scenarios for the period 2021-2040 and 2051-2070 the daily temporal resolution interpolated with nearest RCM (RACMO22T) grid points to all weather observation stations of the catchment. Other climate variables such as wind speed, solar radiation, and relative humidity were assumed to be constant throughout the future simulation periods. Land use land cover in this study was assumed to be constant throughout the future simulation periods. This study area geographically limited to 7º21'34'' to 8º9'55'' North latitudes and 38º53'57'' to 39º24'46'' East longitudes.

2. LITERATURE REVIEW

2.1. Global Climate Change

Climate is the average weather or the regular variations in weather in a region over a period of years. It defines typical weather conditions for a given area based on long-term averages, usually decades or longer. According to the intergovernmental panel on climate change (IPCC, 2013) the precipitation pattern and the temperature will significantly change by the end of 21st century, which will affect the hydrologic regime. The change in temperature, precipitation and evaporation may impacts the measure of water course through the hydrologic cycle by increase or decrease the runoff and thus may affect the flow regime of watershed (Nan *et al*., 2011).

Climate change may alter quantity, quality, distribution and timing of water due to resulting changes in the hydrological cycle. The distribution and changes of water resources in space will cause the human society and ecosystem alteration a lot. It has been predicted that climate change and the resulting changes in precipitation and temperature regimes will affect the availability of water resources in different regions of the world (Xu and Luo, 2015; Nurtaev, 2015). The changing variability of rainfall patterns and rising temperatures associated with climate change is expected to contribute to increased frequency of water scarcity and droughts (UNFCCC, 2014). The risk of water scarcity is exacerbated by socioeconomic drivers such as population growth, economic development and associated increases in per capita water use, as well as expansion of agricultural and industrial activities (IPCC, 2014).

The respond of climate change and variability requires knowledge of how the existing system is operating, how they are affecting water availability today and how they might respond to changes in the future. Climate and hydrologic recorded data over a long period of time help one understand the relationship between climate change and the available water in a given region or location.

2.2. Impacts of climate change in Ethiopia

The IPCC findings indicate that developing countries, such as Ethiopia is one of the most vulnerable countries to climate variability and climate change due to its high dependence on rain-fed agriculture and natural resources, and relatively low adaptive capacity to deal with these expected changes. The country has frequently experienced extreme events like droughts and floods, in addition to rainfall variability and increasing temperature which contribute to adverse impacts to livelihoods. Climate change and its impacts are, therefore, a case for concern to Ethiopia. Hence, assessing susceptibility to climate change impact mapping and preparing adaptation options as part of the national program is very crucial for the country (NMSA, 2005).

2.2.1. Rainfall variability and trend

Rainfall trends across Ethiopia are highly variable, some areas of the country are expected to experience a reduction or increase in rainfall. According to (USAID, 2016) the south-central region of the country has experienced a 20% decrease in rainfall since 1960. On the other hand an increasing trend in annual rainfall has been observed in central Ethiopia (MoEF, 2015). According to Ministry of Environment and forest, Projected trends of rainfall indicate as much as a 20% decline in spring and summer rainfall in southern and south-central regions. However, an increase is expected for southwest and southeast areas; northern areas are near uniformly expected to experience a general decrease in rainfall.

2.2.2. Temperature variability and trend

The comprehensive temperatures are expected an increasing trend for Ethiopia, with mean monthly temperature changes expected to increase by 1.8°C by the 2050s and by 3.7°C by end of the century, under a high-emission scenario (Mcsweeney *et al*., 2009). According to (USAID, 2016) the observed average temperatures in Ethiopia have increased by an average of 1°C since1960, at an average rate of 0.25°C per decade. Increases have been most noticeable from July through September.

This climate change analysis, along with common perceptions derived from other research findings demonstrates that temperatures are projected to increase significantly, while rainfall is expected to increase in some areas during the Kiremt season, whereas significant reductions in the Belg season are being experienced.

2.3. Impacts of climate change on water resource

The most vital climatic drivers of hydrology and water availability are temperature, precipitation and evaporation (IPCC, 2007). According to ministry of Environment and forest

(MoEF, 2015) projected trends of increased temperatures and precipitation patterns may further reduce availability in water-scarce regions (southern, eastern and central).

Many studies show the importance of relations between climate change and hydrological regimes and how these impact on the water resources. Using hydrological models a number of hydrological studies into the effects of climate change have concentrated on potential changes on stream flow and runoff (Melesse & Abtew, 2015) studied the Impact Climate Change on Stream Flow in the Upper Gilgel Abay Catchment, Blue Nile basin, Ethiopia. The results of this study showed that precipitation and temperature reveal a systematic increase in all future time periods for both A2 and B2 scenarios. These increases in climate variables are expected to increase mean annual stream flow. (Shanka, 2017) investigated the impact of climate change on Run-Off in the Gidabo River Basin: Southern Ethiopia. The results obtained from this study indicate that there is significant variation in the monthly, seasonal and annual runoff. The climate change impacts might cause increases in average monthly runoff in the 2020's, 2050's and 2080's for both A2a and B2a scenario. Ethiopia is seriously threatened by climate change, which contributes to frequent drought, flooding, and rising average temperatures (Emerta & Aragie, 2013).

By far the majority of studies into the effects of climate change on river flows have used GCMs to define changes in climate that are applied to observed climate input data to create perturbed data series. These perturbed data are then fed through a hydrological model and the resulting changes in river flows assessed. Since the SAR, there have been several global-scale assessments and a large number of catchment-scale studies. Global climate change (GCC) is projected to bring higher intensity precipitation and higher variability temperature regimes. With growing populations, industrialization, climate change and its variability the situation becomes more and more tense (Desta & Lemma, 2017b). Therefore, Knowledge about availability of future water resources in this region and studies providing insights of climate change, and their impacts on the hydrology are of outmost importance.

2.4. Climate Scenario

Climate scenario (climate projection) refers to a probable representation future climate that has been constructed for explicit use in investigating the potential consequences of anthropogenic climate change (IPCC, 2013). Future levels of global greenhouse gas (GHG) emissions are the products of a very complex, determined by driving forces such as demographic development, socio-economic development and technological progress. Scenarios are alternative images of how the future might reveal and proper tool with which to analyze how driving forces may influence future emission outcomes and to assess the associated uncertainties. In climate research, they assist in climate change analysis, including climate modeling and the assessment of impacts, adaptation, and mitigation (IPCC, 2014)

Table 2.1 History of scenarios (Hayhoe et al., 2017)

Year	Name	Used
1990	SA90	First Assessment Report
1992	IS92	Second Assessment Report
2000	SRES-Special report on Emissions and Scenarios	Third and Four Assessment Report
2009	RCP-Representative Concentration Pathway	Fifth Assessment Report

Emission scenarios which present in the general circulation model (GCM) simulations are the base for the last three assessment reports of the IPCC. Special report on Emissions and Scenarios (SRES) scenarios quantify anthropogenic emissions of greenhouse gases (and some other pollutants), land-use and other factors for the 21st century by giving a wide range of possible alternatives (Illy *et al*., 2017). Representative Concentration Pathway (RCP) scenarios are the most recent, innovative for the last IPCC Assessment Report (AR5) using integrated assessment modelling, climate modelling and impact modelling. The basic concept of RCP is different from the SRES: instead of socio-economic scenarios, these scenarios define pathways of the additional radiative forcing caused by anthropogenic activity till the end of the 21st century (Illy *et al.*, 2017).

2.5. Climate models

Climate models are used to project the possible future evolution of the climate system as well as to understand the climate system itself (Illy *et al*., 2017). Global and regional climate models, are the primary tools that aid in our understanding of the many processes that govern the climate system (Kattsov *et al*., 2013).

2.5.1. General circulation model (GCM)

The General Circulation Models (GCMs) used to simulate the present and project future climate with forcing by greenhouse gases and aerosols, typically divide the atmosphere and ocean into a horizontal grid with a resolution of 2 to 4º latitude and longitude, with 10 to 20 layers in the vertical (IPCC, 2007). 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. According to many research GCMs are the valuable tools used to perform climate change experiments regionally, globally and very fine scale up to point climate pattern from which climate change scenarios are derived; but they have main drawbacks because of their course resolution. 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, 2013). Therefore, downscaling is required to resolve the course spatial resolution of GCMs to fine resolution of regional scale.

2.5.2. Regional climate model (RCM)

Regional Climate Models (RCMs) are applied over a limited-area domain with boundary conditions either from global reanalyzes or global climate model output (Kattsov *et al*., 2013). A regional climate model (RCM) is a climate model of higher resolution than a global climate model (GCM). It can be nested within a global model to provide more detailed simulations for a particular location. Regional models have been used to conduct climate change researches for many regions of the world to dynamically GCM results to smaller scale (~10–50 km) (Ashfaq *et al.*, 2020; Al *et al.*, 2020). These methods of obtaining sub-grid scale estimates (commonly down to 50 km resolution or less) are able to account for important local forcing factors such as surface type and elevation, which conventional GCMs are unable to resolve.

2.6. Downscaling techniques

The technique**s** used to convert GCM outputs into local weather variables required for reliable hydrological modeling are usually referred to as “downscaling” techniques. As a consequence, two sets of techniques have emerged as a means of deriving local scale surface weather from regional scale atmospheric predictor variables. These are statistical downscaling and dynamical downscaling.

2.6.1. Dynamical downscaling

Dynamical downscaling involves the use of higher resolution regional climate models (RCMs) that use GCM output as the input or boundary conditions and simulates the climate over a smaller region. The use of a RCM in dynamical downscaling requires substantial computational effort and cost and typically limits the length of the simulation period to about 10 years. Dynamical downscaling is most useful for diagnostic studies to understand local climate (Bhuvandas *et al*., 2014). The major drawback of dynamic downscaling, which restricts its use in climate change impact studies is its complicated design and high computational cost. Moreover, it is inflexible in the sense that expanding the region or moving to a slightly different region requires redoing the entire experiment.

2.6.2. Empirical (statistical) downscaling

Empirical downscaling is based on the view that the regional climate is conditioned by two factors: the large-scale climatic state and local physiographic features (example: topography, land-sea distribution and land use). From this perspective, regional or local climate information is derived first by determining a statistical model which relates large-scale climate variables (predictors) to regional and local variables (predictands). So statistical downscaling involves developing quantitative relationships between large-scale atmospheric variables (predictors) and local surface variables (predictands). The most common form has the predictand as a function of the predictor(s). The large-scale output of a GCM simulation is fed in to this statistical model to estimate the corresponding local and regional climate characteristics. Statistical downscaling methodologies have several practical advantages over dynamical downscaling approaches (Fowler *et al*., 2007). In situations where low–cost, rapid assessments of localized climate change impacts are required, statistical downscaling (currently) represents the more promising option

2.6.3. Comparative Skill of Statistical and Dynamical Downscaling technique

Several studies are available in the literature to review downscaling work and discuss the relative merits and limitations of the different techniques.

Table 2.2 Main strengths and weakness of statistical and dynamical downscaling

	Statistical downscaling	Dynamical downscaling
Strength	✓ Applicable to 'exotic' predictands such as air quality and wave heights ✓ Station–scale climate information from GCM–scale output ✓ Cheap, computationally undemanding and readily transferable ✓ Ensembles of climate scenarios permit risk/ uncertainty analyses	✓ Resolve atmospheric processes such as orographic precipitation ✓ Consistency with GCM ✓ 10–50 km resolution climate information from GCM–scale output ✓ Respond in physically consistent ways to different external forcing
Weakness	✓ Requires high quality data for model calibration ✓ Choice of empirical transfer scheme affects results ✓ Choice of predictor variables affects results ✓ Predictor–predictand relationships are often non–stationary	✓ Requires significant computing resources ✓ Consistency with GCM ✓ Not readily transferred to new regions or domains ✓ Ensembles of climate scenarios seldom produced

2.7. Coordinated Regional Downscaling Experiment (CORDEX)

CORDEX initiated by World climate Research program (WCRP) provides an opportunity for the generation of high-resolution regional climate projections over different region of the world that is used to assess future impacts of climate change at regional and local scales (Giorgi *et al*., 2017). The global climate change projection framework within CORDEX is based on the set of new global model simulations planned in support of the IPCC Fifth Assessment Report (AR5). This simulation is based on Representative concentration pathways (RCPs), i.e., prescribed greenhouse-gas concentration pathways throughout the 21st century, corresponding to different radiative forcing stabilization levels by the year 2100. Four Representative Concentration Pathways (i.e., RCP2.6, RCP4.5, RCP6.0, and RCP8.5) were selected. These scenarios are stated to as a low (RCP2.6); a medium (RCP4.5) and a high (RCP8.5) emission scenario in this profile.

CORDEX-Africa RCMs generate an ensemble of resolution historical and future climate projections at regional scale by downscaling different GCMs forced by RCPs based on the Coupled model Intercomparison Project Phase 5 (CMIP5) simulations used for impact and adaptation studies (Gbobaniyi *et al.*, 2014; Kim *et al.*, 2014). A number of studies, within Coupled model Intercomparison Project Phase 5 (CMIP5), the highest-priority global model simulations have been selected the RCP4.5 and RCP8.5, which roughly corresponds to the IPCC SRES emission scenarios of B1 and A1B, respectively.

2.8. Bias Correction

Bias correction is applied to compensate for any tendency to overestimate or underestimate the mean of downscaled climatic variables (Rathjens et al., 2016). There are different bias correction method applied for precipitation i.e. linear scaling (LS), local intensity scaling (LOCI), power transformation (PT), distribution mapping (DM) and quantile mapping (QM), while temperature correction methods are LS, variance scaling (VARI) and DM. The choice of bias correction algorithm plays a large role in assessing hydrological change. Several studies were carried out to compare these bias correction (Chen *et al*., 2013); Pierce *et al.*, 2015). Bias correction factors are computed from the statistics of observed and simulated variables. Bias correction, from very simplistic methods, such as the so-called delta method only correcting the statistical mean of the simulations, to more sophisticated ones for example based on distribution mapping is higher-skill and best performed bias correction method (Teutschbein & Seibert, 2012). Therefore, hydrological simulations driven by corrected simulated climate data match simulations using observed climate data reasonably well.

a. Linear Scaling

The linear scaling method is the simplest bias correction method; it has been the most widely used approach. The multiplicative correction approach is applied to precipitation. In this case, the ratio of the mean monthly observed precipitation and that of the model is used to scale model data at each time step (Equation (2.1)). Temperature was corrected by the additive correction approach under linear scaling. The mean monthly difference of the model and observed data was calculated and added to the model data at each time step (Equation (2.2)).

The linear scaling approach can be defined as:

$$P_{cor} = \mathrm{P_{unc}} \times \left(\overline{P_{obs,ctr}}/\overline{P_{rcm,ctr}}\right) \tag{2.1}$$

$$T_{cor} = \mathrm{T_{unc}} + \left(\overline{T_{obs,ctr}} - \overline{T_{rcm,ctr}}\right) \tag{2.2}$$

where P_{cor} is corrected precipitation, T_{cor} is corrected temperature,$\overline{P_{obs,ctr}}$ and $\overline{P_{rcm,ctr}}$ are the mean value of observed and simulated precipitation, respectively, and T stands for temperature.

b. Distribution Mapping

The Distribution Mapping is to correct the distribution function of raw RCM climate values to matches with observed distribution function. The distribution mapping method deliberates computing parameters, the Gamma distribution with shape parameter (α), and scale parameter (β) often used for precipitation distribution.

$$f_{y(x/\alpha,\beta)} = X^{x-\alpha}.\frac{1}{\beta^{\alpha} I(\propto).}.e^{\frac{-x}{p}};\ X \geq o; \quad \propto, \beta \tag{2.3}$$

where $f_{y(x/\alpha,\beta)}$ is the gamma function. Since the raw RCM simulated precipitation contains a large number of drizzle days, which may substantially distort the raw precipitation distribution, the correction is done on LOCI-corrected precipitation PLOCI, m, d:

$$P_{cor,m,d} = F_r^{-1}(F_r\left(\frac{P_{LOC,m,d}}{\propto_{LOC,m,}}, \beta_{LOC,m,}\right)/\propto_{Obs,m,}\ \beta_{Obs,m,}) \tag{2.4}$$

where $F_r(.)$ and $F_r^{-1}(.)$ are the gamma CDF (cumulative distribution function) and its inverse. $\alpha_{LOC,m}$ and $\beta_{\mathrm{LOCI,m}}$ are the fitted gamma parameters for the LOCI-corrected precipitation in a given month m, and $\alpha_{\mathrm{obs,m}}$ and $\beta_{\mathrm{obs,m}}$ are these for observations.

Temperature is defined by the Gaussian distribution (or normal distribution) with mean μ and standard deviation σ that describe temperature best(Olsson *et al.*, 2015). Corrects mean, standard deviation (variance), wet-day frequencies and intensities.

$$f_N\left({}^{x}/_{\mu}, \sigma\right) = \frac{1}{\sigma \times \sqrt{2\pi}} \times e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{2.5}$$

And then similarly the corrected temperature can be expressed as

$$T_{cor,m,d} = F_N^{-1}\left(\frac{F_N\left(\frac{T_{raw,m,d}}{\mu_{raw,m.d.}\sigma_{raw,m}}\right)}{\mu_{obs,m,}\sigma_{obs,m}}\right) \quad (2.6)$$

where F_N (.) and F_N^{-1} (.) are the Gaussian CDF and its inverse, $\mu_{raw,m.d}$ and $\mu_{obs,m,}$ are the fitted and observed means for the raw and observed temperature series at a given month m, and $\sigma_{raw,m}$ and $\sigma_{obs,m}$ are the corresponding standard deviations, respectively.

c. Delta Change Method

The delta change method consists of altering an observed (reference) climate series with change factors to obtain a new series representative of future changes. For the flux variables like precipitation relative change factors applied whereas for state variables like temperature absolute change is applied. Monthly change factors are derived and perturbed as follows for day and month (i, j), where i = 1, 2, 3, …., 31 and j = 1, 2, …., 12:

$$P_{obs}=P_{ref} \quad (2.7)$$

$$P_{(i,j)} = \Delta_{P(j)} \times P_{obs(i,j)} \quad ; \Delta_{P(j)}= \frac{P^{Avg}_{fut(j)}}{P^{Avg}_{ref(j)}} \quad (2.8)$$

$$T_{obs}=T_{ref} \quad (2.9)$$

$$T_{(i,j)} = \Delta_{T(j)} + T_{obs(i,j)}; \Delta_{T(j)}= T_{fut(j)} - T_{ref(j)} \quad (2.10)$$

Where $P_{(i,j)}$ and T $T_{(i,j)}$ are delta change perturbed daily climate change variables, $P_{obs(i,j)}$ and $T_{obs(i,j)}$are observed precipitation and temperature climate variables in the reference period, $\Delta_{P(j)}$ and $\Delta\Delta_{T(j)}$ are the changes in climate as simulated by RCM-RCP scenarios and $P^{Avg}_{(j)}$, $T^{Avg}_{(j)}$are daily precipitation and climate means by month, the index ref indicates the reference (control) and fut indicates a future period.

2.9. Hydrologic Modeling

In basin hydrology, it is impossible to measure everything in practice due to high basin heterogeneity and the limitations of measurement in space and time. These limitations initiated the application of hydrological models. Hydrologic models are simplified, conceptual representations of a part of the hydrologic cycle. Hydrological modeling incorporates the application of mathematical expressions that define quantitative relationships between inputs and outputs. They are primarily tool to assess the impact of future hydrological change. A wide range of hydrological (rainfall-runoff) models are used by the researchers, however the choice hydrologic model is very important for getting good results.

2.9.1. Selection criteria for hydrological models

There are different criteria which can be used for selecting the "appropriate" hydrologic model. Although there are no clear rules for making a choice between models, some simple guidelines can be stated. According to (Cunderlik, 2003) these criteria are user depended (and therefore subjective), such as the personal preference for graphical user interface, computer operation system, input-output (I/O) management and structure. For example, Cunderlik has also listed based on project-dependent criteria accordingly there are four common, fundamental questions that must be always answered during model selection.

I. Does the model predict the variables required by the project such as peak flow, event volume and hydrograph, long-term sequences of flows?
II. Is the model capable of simulating snow accumulation and melt, single-event or continuous processes?
III. Availability of input data (Can all the inputs required by the model be provided within the time and cost constraints of the project?),
IV. Price (Does the investment appear to be worthwhile for the objectives of the project?).

Therefore, to achieve the objectives of this research in the katar sub basin as case study, the following selection criteria were defined against which models could be evaluated for suitability.

- ✓ A model should be able to simulate different components of the stream flow including surface runoff, lateral flow and base flow that are important components of the flow in perennial rivers.
- ✓ A model should be easily and freely available, both for research and for future use in Ethiopia to increase the application of the model in different part of Ethiopian basins.
- ✓ Model calibration can be done either manually or automatically at a place where observational flows are available for the sake of determining un-gauged flow from un-gauged part of Katar sub-basin.

- ✓ The minimum input data requirements by the model must be readily available or can be synthesized with some efforts through application of general formula, for example to convert sunshine hours to solar radiation.
- ✓ Its temporal scale should be long term, continuous and able to simulate on daily bases for water budget analyses at watershed and sub-basin levels for current and future time frame.
- ✓ And the model should be applied in different sizes of the basin starting from small scale to large scale basin.

For this research Soil and Water Assessment Tool (SWAT) and SUFI-2 linked in SWAT-CUP was selected depending upon the above selection criteria.

2.9.2. Description of SWAT model

Soil Water Assessment Tool (SWAT) is a semi-distributed physically based hydrological model developed by the United States Department of Agriculture (USDA) for evaluating the impact of agricultural management on water, sediment and agriculture chemical yield with varying conditions over long periods of time (Arnold *et al*., 1998). In the model, a basin is divided into multiple subbasins, which are then further subdivided into Hydrologic Response Units (HRUs) that consist of homogeneous land use, management, and soil characteristics (Gassman *et al*., 2007). For each HRU the model simulates relevant hydrologic components such as evapotranspiration, surface runoff and peak rate of runoff, ground water flow and sediment yield. SWAT application is interfaced with different a geographic information system (GIS) and databases that can integrate various spatial data including soil, land cover, and topographic features in defining HRUs. SWAT Is widely used in different parts of the world to assess the impact of climate change on hydrology (Mishra *et al*., 2018; Musau *et al*., 2015; Zahabiyoun *et al*., 2013). Several studies have also investigated the impacts of climate change on hydrology in the Ethiopia using SWAT model (Roth *et al*., 2018; Adem *et al*., 2016; Shawul *et al*., 2016). The reasons why the SWAT model has been widely used was the range of facilities it affords, the facility to freely download the model, the links to GIS databases, the way it can imitate catchment characteristics and land management strategies, and the way in which can be applied to ungauged catchments using default parameters.

