UNCERTAINITY REDUCTION IN CLIMATE AND HYDROLOGICAL MODELS PREDICTIONS AT CATCHMENT SCALE IN THE UPPER GREAT RUAHA RIVER SUB-BASIN, TANZANIA

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EXTENDED ABSTRACT

Water resources have become scarce in most tropical areas of Tanzania due to climate change. Any changes to the hydrological cycle may have significant effects on the water resources in the river basins of Tanzania. The impact of climate change on water resources in Tanzania have been studied using General Circulation Models (GCM) which run at low spatial resolutions of 100-300 km. The resolution is too coarse to provide useful information about climate change impact in small catchments as many physical processes which control local climate e.g.; vegetation, hydrology, topography is not fully parameterized and hence results on uncertainty in model prediction.

The main aim of this research was to quantify the uncertainty in model predictions for the Mbarali River Sub-catchment of the Upper Great Ruaha River Sub-basin in the Rufiji River Basin, Tanzania. Three research objectives were analyzed; the first objective was to evaluate the performance of the Coordinated Regional Downscaling Experiment Regional Climate Model (CORDEX, Regional Climate Models) in simulating rainfall characteristics of the Mbarali River Sub catchment. The area weighted average method was used to calculate the average rainfall from the CORDEX RCMs and from ERA-Interim reanalysis over the entire Mbarali River sub-catchment. Comparison between rainfall data from CORDEX RCMs and ERA-Interim reanalysis was done to test the ability of the CORDEX RCMs to reproduce the annual cycles, interannual variability, annual total and trends of rainfall as presented by the ERA-Interim reanalysis.

The second objective assessed the impact of climate change on hydrological characteristics using the Soil and Water Assessment Tool (SWAT) model. The ability of the SWAT model to simulate catchment processes was assessed through a calibration and

validation process, which was a key factor in reducing uncertainty and increasing user confidence in its predictive abilities. The SWAT model was driven by high resolution climate simulations for historical climate condition (1971-2000) as well as future climate projections (2011-2040, 2041-2070 and 2071-2100) for two Representative concentration Pathways (RCPs): RCP 4.5 and RCP 8.5. Furthermore, Ensemble of RCMs was applied into SWAT to simulate water resources availability and the results were compared with individual models (HIRHAM5, CCLM4, RACMO22T, RCA4). The Rainfall and Temperature data were obtained from the selected four CORDEX RCMs driven by three different General Circulation Models (GCMs). Inverse Distance Weight Average (IDWA) was used to interpolate model gridded climate simulation to the location of weather station. The third objective assessed the impacts of land use and land cover change on the hydrology using integration of remote sensing data, QGIS and SWAT model. The land use and land cover (LULC) maps for three window period snapshots, 1990, 2006 and 2017 were created from Landsat TM and OLI_TIRS. Supervised classification was used to generate LULC maps using the Maximum Likelihood Algorithm and Kappa statistics for assessment of accuracy.

The findings of the first objective are that CORDEX RCMs were able to capture well the seasonal and annual cycles of rainfall. However, they underestimated the amount of rainfall in March, April and May (MAM) and overestimated in October, November and December (OND) respectively. CORDEX RCMs reproduce interannual variation of rainfall. The source of uncertainties was revealed when the same RCMs driven by different GCMs and when different RCMs driven by the same GCM in simulating rainfall. It was found that the error and biases from RCMs and driving GCMs contribute roughly equally. Overall, the evaluation found reasonable (although variable) model capability in representing the mean climate, interannual variability and rainfall trends.

The results suggest that CORDEX RCM is suitable in simulating rainfall, maximum temperature and minimum temperature.

The findings of the second objective showed that SWAT model simulated stream flow and water balance components differently when two different RCMs were forced by the same GCMs as well as when the same RCMs were forced by different GCMs. The differences are related to the formulation of the RCMs themselves. For example, RACMO22T and HIRHAM5 driven with the same GCM (ICHEC-EARTH) simulate different amount of stream flows, surface runoff, water yield and groundwater yield in historical (1971–2000) as well as in present century (2011-2040), mid-century (2041-2070) and end century (2071-2100). Ensemble RCMs projected decrease in stream flows by 13.67% under RCP 8.5. However annual rainfall was shown to increase in averages by 1.62% under RCP 4.5 and by 1.96% for RCP 8.5 relative to the 1177.1mm of the baseline period (1971-2000).

The results also showed that, temperature will slightly increase relative to the baseline during present century (2011-2040) for RCP 4.5 and RCP 8.5. The ensemble average project that the minimum temperature will increase by 14% (1.9^{0}C) under RCP 8.5 and maximum temperature by 7.68% (1.8^{o}C) under RCP 4.5

The findings of the third objective showed that there were significant changes in land use and cover for the three-time periods (1990, 2006 and 2017). The cultivated land and built up area increased from 25.69% in 1990 to 31.53% in 2006 and 43.57% in 2017 compared to other land classes. Increase of cultivated land and built up area led to decrease in forest cover. Forests occupied 7.54% in 1990, but decreased to 5.51% in 2006 and 5.23% in 2017. This decrease in forest cover has resulted in increased surface runoff for the same periods (2006-2017). The increase in surface runoff in the study area could be attributed to deforestation and poor land husbandry, where during land preparation much of the vegetation is cleared, hence decreasing canopy interception and allowing water to drain off. Also, poor farming practices including cultivation on hillslopes without soil conservation, reducing soil compaction, hence allowing more water to drain as surface runoff.

The calibrated SWAT model using the three different land use and land cover change of 1990, 2006 and 2017 indicate that during the wet season, the mean monthly flow increased by 1.48% relative to the 28.09 m^3/s of the baseline 1990 while during the dry season, the mean monthly flow decreased by 16.7% relative to the 0.20 m^3/s baseline flow. Assessment of the impacts of land use and land cover changes on catchment water balance component revealed that surface runoff increased by 3.9% in 2006 and 9.01% in 2017 while groundwater contribution to stream flow decreased by 6.3% and 12.86% in 2006 and 2017, respectively. The decrease in stream flow could also be attributed to abstraction of water for irrigation activities upstream of the Igawa gauge station.

The findings of the study may help basin water officers, planners in water sector and agriculture sector in addressing uncertainty in policy and decision-making specifically when preparing strategies and adaptations plans for river catchment. The science used in this study can be applicable to another river basin in Tanzanian in a climate change impact study.

DECLARATION

I, EDMUND ISHENGOMA MUTAYOBA do hereby declare to the Senate of Sokoine University of Agriculture that this thesis is my original work done within the period of registration and that it has neither been submitted nor being concurrently submitted in any other institution.

Edmund Ishengoma Mutayoba Date

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The above declaration is confirmed by;

Prof. Siza D. Tumbo Date

(Supervisor)

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DEDICATION

I dedicate this Thesis to the Holy Spirit -The Spirit of the Living God, who guided and provided me with strength to accomplish this work (Zachariah 4:6).

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

CORDEX	Coordinated Regional Climate Downscaling Experiment
DD	Dynamic Downscaling
DEM	Digital Elevation Model
ETM	Enhanced Thematic Mapper
GCMs	General Circulation Models
HRU	Hydrological Response Unit
IDWA	Inverse Distance Weight Average
IPCC	Intergovernmental Panel on climate change
ITCZ	Inter-tropical Convergence -Zone
NASA	National Aeronautics and Space Administration
NCEP	National Center for Environmental Protection
OLI-TIRS	Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)
QGIS	Quantum Geographical Information System
RCMs	Regional Climate Models
RCPs	Representative Concentration Pathways
SD	Statistical Downscaling
SRTM	Shuttle Radar Topography Mission
SUFI-2	Sequential Uncertainty of Fit version 2
SWAT	Soil and Water Assessment Tool
TM	Thematic Mapper
TMA	Tanzania Meteorological Agency
URT	United Republic of Tanzania

CHAPTER ONE

1.0 INTRODUCTION

Global climate change is expected to have a strong impact on water resources (Huntington, 2006; Intergovernmental Panel on Climate Change (IPCC), 2014). Changes in precipitation patterns directly affect runoff and water availability, while changes in temperature, radiation and humidity have an effect on evapotranspiration (Fowler *et al.*, 2007). Various efforts have been made to evaluate the impact of climate change on hydrology in river basins (Chen *et al.*, 2013; Xu *et al.*, 2013). Their findings have revealed that climate change does not pose major threat on average water availability, but will be adverse on temporal flow variations in the future.

Spatial and temporal rainfall variability plays a major role in the hydrological response of catchments; affecting runoff timing, streamflow volume and peak discharge (Yakir *et al.*, 2011; Paschalis *et al*., 2014). The hydrological response is more sensitive to spatial rainfall variability in very small catchments of, say less than 1 km^2 (Bahat *et al.*, 2009) to few dozen catchments (Zoccatelli *et al*., 2011) than in large catchments (i.e.> 100 km^2; Arnaud *et al.*, 2011). Therefore, it is essential to use climate data with high spatial and temporal resolution for hydrological modeling purpose. Such resolution can be provided for small and medium sized catchments by weather radar data (e.g. 1.5 km^2 and 3 min) and for large catchments by satellite data (Peleg *et al.*, 2015).

In catchment hydrology, it is in practice impossible to measure everything we would like to know about the hydrological system, mainly due to high catchment heterogeneity and the limitations of measurement techniques. These limitations and the need to extrapolate information from the available measurements in both space and time initiated the application of hydrological models. However, hydrological models suffer from uncertainty in their predictions, which reduces applicability of and confidence in such models. Uncertainty in model predictions arises from several sources: natural randomness, measurement errors in the observed data set that are used as inputs (forcing) for modeling purpose, model parameters and model structure (Refsgaard *et al.*, 2006). A realistic assessment of the various sources of error is important for science-based decision making (Refsgaard *et al.*, 2006) as well as to direct the research towards model structural improvements and uncertainty reduction. It is an accepted fact that hydrological model simulations should explicitly include an estimate of their associated uncertainty.

Many studies on climate change impact on streamflow in Tanzania have been conducted in Wami River sub-basin. Wambura (2014) studied the response of streamflow under changing climate using individual General circulation Model (GCM) and the result indicate the highest skill score in predicting the historical climate. In the Pangani Basin, Notter *et al.* (2013) studied climate change impact on streamflow using two individual GCMs representing the extremes of available IPCC predictions (i.e. the driest and wettest conditions); while in the Ruvu River sub-basin, Mwandosya *et al.* (1998) researched on the impact of climate change on streamflow using individual GCM and their findings showed the lowest Root Mean Squared Error (RMSE) in predicting the historical climate.

All studies applied GCMs with low spatial resolution in the range of 100-300 km (Villegas and Jarvis, 2010). This resolution is too coarse to provide useful information about climate change impact at catchment scale (Vigaud *et al.*, 2013), as many physical processes which control local climate, e.g. topography, vegetation and hydrology are not fully parameterized. Studies by Jones *et al*. (2013) indicate that the use of GCM outputs is associated with the mismatch of spatial grid scales and hydrological processes.

A number of studies, which focused on climate and the hydrology of the Great Ruah river, have been conducted in the past. Tumbo *et al*. (2014) applied a hydrological modeling approach for understanding hydrology of the Great Ruaha River. The approach employed in this study represents a major step towards the identification of uncertainty. Faraji and Masenza (1992) undertook a hydrological study of the Usangu Plains with particular reference to flow entering the Mtera Reservoir, and Mwakalila (2001) modeled the hydrological response of the Great Ruaha River Basin as a function of physical characteristics. However, none of these studies explain uncertainty in hydrological model predictions at the catchment scale using coordinated regional downscaling experiment (CORDEX), the Regional Climate Models (RCMs).

1.1 Hydrological Models

The field of hydrology focuses on the terrestrial part of the hydrological cycle, which involves the occurrence, transport and composition of water stocks and fluxes below and on the earth's surface (RNAAS, 2005). Hydrology is an interdisciplinary science (mathematics, fluid mechanics, soil mechanics, meteorology, etc.), that attempts to understand how the hydrological cycle interacts with the geosphere, atmosphere and biosphere. Hence, hydrological research plays an important role in helping to solve global problems, such as water scarcity and food insecurity under interdisciplinary research. As such, it provides the scientific knowledge and the predictive or descriptive models in the form of black box, process and conceptual models for decision support in the development of methodologies and policies of sustainable water resource management.

1.2 Classification of Hydrological Models

The rainfall-runoff models range from very simple black box schemes to complex, differential, distributed models (Tan *et al.,* 2004). Thus, rainfall-runoff models can be classified in terms of how hydrological processes are represented, the time and space scale that are used and what methods are used to solve model equations (Singh, 1995). The main features for distinguishing the approaches are the nature of basic algorithms (empirical, conceptual or process-based), whether a stochastic or deterministic approach is taken to define input or parameters and whether the spatial representation is lumped or distributed (Melone *et al.,* 2005). Distributed, semi-distributed and lumped models are model classes based on spatial variability representation (Melone *et al.,* 2005). A lumped model spatially averages (Burnash, 1995) catchment model parameters and takes no account of the spatial distribution of the inputs or parameters thus treating the catchment as a single unit, whereas distributed and semi-distributed models take an explicit account of spatial variability of processes, input, boundary conditions, and/or watershed characteristics (Sahoo *et al.,* 2006). These watershed characteristics include distribution of topography, soil types, vegetation types, geology and spatial variability in meteorological conditions.

1.3 Attributes of SWAT Model

The Soil Water Assessment Tool (SWAT) is an integrated watershed model widely applied across the world to study hydrology, sediment, in-stream water quality, impact of land use, climate change and various water management interventions on water quantity and quality. SWAT can manipulate and analyze many hydrological and agronomic data in order to predict the effects of land management on water resources. It simulates transfers of nutrients, sediments and pesticides to the drainage network and to aquifers. SWAT also simulates crop yields according to the environmental conditions and cultivation techniques. Watersheds represented in this model have areas ranging from hundreds to several thousand km^2.

The model considers the entire hydrological cycle, represented in the watershed spatial manner. SWAT can analyze the watershed as a whole or by splitting small spatial unit of the watersheds called Hydrological Response Units (HRU).

1.4 Climate Model Projection

Projections of future climate and the implications for regional hydrology are of great importance for identifying appropriate mitigation and adaptation strategies under a changing climate. The most common tools for simulating complex climate processes are general circulation models (GCMs) using a rather coarse grid with current resolutions of 100–250 km. For regional climate-change impact studies, GCMs are problematic due to their lack of detailed regional information (IPCC, 2007). Typical precipitation and streamflow models require fine-scale climate parameters that can be obtained by downscaling GCM simulations. This can either be done with a statistical (SD) or a dynamical downscaling (DD) approach. The SD method establishes statistical relationships between large-scale climate information and local/regional variables (Hewitson and Crane 1996; Wilby *et al.*, 2004), whereas DD employs regional climate models (RCMs) for limited regions with boundary conditions from GCM simulations. Both downscaling methods have strengths and limitations. Wilby *et al.* (2002) summarize some characteristics of SD and DD as follows: SD is computationally cheap, flexible and allows uncertainty analyses. The success is dependent on data quality for calibration, choice of predictor, choice of empirical transfer scheme and choice of SD method. DD resolves atmospheric processes, agreed with the GCM output. The drawbacks are the requirement of powerful computing capacities and the dependency on initial boundary conditions. There is also still a lack of readily available climate-scenario ensembles for most regions in the world, although the number of public-available ensemble archives from European projects on similar grid size is increasing, e.g. ENSEMBLES (Van der

Linden and Mitchell, 2009) and PRUDENCE (Christensen *et al.,* 2007). Both SD and DD are dependent on GCM boundary forcing, domain size and location.

Climate models use quantitative methods to simulate the interactions of the important drivers of climate, including atmosphere, oceans, land surface and ice. They are used for a variety of purposes from study of the dynamics of the climate system to projections of future climate (Marriott, 2011). Coupled Atmosphere – Ocean General Circulation Model (AOGCM) have been extensively used to investigate issues of climate variability and climate change over Africa (Marriott, 2011). These models can provide broad scale patterns of climate variability and change and their information can be regionally refined through the use of different dynamic and statistical downscaling techniques (Giorgi, 2011). One of these techniques is the use of nested Regional Climate models (Giorgi, 2011) which have increasingly been used throughout the world to generate regional and local climate change scenarios. RCMs have proven to be valuable tools for regional climate downscaling (Sylla, 2012). They have been mostly used over mid latitude regions, and only recently they have been applied for climate studies over different African domains (Sylla *et al*., 2013). The use of high-resolution regional climate models to examine the hydrological impacts of climate change has grown significantly in recent years due to the improved representation of the local climate (Roosemalen *et al*., 2012). Regional climate models are a standard tool for downscaling climate forecasts to finer spatial scales. The evaluation of RCMs against observational data is an important step in building confidence in the use of RCMs for future prediction (Winger, 2015). In addition to model performance in climatological means and marginal distributions, a model's ability to capture spatio-temporal relationships is very important. The most commonly known Cordex RCMs that are being applied in Africa continent include the CCLM. RACMO2, HIRHAM, RCA. etc.