2.9.3. SWAT- Calibration and Uncertainty Program (SWAT-CUP)

The Soil and Water Assessment Tool-Calibration and Uncertainty Program (SWAT-CUP) in combination with the Sequential Uncertainty Fitting ver. 2 program (SUFI-2) is used to perform calibrations, uncertainty analysis and validation of hydrologic model (Abbaspour, 2015). It is an open space interface that was developed for SWAT by using the generic interface, any calibration, uncertainty or sensitivity program can be easily linked to SWAT model. SUFI-2 is capable of analyzing a large number of parameters and measured data from many gauging stations simultaneously (Abbaspour *et al*., 2015). It is used to calculate 95% prediction uncertainty band for the outputs to characterize model uncertainty.

3. MATERIALS AND METHODS

3.1. Descriptions of the Study Area

Katar catchment is located in the Oromia Regional State of central Rift valley (CRV) basin of Ethiopia. This study area lies in northern part of CRV basin in the part of the Ziway Shala sub basin. In terms of geographic coordinate system, the catchment lies between 7^{0}21'34'' to 8^{0}9'55'' North latitudes and 38^{0}53'57'' to 39^{0}24'46'' East longitudes. The Katar River and its tributaries start from the eastern parts of mountains Chilalo, Galema and Kakka of Arsi Zone and drains to Lake Ziway. The over flow of Lake Ziway drains to Lake Abiyata. Topographically, the Katar catchment shows variation with altitude ranging from around 1,661m near Abura (at gauging Station) to about 4182m above mean sea level on the high volcanic ridges along the eastern watershed. The total area of the catchment, upstream the gauging station is estimated to be 3190.48 km^2.

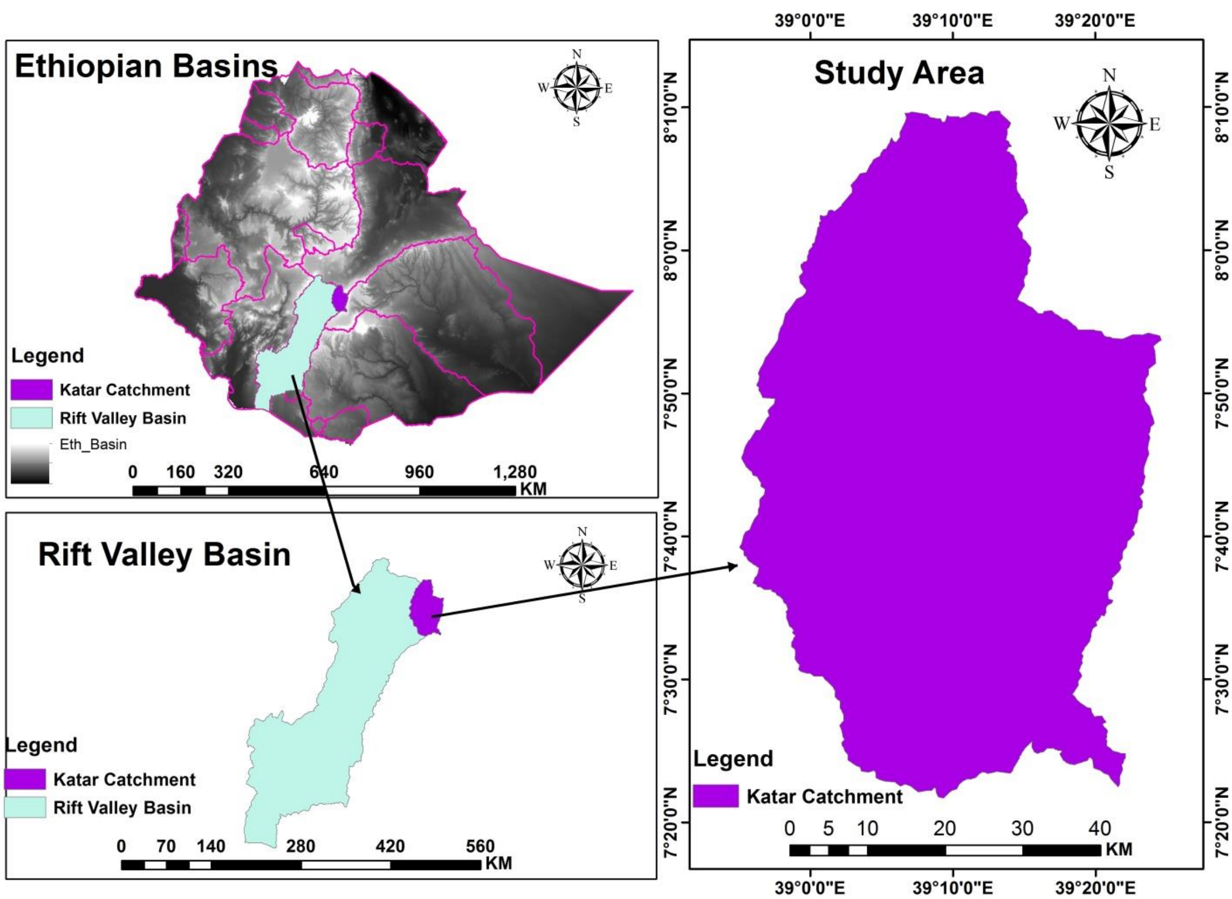


Figure 3. 1 Location of study Area

3.2. Data Availability

To get a better result, it is critical to use all relevant and good quality data required. The outcome depends on the quality and quantity of data used because the spatial and temporal resolution of data used in modelling will greatly influence the model performance. The SWAT (Soil and Water Assessment Tool) needs good quality of digital elevation model (DEM), Soil and Land use/land cover and meteorological data above all other necessary data to simulate the discharge and sediment from a given watershed. The length of period of weather and climatic data also affect the SWAT model performance. The output from the SWAT model can be affected by the DEM data resolution, mesh size, soil data resolution and soil map scale, watershed subdivision which on the other hand is affected by DEM data resolution etc. The required DEM data, soil data, land use/land cover data, flow data and climatic data was collected from different sources. The quality and quantity of data used in the development of SWAT project in this study will be discussed in the next sections.

3.2.1. Digital elevation model (DEM) data

Digital Elevation Model data (30x30m) resolution was downloaded from the USGS databases of the SRTM (Shuttle Radar Topography Mission) website (https://earthexplorer.usgs.gov/). DEM is used in the SWAT model along with soil and land use/land cover data to delineate the watershed and to further divide the watershed into sub-watersheds and hydrologic response units (HRUs). Fig.3.2 shows the digital elevation model (DEM) of the Katar Katchment.

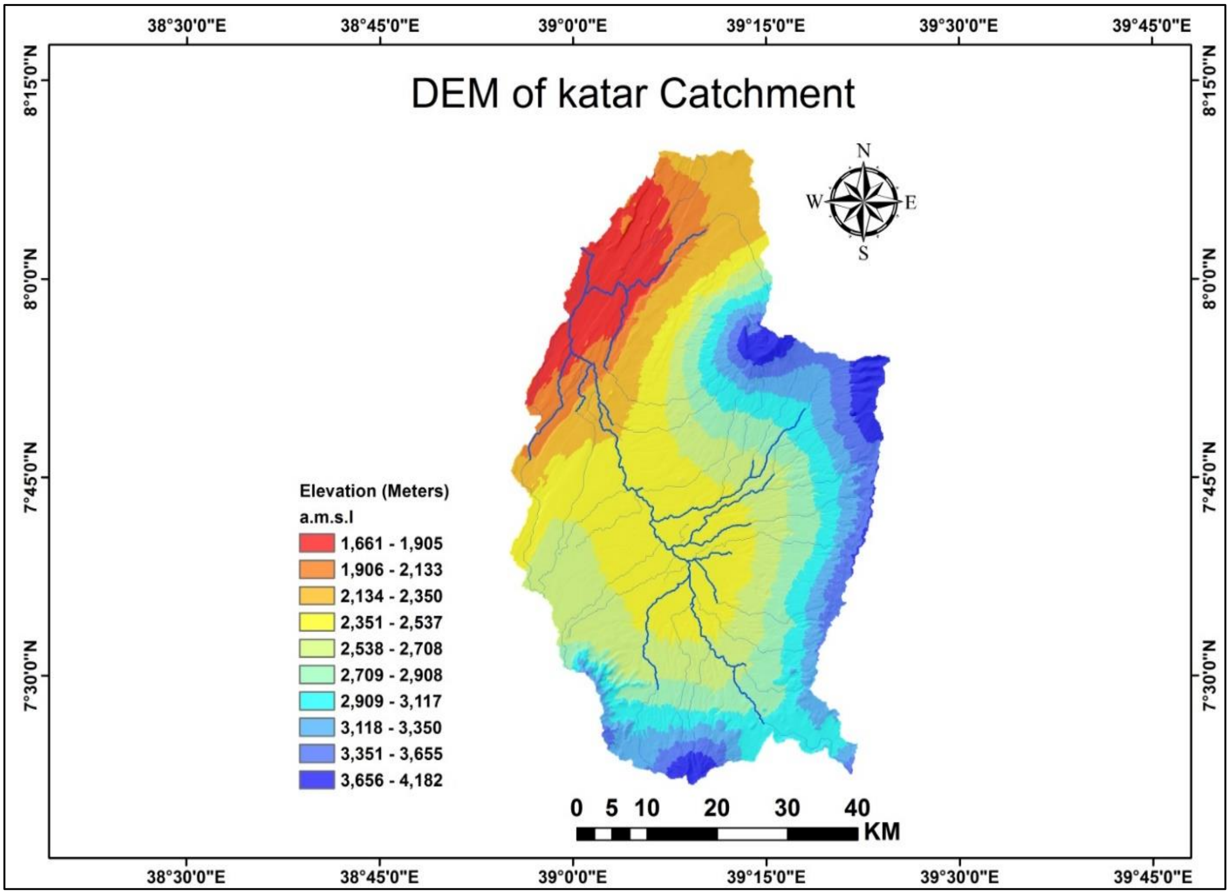


Figure 3.2 Digital Elevation Model (DEM) of the Katar Katchment.

3.2.2. Soil data

Soil data was downloaded from the FAO Digital Soil Map of the World (DSMW) database at http://www.fao.org. The watershed boundary was used to extract the soil data from the FAO soil database of the African soils slice. The attributes of these soils in Fig. 3.3 were updated using a “usersoil” table from the MapWindow SWAT12 database due to the fact that the “usersoil” table of ArcSWAT12 soil database contains USA soils only. SWAT model requires different soil Textural and physicochemical properties such as soil texture, available water content, hydraulic Conductivity, bulk density, hydrological soil groups and organic carbon content for different layers of each soil type. Soils in the study watershed are classified based on the FAO/Globe soil (FAO/UNESCO,) classification system. According to FAO, five major soils types are identified for the study area as shown in figure 3.3 below. Haplic Xerosols (Silt_Loam), Eutric Nitosols (Clay), Haplic Xerosols (Loam), Dystric Regosols (Loam) and Pellic Vertisols (Clay) are found in the study area.

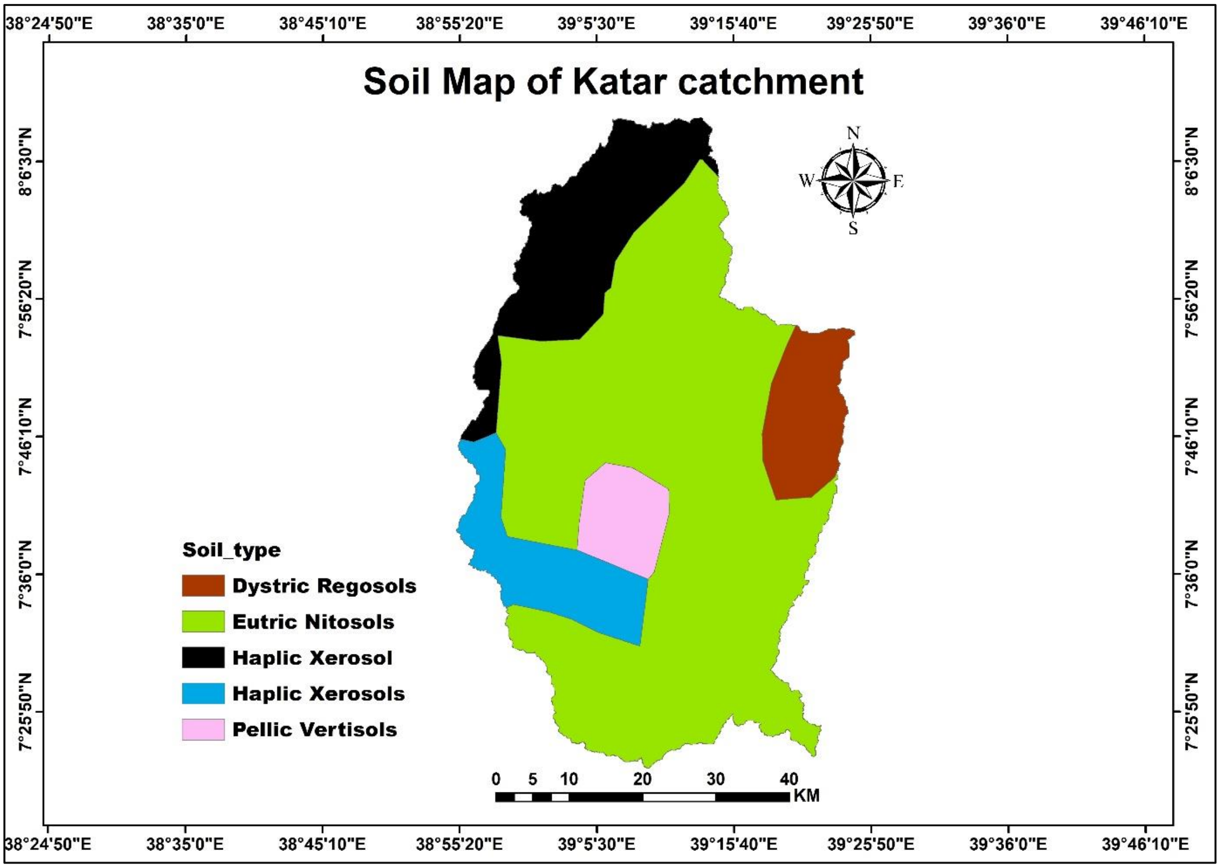


Figure 3. 3. Soil map of Katar Catchment

Table 3. 1.Soil types of Katar Catchment

Soil Group	SNAME	Soil Group	Texture	Area(km^2)	%Area
Haplic Xerosol	Xh16-a-309	C	Silt_Loam	476.8	14.94
Eutric Nitosols	Ne10-3b-154	C	Clay	2077	65.1
Haplic Xerosols	Xh17-2a-310	D	Loam	272.6	8.54
Dystric Regosols	Rd2-2c-229	C	Loam	216.9	6.8
Pellic Vertisols	Vp1-3a-283	C	Clay	147.1	4.61
TOTAL				3190.48	100

3.2.3. Land use/cover data

Land use/cover (LULC) map is extracted through the processing of satellite Landsat 7 image which is downloaded from USGS database website (http://earthexplorer.usgs.gov/) that has a spatial resolution of 30 m. In this study Land sat images of 05/12/2000 for Path/row

(168/54,55) was used for mapping LU/LC map of the Katar river basin. The supervised classification in ArcGIS10.3 is done to reclassify the land use of the area which used for the HRUs analysis. The reclassification of the land use map was made to represent the land use according to the specific LULC types and the respective crop parameter for SWAT database. A lookup table that identifies the SWAT land use code for the different categories of LULC was prepared to relate the grid values to SWAT LULC classes. SWAT require land use data to determine the area of each land category to be simulated within each sub basin. It affects the runoff in the watershed. The land use/cover of the study area is shown in the figure.3.4 below.

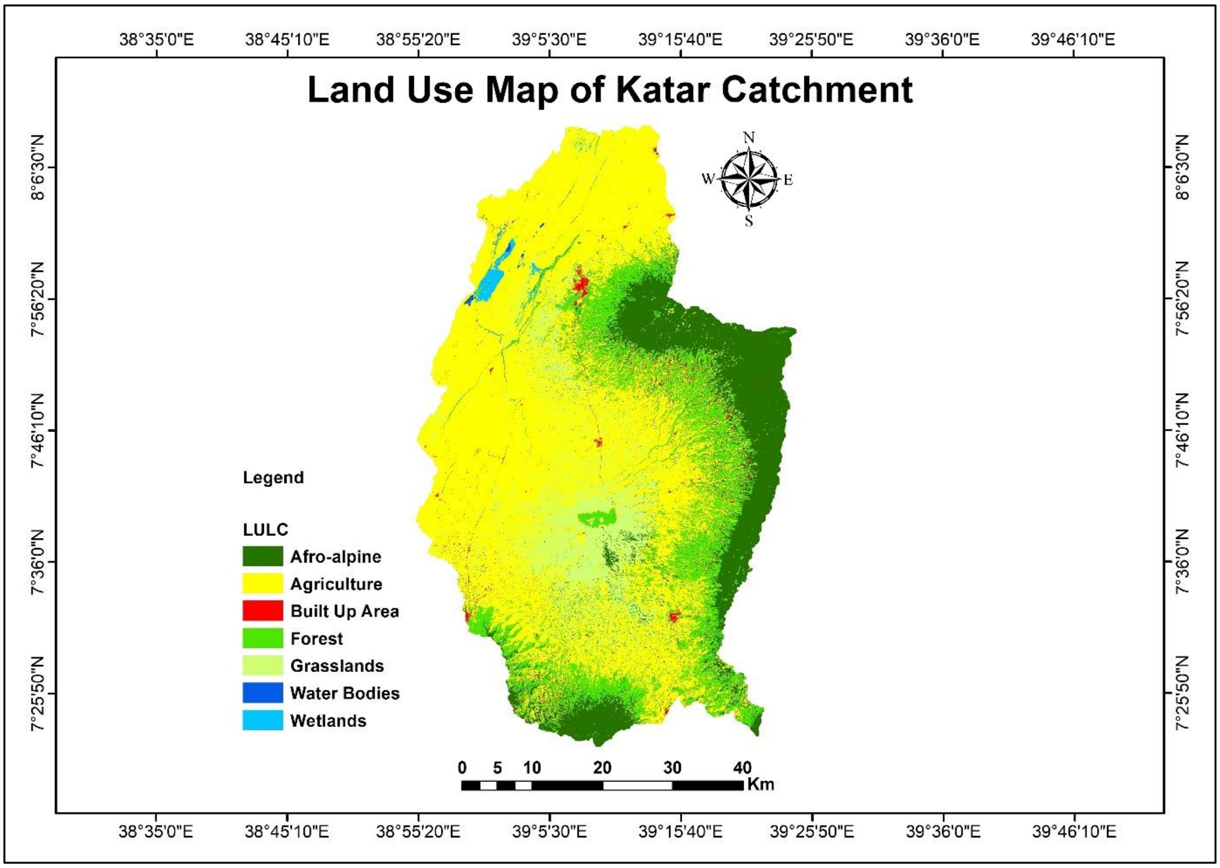


Figure 3. 4. Land use land cover (LULC) of Katar Catchment

The summary of the land use of Katar Catchment is given in the Table 3.2 below. These percentages are based on the total area of the catchment delineated by Arc SWAT.

Table 3.2 Land use land cover proportion of Katar Catchment

Land use	**Land use according to SWAT database**	**SWAT code**	**Area (km^2)**	**% Area Coverage**
Forest	Forest-Mixed	FRST	38.92	1.22
Agriculture	Agricultural Land-Row Crops	AGRR	1818.53	57
Grasslands	Pasture	PAST	465.29	14.58
Built Up Area	Residential-Medium Density	URMD	312.16	9.78
Wetlands	Wetlands-Non-Forested	WETN	22.95	0.72
Afro-alpine	Forest-Evergreen	FRSE	528.59	16.57
Water Bodies	Water	WATR	1.43	0.13
	Total		3190.48	100

3.2.4. Slope

The slope map was derived from the DEM using the Spatial Analyst tool. This slope was used for the development of Hydrological Response Unit in addition to land use and soil input parameters. Arc SWAT allows the integration of land slope classes (up to five classes) when defining hydrologic response units. There are possibilities to choose simply a single slope class, or choose multiple classes. This study considers five slope classes for Katar Catchment. Table 3.3 below shows the slope distribution of Katar Catchment.

Table 3. 3. Slope distribution of Katar Catchment.