CCLM is based on the regional climate model of the international Climate Limited-area modeling community (Winger, 2015). The model RACMO2, was provided by The Royal Netherlands Meteorological Institute. The regional climate model RACMO2 (Lenderink *et al.,* 2003; van den Hurk *et al.,* 2006) is forced with output from a transient run conducted with the ECHAM5 GCM. The model 'METNO HIRHAM' was developed by the Norwegian Meteorological Institute and it is based on Version 5 of the HIRHAM regional climate model (Christensen *et al.,* 2013) driven by the Bergen Climate Model (BCM).

1.5 Justification

Climate variability and projected future climate change will have increasingly negative impacts on Tanzanian water bodies, and will exceed the limits to adaptation in the most vulnerable catchments regions. This study intends to reduce uncertainties in modeling the impact of climate change on river runoff and land use covers that combine methodology for downscaling climate change scenarios at a catchment scale with a hydrological model to estimate the impact of climate change on river runoff. In order to understand the uncertainty issues in modeling, the research used the integrated Remote sensing, GIS and Hydrological model SWAT using Different land cover scenarios. Such an arrangement will enable the improvement of the uncertainty of historical and future conditions for the study, and also consider the spatial variability of hydrological properties in the catchment by maintaining the physical details at a given grid size. Current policy development processes require the integration of climate change concerns into water policies. However, sector-oriented studies often fail to address all the dimensions of climate change implication. Climate change research in previous studies has evidenced the need for more integrated studies and methodologies that are capable of addressing the multi-scale and multi - dimensional nature of climate change.

1.6 Objectives

1.6.1 Overall objective

The overall objective was to assess uncertainties in hydrological model predictions at catchment scale in the Upper Great Ruaha River Sub-basin.

1.6.2 Specific objectives

The specific objectives of the study were:

i. To evaluate the performance of the CORDEX Regional Climate Models in simulating rainfall characteristics

ii. To assess the impacts of climate change on hydrological characteristics using high resolution climate simulations from CORDEX Regional Climate Models

iii. To assess the Impacts of Land Use and Land Cover Changes on Hydrology

1.7 Conceptual Framework

The conceptual framework of this study was represented by the three interrelated components, climate modeling and downscaling, hydrological modeling, assessment of socio-economic impact pathways and vulnerability (Fig. 1.1). All the three components are dependent on access to data and their availability. The data was generated from the Coordinated Regional Downscaling Experiment (CORDEX) to derive a regional climate model (RCM) for regional downscaling at a resolution of approx. 4 km using a number of climate projections. The resolution used depend upon the size of the catchment (in this case the whole Mbarali River sub-catchment), Area covered by meteorological records and effects on key model outputs (e.g. precipitation rates). The RCM’s outputs such as precipitation and temperature were fed into a hydrological model to predict river runoff, groundwater recharge, extraction rates, etc.

Socio-economic and environmental impact need was identified in order to measure the effects of climate change within a sustainable development context.

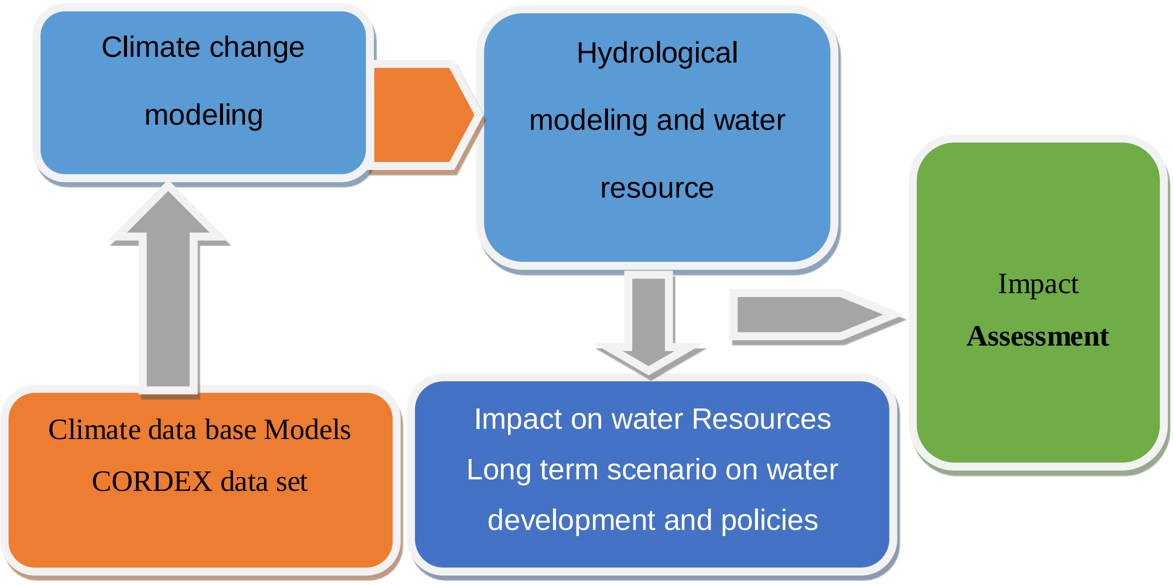

Figure 1.1: Conceptual framework for the study
Source: Adopted and modified from Tarek *et al.* (2015).

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CHAPTER TWO

2.0 Evaluation for the Performance of the CORDEX Regional Climate Models in Simulating Rainfall Characteristics Over Mbarali River Sub-catchment in the Rufiji Basin Tanzania

2.1 Abstract

This study aims to evaluate the performance of the individual Regional Climate Models (RCMs) used in Coordinated Regional Climate Downscaling Experiment (CORDEX) and the ensemble average of the four RCMs to feign the characteristics of rainfall pattern for the Mbarali river sub-catchment in Rufiji basin for the period of 1979 to 2005. Statistical analysis for model performance such as Root mean square error, Mean error, Pearson correlation coefficient, Mean, Median, standard deviation and trend analysis are used. In addition to the statistical measure of model performance, the models are tested on their ability to capture the observed annual cycles and interannual variability of rainfall. Results indicated that the RCMs from the CORDEX indicated a better performance to reproduce the rainfall characteristics over Mbarali river sub-catchment in Rufiji basin. They reproduced fairly the Era Interim annual cycle and inter-annual variability of rainfall. The ensemble average performed better than individual models in representing rainfall over Mbarali river sub-catchment in Rufiji basin. The findings suggest that rainfall simulation from the ensemble average can be used for the assessment of the hydrological impact studies over Mbarali river sub-catchment in Rufiji basin.

Key words: Climate change, CORDEX, Regional climate models (RCMs), Ensemble average.

2.2 Introduction

The General Circulation Models (GCMs) are currently the most advanced tools available for simulating the response of the global climate system, to increased greenhouse gas concentration in the atmosphere (Luhuga *et al.,* 2016; IPCC, 2013). They use variety of fluid dynamical, chemical and biological equations to describe important physical elements and processes in different components of climate systems: atmosphere, oceans, cryosphere and land surface (Jones and Mann, 2004). One disadvantage of GCMs is that, they have a low spatial resolution which is restricted in the range of 100-300 km (Villegas and Jarvis, 2010). This resolution is too small to provide useful information about climate change for impact studies on hydrology, ecosystem services, and other landscape and agriculture related matters (Villegas and Jarvis, 2010; Tumbo *et al.,* 2012; Luhuga and Djolov, 2017; Hassan *et al.,* 2013 and Daniels *et al.,* 2012). In order to bridge the gap between what is supplied by the GCMs and what is required for impact studies, scientists have developed two types of downscaling techniques: statistical and dynamical downscaling.

Dynamical downscaling is the most appropriate downscaling technique which provides better representation of orographic effect on climate variables. Its main approach is based on nesting high resolution Regional Climate Model (RCM) and run it using boundary condition from the GCM (Denis *et al.,* 2002). Generally dynamical downscaling is computationally expensive. At present many collaboration projects are generating climate simulation from dynamical downscaling for model inter-comparisons and impact assessments. These projects include the Coordinated Regional Climate Downscaling Experiment (CORDEX) that produce dynamical downscaled climate simulation for all continents, and the North American Regional Climate Change Assessment Program (NARCCAP) that provide high resolution climate simulation for United States, Northern

Mexico, and Canada (Glotter, 2014). These projects have made available large number of high-resolution climate simulations that can be used for impact assessments.

However, before using climate simulation from dynamical downscaling it is appropriate to evaluate their performance at different spatial scale. This is of the utmost important for choosing appropriate climate model to be used for impact assessment at location since the performance of the dynamical downscaled data differs from location to location and from one RCM to another (Luhuga *et al.*, 2016).

Several studies have evaluated the performance of the output from dynamical downscaled data especially those generated by CORDEX (Engelbrecht *et al.*, 2009; Endris *et al.*, 2013; Shongwe *et al.*, 2015 and Luhuga *et al.*, 2016). Shongwe *et al.* (2015), examined the performance of the output from CORDEX RCMs in simulating precipitation over Southern Africa. They found that the RCMs adequately captured the reference precipitation probability density functions, with a few showing a towards excessive light rainfall events. Huang *et al.* (2015) assessed the performance of CORDEX regional climate model to simulate precipitation climatology in East Asia. They found that CORDEX RCMs can simulate the annual cycle, seasonal mean, and inter-annual variability of rainfall acceptably. Very recently Luhunga *et al.* (2016) evaluated the performance of the CORDEX RCMs in simulating minimum air temperature and maximum air temperature and rainfall over Tanzania. They evaluated CORDEX RCMs against observed station data that are scattered over complex topographical terrain. They found that CORDEX RCMs perform differently in simulating rainfall over different regions in Tanzania. Although the evaluation by Luhunga *et al.* (2016) was comprehensive at station scale throughout the country but there is need to evaluate the performance of the CORDEX RCM at catchment scale. This study is devoted to evaluate the performance of the CORDEX RCMs to simulate rainfall climatology over Mbarali River sub-catchment. The output from this study is intended to be used for climate change impact assessment on hydrology over the Mbarali River sub-catchment.

2.3 Data and Methodology

2.3.1 Study area

The United Republic of Tanzania is in East Africa between latitudes 1°S and 12°S and longitudes 29°E and 41°E. It has a tropical type of climate but has regional variation of its climate due to high regional heterogeneity that covers a land area of 885 800 km^2 that extends from the Indian Ocean coastline to more than 1000 km inland (Luhuga *et al*., 2014). Based on the land morphology, Tanzania has nine basins that include Lake Victoria, Wami-Ruvu, Lake Tanganyika, internal drainage, Pangani, Rufiji, Lake Nyasa, Rukwa, and Ruvuma basins (URT, 2013). The Mbarali River sub-catchment that covers an area of 1530 km^2 within the Upper Great Ruaha is located in the Rufiji basin in the south-eastern highlands of Tanzania along latitude 7^0 and 9^0 and longitude 33.8^0 and 35^0 (Fig. 2.1). The River catchment is at an altitude ranging from 1000 to 1800 meters above sea level. Seasonal rainfalls are in the range of 450 to 650 mm that start from October through to April or May (Luhunga, 2016). The average temperature in the catchment ranges from 25^0C to 30^0C.

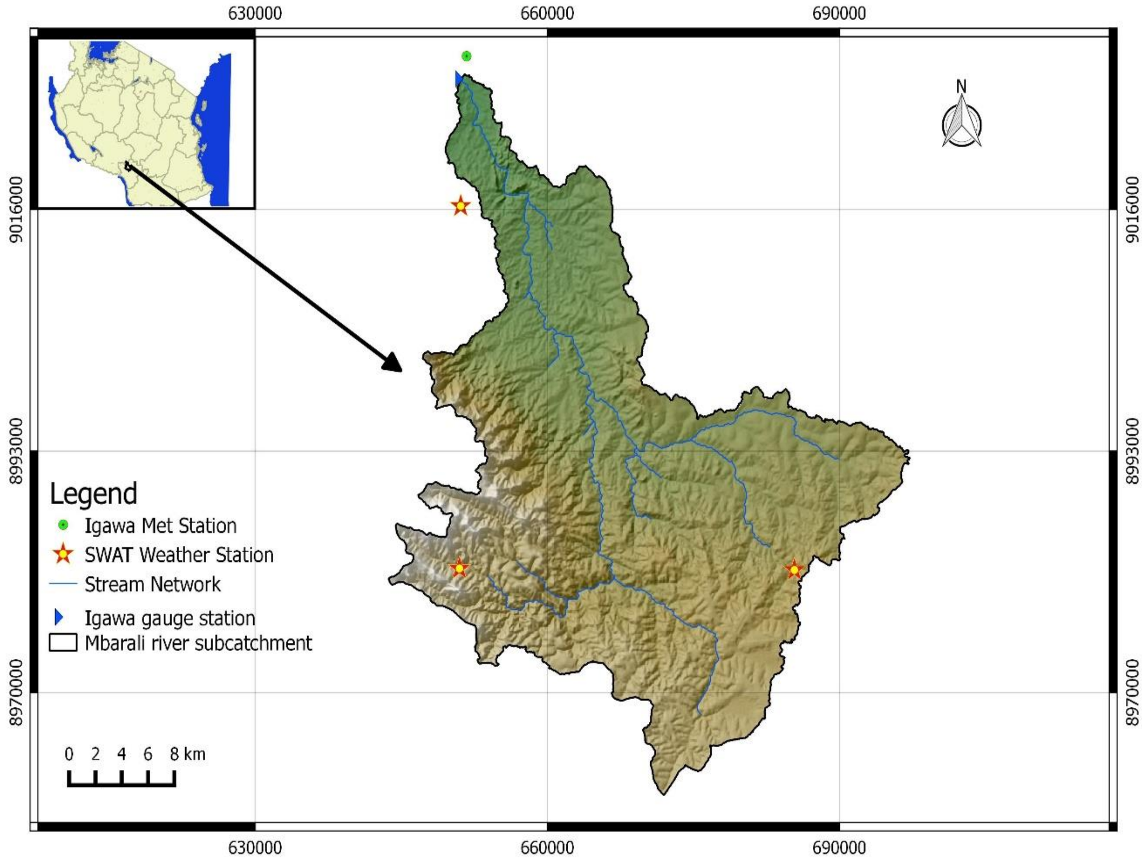

Figure 2.1: Study area Mbarali River sub-catchment

2.3.2 Data from the regional climate model

This study uses rainfall simulated from four regional climate models in the Coordinated Regional Climate Downscaling Experiment (CORDEX) database. These data were obtained from http://cordexesg.dmi.dk/esgf-web-fe/. The output from CORDEX RCMs are quality controlled and can be used according to the terms of use (http://wcrp-cordex.ipsl.jussieu.fr/). Monthly rainfall data for the period of 34 years (1971-2005) were derived from four CORDEX RCMs listed in Table 2.1. It should be noted that all CORDEX RCMs are set to 0.44^0 by 0.44^0 spatial resolutions. This corresponds to 50 km by 50 km. The CORDEX RCMs and their driving GCMs written in short forms as (CNRM) for the CNRM-CERFACS-CNRM-CM5, (ICHEC) for the ICHECEC-EARTH and (MPI) for the MPI-M-MPI-ESM-LR (Table 2.1).