No	**Slope (%)**	**Area (km^2)**	**% Area of coverage**
	0-5	1258.22	39.44
	5-10	913.75	28.64
	10-15	444.66	13.94
	15-20	236.52	7.41
	>20	337.33	10.57
Total		3190.48	100%

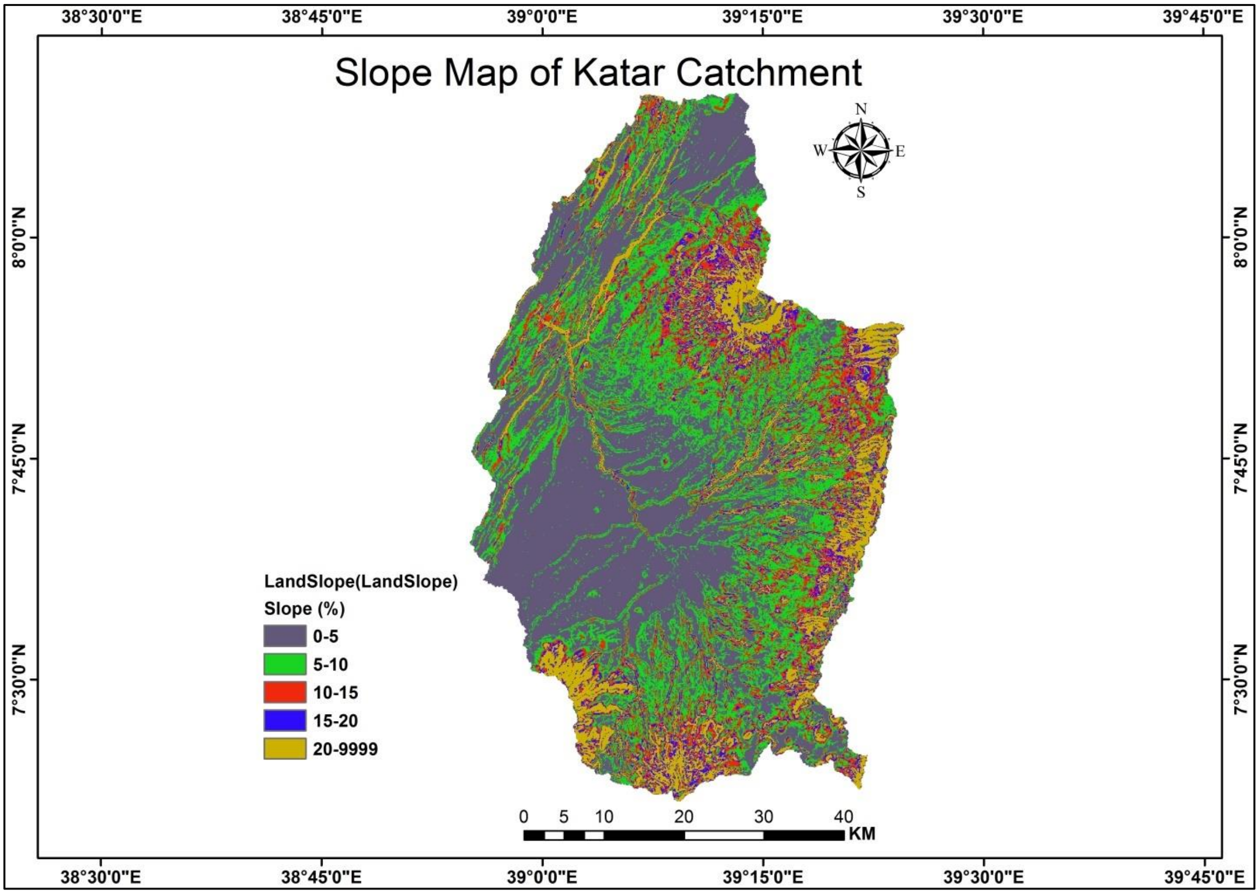


Figure 3. 5 Slope map of Katar Catchment

3.2.5. Meteorological data

SWAT requires daily values of precipitation, maximum and minimum temperature, solar radiation, and relative humidity and wind speed. These were collected from the National Meteorological Agency (NMA) of Ethiopia. The meteorological stations in the watershed are first class, third class and fourth classes. The first-class gauging stations (Kulumsa) contains all meteorological data i.e., precipitation, maximum and minimum temperature, relative humidity and sunshine hours. Third class stations (Asela, Arata, Bekoji and Ogolcho) has rainfall data and maximum and minimum temperature. The fourth-class gauging station contains (kersa) the precipitation data only. Sagure and Meraro stations were left due to short year recorded time series. For this purpose, five stations, namely, Kulumsa, Bekoji, Ogolcho, Asela and Arata (Table 3.4), were selected based on the quality and the availability of long year recorded data.

All the meteorological stations in the study area and the other neighbor stations nearest to the study area are shown in the figure 3.6 below.

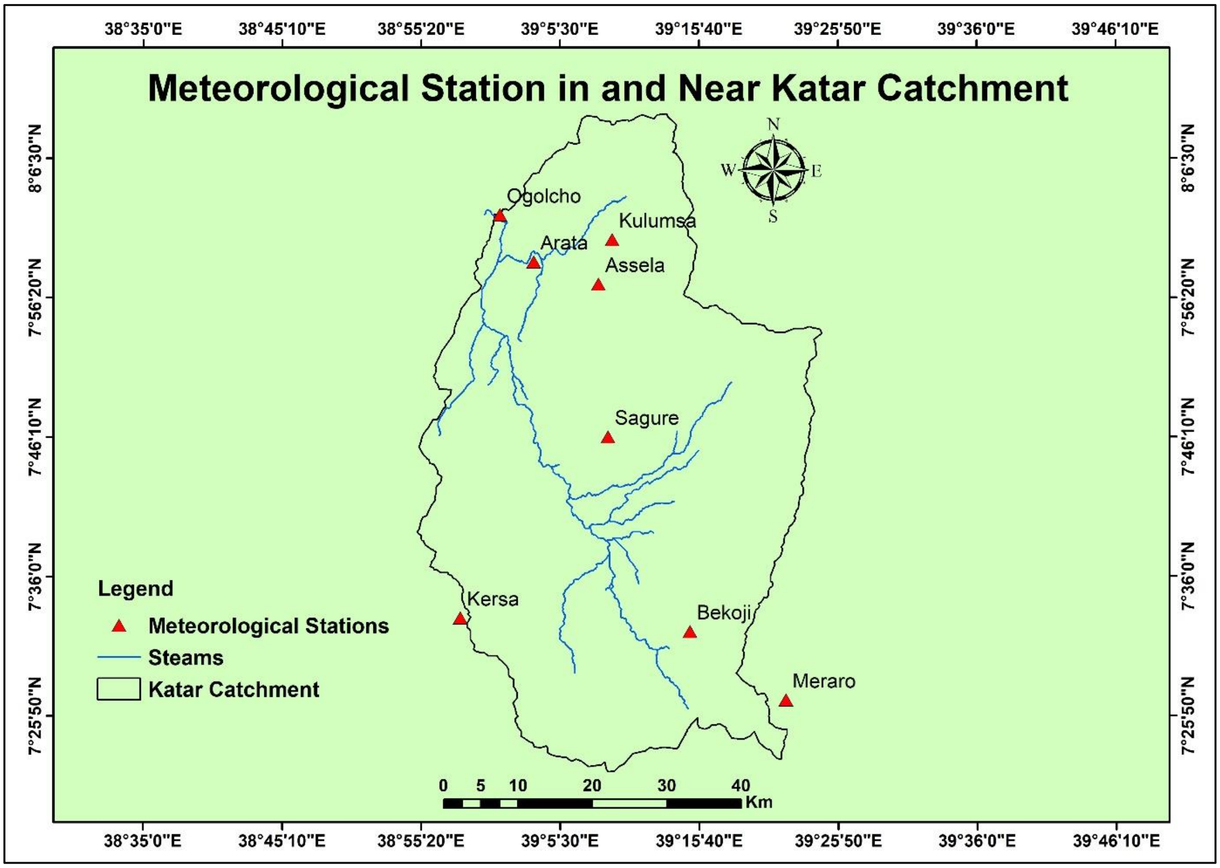


Figure 3. 6. Meteorological stations in and at the surrounding area of Katar Catchment

Table 3. 4 Meteorological station locations and length of data series.

	Name of station	Latitude	Longitude	Elevation(m)	Data series
	Ogolcho	8.0398	39.0182	1682	1986-2017
	Sagure	7.77	39.15	2480	1999-2017
	Bekoji	7.5333	39.25	2881	1986-2017
	Meraro	7.45	39.36667	2940	2006-2017
	Kulumsa	8.0097	39.1553	2211	1986-2017
	Asela	7.9557	39.1383	2413	1986-2017
	Arata	7.982778	39.05944	1777	1986-2017
	Kersa	7.55	38.97	2700	1986-2017

3.2.6. Hydrological data

Stream flow data was required for performing sensitivity analysis, calibration and validation of the SWAT model. The observed stream flow data 1991-2004, for Abura (the outlet of the watershed) was taken from Ministry of water resources, Irrigation and energy, Hydrology department. This flow data was arranged as to the requirement of the Arc SWAT model and used for model calibration and validation. The stream flow data from 1991 to 1996 was used for model calibration and 1997-2000 for model validation.

3.2.7. Projected Climate data

*In this paper, downscaled climate variables (daily rainfall, minimum and maximum temperatures) from the historical (1981-2005), future (2021-2040) and (2041-2070) climate projections, under two Representative Concentration Pathways (RCP): RCP 4.5 and RCP 8.5 have been used to evaluate the climate change. These climate Variables were downloaded from website (*https://esgf-data.dkrz.de/search/cordex-dkrz*) under CORDEX (Coordinated Regional Downscaling Experiment) Africa regional climate models, with a spatial resolution of 0.44◦×.44◦(50km×50km). The regional climate models (RCMs), RACMO22T (Regional Atmospheric Climate Model, version 2.2) with the driving model ICHEC-EC-EARTH was used. In this study, ensemble of CORDEX-Africa RCMs under RCP4.5 and RCP8.5 climate scenarios with bias correction methods were used as an input for SWAT to assess the impact of climate change on stream flow of Katar Catchment. The analyses were performed in two-time horizons in a time period of 20 years for both baseline and future periods. The baseline period used for this study was 1986–2005, while future scenario analysis involved 2021–2040 (2030s) and 2051–2070 (2060s).*

Table 3.5 Summary of CORDEX-Africa data portal

Model selection criteria	Variables
Project	CORDEX
Institute	KNMI
Experiment	Historical, RCP 4.5, and 8.5
Ensemble	r1i1p1
Variable	pr, tmax, tmin
Time-frequency	Daily
Regional climate model (RCM)	RACMO22T
Driving-model	ICHEC-EC-EARTH
Domain	AFR-44

Where r1i1p1, which represents realization #1, initialization I #1, and physics p #1; KNMI: (Royal Netherlands Meteorological Institute; RACMO22T: Regional Atmospheric Climate Model, version 2.2; pr: precipitation; tmax: maximum temperature; tmin: minimum temperature

3.2.8. Summary of Data's and materials used for this study

Table 3. 6 Data's used and their sources for this study

Data Type	**Data Sources**	**Description**
Rainfall, Temperature, Wind speed, Sun Shine Hr, Relative Humidity	National Meteorological Service Agency	For WGEN preparation and weather data definition
Hydrology/Stream flow	Ministry of Water Irrigation and Energy	For performance checking with simulated data
SRTM DEM-30x30m	http://earthexplorer.usgs.gov/	Used to delineate the watershed &For HRU analysis in SWAT
Soil/ FAO UNESCO	http://www.fao.org.	For HRU analysis in SWAT
Land cover/ Landsat 7	http://earthexplorer.usgs.gov/	For HRU analysis in SWAT
Climate Scenario	https://esgf-data.dkrz.de/search/cordex-dkrz	For analysis of future climate scenario

Table 3.7 Software tools used and their purpose in this study

Name of software's	**Purpose**
Arc SWAT 2012	Uses for simulation and act as a GIS interface for SWAT modeling
ArcGIS 10.3.1	Uses for map preparation and uses SWAT models extension
CMhyd tool	Used to correct biases between observed and simulated climate data
Swat cup	Used to test the performance of SWAT model
map window	Used to update SWAT12 soil database
mwswat2012	Act as map window interface to update SWAT12 soil database
pcpSTAT	For weather generator preparation for the SWAT model
dewpoint	For weather generator preparation for the SWAT model
MS-Excel	For statistical data analysis, Chart and graphs
Xlstat	For data Quality analysis
Mendeley	Used to insert citation and bibliography

3.3. Modeling Approach and Data Analysis

This study elaborates the impact of climate change on of stream flow of katar catchment. Before starting any data analysis, the quality of all observed climate and streamflow data (missing data, consistency, homogeneity) were checked using double mass curve analysis. Then, the baseline and two future climate scenarios (RCP4.5 and RCP8.5) were statically downscaled using the CORDEX-Africa output data from GCMs/ICHEC-EC-EARTH models. The downscaled climate datasets were corrected from model biases using the Distribution Mapping method. Then the future changes in precipitation and maximum and minimum temperature were assessed in the basin. The Soil and Water Assessment Tool (SWAT) model was calibrated and validated using historical bias-corrected climate and streamflow data. Finally, the calibrated and validated SWAT model was used to simulate the projected stream flows during the 2030s and 2060s. The detailed procedures for the climate and SWAT model are presented as follows.

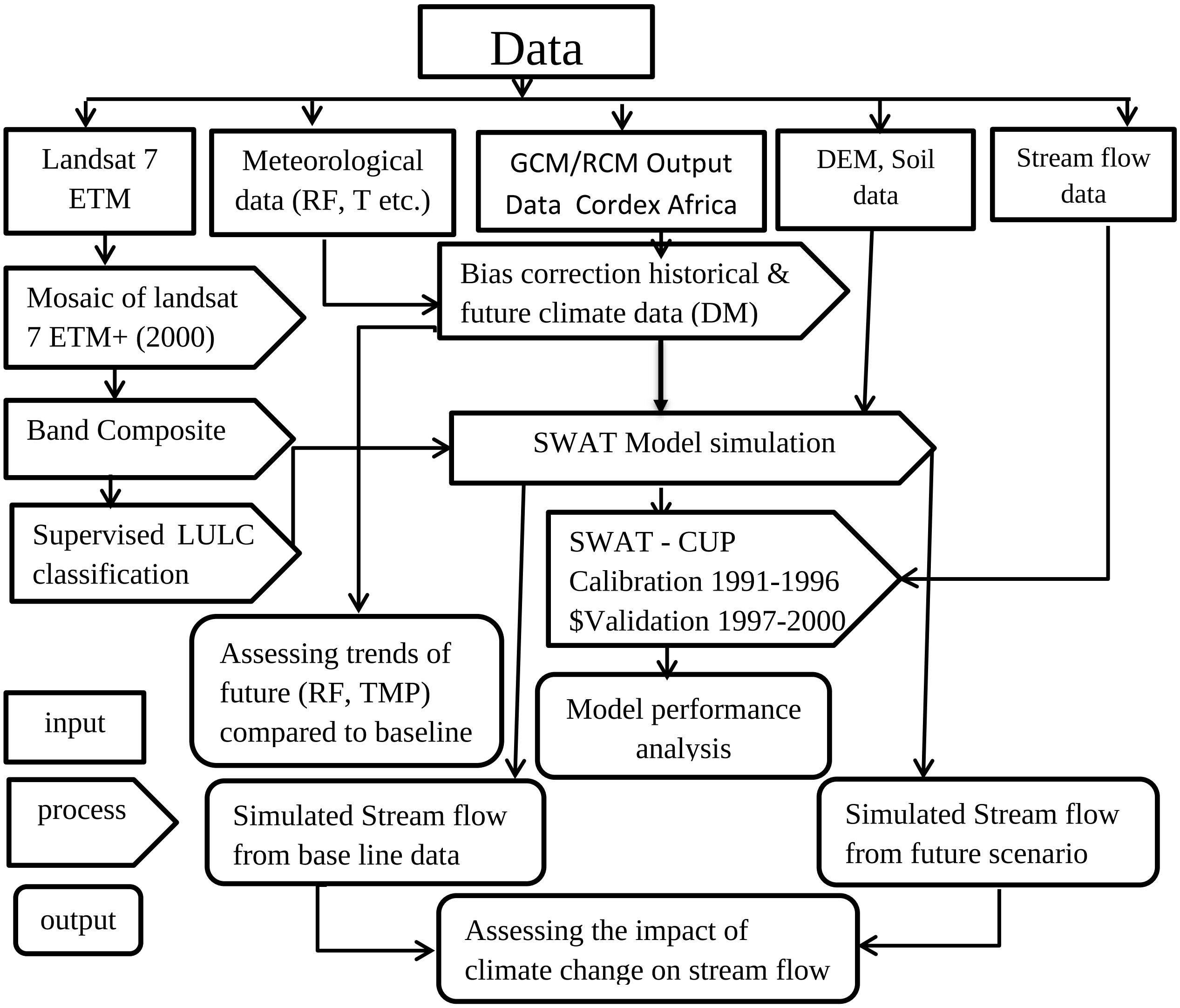


Figure 3. 7 Conceptual diagram of SWAT modeling process with climate

3.3.1. Data Quality analysis

The precipitation data was checked for inconsistency before it is used for further analysis. The quality control can be done by visual inspection, filling of missing data if there is any, accumulated plot and double mass curve. This will help to identify if there are any gaps or unphysical peaks in data series and correct them before the data is used as input to the model. Otherwise, using the incorrect data as input to the model will give incorrect output from the model. The series data Stream flow of Katar catchment were checked the unrealistic data record or the outlier. An outlier is an observation that appears to deviate markedly from other observations in the sample. The monthly flow data of the Katar River was checked by through the steps calculating the quartiles, calculating the upper and lower boundaries and evaluating the results in excel spread sheet and there was no outlier identified.

3.3.1.1. Visual inspection

The quality control checks by visual inspection to ensure that data is with invalid ranges and no strange values are entered. This can be done by checking if date and time record is complete, unphysical values (spikes and negatives), flat regions (sensor or transfer system fall out) and unphysical variation patterns (sensor malfunctioning). The visual inspection was done by excel spread sheet.

3.3.1.2. Filling of missing data

Precipitation stations may have short breaks in the records because of absence of the observer or because of instrumental failures. It is often necessary to estimate or fill in this missing record. In this study missing of observed rain rainfall and Temperature values are estimated by multiple regressions using XLSTAT by filling each from its neighboring stations. For Missing weather data will leave as it was in name.txt format and a negative (-99.0) inserted for missing data. This value tells SWAT to generate weather data for that day. The model generates a set of weather data for each sub basin. The same weather generator technique was applied for filling in maximum and minimum temperature.

3.3.1.3. Checking homogeneity of selected stations by non- dimensional parameterization

Homogeneity analysis was used to separate a change in the statistical properties of the time series data. This was tested by computing non-dimensional of rainfall data by dividing the monthly time series data by the average rainfall amount of the respective year. As shown in the Figure 3.8, one can see the homogeneous nature of the stations in study region.

$$Pi = \frac{\overline{Pi}}{\overline{P}} \times 100 ----------------------------------3.1$$

Where:

Pi - is non- dimensional value of precipitation for the month in the station i

$\overline{Pi}$ - is over year’s average monthly precipitation for the station i

$\bar{P}$-is over year average yearly precipitation for station i

The selected stations were plotted for comparison and the stations have the same trend of the hence the group of station selected are homogeneous.

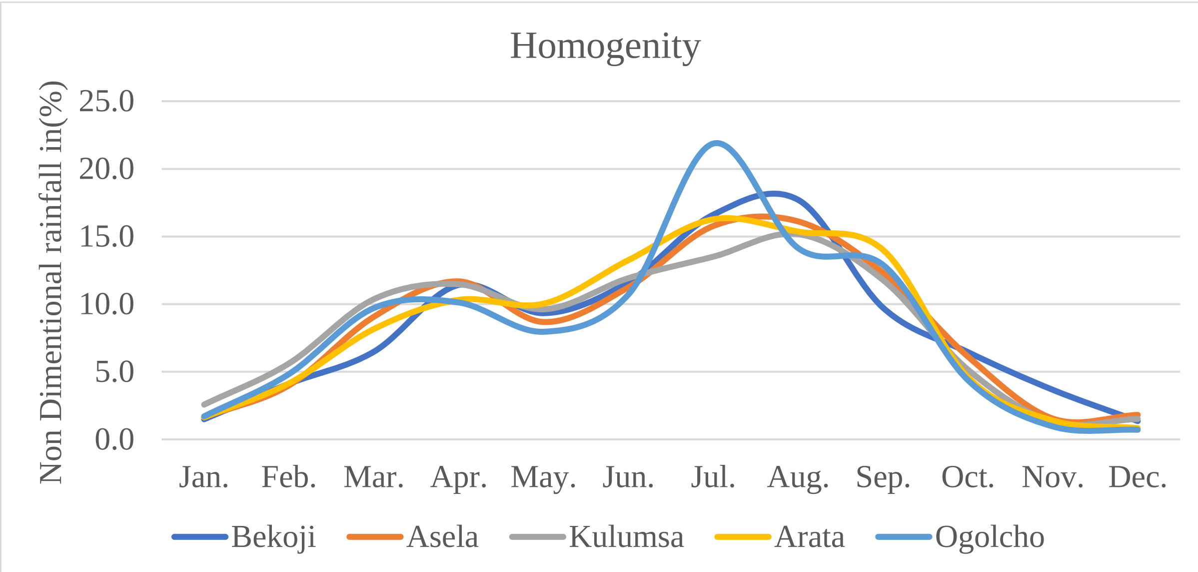


Figure 3. 8. Homogeneity tests for selected weather station at Katar catchment

3.3.1.4. Checking consistency of gauging stations

Double Mass Curve analysis has been used to assess the data consistency of the station for the period of 1986-2005. Cumulated values of a given station are plotted against accumulated values of the average value of other stations, over the same period of time. Through the double mass curve in homogeneities in the time series (in particular jumps) can be investigated, if for a change in observer record, in rain-gauge type, etc. This is indicated in double mass plot, showing an inflection point in the straight line. The data series, which is inconsistent, can be adjusted to consistent values by proportionality. Figure 3.9 shows all the stations were consistent.