Table 2.1: Indicate the CORDEX-RCMs and their driving GCMs used in this study

S/N	RCM	Mode Centre	Short name	GCMs
1	DMI HIRHAM5	Danmarks Meteorologiske Institut (DMI), Denmark	HIRHAM5	ICHEC
2	CLMcom COSMO-CLM (CCLM4)	Climate Limited -Area Modelling (CLM) Community	CCLM4	CNRM
3	KNMI Regional Atmospheric Climate Model, version (RACMO2.2T)	Koninklijk Nederlands Meteorologisch Instituut (KNMI), Netherlands	RACMO22T	ICHEC
4	SMHI Rossby Center Regional Atmospheric Model (RCA4)	Sveriges Meteorologiska Och Hydrologiska Institut (SMHI), Sweden	RCA4	MPI

2.3.3 Climate data ERA interim reanalysis

One of the main problems in evaluating the RCM simulations over Africa is the lack of the quality of observed data set at suitable temporal and spatial resolution (Nikulin *et al.*, 2012). There are no observed meteorological station networks in the Mbarali River sub-catchment. The nearby meteorological stations are found in Mbeya and Iringa regions. This leads to use monthly rainfall data from the ERA-Interim re-analysis. The details on how these data are produced and quality controlled the reader may consult (Nikulin *et al.*, 2012). Rainfall data for the period from 1979-2015 are used to compare with model simulation over the Mbarali River sub-catchment.

2.3.4 Analysis

The area weighted average method was used to calculate the average rainfall from the CORDEX RCMs and from ERA-Interim reanalysis over the entire Mbarali River sub-catchment (latitude 7^0 and 9^0 and longitude 33.8^0 and 35^0). Comparison between rainfall data from CORDEX RCMs and ERA-Interim reanalysis was done to test the ability of the CORDEX RCMs to reproduce the annual cycles, interannual variability, annual total and trends of rainfall as presented by the ERA-Interim reanalysis.

2.4 Evaluation Criteria for Model Performance

Statistical methods for evaluation of model performance that include the Root Mean Square Error (RMSE), Mean Error (ME), Pearson correlation coefficient (r), Mean, Median, Standard Deviation were used for evaluating model performance as it presented in the equations 1, 2 and 3 while the Mann - Kendall Test are used for trend analysis.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{RCM_i} - \mathrm{ERA_i})^2} \quad \ldots\ldots(1)$$

$$\mathrm{ME} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{RCM_i} - \mathrm{ERA_i}) \ldots\ldots(2)$$

$$r_{(RCM,ERA)} = \frac{\sum_{i=1}^{N}(RCM_i - \overline{RCM})(ERA_i - \overline{ERA})}{\sqrt{\sum_{i=1}^{N}(ERA_i - \overline{ERA})^2}\sqrt{\sum_{i=1}^{N}(RCM_i - \overline{RCM})^2}} \ldots\ldots(3)$$

where RCM and ERA are, the RCMs simulated and ERA-interim reanalysis rainfall data respectively, while i is the RCMs simulated and ERA-interim reanalysis pairs and N is the number of such pairs.

2.5 Trends in Rainfall

2.5.1 Mann-Kendall trend test and estimation of gradient of trend

Among the statistical trend analysis methods that have been mostly used to detect trends in meteorological time series is the Mann-Kendall trend test which is non-parametric (Rodrigo and Trigo, 2007). It is a rank-based procedure, which is robust to the influence of outliers and extreme values. With this test, the null hypothesis H_0 states that, there is no trend in data. This means that the data is independent and identically distributed random, this is tested against the alternative hypothesis H_1 which assumes that there is a trend. The Mann- Kendall test is calculated by considering the time series of n data points and x_i, *and* x_j , as two subsets of data where i=1, 2, 3………, n-1 and j=i+1, i+2 +i+3……., n. The values are evaluated as an ordered time series. Each data value is compared with all subsequent data values and if a data value from a later time period is higher than a data value from an earlier time period, the statistic S is incremented by 1. Likewise, if the data value from a later period is lower than a data value sampled earlier, S is decremented by 1. The net result of all such increments and decrements yields the final value of S.The Mann-Kendall S Statistic is computed using equation 4, and the test of significance is computed using equation 5:

$$S = \sum_{n=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \quad \ldots\ldots (4)$$

$$\text{sgn}\ (x_j - x_i = \begin{cases} +1 \text{ if } (x_j - x_i) > 0 \\ 0 \text{ if } (x_j - x_i) = 0 \\ -1 \text{ if } (x_j - x_i) < 0 \end{cases} \quad \ldots\ldots (5)$$

where x_i , and x_j , are the annual values in years i and j, $j > i$ respectively.

When the sample size n is less than 10, the value of $|S|$, is compared directly to the theoretical distribution of S derived by Mann and Kendall (calculated using Equation 4 and 5) and is asymptotically normal (Robert and Slack, 1984). The two-sided test is used, at certain probability level H_0 is rejected in favour of H_1 if the absolute value of S equals or exceeds a specified value Sα/2, where Sα/2 is the smallest S which has the probability less than α/2 to appear in case of no trend. A positive value of S designates an ‘increasing trend’; likewise, a negative designates descending trend.

For $n \geq 10$ the statistic S is approximately normally distributed with the mean and variance as follows:

$E(S) = 0$ ……………………………………………………………………………...(6)

The variance σ^2 , for the S statistic is defined as follows:

$$Var(S) = \left[\frac{n(n-1)(2n+5) - \sum_{t} t_i(i)(i-1)(2i+5)}{18} \right] \qquad \text{(7)}$$

in which t_i, denotes the number of ties to the extent i. The summation term in the numerator is used only if the data series contains tied values. The standard test statistic Z is calculated as follows:

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} & \text{if} \quad S > 0 \\ 0 & \text{if} \quad S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} & \text{if} \quad S < 0 \end{cases} \qquad \text{(8)}$$

The test statistic Z is used as a measure of significance of trends. In fact, this test statistic is used to test the null hypothesis, H0. If | Zs| is greater than Zα/2, where α represents the chosen significance level (e.g.: 5% with Z 0.025 = 1.96) then the null hypothesis is invalid implying that the trend is significant. In this study, Mann-Kendall test is used to detect if a trend in rainfall in monthly time series is statistically significant at 1% and 5% levels over the period of 1979-2005.

SEN'S Slope Estimator is used to estimate the gradient of the trends in rainfall (Sen, 1968). This method provides a more robust slope estimate than the least square method because it is sensitive to the outliers or extreme values. The slope is estimated as follows:

$$T_i = \frac{x_j - x_k}{j - k} \text{ for i= 1,2,……., N} \quad \text{……………………………………………………(9)}$$

Where xj and x_k are data values at time j and k and j>k correspondingly. The median of these N values of T_i is considered as Sen's estimator of slope which is given as

$$Qi = \begin{cases} T_{\frac{N+1}{2}} & N \text{ is odd} \\ \frac{1}{2}\left(T_{\frac{N}{2}} + T_{\frac{N+2}{2}}\right) & N \text{ is even} \end{cases} \quad \text{……………………………..…………………(10)}$$

Sen's estimator is calculated as Q_i=T $_{(N+1)/2}$ if N is odd, and it is computed as $Q_i=[T_{N/2}+T_{(N+2)/2}]/2$ if N is even. Lastly Q_i is estimated by a two sided test at 100 (1-α)% confidence interval and then a true slope can be derived by the non-parametric test Q_i with a positive value indicates an upward or increasing trend and a negative value of Q_i signifies a downward or decreasing trend in the time series. In addition to statistical tests and the trend analysis, the CORDEX RCMs are tested on their ability to reproduce the annual cycles and inter-annual variation of rainfall.

2.6 Results and Discussion

2.6.1 Rainfall distribution

Mbarali River sub-catchment is situated within the semi-arid belt which runs from north to south through the central portion of Tanzania. The mean annual rainfall ranges from 400 mm to 1200 mm. Rainfall increases southwards and is highest on the slopes of the Kipengere Mountain. The seasonal variation of rainfall indicates that the River Catchment experiences a unimodal rainfall regime characterized by a single rainy season extending usually between late November - early December to early - mid May. The eastern portion of the River catchment receives slightly reduced rainfall amounts in February, while the main rainy season peaks in April. The dry season occurs earlier in the central part. The rainfall variability is high, and precipitation is often in the form of heavy showers causing rapid surface runoff and a sudden spate in seasonal streams and rivers (SMUWC, 2001).

We first present the spatial rainfall distribution within the Mbarali river sub-catchment for the period of 30 years, starting from 1979-2009 (Fig. 2.2). The Figure 2.2 is developed using open source software GrADS (Grid Analysis and Display System) version 2.1.0 (http://cola.gmu.edu/grads/downloads.php). It is clear from the figure that high amount of rainfall (more than 20 mm/day) is observed in south eastern, south-west and western part of the river catchment. However, the central and the eastern part of the catchment experienced low rainfall amount (16 mm/day).

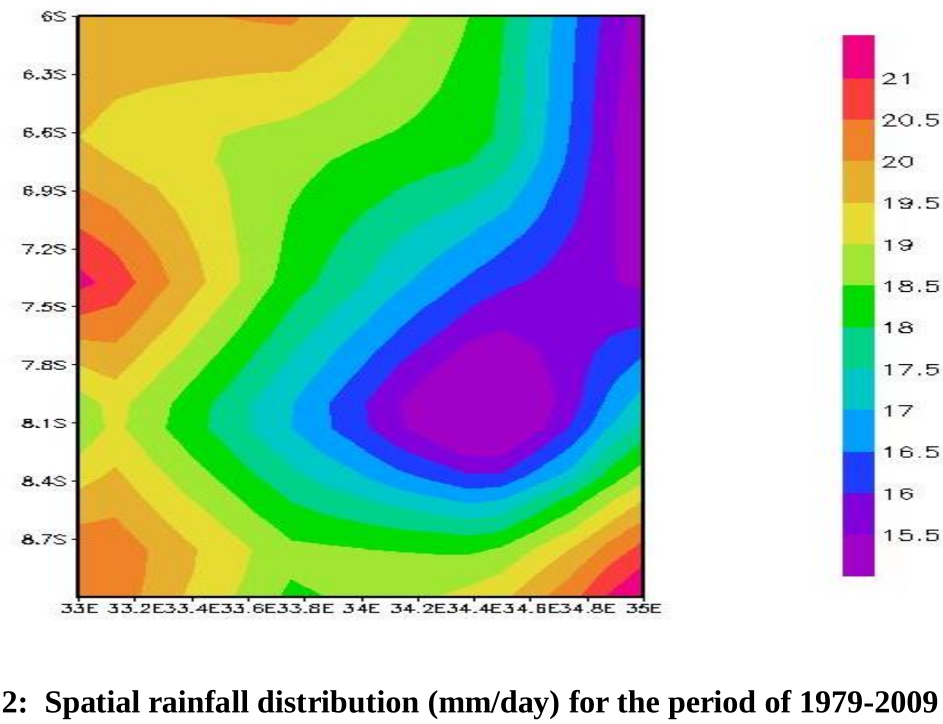

Figure 2.2: Spatial rainfall distribution (mm/day) for the period of 1979-2009 over the Mbarali River Sub- Catchment

2.6.2 Evaluation of RCMs

First, we analyze the available ERA Interim Reanalysis data used over Mbarali River sub-catchment for model validation purposes. This was done by purposive sampling of the coordinate points within the catchment. Each coordinate point reproduces rainfall amount at a specified location and then average all the rainfall data set in order to represent the entire rainfall generated by the ERA-Interim Reanalysis. Then the second step was to evaluate the regional climate models and their ensemble against the ERA-Interim reanalysis data.

Table 2.2 represents the RMSE, Mean error and the correlation coefficient between simulated rainfall from the RCMs and rainfall from the ERA-Interim data. CCLM4 model shows the greatest value of RMSE compared to other models. The ensemble mean like most of RCMs exhibits smallest value of RMSE. The same Table 2.2, shows relative error with respect to ERA Interim over the catchment for the individual RCMs and their ensemble mean.

The RCA4 and HIRHAM5 underestimate rainfall, while RACMO and CCLM4 overestimate the reanalysis data values. Table 2.2 also shows that the ensemble average of four RCMs performed better in simulating rainfall over Mbarali river sub-catchment compared to the individual RCMs. The correlation coefficient between rainfall data from the ERA -Interim and simulated rainfall from the RCMs are also presented in Table 2.2. It is evident that all the RCMs and the ensemble average are strongly correlated with rainfall from the ERA-Interim reanalysis. The distribution parameters for the mean monthly rainfall are shown and compared in Table 2.3. It is clear that the ensemble average performs better compared to the individual RCMs. The mean, standard deviation and median of the ensemble average are close to those from the ERA interim reanalysis.

Table 2.2: Comparison of mean monthly rainfall RCMs in mm and ERA interim (1979-2005)

(mm)	RCA	HIRHAM	RACMO	CCLM	ENSEMBLE
RMSE	48	33.9	24.3	69.7	13.0
ME	- 12.1	-19.2	15.0	35.4	4.8
R	0.83	0.77	0.99	0.98	0.98

Table 2.3: Parameter distribution on mean monthly values

	Era interim	RCA	HRLHAM	RACMO	CCLM	Ensemble
Mean	67	55	48	82	103	72
Standard deviation	83	57	58	96	142	85
Median	24	38	20	32	21	27

2.6.3 The annual cycle of rainfall

Figure 3.3 presents the ability of the RCMs to simulate the annual cycle of rainfall over Mbarali River sub-catchment. It is clear that all the RCMs and the ensemble average reproduce the annual cycles of rainfall over the Mbarali River sub-catchment. However, CCLM and RACA4 overestimate and underestimate seasonal rainfall respectively. Furthermore, the ensemble average performs better in simulating rainfall amount over Mbarali River sub catchment in all seasons. These findings confirm the earlier results by Luhunga *et al*. (2016) that the ensemble average can simulate rainfall characteristics better than individual RCMs.

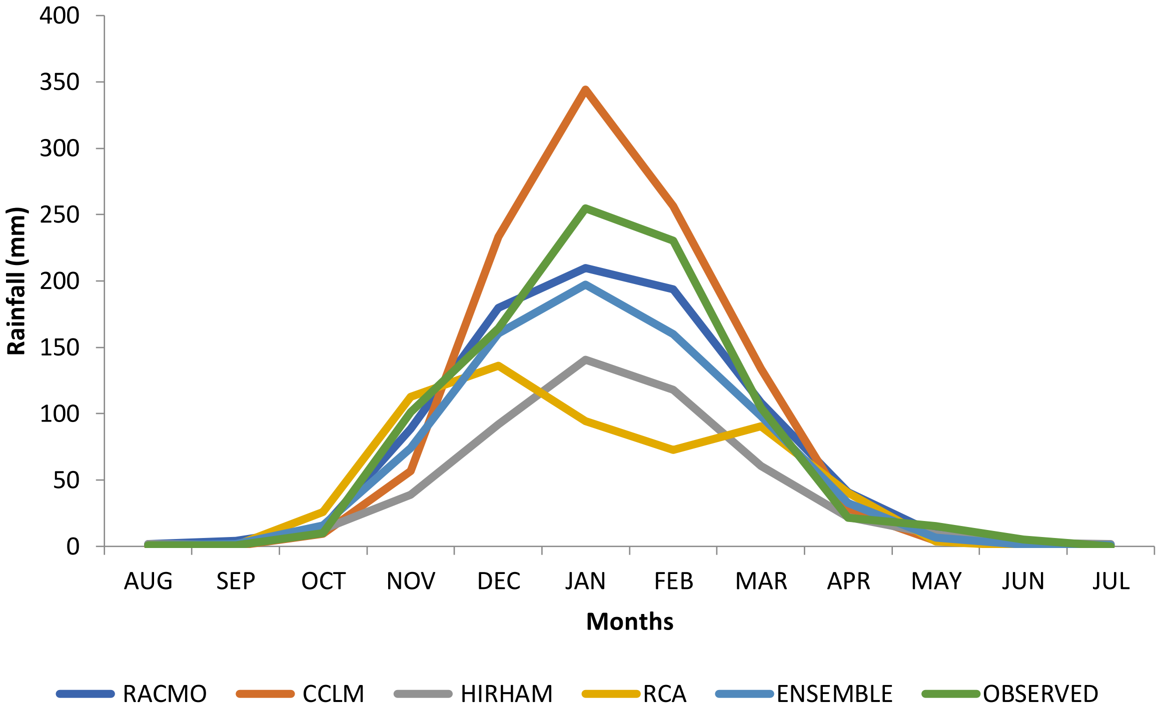

Figure 2.3: Average annual cycle for precipitation over Mbarali River sub-catchment (calculated from 1971-2005)

2.6.4 Inter-annual variability

The ability of the RCMs to reproduce the inter-annual variation is presented in Fig. 2.4. The data for the RCMs driven by the Era interim reanalysis are available from 1989 -2008 and can be accessed through https://esgf-index1.ceda.ac.uk/search/cordex-ceda/.