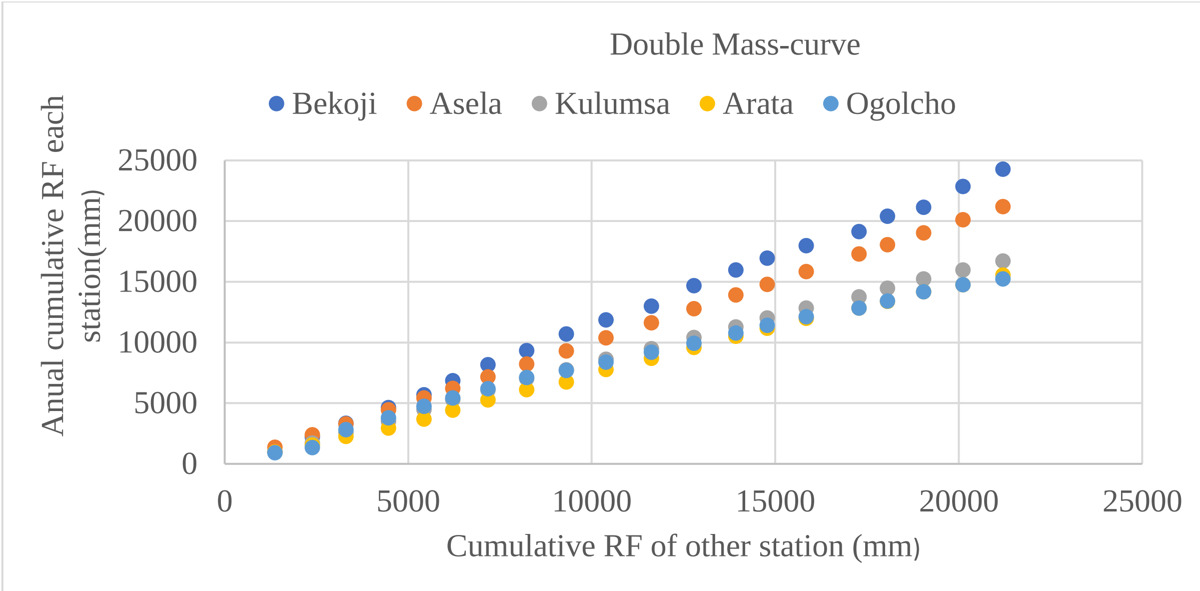


Figure 3.9. Consistency test graph for Selected the stations of Katar Catchment

3.3.2. Weather generator data preparation

SWAT Weather Database is designed to be a friendly tool to store and process daily weather data to be used with SWAT projects (Essenfelder, 2016). The model generates a set of weather data for each sub basin. SWAT requires daily precipitation (mm), maximum/minimum air temperature (°C), solar radiation (MJ/m²/day), wind speed (m/s) and relative humidity (percentage). In order to generate data, weather parameters were developed by using the weather parameter calculators pcpSTAT.exe And DEW02, which were downloaded from the SWAT website (http://www.brc.tamus.edu/swat/soft_links.html). The statistical parameters for precipitation and temperatures were calculated using the programme pcpSTAT.exe and Dew02 software respectively. This programme calculates the statistical parameters of daily precipitation data used by the weather generator of the SWAT model. The result is shown in Appendix D1. On the other hand, the statistical calculator Dew02 software calculated statistical parameters calculation for temperature data (Liersch, 2003). In this study weather, generator parameters were calculated for Kulumsa observation station. weather generator requires first class meteorological stations i.e. Full off all the meteorological data (precipitation data, maximum and minimum temperature, relative humidity, wind speed and sunshine hours) with different degree of missing data.

3.3.3. Solar Radiation

Once water is introduced to the system as precipitation, the available energy solar radiation exerts a major control on the movement of water in the land phase of the hydrologic cycle. Arc SWAT takes the daily solar radiation but the data acquired from the National Meteorological Agency (NMA) is sunshine hour, hence a conversion of variable were made using (Angstrom, 1994) empirical equation.

$$R_s = \left(a_s + b_s \frac{n}{N}\right) R_a \qquad (3.1)$$

Where Rs solar or shortwave radiation $[MJm^{-2}day^{-1}]$

n actual duration of sunshine [hour]

N maximum possible duration of sunshine or daylight hour [hour]

R_s extraterrestrial radiation $[MJm^{-2}day^{-1}]$

a_s regression constant, expressing the fraction of extraterrestrial radiation reaching the earth on overcast days(n=0)

$a_s + b_s$ fraction of extraterrestrial radiation reaching the earth on clear days (n=N).

3.3.4. Bias Corrections of regional climate data

Raw regional climatic model output data cannot always be used directly as input in several hydrological climate-change impact studies. Although RCMs are able to simulate local climate at finer resolutions. This has led to the development of a number of correction approaches that used adjust simulated climate data at an appropriate spatial and temporal scale. The choice of bias correction method also plays a great role in assessing the impact of climate change on hydrology. There are different methods of bias correction i.e. Linear scaling (LS), power transformation (PT), variance of scaling (VS), and distribution mapping were used in different studies. Distribution mapping is higher-skill and best performed bias correction method for climate projection and hydrological climate change impact studies (Teutschbein & Seibert, 2012). Therefore, in this study distribution mapping was selected to adjust raw ensemble of CORDEX-Africa RCMs RCP scenarios output simulation data. CMhyd (Climate Model data for hydrologic modeling) tool was used to extract and bias-correct data obtained from global and CORDEX-Africa RCMs from the grid cells covering the katar river basin. Rainfall, maximum temperature, minimum temperature variables were extracted for historical time period of 1986-2005, future data (rcp4.5 and rcp8.5) 2021-2040 and 2051-2070. The choice between bias correction algorithms plays a large role in assessing hydrological climate change impacts. For current conditions, I have limited this choice to the one that performed best. In this research, distribution mapping was selected to adjust raw ensemble of CORDEX-Africa RCMs RCP scenarios output simulation data.

Distribution Mapping

The Distribution Mapping is to correct the distribution function of raw RCM climate values to matches with observed distribution function. The distribution mapping method deliberates computing parameters, the Gamma distribution with shape parameter (α), and scale parameter (β) often used for precipitation distribution.

$$f_{y(x/\alpha,\beta)} = X^{x-\alpha}.\frac{1}{\beta^{\alpha}I(\propto).}.e^{\frac{-x}{p}};\ X \geq o;\quad \propto,\beta \qquad (3.2)$$

where I(.) is the gamma function. Since the raw RCM simulated precipitation contains a large number of drizzle days, which may substantially distort the raw precipitation distribution, the correction is done on LOCI-corrected precipitation PLOCI,m,d:

$$P_{cor,m,d} = F_r^{-1}\left(F_r\left(P_{LOC,m,d}/\propto_{LOC,m,},\beta_{LOC,m,}\right)/\propto_{Obs,m,}\ \beta_{Obs,m,}\right) \qquad (3.3)$$

where $F_r(.)$ and $F_r^{-1}(.)$ are the gamma CDF (cumulative distribution function) and its inverse. $\alpha_{LOC,m}$ and $\beta_{\mathrm{LOCI,m}}$ are the fitted gamma parameters for the LOCI-corrected precipitation in a given month m, and $\alpha_{\mathrm{obs,m}}$ and $\beta_{\mathrm{obs,m}}$ are these for observations.

Temperature is defined by the Gaussian distribution (or normal distribution) with mean μ and standard deviation σ that describe temperature best (Olsson et al., 2015).

$$f_N\left({}^{x}/_{\mu},\sigma\right) = \frac{1}{\sigma\times\sqrt{2\pi}} \times e^{\frac{-(x-\mu)^2}{2\sigma^2}} \qquad (3.4)$$

And then similarly the corrected temperature can be expressed as

$$T_{cor,m,d} = F_N^{-1}\left(\frac{F_N\left(\frac{T_{raw,m,d}}{\mu_{raw,m.d.}\sigma_{raw,m}}\right)}{\mu_{obs,m,}\sigma_{obs,m}}\right) \qquad (3.5)$$

where F_N (.) and F_N^{-1} (.) are the Gaussian CDF and its inverse, $\mu_{raw,m.d}$ and $\mu_{obs,m,}$ are the fitted and observed means for the raw and observed temperature series at a given month m, and $\sigma_{raw,m}$ and $\sigma_{obs,m}$ are the corresponding standard deviations, respectively

3.3.5. Climate Change Analysis

The annual projected climatic variables (rainfall, maximum and minimum temperature) from (2021 - 2040) and (2051 - 2070) under RCPs 4.5 and 8.5 were compared with historical values in a baseline period (1986 - 2005). Thus, the variations of mean precipitation, maximum and minimum temperature, at different time periods were calculated in relation to the baseline period (1986 - 2005). The variations are expressed as a percentage and are calculated according to the following formula:

$$\Delta_i^{hori} = \frac{\left(\overline{X_i^{fut}} - \overline{X_i^{ref}}\right)}{X_i^{ref}} \times 100 \qquad (3.7)$$

Where Δ_i^{hori} is rate of change in percentage, X_i^{fut} is the annual mean value calculated over the future time period, X_i^{ref} is the annual mean value calculated over the reference period and i is the time step. This rate of change represents the relative increase or decrease in annual precipitation, temperature.

3.3.5. Hydrological Modeling Using SWAT

The Soil and Water Assessment Tool (SWAT) model is a semi-distributed and physically based watershed model that operates at a continuous time-step at basin scale (Arnold et al., 2012). The model is designed to simulate the effects of changes in the catchment management practices on water, sediment, and agricultural chemical yields in large complex watersheds with varying soils, land use, and management conditions over long periods of time (Neitsch et al., 2005). SWAT model is widely used in central Rift valley basin to assess the impact of land use, land management practices, and climate change and showed satisfactory results (Gadissa *et al*., 2018; Desta & Lemma, 2017; T Abraham *et al*., 2018). In SWAT, a basin is divided into numerous sub basins, which are then further subdivided into hydrologic response units (HRUs)that consist of homogeneous land use, management, and soil characteristics. The model is used to simulates the hydrological process ultimately stream flow at each HRU using water balance equation, contains precipitation, surface runoff, evapotranspiration, infiltration, and subsurface inflow. The water balance equation of the hydrologic cycle

$$SW_t = SW_O + \sum_{i=1}^{t}\left(R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}\right) \qquad (3.8)$$

In which SW_t is the final soil water content (mm), SW_O is the initial soil water content on day i (mm), t is the time in days, $R_{day}$is the amount of precipitation on day i (mm), Q_{surf} the amount of surface runoff on day i(mm), E_a is the amount of evapotranspiration on day i (mm), W_{seep} is the amount of water entering to vadose zone from the soil profile on day i (mm), and $Q_{gw}$is the amount of return flow on day i (mm).

Surface runoff was estimated using Soil Conservation Service Curve Number (SCS-Curve number) method

$$Q_{surf} = \frac{\left(R_{day} - I_a\right)^2}{\left(P_{day} - I_a + S\right)} \qquad (3.9)$$

Where I_a is the initial abstraction which includes surface storage, interception, and infiltration prior to runoff and S is the retention parameter (mm).

Retention parameter defined by

$$S = 25.4\left(\frac{1000}{CN} - 10\right) \qquad (3.10)$$

CN is the curve number for the day which varies from 0 to 100 depending on soil permeability, land use, and the antecedent soil water condition.

Initial parameter approximated as 0.2 S, Eq. (3.9) becomes

$$R_{sur} = \frac{\left(P_{day} - 0.2S\right)^2}{\left(P_{day} + 0.8S\right)} \qquad (3.11)$$

3.3.5.1. Model setup

The first step in model set up was creating the new SWAT project in Arc SWAT, then the DEM map was imported in to Arc SWAT. Before working with spatial input data i.e. the soil map, Land use/land cover map and the DEM were projected into UTM Zone 37N, which is a projection parameter for Ethiopia.

3.3.5.2. Watershed delineation

The watershed delineation includes five major steps, DEM setup, stream definition, outlet and inlet definition, watershed outlets selection and definition, and calculation of sub-basin parameters. For the stream definition, the threshold-based stream definition option was used to define the minimum size of the sub-basin.

3.3.5.3. Hydrological response units (HRUs)

Hydrological response units (HRUs) have been defined in Arc SWAT by overlaying soils, land use and slope classes. One or more unique land use/soil/slope combination(s) (hydrologic response units (HRUs) can be created for each sub basin. The land use, soil and slope map were reclassified in order to correspond with the parameters in the SWAT database. After reclassifying the land use, soil and slope in SWAT database, all these physical properties were made to be overlaid for HRU definition. For this specific study a 5% threshold value for land use, 10% for soil and 10% for slope were used. The HRU distribution in this study was determined by assigning multiple HRU to each sub basin. 31-sub basin and 342 HRUs were created by integrating land use, soil and slope maps.

3.3.5.4. Importing climate data

The climatic variables required by SWAT consist of daily precipitation, maximum/minimum temperature, solar radiation, wind speed and relative humidity. Before loading these climatic variables into Arc SWAT model. Meteorological station data were prepared based on Arc SWAT 2012 input format and integrated with the model. Then these data were loaded on the Arc SWAT model at the stage of write input table after HRU analysis is completed. Kulumsa meteorological station data were selected as synoptic station because of data availability relative to other stations and used as weather generator which was embedded in SWAT user database for this study.

3.3.6. Sensitivity analysis

Sensitivity analysis is the procedure of determining how sensitive the model output for selected input parameters in the simulation of hydrological process. Sensitivity analysis helps to identify and rank parameters that have significant impact on the specific model output. This was achieved using the global sensitivity approach in SWAT-CUP semi-automated Sequential

Uncertainty Fitting (SUFI2) algorithm. The global sensitivity analysis method takes into consideration, the sensitivity of one parameter relative to the other in order to give their statistical significances. The t-statistics and p-values of the parameters were used to rank to the different parameters considered to influence flow and the final selection done based on the significance of the ranked values. Therefore, for this study, sensitivity analysis was done prior to the calibration process in order to identify important parameters for model calibration.

3.3.7. Calibration and validation of model

Calibration is the process of adjusting selected input parameter values and initial condition to obtain simulated values that match measured observations with desired accuracy. Whereas Validation is comparison of the model outputs with an independent dataset without altering the calibrated parameters. The Sequential Uncertainty Fitting (SUFI-2) algorism within the SWAT-CUP (Calibration and Uncertainty Procedures) was used to perform calibration and validation process. In this study, the model was calibrated with observed Monthly discharge data for the period of 1991 to 1996 and validated for the period of 1997 to 2000 including model a warm-up period from 1986 to 1990.

3.3.8. Evaluation of model performance

The model performance is techniques that evaluate how well simulated values represent measured observations over specified time period. These were evaluated using numerical model performance measures i.e. coefficient of determination (R^2), Nash Sutcliff efficiency (NSE), percent of bias (PBIAS) recommended by (Moriasi et al., 2007).

Coefficient of determination (R^2): provides the degree of relation between observed and simulated values. R^2 value ranges from 0 to 1, a value close to 0 means very low correlation whereas a value close to 1 represents high correlation between observed and simulated discharge. It is computed as shown in equation 3.12

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(Q_i^{Obs} - Q_{Obs}^{Mean}\right)\left(Q_i^{sim} - Q_{sim}^{Mean}\right)\right]^2}{\sum_{i=1}^{n}\left(Q_i^{Obs} - Q_{Obs}^{Mean}\right)^2 \sum_{i=1}^{n}\left(Q_i^{sim} - Q_{sim}^{Mean}\right)^2} \qquad (3.12)$$

Where Q_i^{Obs} is the i^{th} observed stream flow of day i, Q_i^{Sim} is the i^{th} simulated streamflow of day i , Q_{Obs}^{Mean} is the mean of observed streamflow, and Q_{Sim}^{Mean} is the mean of simulated streamflow.

Nash-Sutcliffe efficiency (E_{NS}): determines the relative magnitude of the residual variance compare to the measured data variance (Moriasi *et al*., 2007). It indicates how well the plot of observed versus simulated data fits the 1:1 line. The optimal values to get best model performance is at E_{NS} =1. E_{NS} is computed as shown in equation 3.13:

$$E_{NS} = 1 - \left[\frac{\sum_{i=1}^{n}\left(Q_i^{Obs} - Q_i^{Sim}\right)^2}{\sum_{i=1}^{n}\left(Q_i^{Obs} - Q_{Obs}^{Mean}\right)^2}\right] \qquad (3.13)$$

Where Q_i^{Obs} is the i^{th} observed stream flow of day i, Q_i^{Sim} is the i^{th} simulated streamflow of day i , Q_{Obs}^{Mean} is the mean of observed streamflow, and Q_{Sim}^{Mean} is the mean of simulated streamflow.

Percent bias (PBIAS): PBIAS measures the difference between the simulated and observed quantity and its optimum value is 0, with low magnitude values indicating accurate model simulation. A positive value of the model represents underestimation whereas a negative value represents the model overestimation. BIAS is calculated by Equation 3.14

$$PBIAS = \left[\frac{\sum_{i=1}^{n}\left(Q_i^{Obs} - Q_i^{Sim}\right) * (100)}{\sum_{i=1}^{n}\left(Q_i^{Obs}\right)}\right] \qquad (3.14)$$

Where Q_i^{Obs} is the i^{th} observed stream flow of day i, Q_i^{Sim} is the i^{th} simulated streamflow of day i , Q_{Obs}^{Mean} is the mean of observed streamflow, and Q_{Sim}^{Mean} is the mean of simulated streamflow.

Table 3.8 SWAT model performance evaluation criteria (Moriasi et al., 2007)

Model Evaluation	R^2	E_{NS}	PBIAS
Excellent	0.70<R^2≤*1.00*	0.75<E_{NS}≤*1.00*	PBIAS ≤ ±10
Good	0.60<R^2≤*0.70*	0.65 < E_{NS} ≤ 0.75	±10 < PBIAS ≤ ±15
Satisfactory	0.50<R^2≤*0.60*	0.50 < E_{NS} ≤ 0.65	±15 < PBIAS ≤ ±25
Unsatisfactory	0.00<R^2≤*0.50*	0.00 < E_{NS} ≤ 0.50	PBIAS >± 25

3.3.9. Climate Change Impact on Stream flow

After completing the calibration and validation process for the observed climate data the model was run for the historical period (1986-2005) and resulted a good performance measure for the data derived from an ensemble of downscaled climate data based on the Coordinated Regional climate Downscaling Experiment over African domain (CORDEX-Africa) with Coupled Model Intercomparison Project Phase 5 (CMIP5) simulations under Representative Concentration Pathways viz. RCP4.5 and RCP8.5 climate scenarios. The input climate data (daily rainfall, minimum and maximum temperature) under each RCP scenarios were used by keeping all other climate variables such as wind speed, solar radiation, and relative humidity constant throughout the future simulation. The impact of climate change was analyzed taking the historical simulated flow from (1986-2005) as the baseline against which the future flow is compared for two future periods of 20 years: near future (2021-2040) and far future (2051-2070).

4. RESULTS AND DISCUSSIONS

4.1. Projected changes of precipitation and temperature

The trends of projected precipitation and temperature under RCP4.5 and RCP8.5 scenarios compared with baseline period. The evaluation was made over two consecutive 20-years period of the 2030s and the 2060s, respectively. Accordingly, the future climate change was estimated for each RCP based on the baseline period (1986–2005). Before Climate Change Analysis bias correction was done for RCM simulated (Raw) precipitation and Temperature with observed climatic variables. Accordingly, distribution mapping method was applied to minimize model biases using gamma distribution function for precipitation and Gaussian distribution function for temperature. Figure. 4.1 shows the comparison of the present monthly mean precipitation of Observed, Bias corrected and raw data averaged over the katar river basin, for the baseline period (1986 –2005). This method eradicates the poor ability of CORDEX-Africa RCP scenarios in simulating the precipitation and temperature distribution.

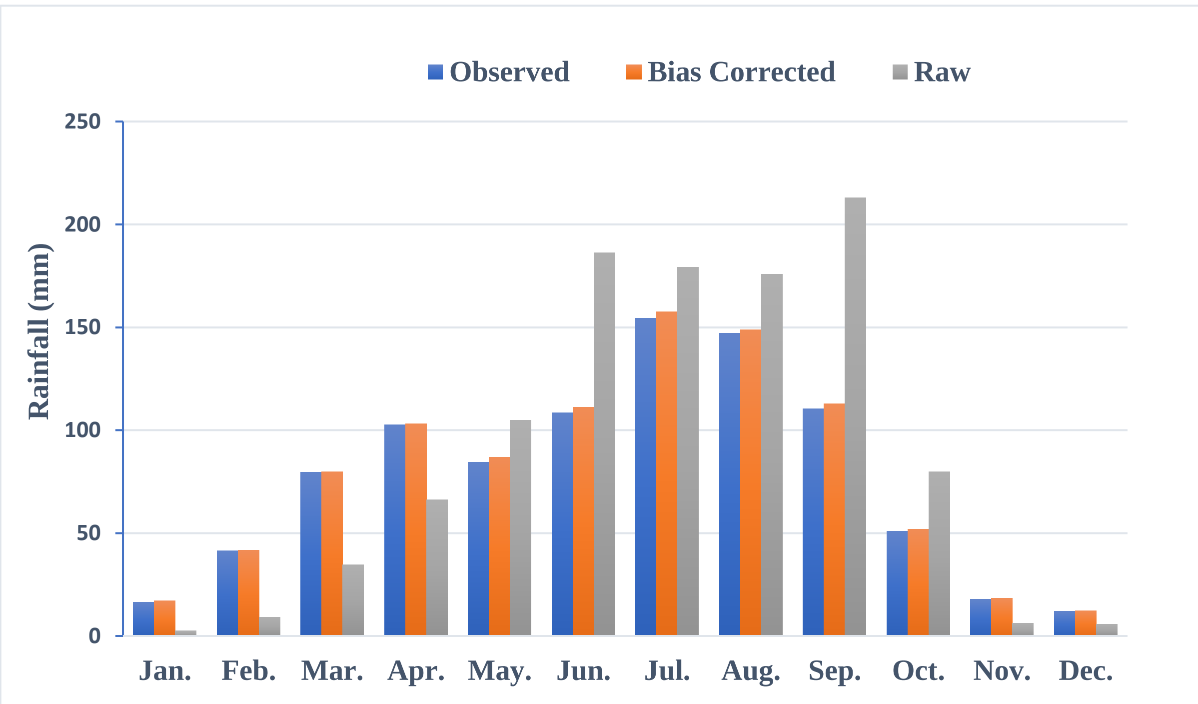


Figure 4.1 Monthly mean observed, RCM simulated (Raw) and Bias Corrected rainfall from Katar River basin during1986-2005.

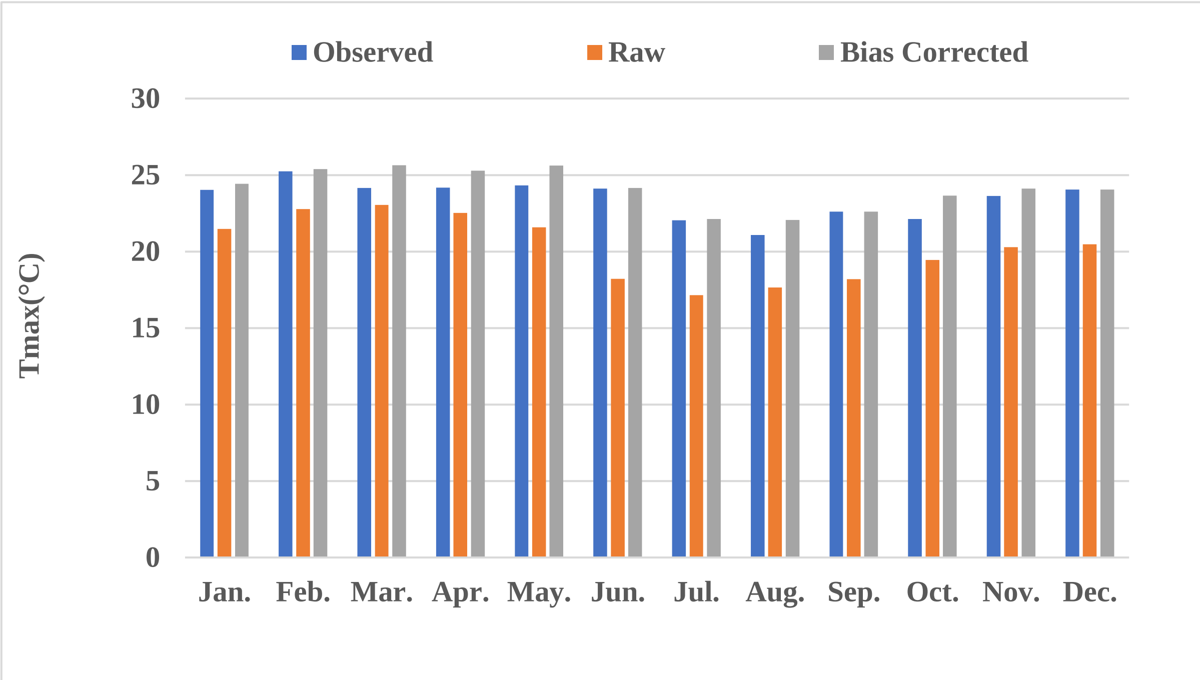


Figure 4.2 Monthly mean observed, RCM simulated (Raw) and Bias Corrected maximum temperature from Katar River basin during1986-2005.

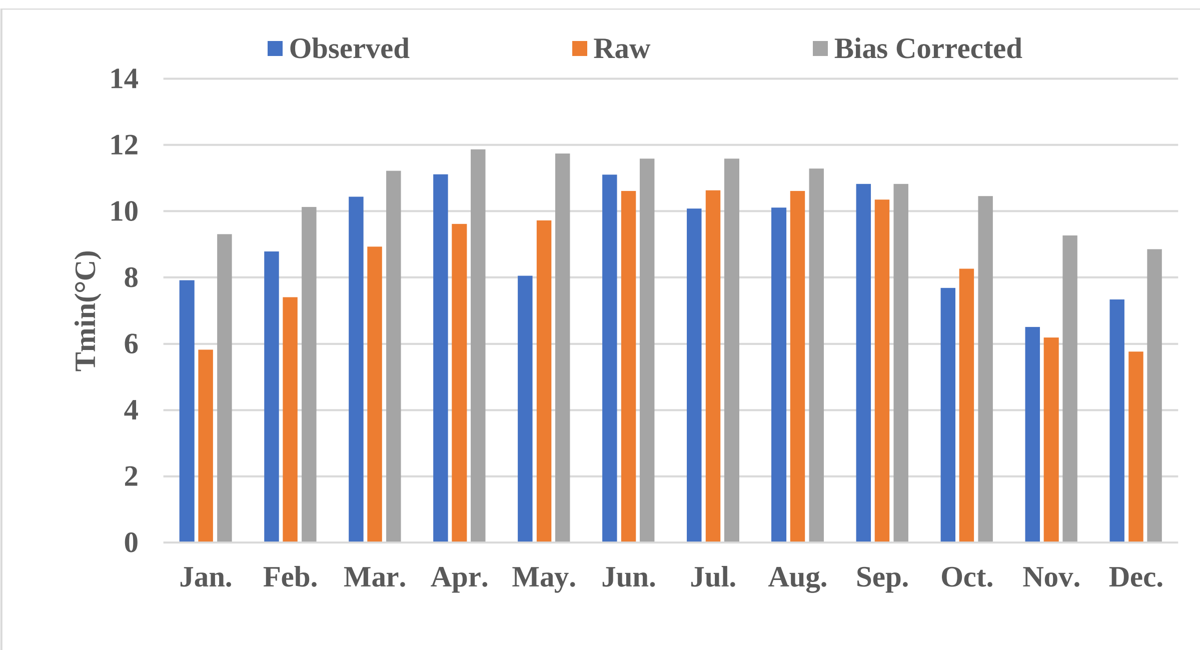


Figure 4.3 Monthly mean observed, RCM simulated (Raw) and Bias Corrected minimum temperature from Katar River basin during1986-2005

4.1.1. Projected changes of Precipitation

The result of the study after bias corrections shows that the mean annual rainfall under RCP4.5 and RCP8.5 scenarios are projected to be lower than the baseline period over Katar river Basin (Figure 4.4). On a seasonal scale, the rainfall under RCP8.5 is larger than the baseline values during wet seasons (summer). However, the rainfall under RCP4.5 and RCP8.5 may decrease during bega and belg seasons (Figure 4.5). In both RCP4.5 and RCP8.5 scenarios, the results showed a decrease in the precipitation patterns in January –May, whereas they showed an increased precipitation patterns in August in the 2030s and the 2060s (Figure 4.6), respectively.

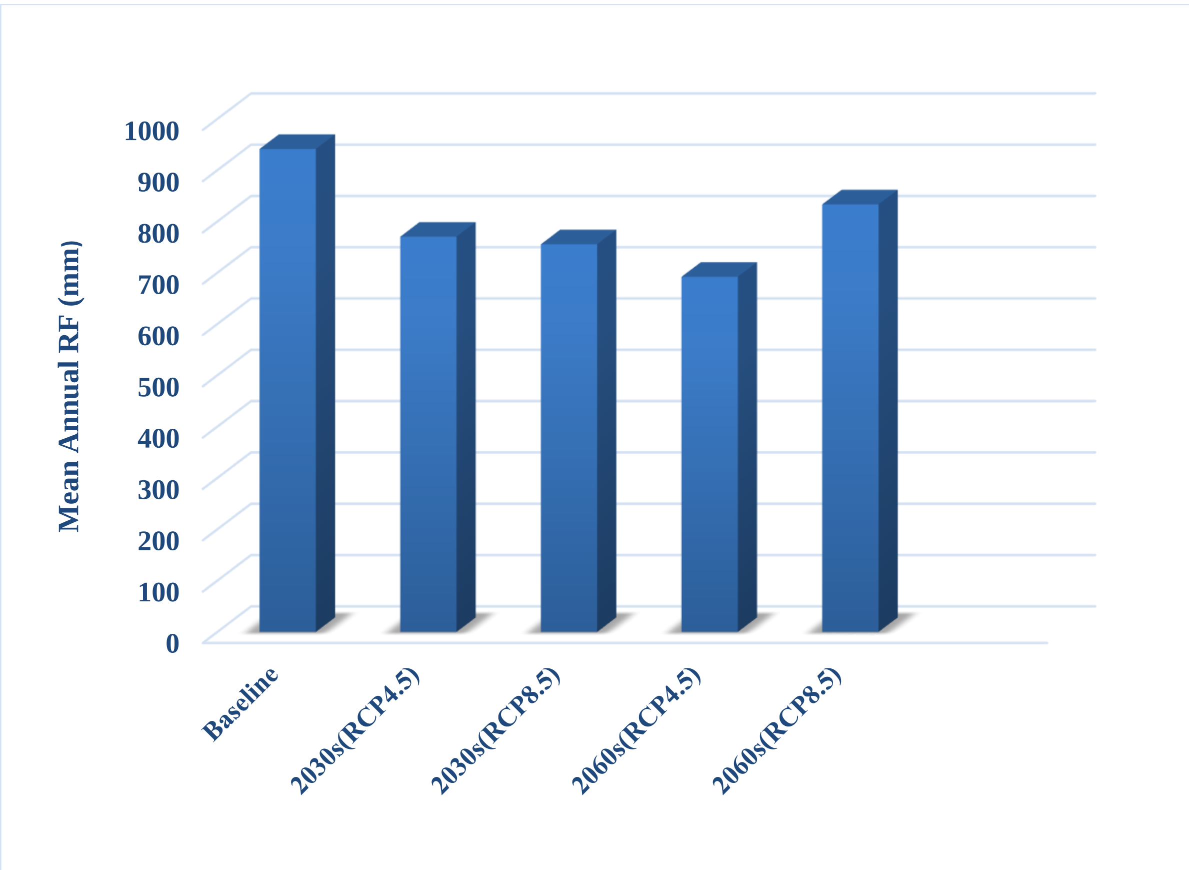


Figure 4.4 The changes of annual rainfall distribution in the Katar river basin.

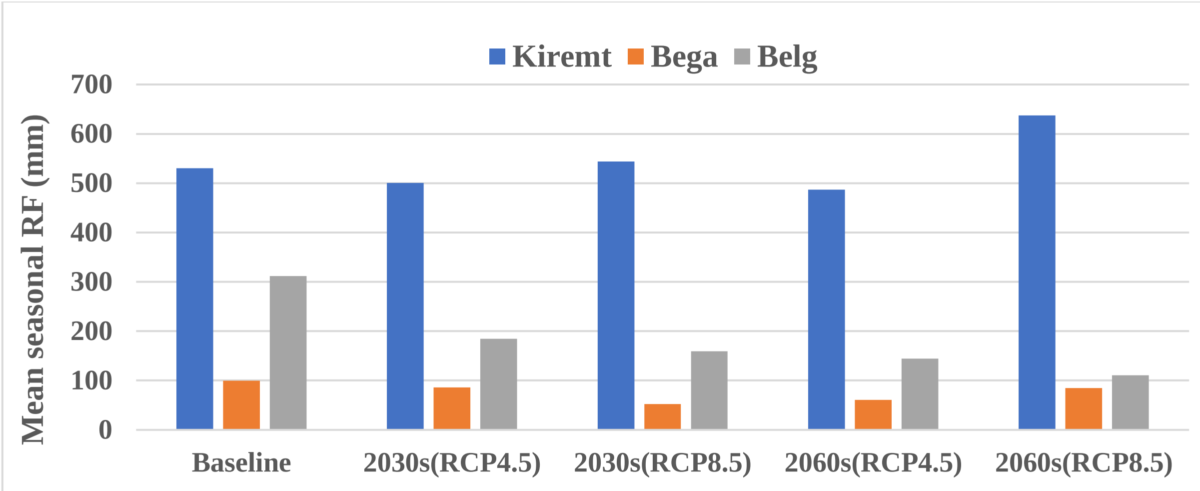


Figure 4.5 The changes of seasonal rainfall distribution in the Katar river basin.

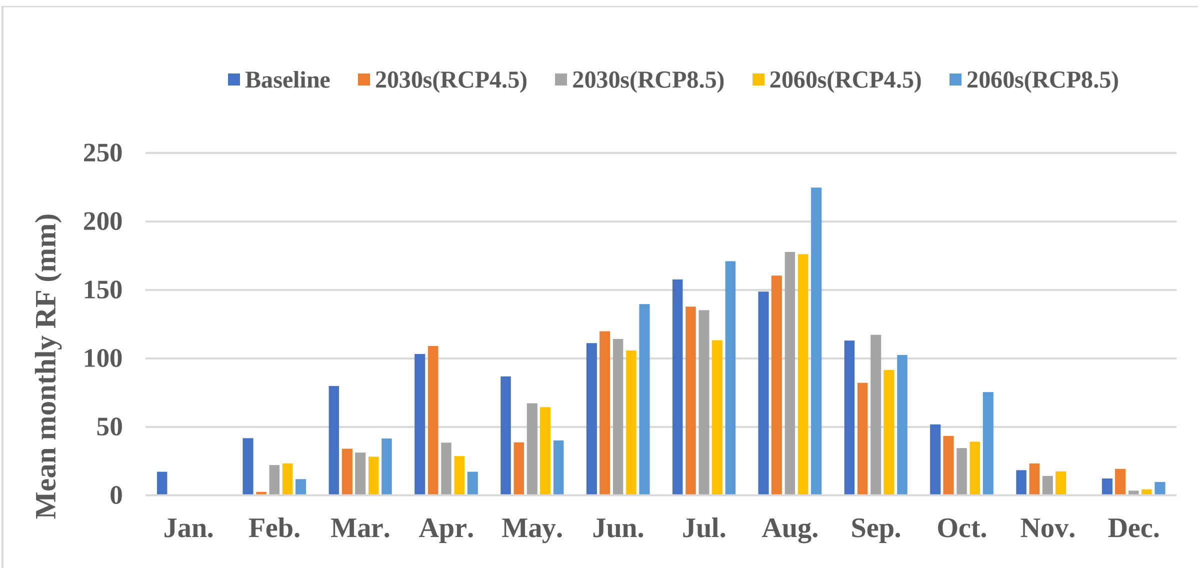


Figure 4.6 The changes of mean monthly rainfall distribution in the Katar river basin.

For annual mean Precipitation, Table 4.1 shows a decrease for the two scenarios in the basin when compared to the baseline (1986–2005). The average annual precipitations were projected under RCP4.5 to decrease by 17.8% and 26% for the 2030s and the 2060s, respectively. Likewise, for RCP8.5, the average annual precipitation decreases were found to be 19% in the 2030s and 10% in the 2060s. The study conducted by (Gadissa *et al*., 2018) on the Central Rift Valley showed that there might be a decrease in mean annual precipitation for the time period from 2041-2071 under both scenarios by 7.97% and 2.55% under RCP4.5 and RCP8.5, respectively.

Table 4.1 Projected changes of Precipitation in the Katar River Basin under RCPs 4.5 and 8.5

Station	Precipitation (%)		Precipitation (%)	
	2030s(2021_2040)	2030s(2021-2040)	2060s(2051-2070)	2060s(2051-2070)
	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Arata	-12.6	-13.9	-22.7	-4.2
Asela	-15.3	-19.2	-23.3	-13.8
Bekoji	-24.1	-27.5	-33.7	-19.1
Kulumsa	-17.0	-19.9	-25.0	-14.3
Ogolcho	-19.8	-14.4	-25.1	-0.8
Avg Annual	-17.8	-19.0	-26.0	-10.5

4.1.2. Projected changes of temperatures

The analysis of the projected maximum and minimum temperature under scenarios RCPs 4.5 and 8.5 showed increasing trend when compared to the baseline (1986–2005) in the Katar River Basin by Figure below.

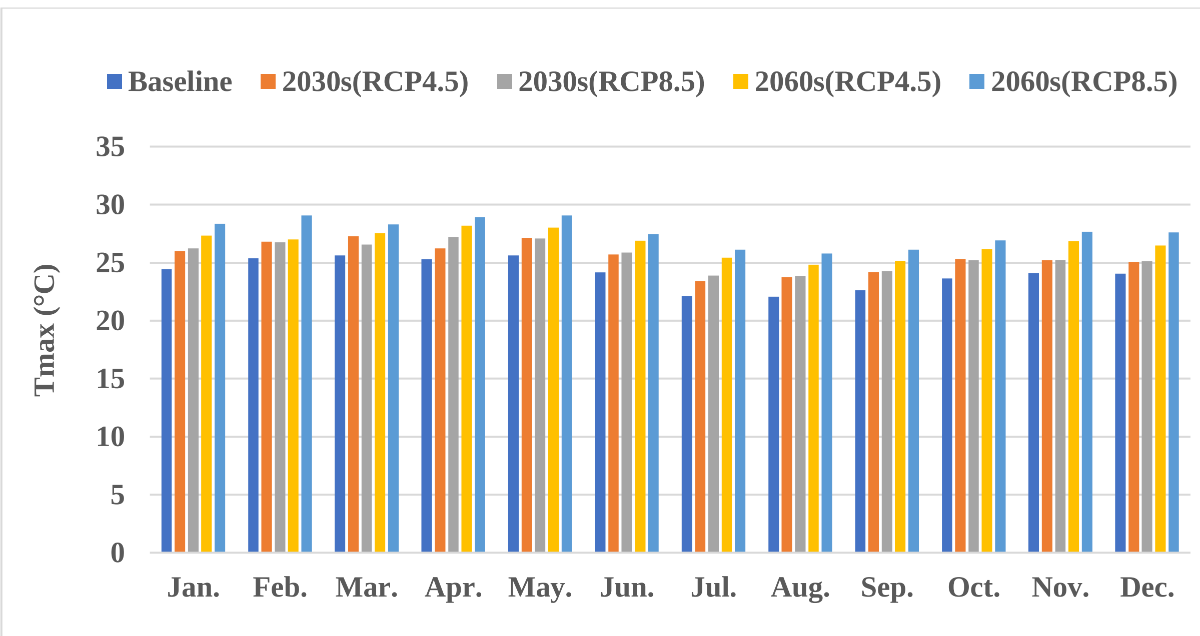


Figure 4.7 Changes in the monthly mean maximum temperatures in Katar River Basin.

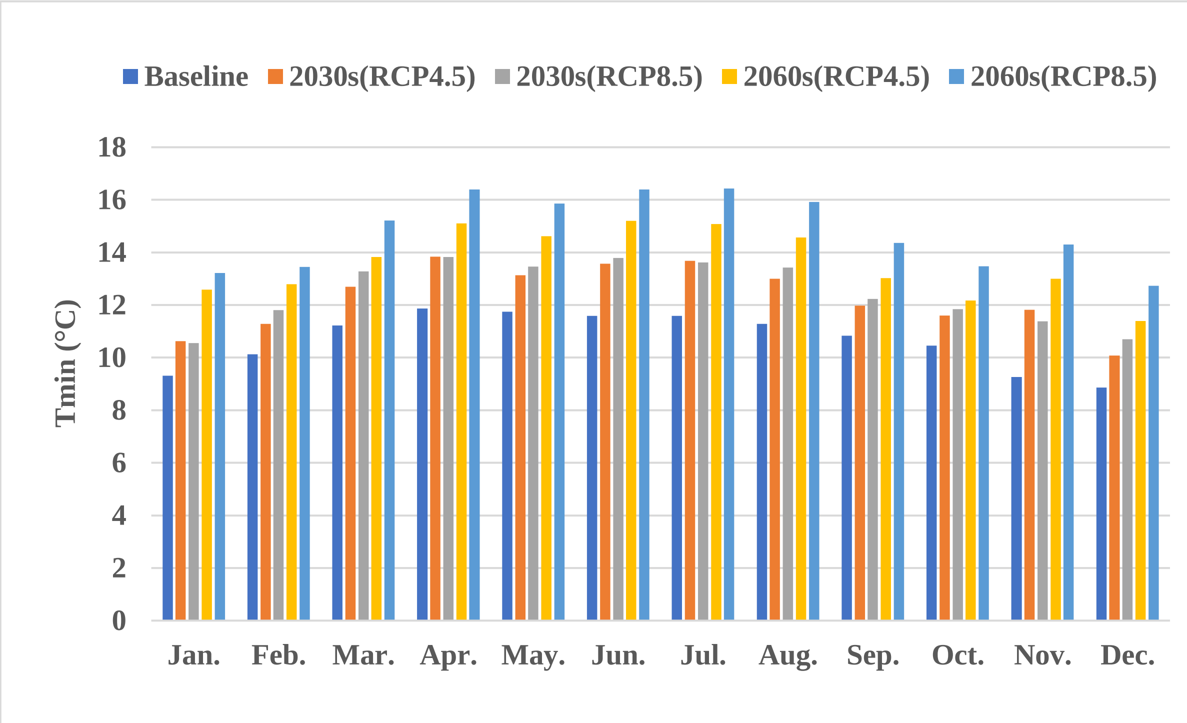


Figure 4.8 Changes in the monthly mean Minimum temperature in Katar River Basin.

The maximum and minimum temperature, Table 4.2 shows an increase in both scenarios. Under RCP4.5, changes in monthly maximum temperatures ranged from 0.94◦C to 1.68 ◦C with an average annual of 1.42◦C by the 2030s and from 1.61◦C to 3.32◦C with an average annual of 2.56◦C by the 2060s. For the RCP8.5 scenario, the monthly maximum temperature increased from 0.91◦C to 1.93◦C and from 2.67◦C to 4.00◦C with average annuals of 1.51◦C and 3.52◦C for the 2030s and the 2060s, respectively. The results also indicated that all the values of monthly minimum temperature increased from 1.14◦C to 2.56◦C by the 2030s and from 1.72◦C to 3.74◦C by the 2060s under RCP4.5 with average annuals of 1.60◦C and 2.93◦C, respectively. For the RCP8.5 scenario, the monthly minimum temperature increased from 1.24◦C to 2.21◦C and from 3.02◦C to 5.03◦C with average annuals of 1.81◦C and 4.13◦C for the 2030s and the 2060s, respectively.

Table 4.2 Projected changes of Maximum and Minimum temperature in the Katar River Basin under RCPs 4.5 and 8.5.

Period	Maximum Temp		Minimum Temp		Maximum Temp		Minimum Temp	
	2030s	2030s	2030s	2030s	2060s	2060s	2060s	2060s
	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
Jan.	1.59	1.78	1.31	1.24	2.89	3.93	3.27	3.90
Feb.	1.43	1.36	1.15	1.68	1.61	3.70	2.66	3.32
Mar.	1.65	0.91	1.48	2.05	1.93	2.67	2.60	3.99
Apr.	0.94	1.93	1.97	1.96	2.91	3.63	3.24	4.53
May.	1.53	1.47	1.38	1.71	2.40	3.45	2.88	4.11
Jun.	1.53	1.72	1.98	2.21	2.73	3.30	3.61	4.81
Jul.	1.30	1.76	2.09	2.03	3.32	4.00	3.49	4.84
Aug.	1.67	1.78	1.71	2.14	2.74	3.71	3.29	4.63
Sep.	1.56	1.65	1.15	1.41	2.53	3.52	2.19	3.53
Oct.	1.68	1.57	1.14	1.39	2.53	3.28	1.72	3.02
Nov.	1.08	1.13	2.56	2.11	2.75	3.56	3.74	5.03
Dec.	1.03	1.09	1.22	1.84	2.44	3.56	2.53	3.87
Avg Annuals	1.42	1.51	1.60	1.81	2.56	3.52	2.93	4.13

In general, bias corrected projected annual precipitation showed a decreasing and temperature showed an increasing trend in 2030s and 2060s over Katar sub basin under RCP4.5 and RCP8.5 climate scenarios. The projected annual precipitation and temperature results confirmed the same trend with the study conducted by (Gadissa *et al*., 2018) on the Central Rift Valley showed that there might be a decrease in mean annual precipitation for the time period from 2041-2071 under both scenarios by 7.97% and 2.55% while maximum and minimum temperature increases under RCP4.5 and RCP8.5, respectively.