It is evident that all the RCMs and the ensemble average reproduce the inter-annual variation of rainfall over Mbarali River sub-catchment. It can be seen also that the ensemble average reproduces the magnitude of rainfall in the ERA-interim reanalysis compared to the individual RCMs.

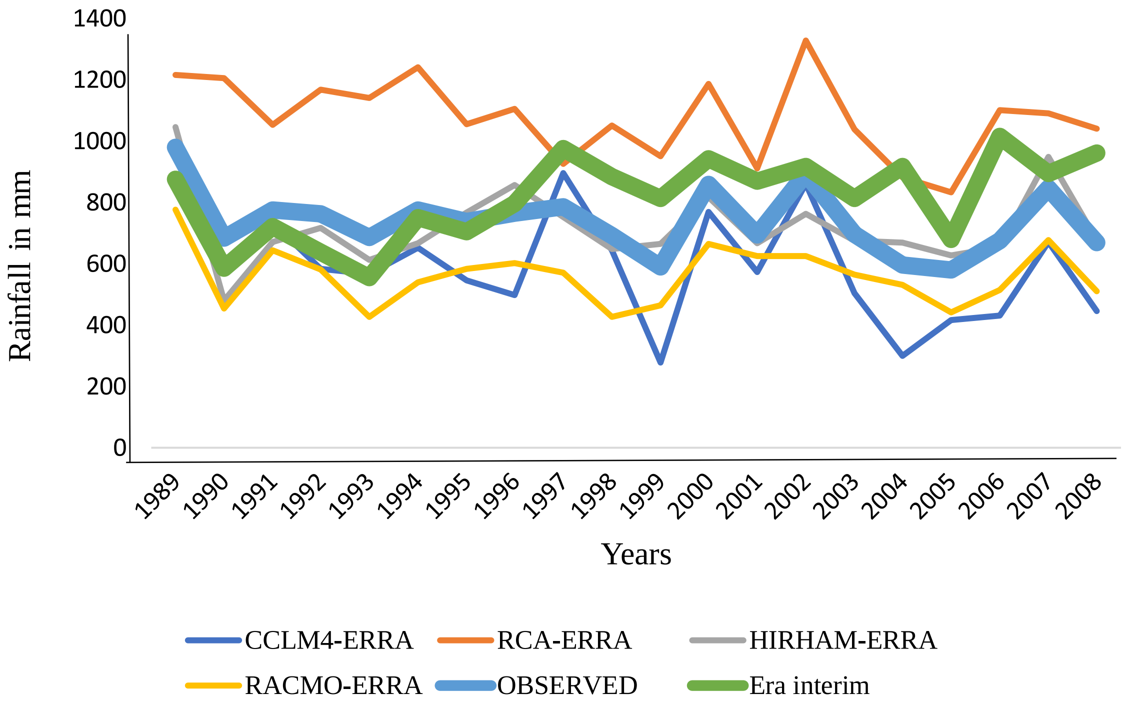

Figure 2.4: Annual average RCMs driven by ERA reanalysis, ensemble RCM, and the ERA Interim reanalysis for the Rainfall over Mbarali River sub-catchment

2.6.5 Trends analysis

The performance of RCM required further examination for their ability to simulate trend in rainfall. The trend of individual models, ensemble RCMs and the Era Interim reanalysis over the Mbarali river sub-catchment are presented in the Table 2.4. It is clear from this table that RCMs forced by GCMs fail to simulate the trends in rainfall. However, the RCMs forced by ERA-Interim reanalysis data simulate the trends in rainfall fairly well. It is important to note that the ensemble average reproduces the trends better than some individual models and some models, for example RCA4 perform better in representing the trends in rainfall than the ensemble average (Table 2.5).

Table 2.4: Mann Kendall trend in rainfall and sen"s slope estimate in RCMs and ERA Interim (calculated for the period 1979-2005)

	ERA	CCLM	HIRHAM	RACMO	RCA4	ENSEMBLE
Test z	2.08	0.13	-0.38	1.13	-0.29	0.00
Significance level (α)	*	**>0.1**	**>0.1**	**>0.1**	**>0.1**	**>0.1**
Sen's slope estimate	6.890	0.550	-1.087	3.835	-0.528	0.030

(*): if trend at α = 0.05 level of significance

Table 2.5: Trends in Rainfall, ERA driven by All RCMs (calculated for the year 1989-2008)

	CCLM-ERA	RCA-ERA	HIRHAM-ERA	RACMO-ERA	ENSEMBLE	ERA interim
Test z	-1.85	-2.24	-0.03	-0.55	-1.27	2.69
Significance level (α)	*	*				**
Sen's slope estimate	-11.819	-11.665	-1.087	0.269	-6.214	15.062

(**): trend significant at α = 0.01; (*): trend significant at α = 0.05; and ( ): trend not significant

2.7 Conclusion and Recommendation

In this study, the performance of CORDEX regional climate models in simulating the rainfall characteristics over Mbarali River sub-catchment is presented. The evaluation is based on determining how well the CORDEX RCMs reproduce annual cycles, inter-annual cycles and trends in the rainfall as reproduced by the ERA-Interim reanalysis. It was found that the CORDEX RCMs and the ensemble average reproduce the annual and interannual cycles of rainfall over Mbarali River sub-catchment. The ensemble average reproduces better the magnitude and the trends of rainfall compared with the individual models. Although the CORDEX RCMs and the ensemble average reproduce the annual and inter annual cycles of rainfall the models fail to reproduce correctly the magnitudes of rainfall.

The results of this study will be useful for assessment of climate change impact on stream flow and catchment water balance sensitivity to climate change for the Mbarali River sub-catchment in Rufiji Basin. Therefore, it is recommended that for the coming study, the bias correction is essential to be performed to correct the RCMs and their ensemble average for the impact studies.

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CHAPTER THREE

3.0 Stream Flow Simulation for the Mbarali River Sub-Catchment Using Soil and Water Assessment Tool

3.1 Abstract

The use of catchment models is essential for assessing water resources, particularly in sub catchments such as the Mbarali river sub-catchment of the Rufiji River basin in Tanzania, where modeling efforts are challenging due to variation in altitude. The ability of the catchment model to simulate catchment processes was assessed through a calibration and validation process, which is a key factor in reducing uncertainty and increasing user confidence in its predictive abilities. The study was conducted using a 26 year -daily flow record from January 1990 to December. 2016. Daily flow data from January 1990 to Dec. 2010 were used for SWAT calibration and Jan 2012 to Sept. 2016 for validation. The statistical analysis for model performance showed that, simulated monthly stream flow captured well with the observed flow, with a coefficient of determination (R^2) value of 0.74 and Nash–Sutcliffe efficiency (NSE) value of 0.70 for calibration and R^2 = 0.76 while NSE value significantly improved to 0.74 for validation. Simulated monthly mean flow was 11.74m^3/sec compared to observed flows of 11.50 m^3 /sec. The model revealed that 2% of the rainfall contributed in recharging the aquifer. However, much of the stream flow was from the base flow that contributed 87%. The results indicate that the SWAT model is an effective tool for describing monthly stream flows for the Mbarali river sub-catchment. A well calibrated and validated model can be a useful tool to predict the effect of climate change as well as the effect of land use changes on the hydrologic response of a catchment.

Keywords: Stream flow, SWAT, Mbarali River sub-catchment.

3.2 Introduction

Water resource planning and management requires, among other things, knowledge on catchment stream flow and its dynamics (Bloschl & Sivapalan, 1995). This is because catchments behave differently to similar drivers due to varying hydro-geologic and physio-geographic features (Kirchner, 2009). Such drivers are known to be heterogeneous and complex over time and space, resulting in scale problem (Bloschl and Sivapalan, 1995). One of the ways to better understand catchment behaviour is to model its hydrology (e.g., surface water, soil water, wetland, groundwater) in order to help understand, predict, and manage its resources. Understanding the behaviour of the catchment hydrology brings confidence to the users, which is a critical factor in uncertainty reduction. To date, hydrological models have been used as management tools in impact assessment, land use planning, water resource management, and pollution control. Many of the models attempt to integrate the dynamics of the catchments and the spatial and temporal distribution of soil, vegetation cover, landscape, land use, precipitation, and evapotranspiration. Such models include the Hydrologiska Byråns Vattenbalansavdelning (HBV), lumped HBV (Lü *et al.*, 2016), Agricultural nonpoint source (AGNPS) (Young *et al.*, 1995), Hydrological Simulation Program-Fortran (HSPF), European Hydrological System (MIKE SHE) (Abbott *et al.*, 1986), and the Soil Water Assessment Tool (SWAT) (Abbott *et al.*, 1986), The SWAT is a well-known model that can analyse the interaction of land use management issues, surface and groundwater, river sediment transport and pollutions emanating from various point sources in a catchment.