4.2. SWAT Model Performance

4.2.1. Stream Flow Sensitive Parameters

Before undertaking the calibration and validation a sensitivity analysis has been carried out for Twenty-one hydrological parameters using SWAT-CUP global sensitivity analysis. After sensitivity analysis more sensitive SWAT parameters are identified based on their p-value and t-value of statistical significance for the watershed. Based on this ranking, the eight most sensitive parameters for this area were chosen for calibration. The post calibration fitted values of these parameters by means of SUFI2 are listed in Table 4.3.

Table 4.3 List of parameters and their initial ranges used for Sensitive analysis

Parameters	Definition	Range Value	
		Min	**Max**
CN2.mgt	SCS runoff curve number (dimensionless)	-0.2	0.2
ALPHA_BF.gw	Base-flow alpha factor (days)	0	1
GW_DELAY.gw	Groundwater delay (days)	30	450
GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0	5000
GW_REVAP.gw	Groundwater “revap” coefficient (dimensionless)	0.02	0.2
REVAPMN.gw	Threshold depth of water in the shallow aquifer for “revap” to occur (mm)	0	500
RCHRG_DP.gw	Deep aquifer percolation fraction (dimensionless)	0	1
SOL_AWC().sol	Available water capacity of the soil layer (mm H2O/mm soil)	-0.25	0.25
SOL_K ().sol	Saturated hydraulic conductivity (mm/h)	-0.25	0.25
SOL_ALB ().sol	Moist soil albedo	-0.25	0.25
CH_N2.rte	Manning’s “n” value for the main channel	-0.01	0.3
CH_K2.rte	Effective hydraulic conductivity in main channel alluvium (mm/h)	-0.01	500
ALPHA_BNK.rte	Base-flow alpha factor for bank storage (dimensionless)	0	1
TLAPS.sub	Temperature laps rate (0C/km)	-10	10
SLSUBBSN.hru	Average slope length (m)	10	150
HRU_SLP.hru	Average slope steepness	0	1
OV_N.hru	Manning’s n value for overland flow	0.91	31
CANMX.hru	Maximum canopy storage (mm)	0	100
ESCO.hru	Soil evaporation compensation factor (dimensionless)	0	1
EPCO.hru	Plant uptake compensation factor	0	1
SURLAG.bsn	Surface runoff lag time (days)	0.05	24

After a thorough preprocessing of the required input for SWAT model, flow simulation was performed for 20 years of recording periods starting from 1986 through 2005.The first five years of which was used as a warm up period and the simulation was then used for sensitivity analysis of hydrologic parameters and for calibration of the model. Out of the 21 parameter 8 of them are the most sensitive value. The sensitive parameters are identified based on the value of P-value and t-stat. the P- value having less than 0.05 is the more sensitive model parameter. The global sensitivity analysis of twenty-one flow parameters showed that, only eight were very sensitive to flow. The rankings of the flow parameters are presented in Table 4.4 while the fitted values for the most sensitive parameters are indicated in Table 4.5.

Table 4.4 Sensitivity rankings of stream flow parameters in the Katar river basin

Parameter Name	t-Stat	P-Value	Rank
1: R__CN2.mgt	25.53	0.00	1
4: V__GWQMN.gw	3.64	0.00	2
5: R__GW_REVAP.gw	2.56	0.02	3
13: R__RCHRG_DP.gw	-2.50	0.02	4
21: R__SURLAG.bsn	-2.28	0.03	5
16: R__ALPHA_BNK.rte	-2.01	0.04	6
10: R__HRU_SLP.hru	2.01	0.04	7
14: R__CH_N2.rte	-1.91	0.04	8
20: R__SOL_ALB(..).sol	1.56	0.13	9
18: R__TLAPS.sub	1.38	0.18	10
2: V__ALPHA_BF.gw	1.25	0.22	11
9: R__SLSUBBSN.hru	1.25	0.22	12
3: V__GW_DELAY.gw	-1.25	0.23	13
8: R__SOL_AWC(..).sol	1.10	0.28	14
7: R__ESCO.hru	1.08	0.29	15
17: R__SOL_K(..).sol	1.07	0.29	16
19: R__EPCO.hru	1.02	0.32	17
11: R__OV_N.hru	-0.97	0.34	18
15: R__CH_K2.rte	0.25	0.80	19
12: R__CANMX.hru	-0.17	0.87	20
6: R__REVAPMN.gw	-0.03	0.98	21

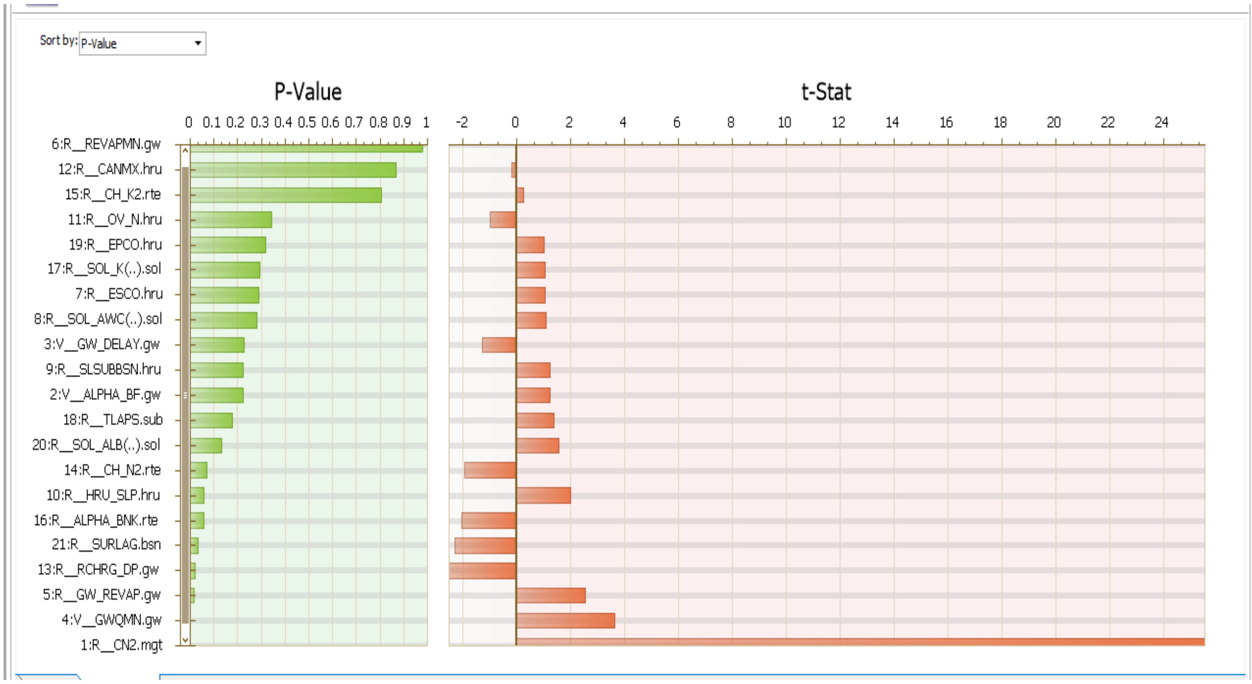


Figure 4.9 Global sensitive parameter (p-value) and (t-stat) of the study area

The most sensitive parameter was the SCS runoff curve number (CN2). The curve number estimates runoff based on the relationship between precipitation, hydrologic soil group and land uses. The other sensitive parameters included the threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN), Groundwater “revap” coefficient (GW_REVAP), Deep aquifer percolation fraction (RCHRG_DP), Surface runoff lag time (SURLAG), Base-flow alpha factor (ALPHA_BNK), Average slope steepness (HRU_SLP), Manning’s “n” value for the main channel (CH_N2).

Table 4.5 List of sensitive parameters, their calibrated and fitted values

Parameter_Name	Fitted_Value	Min_value	Max_value
R__CN2.mgt	0.16	-0.2	0.2
V__GWQMN.gw	1500.00	0	5000
R__GW_REVAP.gw	0.19	0.02	0.2
R__RCHRG_DP.gw	0.01	0	1
R__SURLAG.bsn	18.94	0.05	24
V__ALPHA_BF.gw	0.81	0	1
R__HRU_SLP.hru	0.37	0	1
R__CH_N2.rte	0.06	-0.01	0.3

The extension (.mgt, .gw, .rte, .hru, .bsn) refers to the SWAT input file where the parameter occurs. The qualifier (R__) refers to relative change in the parameter where the value from the SWAT database is multiplied by 1 plus a factor in the given range, while the qualifier (V__) refers to the substitution of a parameter by a value from the given range.

4.2.2. Calibration and Validation of stream flow

Calibration and Validation streamflow was done by comparing the observed and the simulated flow values for a 15-years period (1986–2000). The first five years (1986–1990) were considered as a warm-up period, the 1991–1996 period was used for the model calibration, and the 1997–2000 period was used for the validation period. Both calibration and validation for streamflow simulation obtained good results of fit with R2 of 0.66 and 0.65 and NSE coefficients of 0.65 and 0.62, respectively (Table 4.4 and Figure 4.4). The results revealed that the variation pattern of simulated streamflow was generally consistent with that of the observed streamflow.

Table 4.4 Calibration and Validation of stream flow (monthly) at Katar river outlet

	p-factor	r-factor	R^2	NSE	PBIAS
Calibration	0.88	1.76	0.66	0.65	-2.4
Validation	0.86	1.72	0.65	0.62	-8.8

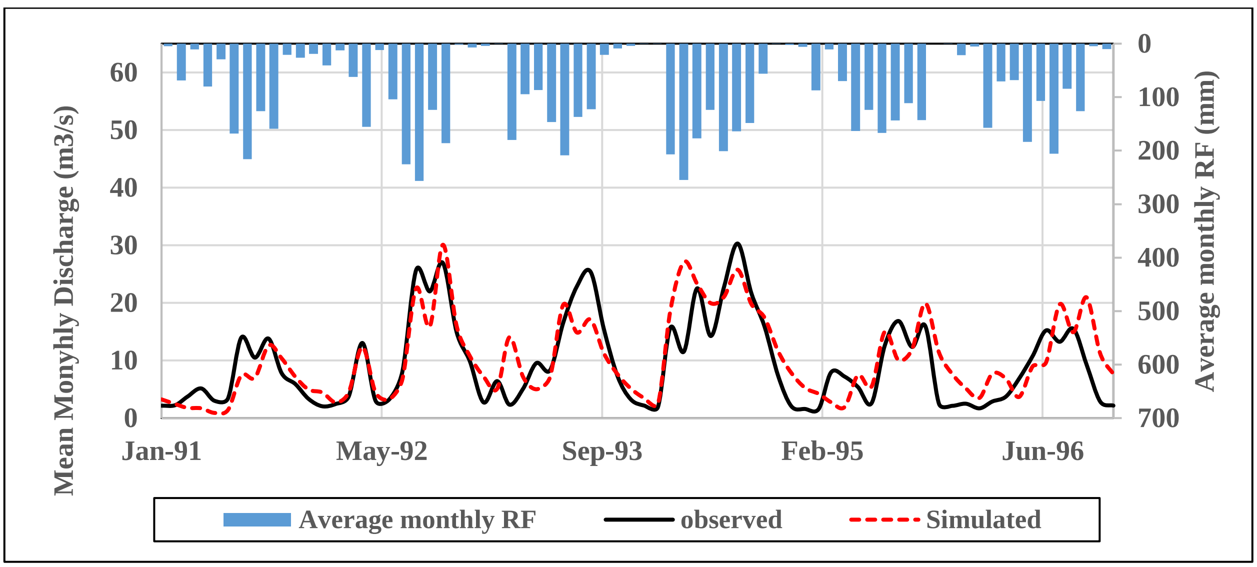


Figure 4.10 Observed and simulated monthly streamflow hydrographs during Calibration.

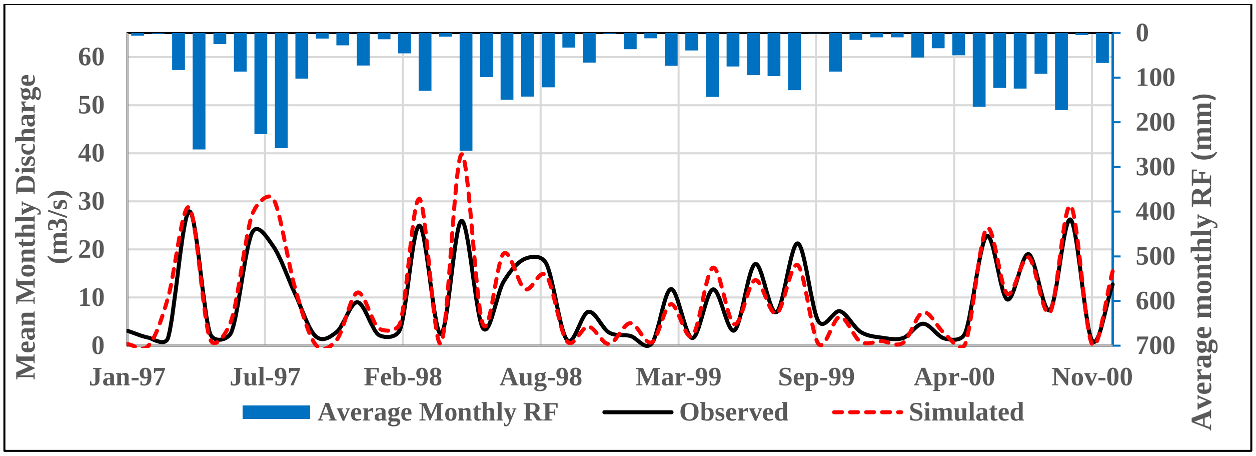


Figure 4.11 Observed and simulated monthly streamflow hydrographs during validation periods.

4.3. Impact of Climate Change on Stream Flow

The impact of climate change on stream flow over the study area was investigated as a percentage change with respect to the baseline period (1986–2005) under the two scenarios in two time periods 2030s (2021–2040) and 2060s (2051–2070). The downscaled climate variables (daily precipitation and minimum and maximum temperature) are adjusted for SWAT model simulation for baseline and future period. Other climate variables as wind speed, solar radiation, and relative humidity were assumed to be constant throughout the future simulation periods. The Projected climate variables on monthly from regional climate models (RCMs) in the study show that precipitation will decrease, while the minimum and maximum temperature will increase. Accordingly, the collective impacts of decrease in precipitation and increase in temperature in the future period might cause a reduction in streamflow. Thus, mean annual stream flow may decrease by 7.38 and 33.49% for 2030s and 2060s, respectively, from the baseline for RCP4.5 whereas for RCP8.5, the model shows a decrease by 19.44 and 8.79% for 2030s, and 2060s, respectively. Figure 4.5 showed the percentage change of mean monthly and annual streamflow for both climate scenarios and the two-time periods. Mean monthly percentage change of streamflow under both climate scenario showed mixed trends.

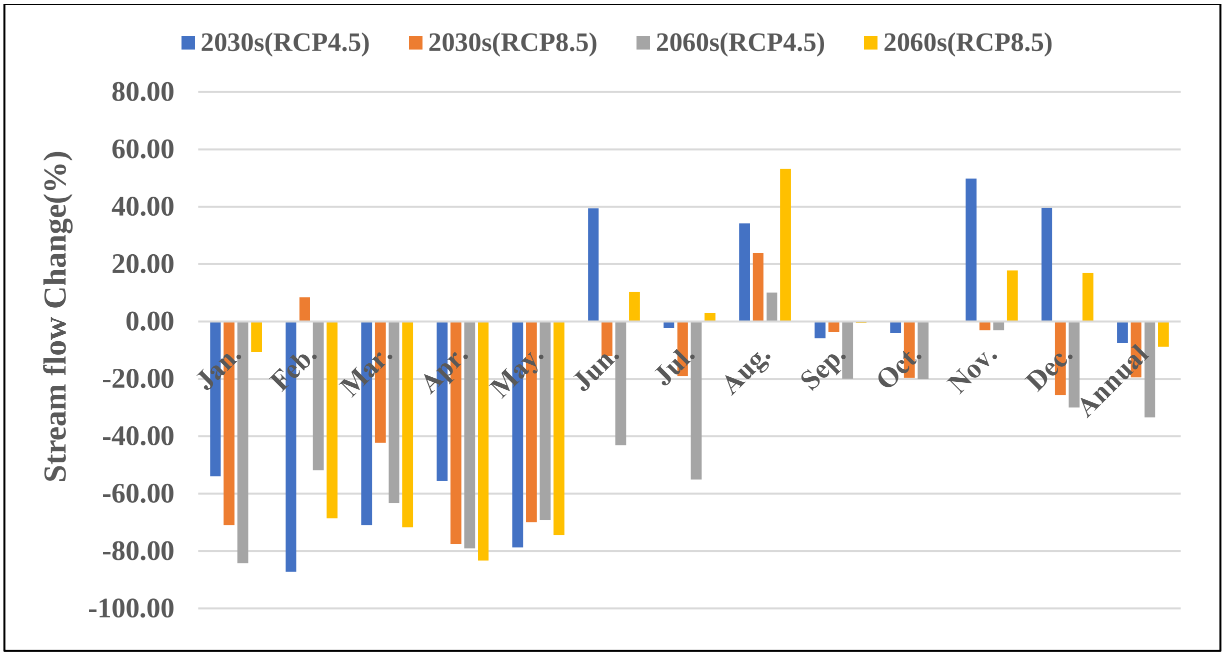


Figure 4.12 Mean monthly and annual difference in streamflow between the baseline and future scenarios in percent (%)

The variability and changes of monthly streamflow will be much greater than the annual streamflow changes in both scenarios in all time periods. This result showed that it is important for the water resource planners and managers to consider, the monthly streamflow variability and changes for future planning and management in catchment under study. This result confirms study conducted by (Tesfalem. A *et al*., 2018) on the Hydrology of Lake Ziway showed that an annual decrement in runoff depth up to 20.28% during 2080s under RCP8.5.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusion

This study investigated the impacts of climate change on stream flow of Katar catchment in the Central Rift Valley basin, Ethiopia. Future climate (temperature and precipitation) projected in regional climate models (RCMs) (i.e., RACMO22T) of CORDEX-Africa derived from the GCMs/ICHEC-EC-EARTH model. This climatic variable was used for RCP4.5 and RCP8.5 by the 2030s and by the 2060s and compared to the baseline period (1986–2005). Distribution mapping techniques was used for bias correction of the RCM data.

Results showed that trends projected mean annual precipitation would decrease, while the maximum and minimum temperatures would increase under RCP4.5 and RCP8.5 scenarios. The projected annual precipitations under RCP4.5 in the 2030s and the 2060s would decrease by 17.8% and 26.0%, respectively, and in the RCP8.5 scenario would decrease by 19.0% and 10.5% for the 2030s and the 2060s, respectively.

The SWAT hydrological model was used to simulate historical and future changes in stream flow, and the SUFI-2 algorithm in the SWAT-CUP program was used for parameter adjustment. The performance of SWAT model in simulating the stream flow was shown to be good with a coefficient of determination (R2) 0.66 and 0.65 and the Nash and Sutcliffe efficiency (NSE) of 0.65 and 0.62 for calibration and validation periods, respectively.

Results of climate change impacts on stream flow indicated that stream flow would decrease in both RCP scenarios. The mean annual stream flow was predicted to decrease by 7.38 % by the 2030s and by 33.49% by the 2060s under RCP4.5. For RCP8.5, they were found to be 19.44 % and 8.79% by the 2030s and the 2060s, respectively. The increase in temperature is further related with an increase in evapotranspiration. Thus, the combined effects of decrease in precipitation and increase in temperature in the future period would decrease stream flow. This indicated that the projected stream flow was found to be a similar pattern of precipitation.

5.2. Recommendation

This study considers single GCM model and two RCPs scenarios in predicting the future climate data. However, it is recommended to apply different GCMs and emission scenarios to analyze the associated uncertainties in the modeling approach.

This study considers one bias correction technique, further studies are recommended to apply various bias correction methods to quantify the projected change in streamflow.

Land use land cover in this study was assumed to be constant throughout the future simulation periods. Hence, further research is recommended to study the predicted future LULC along with the predicted future meteorological parameters to understand the combined effect of both LULC and climate on the hydrological parameters of the basin., which in turn affects the stream flow.

Accessibility of hydrological and meteorological data are very important while using any hydrological model. The distribution and recorded time series of these gauging stations in studied basin is not well organized. It is highly recommended to improve both hydrological and meteorological monitoring system in the whole Katar catchment.

Climate change would have a significant impact on stream flow causing a possible reduction water availability in Katar catchment. Hence, it is strictly recommended that the adaptation measures such as watershed based integrated water resource management approach, constructing water harvesting structures to store excess water flowing during rainy season so as to use it for dry season.

REFERENCES

Abbaspour, K C, Rouholahnejad, E., Vaghefi, S., Srinivasan, R., Yang, H., & Kløve, B. (2015). A continental-scale hydrology and water quality model for Europe : Calibration and uncertainty of a high-resolution large-scale SWAT model. *Journal of Hydrology*, *524*, 733–752. https://doi.org/10.1016/j.jhydrol.2015.03.027

Abbaspour, Karim C. (2015). *SWAT - CUP SWATCalibration and Uncertainty Programs*.

Abraham, T., Woldemicheala, A., Muluneha, A., & Abateb, B. (2018). *Climatic Change Hydrological Responses of Climate Change on Lake Ziway Catchment , Central Rift Valley of Ethiopia*. *9*(6). https://doi.org/10.4172/2157-7617.1000474

Adem, A. A., Tilahun, S. A., Ayana, E. K., Worqlul, A. W., Assefa, T. T., Dessu, S. B., & Melesse, A. M. (2016). *Climate Change Impact on Stream Flow in the Upper Gilgel Abay Catchment , Blue Nile basin , Ethiopia*. 645–673. https://doi.org/10.1007/978-3-319-18787-7

Al, S. E. T., Avazos, T. E. C., Hristensen, J. E. N. S. H. C., Hristensen, O. L. E. B. C., Oppola, E. R. C., Vans, J. A. E., Eyer, B. E. G., Iorgi, F. I. G., Adjinicolaou, P. A. H., Acob, D. A. J., Atzfey, J. A. C. K. K., Oenigk, T. O. K., Aprise, R. E. N. É. L., Ennard, C. H. J. L., Urnaz, M. L. E. K., Elei, D. L. I., Lopart, M. A. L., Ormick, N. I. M. C. C., & Aumann, G. U. N. (2020). *Future Global Meteorological Drought Hot Spots : A Study Based on CORDEX Data*. *November 2019*, 3635–3661. https://doi.org/10.1175/JCLI-D-19-0084.1

Animesh K. Gain, C. G. and F. G. R. (2012). *Climate Change Adaptation and Vulnerability Assessment of Water Resources Systems in Developing Countries: A Generalized Framework and a Feasibility Study in Bangladesh*. 345–366. https://doi.org/10.3390/w4020345

Arnold, J. G., Moriasi, D. N., Gassman, P. W., & White, M. J. (2012). *SWAT : Model use , calibration , and validation*.

Ashfaq, M., Cavazos, T., Simões, M., José, R., Torres, A., Eun, A., & Im, S. (2020). Robust late twenty - first century shift in the regional monsoons in RegCM - CORDEX simulations. *Climate Dynamics*, *0123456789*. https://doi.org/10.1007/s00382-020-05306-2

Bhuvandas, N., Timbadiya, P. V, Patel, P. L., & Porey, P. D. (2014). *Review of Downscaling Methods in Climate Change and Their Role in Hydrological Studies*. *10*, 620–625.

Chen, J., Brissette, P., Chaumont, D., & Braun, M. (2013). *Finding appropriate bias correction methods in downscaling precipitation for hydrologic impact studies over North America*. *49*, 4187–4205. https://doi.org/10.1002/wrcr.20331

Desta, H., & Lemma, B. (2017a). Journal of Hydrology : Regional Studies SWAT based hydrological assessment and characterization of Lake. *Journal of Hydrology: Regional Studies*, *13*(March), 122–137. https://doi.org/10.1016/j.ejrh.2017.08.002

Desta, H., & Lemma, B. (2017b). SWAT based hydrological assessment and characterization of Lake Ziway. *Journal of Hydrology: Regional Studies*, *13*(September), 122–137. https://doi.org/10.1016/j.ejrh.2017.08.002

Emerta, B., & Aragie, A. (2013). *C l i m at e C h a n g e , G r o w t h , and Poverty in Ethiopia*. *June*.

Essenfelder, A. H. (2016). *Weather Database:A Quick Guide. Version: v.0.16.07. doi: 10.13140/RG.2.1.4329.1927*. (Issue March).

Fentaw, F., Hailu, D., Nigussie, A., & Melesse, A. M. (2018). *Climate Change Impact on the Hydrology of Tekeze Basin , Ethiopia : Projection of Rainfall-Runoff for Future Water Resources Planning*. 17–19.

Fikru Fentaw. (2018). *Planning and Operation of Hydropower Reservoir in Tekeze Basin Considering Hydrological Variability and Climate Change*.

Fowler, H. J., Blenkinsop, S., & Tebaldi, C. (2007). *Linking climate change modelling to impacts studies : recent advances in downscaling techniques for hydrological*. *1578*(September), 1547–1578. https://doi.org/10.1002/joc

Gadissa, T., Nyadawa, M., Behulu, F., & Mutua, B. (2018). *The Effect of Climate Change on Loss of Lake Volume : Case of Sedimentation in Central Rift Valley*. https://doi.org/10.3390/hydrology5040067

Gassman, P. W., Reyes, M. R., Green, C. H., & Arnold, J. G. (2007). *The Soil and Water Assessment Tool : Historical Development , Applications , and Future Research Directions The Soil and Water Assessment Tool : Historical Development ,*.

Gbobaniyi, E., Sarr, A., Sylla, M. B., Diallo, I., Lennard, C., Dosio, A., Dhiédiou, A., Kamga, A., Klutse, N. A. B., Hewitson, B., Nikulin, G., & Lamptey, B. (2014). Climatology, annual cycle and interannual variability of precipitation and temperature in CORDEX simulations over West Africa. *International Journal of Climatology*, *34*(7), 2241–2257. https://doi.org/10.1002/joc.3834

Gebre, S. L., Tadele, K., & Mariam, B. G. (2014). *Potential Impacts of Climate Change on the Hydrology and Water resources*. *4*(1), 1–7. https://doi.org/10.4172/2329-6755.1000193

Giorgi, F., Jones, C., & Asrar, G. R. (2017). *Addressing climate information needs at the regional level : the CORDEX framework*. *May*.

Hayhoe, K., Edmonds, J., Kopp, R., & Legrande, A. (2017). *Climate models , scenarios , and projections*.

Illy, T., Jacob, D., Keup-thiel, E., Kotlarski, S., Nikulin, G., Otto, J., Rechid, D., Sieck, K., Sobolowski, S., Szabó, P., Teichmann, C., Vautard, R., Weber, T., & Zsebeházi, G. (2017). *Guidance for EURO-CORDEX climate projections data use*. 1–27.

IPCC. (2007). *C l i m a t e Ch a n g e 2007 : I m p a c t s , A d a p t at io n an d V u ln e ra b il it y Contribution of Working Group II to the Fourth Assessment Report of the IPCC (978 0521 88010-7 Hardback; 978 0521 70597-4 Paperback).*

IPCC. (2008). *Climate Change and Water. Technical Paper of the Intergovernmental Panel on Climate Change, IPCC Secretariat, Geneva, 210 pp.*

IPCC. (2013). *Climate Change , The Physical Science Basis Working Group I Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change Edited by*.

IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)].rmany), Ismail Elgizouli (Sudan), . *IPCC, Geneva, Switxerland: Kristin Seyboth (USA)*, 151. https://www.ipcc.ch/pdf/assessment-report/ar5/syr/AR5_SYR_FINAL_Front_matters.pdf

Juraj M. Cunderlik. (2003). *Hydrologic Model Selection for the CFCAS Project: Assessment of Water Resources Risk and Vulnerability to Changing Climatic Conditions*.

Kattsov, V., Federation, R., Reason, C., Africa, S., Uk, A. A., Uk, T. A., Baehr, J., Uk, A. B., Catto, J., Canada, J. S., & Uk, A. S. (2013). *Evaluation of Climate Models 9*.

Kim, J., Waliser, D. E., Mattmann, C. A., Goodale, C. E., Hart, A. F., Zimdars, P. A., Crichton, D. J., Jones, C., Nikulin, G., Hewitson, B., Jack, C., Lennard, C., & Favre, A. (2014). Evaluation of the CORDEX-Africa multi-RCM hindcast: Systematic model errors. *Climate Dynamics*, *42*(5–6), 1189–1202. https://doi.org/10.1007/s00382-013-1751-7

Kishiwa, P., Nobert, J., Kongo, V., & Ndomba, P. (2018). *Assessment of impacts of climate change on surface water availability using coupled SWAT and WEAP models : case of upper Pangani River Basin , Tanzania*. 23–27.

Legesse, D., Abiye, T. A., Vallet-Coulomb, C., & Abate, H. (2010). Streamflow sensitivity to climate and land cover changes: Meki River, Ethiopia. *Hydrology and Earth System Sciences*, *14*(11), 2277–2287. https://doi.org/10.5194/hess-14-2277-2010

Liersch, S. (2003). *The Programs dew.exe and dew2.exe* (Issue August, pp. 1–5).

Mcsweeney, C., New, M., & Lizcano, G. (2009). *UNDP Climate Change Country Profiles Ethiopia*,. 1–27.

Melesse, A. M., & Abtew, W. (2015). Landscape Dynamics, Soils and Hydrological Processes in Varied Climates. *Landscape Dynamics, Soils and Hydrological Processes in Varied Climates*, *July*, 1–839. https://doi.org/10.1007/978-3-319-18787-7

Mishra, Y., Nakamura, T., Babel, M. S., & Ninsawat, S. (2018). *Impact of Climate Change on Water Resources of the*. 1–21. https://doi.org/10.3390/w10020220

MoEF. (2015). *Ethiopia's,Second National Communication to the United Nations Framework Convention on Climate Change (UNFCCC)*.

Moriasi, D. N., Arnold, J. G., Liew, M. W. Van, Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). *MODEL EVALUATION GUIDELINES FOR SYSTEMATIC QUANTIFICATION OF ACCURACY IN WATERSHED SIMULATIONS*. *50*(3), 885–900.

Musau, J., Sang, J., Gathenya, J., & Luedeling, E. (2015). Regional Studies Hydrological responses to climate change in Mt . Elgon watersheds. *Journal of Hydrology: Regional Studies*, *3*, 233–246. https://doi.org/10.1016/j.ejrh.2014.12.001

Nan, Y., Bao-hui, M., & Chun-kun, L. (2011). *Impact analysis of climate change on water resources*. *24*, 643–648. https://doi.org/10.1016/j.proeng.2011.11.2710

NMSA. (2005). National Metrological Services Agency Agrometeorological Bulletin. *Seasonal Agro Meterological Bulletin Bega,2004/05*, *15*(03), 1–19. http://www.wamis.org/countries/ethiopia/Eth20051503.pdf

Nurtaev, B. (2015). Influence of climate variability on large rivers runoff. *IAHS-AISH Proceedings and Reports*, *371*, 211–214. https://doi.org/10.5194/piahs-371-211-2015

Olsson, T., Jakkila, J., Veijalainen, N., Backman, L., Kaurola, J., & Vehviläinen, B. (2015). *Impacts of climate change on temperature , precipitation and hydrology in Finland – studies using bias corrected*. 3217–3238. https://doi.org/10.5194/hess-19-3217-2015

Pierce, D. W., Cayan, D. R., Maurer, E. P., Abatzoglou, J. T., Hegewisch, K. C., & Al, P. E. T. (2015). *Improved Bias Correction Techniques for Hydrological Simulations of Climate Change*. 2421–2442. https://doi.org/10.1175/JHM-D-14-0236.1

Rathjens, H., Bieger, K., Srinivasan, R., & Arnold, J. G. (2016). *CMhyd User Manual Documentation for preparing simulated climate change data for hydrologic impact studies*.

Roth, V., Lemann, T., Zeleke, G., & Teklay, A. (2018). Effects of climate change on water resources in the upper Blue Nile Basin of Ethiopia. *Heliyon*, *July*. https://doi.org/10.1016/j.heliyon.2018.e00771

S.L. NEITSCH, J.G. ARNOLD, J.R. KINIRY, J. R. W. (2005). *S OIL AND W ATER A SSESSMENT T OOL D OCUMENTATION VERSION 2005*.

Setegn, S. G., Rayner, D., Melesse, A. M., & Dargahi, B. (2011). *Impact of climate change on the hydroclimatology of Lake Tana Basin , Ethiopia*. *47*, 1–13. https://doi.org/10.1029/2010WR009248

Shanka, A. S. (2017). Evaluation of Climate Change Impacts on Run-Off in the Gidabo River Basin: Southern Ethiopia. *Environment Pollution and Climate Change*, *01*(03), 1–6. https://doi.org/10.4172/2573-458x.1000129

Shawul, A. A., Alamirew, T., & Melesse, A. M. (2016). *Climate Change Impact on the Hydrology of Weyb River Watershed , Bale Mountainous Area , Ethiopia*. https://doi.org/10.1007/978-3-319-18787-7

Shitu, K., & Berhanu, S. (2020). *Statistical Downscaling of Daily Temperature and Rainfall Data from Global Circulation Models , in Borkena River Catchment , Ethiopia*. *9*(5), 87–97. https://doi.org/10.11648/j.wros.20200905.11

Smitha, P. S., Narasimhan, B., & Sudheer, K. P. (2017). *MULTI MODEL ENSEMBLE FOR ASSESSING THE IMPACT OF CLIMATE CHANGE ON THE HYDROLOGY OF A SOUTH INDIAN RIVER BASIN*.

Srinivasan, R., Arnold, J. G., & Jones, C. A. (1998). *Hydrologic M ode lling of the Unite d States with the Soil and Water A sse ssme nt Tool*. *14*.

Taye, M. T., Dyer, E., Hirpa, F. A., & Charles, K. (2018). Climate change impact on water resources in the Awash basin, Ethiopia. *Water (Switzerland)*, *10*(11), 1–16.

https://doi.org/10.3390/w10111560

Tesfalem Abraham, Brook Abate, Abraham Woldemicheal, A. M. (2018). *Impacts of Climate Change Under CMIP5 RCP Scenarios on the Hydrology of Lake Ziway Catchment , Central Rift Valley of*. *8*(7).

Teutschbein, C., & Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies : Review and evaluation of different methods. *Journal of Hydrology*, *456–457*, 12–29. https://doi.org/10.1016/j.jhydrol.2012.05.052

UNFCCC. (2014). *Technologies for Adaptation in the Water Sector*. 12.

USAID. (2016). *CLIMATE CHANGE RISKS AND OPPORTUNITIES REPORT* (Issue December).

WaleWorqlul, A., Taddele, Y. D., Ayana, E. K., Jeong, J., Adem, A. A., & Gerik, T. (2018). Impact of climate change on streamflow hydrology in headwater catchments of the upper Blue Nile Basin, Ethiopia. *Water (Switzerland)*, *10*(2). https://doi.org/10.3390/w10020120

Xu, H., & Luo, Y. (2015). Climate change and its impacts on river discharge in two climate regions in China. *Hydrology and Earth System Sciences*, *19*(11), 4609–4618. https://doi.org/10.5194/hess-19-4609-2015

Zahabiyoun, B., Goodarzi, M. R., Bavani, A. R. M., Azamathulla, H. M., Engineering, R., & Pinang, T. P. (2013). *Assessment of Climate Change Impact on the Gharesou River Basin Using SWAT Hydrological Model*. *41*(6), 601–609. https://doi.org/10.1002/clen.201100652

APPENDICES

Appendix A.1: Average daily rain fall data in month at Kulumsa station

Year	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1986	0.0	0.0	3.3	1.2	2.7	4.5	3.0	1.1	3.6	0.8	0.0	0.0
1987	0.8	0.4	0.4	1.8	3.0	3.9	6.8	5.8	3.4	0.1	0.1	0.0
1988	0.1	6.5	1.3	0.7	5.2	1.3	3.6	5.3	1.6	0.4	0.0	0.1
1989	0.4	1.2	0.6	0.0	1.1	2.5	6.9	3.4	4.3	5.7	0.7	0.1
1990	0.3	2.0	0.0	5.6	4.1	2.6	3.3	5.8	1.7	0.1	0.8	0.1
1991	0.3	1.9	0.4	1.7	0.7	3.6	4.0	2.8	4.3	0.3	0.4	0.5
1992	1.5	0.4	2.6	4.2	0.3	3.3	4.2	6.1	3.7	4.8	0.0	0.2
1993	0.3	0.0	5.2	2.2	2.3	4.7	4.6	3.3	3.4	0.2	0.1	0.1
1994	0.1	0.0	7.8	7.6	5.7	3.5	4.4	3.9	4.5	1.0	0.0	0.1
1995	0.1	2.2	0.3	1.2	5.5	3.8	3.7	3.5	3.2	3.2	0.0	0.0
1996	0.7	0.2	4.4	2.0	1.2	5.9	2.6	5.6	1.9	3.7	0.0	0.4
1997	0.2	0.0	2.6	17.5	0.6	1.3	4.3	6.4	2.8	0.0	0.4	2.2
1998	0.8	1.3	5.7	0.2	6.4	1.7	3.2	2.5	3.2	0.3	1.0	0.0
1999	1.2	0.4	2.4	0.8	3.7	1.5	2.1	2.0	3.8	0.0	1.1	0.2
2000	0.5	0.4	2.0	0.6	0.5	4.6	2.4	3.4	2.1	4.5	0.1	2.7
2001	1.3	1.0	2.1	5.0	2.3	3.4	4.4	4.5	2.0	0.4	0.0	0.3
2002	4.7	0.4	3.2	1.9	6.0	1.6	2.1	4.9	3.3	0.9	0.0	0.5
2003	0.0	0.0	1.5	0.1	0.3	5.2	2.2	2.9	2.3	0.1	0.7	0.2
2004	0.0	8.0	0.0	1.5	1.1	5.6	5.4	4.6	6.1	2.2	2.2	1.1
2005	1.6	6.3	10.8	7.9	0.6	3.3	1.2	5.0	5.0	0.0	0.0	0.0

Appendix A.2: Average daily rain fall data in month at Bekoji station

Year	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1986	0.0	0.2	5.0	3.6	4.0	5.3	5.5	3.5	3.2	2.0	0.5	0.0
1987	0.4	0.5	0.1	4.0	2.8	4.3	8.2	12.2	5.6	0.5	1.1	0.1
1988	0.0	5.3	1.3	2.0	6.1	3.0	7.5	8.4	1.1	1.5	0.0	0.3
1989	0.8	0.5	0.4	0.2	1.8	8.3	8.8	5.9	6.2	6.4	3.1	0.2
1990	0.9	2.1	0.0	5.6	4.4	1.9	4.6	8.9	1.5	2.8	1.6	0.7
1991	0.1	3.4	0.3	3.6	1.2	7.4	8.9	5.0	5.6	1.0	1.4	0.7
1992	1.5	0.6	1.5	5.9	0.5	3.4	9.2	9.7	4.0	6.5	0.1	0.2
1993	0.1	0.0	6.6	3.9	3.3	4.8	7.4	5.2	4.0	1.2	0.6	0.2
1994	0.0	0.0	5.7	8.8	5.6	4.4	7.3	6.2	4.6	2.5	0.0	0.1
1995	0.4	4.5	0.4	3.3	4.8	4.1	5.9	5.4	3.8	5.6	0.0	0.1
1996	0.9	0.2	6.0	2.5	3.3	5.8	3.5	6.9	3.4	3.8	0.3	0.3
1997	0.3	0.1	2.9	20.0	1.0	4.5	9.1	9.4	3.7	0.8	1.5	2.4
1998	0.3	2.2	2.7	0.3	10.4	4.9	5.5	6.5	4.4	1.8	3.5	0.1
1999	1.5	0.6	2.4	1.6	5.5	3.4	3.3	4.1	4.1	0.0	4.6	0.8
2000	0.3	0.3	1.6	1.6	2.8	6.0	4.9	4.2	3.7	5.9	0.3	1.5
2001	1.7	2.3	3.2	5.6	3.0	4.2	6.5	7.3	2.4	1.0	0.5	1.0
2002	1.1	0.2	3.5	4.1	9.3	3.4	4.5	8.6	3.5	2.0	0.0	0.5
2003	0.0	0.0	1.1	0.5	1.1	5.0	4.6	5.2	2.5	0.8	2.8	0.5
2004	0.2	6.4	0.0	5.0	1.6	4.9	8.9	7.6	7.8	4.7	9.0	1.0
2005	1.1	5.6	5.7	9.9	1.8	6.0	4.3	6.6	5.5	0.0	0.2	0.0

Appendix A.3: Average daily rain fall data in month at Asela station

Year	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1986	0.0	0.0	3.7	1.9	3.2	5.5	4.6	1.7	4.7	1.2	0.0	0.0
1987	0.7	0.4	0.4	2.5	3.5	4.6	9.2	7.7	4.4	0.1	0.1	0.0
1988	0.0	5.8	1.6	1.2	5.8	1.6	5.4	7.0	2.2	0.7	0.0	0.1
1989	0.3	1.1	0.6	0.0	1.3	3.1	9.0	4.7	5.7	8.2	1.0	0.2
1990	0.2	1.8	0.0	7.3	4.7	3.2	4.9	7.7	2.4	0.3	1.1	0.2
1991	0.2	1.7	0.5	2.2	0.9	4.3	6.0	4.0	5.7	0.6	0.5	0.8
1992	1.2	0.4	2.8	5.3	0.3	3.9	6.5	8.0	5.0	7.0	0.0	0.4
1993	0.2	0.0	5.5	3.0	2.7	5.6	6.6	4.6	4.5	0.3	0.1	0.1
1994	0.0	0.0	8.0	9.9	6.5	4.1	6.4	5.4	6.0	1.6	0.0	0.1
1995	0.0	2.0	0.4	1.8	6.2	4.6	5.5	4.9	4.2	4.7	0.0	0.0
1996	0.6	0.2	4.7	2.7	1.4	7.0	3.9	7.4	2.5	5.3	0.0	0.6
1997	0.1	0.0	2.8	20.7	0.7	1.7	6.2	8.1	3.7	0.1	0.5	3.2
1998	0.6	1.2	6.2	0.3	7.2	2.2	4.9	3.6	4.3	0.6	1.3	0.0
1999	1.0	0.4	2.7	1.3	4.3	2.0	3.1	2.9	5.0	0.0	1.5	0.3
2000	0.4	0.4	2.1	0.9	0.6	5.3	3.9	4.5	2.9	6.5	0.1	3.8
2001	1.0	0.8	2.5	6.6	2.6	3.9	6.6	6.0	2.7	0.7	0.1	0.5
2002	4.1	0.4	3.6	2.7	6.7	2.0	3.3	6.4	4.4	1.4	0.0	0.8
2003	0.0	0.0	1.8	0.3	0.3	6.0	3.4	3.8	3.2	0.1	0.9	0.3
2004	0.0	7.1	0.0	2.4	1.4	6.4	7.8	6.2	8.0	3.3	3.1	1.5
2005	1.3	5.6	11.4	10.2	0.7	4.0	2.2	6.2	6.4	0.0	0.0	0.0

Appendix A.4: Average daily rain fall data in month at Arata station

Year	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1986	0.0	0.0	2.2	1.0	2.5	4.5	3.1	0.8	3.9	0.6	0.0	0.0
1987	0.4	0.2	0.2	1.5	2.8	4.2	8.9	5.5	4.4	0.0	0.0	0.0
1988	0.0	4.9	0.7	0.6	5.2	1.2	3.7	5.3	1.6	0.3	0.0	0.0
1989	0.2	0.8	0.4	0.0	1.0	2.4	9.7	3.0	4.8	4.8	0.7	0.0
1990	0.1	1.4	0.0	4.7	4.0	2.4	3.8	5.4	1.5	0.1	0.7	0.0
1991	0.1	1.2	0.2	1.4	0.6	3.8	4.3	2.4	4.8	0.2	0.3	0.3
1992	0.8	0.2	1.9	3.5	0.2	3.4	4.3	6.1	3.8	4.1	0.0	0.1
1993	0.1	0.0	4.1	1.8	2.2	4.7	5.4	2.8	4.2	0.1	0.0	0.0
1994	0.0	0.0	6.5	6.4	5.5	3.9	5.1	3.6	5.0	0.8	0.0	0.0
1995	0.0	1.3	0.1	1.0	5.5	3.9	4.2	2.8	3.3	2.6	0.0	0.0
1996	0.4	0.1	3.4	1.6	1.1	6.3	2.8	5.5	2.2	3.3	0.0	0.2
1997	0.1	0.0	1.9	14.7	0.5	1.3	5.0	6.7	2.9	0.0	0.3	1.2
1998	0.4	0.9	4.2	0.1	6.5	1.5	3.4	2.1	3.4	0.2	0.9	0.0
1999	0.7	0.2	1.5	0.7	3.6	1.4	2.5	1.5	4.1	0.0	1.1	0.1
2000	0.2	0.2	1.4	0.5	0.4	5.2	2.2	3.3	2.0	3.9	0.0	1.5
2001	0.6	0.6	1.3	4.2	2.2	3.6	4.8	4.2	2.1	0.2	0.0	0.1
2002	3.3	0.2	2.2	1.6	6.0	1.6	2.1	4.9	3.7	0.6	0.0	0.2
2003	0.0	0.0	0.8	0.1	0.2	5.6	2.0	2.8	2.3	0.0	0.5	0.1
2004	0.0	6.1	0.0	1.3	1.0	6.2	6.1	4.2	7.7	1.7	2.4	0.6
2005	0.9	4.8	8.3	6.6	0.6	3.4	0.9	5.6	6.8	0.0	0.0	0.0

Appendix A.5: Average daily rain fall data in month at Ogolcho station

Year	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1986	0.0	0.0	2.6	0.8	1.6	3.2	4.2	0.6	3.5	0.6	0.0	0.0
1987	0.4	0.2	0.3	1.3	2.1	3.5	11.7	4.9	4.6	0.0	0.0	0.0
1988	0.0	5.9	0.9	0.4	4.8	0.7	5.0	4.9	1.3	0.3	0.0	0.0
1989	0.1	0.9	0.5	0.0	0.6	1.6	12.7	2.7	4.4	4.6	0.7	0.0
1990	0.1	1.6	0.0	4.6	3.1	1.6	5.1	4.8	1.1	0.1	0.3	0.0
1991	0.1	1.3	0.2	1.3	0.4	3.1	5.7	2.1	4.3	0.1	0.1	0.2
1992	0.8	0.2	2.2	3.6	0.1	2.7	5.7	5.7	3.1	3.9	0.0	0.0
1993	0.1	0.0	4.8	1.6	1.4	3.5	7.2	2.3	4.1	0.1	0.0	0.0
1994	0.0	0.0	7.5	6.2	4.1	3.5	6.8	3.2	4.5	0.7	0.0	0.0
1995	0.0	1.4	0.2	0.8	4.7	3.1	5.5	2.3	2.9	2.5	0.0	0.0
1996	0.4	0.1	3.9	1.5	0.7	5.3	3.7	5.2	2.0	3.2	0.0	0.1
1997	0.0	0.0	2.2	16.2	0.2	0.9	6.7	6.4	2.4	0.0	0.1	1.1
1998	0.4	0.9	5.0	0.1	5.9	0.8	4.5	1.8	3.0	0.1	0.4	0.0
1999	0.7	0.2	1.8	0.5	2.7	0.8	3.3	1.2	3.7	0.0	0.9	0.1
2000	0.2	0.2	1.6	0.4	0.2	5.0	3.0	3.1	1.6	3.7	0.0	1.4
2001	0.4	0.6	1.6	4.0	1.7	3.0	6.4	3.7	1.8	0.2	0.0	0.0
2002	4.0	0.2	2.5	1.4	5.4	1.1	2.9	4.5	3.3	0.5	0.0	0.1
2003	0.0	0.0	1.0	0.1	0.1	4.8	2.7	2.6	1.9	0.0	0.1	0.0
2004	0.0	7.4	0.0	0.9	0.6	5.6	8.1	3.7	7.5	1.5	2.7	0.5
2005	0.9	5.8	9.7	6.4	0.4	2.6	1.3	5.8	7.0	0.0	0.0	0.0

Appendix B.1: Monthly maximum temperature of Arata station

Year	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1986	22.6	24.1	22.8	24.1	24.0	21.9	20.3	20.7	20.7	21.9	22.1	23.1
1987	22.8	24.2	26.1	24.6	23.3	22.3	19.7	19.3	21.0	23.3	22.6	22.6
1988	22.7	22.9	23.4	24.9	23.8	23.2	20.4	20.5	22.6	22.6	22.9	22.4
1989	23.2	24.0	26.9	26.9	25.9	24.5	20.2	20.3	20.7	20.2	21.7	21.3
1990	21.9	23.4	26.3	23.9	22.5	23.2	20.1	20.6	21.7	22.7	23.1	21.9
1991	23.1	23.4	25.4	25.2	26.2	23.8	21.3	21.6	21.0	22.3	22.2	20.9
1992	22.2	23.5	23.8	23.3	26.1	22.6	19.5	19.9	19.7	19.7	21.3	21.4
1993	21.6	24.3	23.5	23.6	23.4	22.1	19.6	20.7	21.0	21.3	21.5	21.9
1994	22.6	24.4	24.4	21.2	21.8	21.6	19.8	19.2	20.1	21.2	22.0	21.9
1995	22.4	21.7	25.3	24.8	23.4	22.6	20.9	21.1	21.0	20.8	22.0	21.8
1996	22.7	24.6	23.8	23.4	25.3	22.1	21.3	20.8	22.6	21.2	21.3	21.8
1997	22.9	24.2	24.9	21.5	23.7	21.9	20.0	19.5	20.5	22.7	22.6	20.9
1998	23.0	24.4	23.0	25.7	23.9	23.3	21.9	20.7	21.1	21.4	21.9	23.0
1999	22.3	24.7	24.6	25.3	23.1	24.2	22.0	21.4	21.1	24.8	24.2	22.2
2000	23.5	25.3	25.5	25.2	26.2	22.4	21.5	21.3	20.9	21.0	21.9	21.5
2001	21.8	24.1	24.7	23.1	24.7	23.9	21.2	20.8	21.5	22.5	22.1	21.7
2002	22.1	24.9	24.7	25.0	23.7	23.3	20.9	20.9	21.1	22.0	23.6	22.4
2003	23.5	25.2	25.0	26.3	27.3	23.4	20.7	21.7	21.5	23.5	22.9	23.3
2004	24.3	21.1	26.8	24.9	26.4	22.5	21.2	20.3	20.6	21.2	20.8	21.8
2005	21.7	22.2	20.5	21.6	25.3	24.8	21.5	21.3	21.3	24.4	24.5	23.5

Appendix B.2: Monthly minimum temperature of Arata station

Year	Jan.	Feb.	Mar.	Apr.	May.	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
1986	8.3	7.7	10.6	10.4	10.7	10.4	9.7	9.7	10.0	9.9	8.6	8.5
1987	8.3	9.6	9.1	11.5	10.9	10.1	10.0	9.9	7.7	9.1	8.3	6.6
1988	7.8	10.6	9.2	12.3	10.8	10.1	10.7	10.4	8.4	10.9	9.2	8.8
1989	7.7	8.3	10.2	11.0	11.6	11.6	10.6	10.4	10.6	10.4	8.2	7.8
1990	7.2	10.4	9.8	11.5	10.3	9.6	10.5	10.6	8.9	10.1	9.0	9.8
1991	8.4	10.7	9.9	11.6	12.1	11.4	12.3	10.6	10.2	9.5	9.0	8.2
1992	7.8	9.1	9.0	10.0	10.7	9.4	10.4	10.5	10.0	9.6	8.0	8.0
1993	7.5	6.7	9.7	11.4	10.2	10.0	10.4	9.7	9.4	10.8	8.3	7.3
1994	7.3	6.6	11.4	10.6	10.3	8.7	10.1	9.0	10.0	9.4	6.5	6.6
1995	9.2	10.9	9.9	10.8	10.4	10.4	11.0	10.4	10.2	9.9	6.4	6.7
1996	9.6	7.9	11.1	10.2	11.9	10.8	9.7	11.0	9.6	11.0	8.7	6.9
1997	8.0	8.0	9.8	11.5	10.1	9.9	11.0	10.5	10.0	9.4	10.2	10.0
1998	9.7	9.3	10.8	11.4	11.6	11.5	11.5	11.0	10.8	10.5	9.2	8.8
1999	9.7	9.5	10.0	11.3	11.4	11.1	10.7	9.8	10.6	10.4	10.3	7.5
2000	7.6	10.9	10.1	12.1	12.7	11.2	11.4	11.3	10.6	10.8	9.6	10.5
2001	10.1	9.5	11.4	12.3	11.2	11.6	11.3	11.9	10.5	11.4	9.9	9.3
2002	8.1	8.6	12.4	12.6	11.4	11.6	10.7	11.0	10.4	10.6	8.0	7.3
2003	7.4	7.6	11.5	12.2	12.6	10.9	10.9	11.9	10.1	10.4	10.0	8.8
2004	8.6	10.2	9.7	11.9	12.6	11.7	11.5	10.2	11.0	11.4	9.8	7.3
2005	9.8	11.1	11.5	11.8	10.0	11.8	11.1	10.3	10.8	10.2	11.0	7.4

Appendix C: Monthly discharge of Katar River at Abura gauging

Year	**Jan.**	**Feb.**	**Mar**	**Apr.**	**May.**	**Jun.**	**Jul.**	**Aug.**	**Sep.**	**Oct.**	**Nov.**	**Dec.**
1991	2.16	2.24	3.73	5.15	3.01	3.42	13.96	44.95	35.01	7.77	2.89	2.33
1992	2.05	2.46	1.76	3.04	2.99	3.25	8.14	65.56	52.03	26.92	4.92	3.02
1993	2.73	6.42	2.32	5.12	11.16	11.56	16.56	52.18	34.71	21.16	7.33	3.28
1994	2.17	1.92	1.65	1.56	2.52	4.25	22.76	67.08	49.51	8.07	3.30	2.05
1995	1.58	1.58	7.94	7.19	5.39	2.60	12.60	46.86	59.35	5.97	2.48	2.13
1996	2.50	1.69	2.88	3.74	6.87	17.81	21.22	63.25	24.50	9.30	2.86	2.17
1997	3.10	1.66	1.60	5.92	2.56	2.82	13.47	20.61	10.93	5.99	6.87	3.02
1998	2.22	3.45	4.96	2.40	5.97	3.66	13.29	68.05	47.05	31.21	7.04	2.73
1999	2.02	0.45	1.76	1.58	1.70	3.17	16.97	32.97	21.25	45.06	7.17	2.88
2000	1.66	1.60	1.56	1.49	4.66	2.75	9.61	49.03	27.42	26.19	9.10	2.74
2001	1.77	1.56	2.18	2.48	7.60	13.64	33.68	79.28	37.24	12.29	2.76	1.86
2002	1.84	1.89	2.77	2.07	2.81	3.39	7.26	25.90	13.55	3.80	1.66	1.94
2003	2.30	1.54	1.56	3.93	3.40	2.85	16.53	50.67	28.64	8.79	2.23	1.87
2004	1.48	1.34	1.36	8.68	3.45	3.40	19.90	37.43	26.88	13.87	2.55	1.49

Appendix D.1: Projected monthly precipitation of katar under RCP4.5 for 2021-2040

	Arata	Asela	Bekoji	Kulumsa	Ogolcho	Avg pcp
Jan.	0	0	0	0	0	0
Feb.	1.67	4.35	3.13	3.57	0	2.544
Mar.	22.69	33.23	31.79	30.51	51.83	34.01
Apr.	69.56	107.2	98.62	86.43	183.29	109.02
May.	37.75	47.31	55.98	40.76	11.84	38.728
Jun.	127.45	133.23	155.11	114.68	68.51	119.796
Jul.	118.4	155.57	170.93	106.46	137.63	137.798
Aug.	164.76	200.05	212.75	157.83	67.36	160.55
Sep.	83.79	105.38	92.03	78.97	50.31	82.096
Oct.	35.76	62.67	55.25	43.02	19.6	43.26
Nov.	21.96	32.24	38.32	23.7	0	23.244
Dec.	8.58	23.65	6.73	17.09	39.99	19.208

Appendix D.2: Projected monthly precipitation of katar under RCP8.5 for 2021-2040

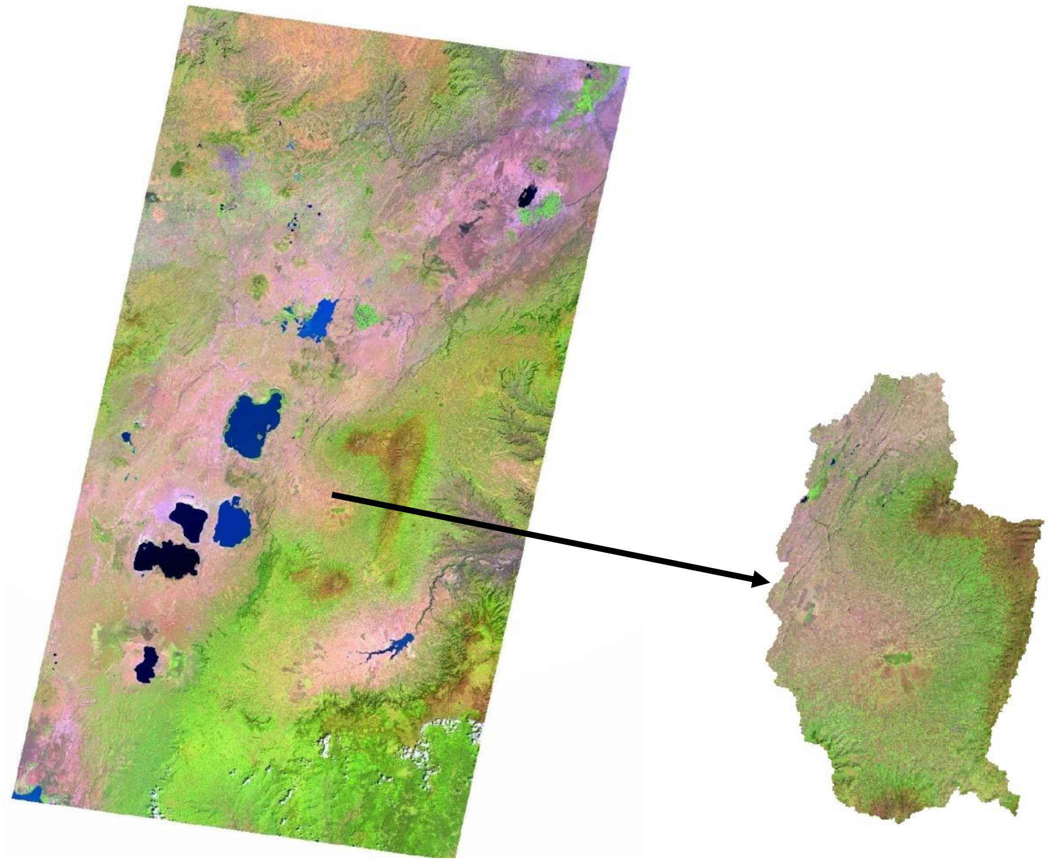
	Arata	Asela	Bekoji	Kulumsa	Ogolcho	Avg pcp
Jan.	0	0	0	0	0	0
Feb.	18.86	21.45	25.02	24.48	20.29	22.02
Mar.	24.52	37.37	33.04	34.66	26.76	31.27
Apr.	31.48	50.14	40.84	39.61	30.64	38.542
May.	62.71	77.31	78.35	67.77	50.2	67.268
Jun.	107.82	118.37	150.59	100.46	93.29	114.106
Jul.	115.4	152.08	156.75	104.21	147.73	135.234
Aug.	163.55	201.24	207.88	157.84	158.2	177.742
Sep.	118.83	137.1	115.83	104.02	109.76	117.108
Oct.	24.07	45.29	50.78	30.28	22.26	34.536
Nov.	11.45	15.64	19.31	10.7	13.94	14.208
Dec.	3.19	7.29	1.63	5.21	0	3.464

Appendix D.3 Projected monthly precipitation of katar under RCP4.5 for 2051-2070

	Arata	Asela	Bekoji	Kulumsa	Ogolcho	Avg pcp
Jan.	0	0	0	0	0	0
Feb.	22.55	30.02	10.47	28.78	24.78	23.32
Mar.	23.23	35.23	23.65	33.81	25.31	28.246
Apr.	22.67	34.65	35.35	27.7	22.34	28.542
May.	57.24	69.76	89.38	60.86	44.36	64.32
Jun.	101.3	116.95	130.34	97.65	82.59	105.766
Jul.	86.56	136.77	145.77	89.23	108.32	113.33
Aug.	161.45	200.11	207.48	156.71	155.11	176.172
Sep.	92.3	112.77	84.71	84.73	82.63	91.428
Oct.	29.39	52.85	50.26	35.95	27.47	39.184
Nov.	12.54	19.72	25.8	12.81	15.87	17.348
Dec.	3.16	9.79	1.67	6.97	0	4.318

Appendix D.4 Projected monthly precipitation of katar under RCP8.5 for 2051-2070

	Arata	Asela	Bekoji	Kulumsa	Ogolcho	Avg pcp
Jan.	0	0	0	0	0	0
Feb.	10.54	10.95	11.65	12.54	13.55	11.846
Mar.	36.46	45.94	40.29	45.68	39.14	41.502
Apr.	10.39	21.78	28.22	16.76	8.95	17.22
May.	36.9	46.41	48.29	40.44	28.68	40.144
Jun.	129.87	138.64	194.1	118.79	116.22	139.524
Jul.	154.15	190.25	180.28	132.45	197.12	170.85
Aug.	213.31	227.1	276.38	186.26	220.62	224.734
Sep.	101.77	121.05	106.35	91.39	91.97	102.506
Oct.	57.28	100.09	96.06	68.73	54.3	75.292
Nov.	0	0	0	0	0	0
Dec.	8.07	18.03	0	12.94	9.17	9.642



Appendix E1:Figure landsat Image band combination(5,4,1 RGB) of the Study Area (Year 2000)

Appendix F1: Pcp stat and dew point results of weather generator meteorological station.

Month	PCP MM	PCPSTD	PCPSKW	PR W1	PR W2	PCPD
Jan.	22.9	4.7342	13.4815	0.0643	0.4868	3.8
Feb.	46.38	6.21	6.2111	0.0812	0.694	6.7
Mar.	87.12	7.9255	5.1722	0.1144	0.7661	10.9
Apr.	95.49	8.9623	6.2216	0.1872	0.7107	12.1
May.	82.54	6.977	4.5812	0.1768	0.7054	12.05
Jun.	101.51	6.2836	3.1284	0.3282	0.7361	17.05
Jul.	115.36	6.7913	4.0314	0.3793	0.7842	20.85
Aug.	127.98	6.59	4.0406	0.4586	0.7813	21.95
Sep.	99.36	5.2027	3.7591	0.3438	0.8088	20.4
Oct.	44.39	5.031	5.1762	0.0758	0.6591	6.6
Nov.	11.1	2.3716	10.6088	0.0396	0.4545	2.2
Dec.	13.36	2.8833	10.2076	0.0478	0.4727	2.75

Month	tmp_max	tmp_min	hmd	dewpt
Jan	22.65	8.41	67.4	10.56
Feb	23.84	9.17	62.28	10.23
Mar	24.58	10.35	65.06	11.66
Apr	24.22	11.41	69.07	12.76
May	24.5	11.17	71.99	13.61
Jun	22.98	10.69	80.26	14.28
Jul	20.7	10.77	85.69	13.92
Aug	20.63	10.5	87.05	14.05
Sep	21.09	9.99	82.83	13.4
Oct	22.04	10.29	63.9	9.84
Nov	22.37	8.91	58.39	8.38
Dec	22.07	8.1	62.41	8.96

PCP_MM = Average monthly precipitation[mm]

PCPSTD = standard deviation

PCPSKW = skew coefficient

PR_W1 = Probability of wet day following a dry day

PR_W2 = Probability of wet day following a wet day

PCPD = average number of precipitation days in a month

mp_max= Average dailly maximum temperature in month [°C]

tmp_min=Average dailly minimum temperature in month [°C]

hmd = Average dailly humidity in month [%]

dewpt = average dailly dew point temperature in month [°C]

Appendix G1: Land use and soil distribution of Katar river basin re-classified by SWAT

Detailed LANDUSE/SOIL/SLOPE distribution SWAT model class Date: 1/26/2021 12:00:00 AM Time: 14:38:16.9722569

	Area [ha]	Area[acres]	
Watershed	319047.7619	788382.9721	
Number of Subbasins: 31			

	Area [ha]	Area[acres]	%Wat.Area
LANDUSE:			
Forest-Evergreen --> FRSE	52858.8369	130616.8289	16.57
Agricultural Land-Row Crops --> AGRR	181853.4144	449368.8797	57.00
Forest-Mixed --> FRST	3892.3820	9618.2706	1.22
Pasture --> PAST	46529.1451	114975.8440	14.58
Residential-Medium Density --> URMD	31216.4445	77137.3953	9.78
Water --> WATR	402.2497	993.9790	0.13
Wetlands-Non-Forested --> WETN	2295.2893	5671.7746	0.72
SOILS:			
Ne10-3b-154	207707.9475	513256.7237	65.10
Rd2-2c-229	21689.1656	53595.0126	6.80
Vp1-3a-283	14714.0034	36359.0381	4.61
Xh16-a-309	47677.2150	117812.7821	14.94
Xh17-2a-310	27259.4304	67359.4156	8.54
SLOPE:			
0-5	125821.6526	310911.5946	39.44
10-15	44466.0211	109877.7614	13.94
15-20	23651.9398	58445.1259	7.41
20-9999	33732.8436	83355.5431	10.57
5-10	91375.3049	225792.9471	28.64