The SWAT has, for a long time, been applied in various catchments in the world for different purposes (Abbaspour *et al.*, 2011). At present, SWAT is increasingly being used to assist catchment water resources management and planning, with modelling applications becoming increasingly sophisticated to solve serious problems on water resource management (Neitsch *et al.,* 2011). The SWAT model has been tested and used in large basins of Tanzania especially in the Wami and Pangan basins, but few studies have focused on small-scale catchments in which much of the area is ungauged (Notter *et al.,* 2013) and where it is easy to understand the catchment hydrology and deal with uncertainty issues in hydrological modelling. Uncertainty analysis has become the standard approach to most hydrological modelling studies, but has yet to be effectively used in practical water resources assessment. This study applied a hydrological modelling approach for understanding the hydrology of a small catchment, the Mbarali River sub-catchment with much of the area of which is ungauged and where the available data (climate, stream flow and existing water use) are subject to varying degrees of uncertainty.

However, to date, applications of SWAT to simulate stream flow in small catchments have been limited (Bogena *et al.,* 2003; Gevaert *et al.,* 2008; Licciardello *et al.,* 2011) and a few studies have focused on applications including detailed water balance estimation on elevation differences. According to Mukundan *et al.* (2010), the effect of elevation zones on water balance components may not be relevant in large catchments, but may be pronounced well in small ones, thus making the formulation and simulation of land-use management strategies appropriate. The purpose of this study was to calibrate and validate the SWAT model and then to evaluate its performance by simulating stream flow at Igawa gauging station. The findings of this study will assist in addressing the complex water resource challenges prevailing in the Mbarali river sub-catchment.

3.3 Materials and Methods

3.3.1 Description of the study area

The Mbarali River sub-catchment that covers an area of 1530 Km^2 within the Upper Great Ruaha is located in the Rufiji basin in the south-eastern highland of Tanzania along latitude 7^0 and 9^0 and longitude 33.8^0 and 35^0 (Fig. 3.1). The River catchment is at an altitude ranging from 1000 to 1800 meters above sea level. Seasonal rainfalls are in the ranges of 450 to 650 mm that starts from October through to April or May (Luhunga, 2016). The average temperature in the catchment ranges from 25^0C and 30^0C. The dominant land use activities in the catchment include agriculture for crop production and livestock keeping. It is estimated that over 83% of residents are engaged in agriculture and paddy being the major food and cash crop.

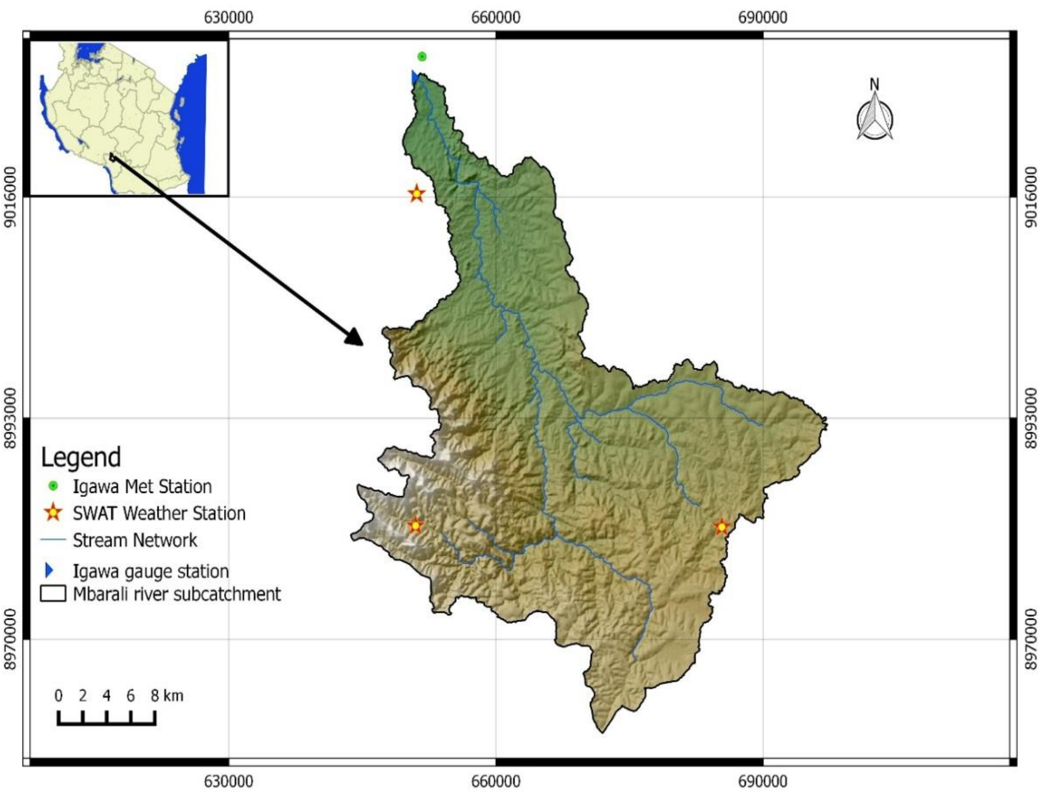
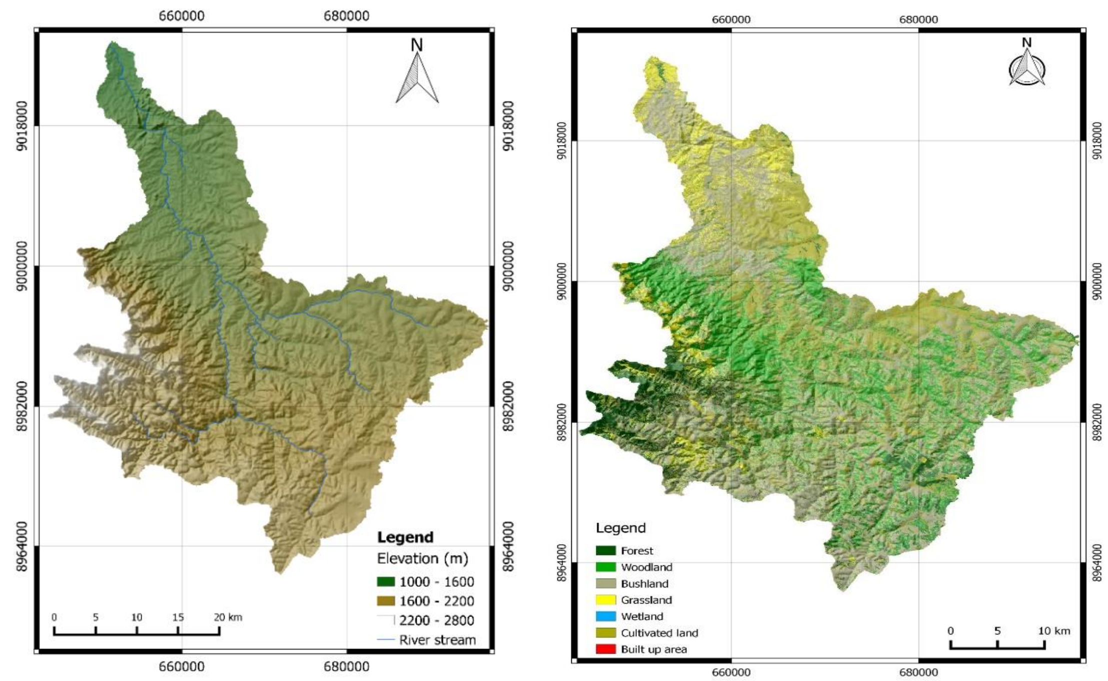


Figure 3.1: Location of the study area

3.3.2 SWAT model set up

A high-resolution (30mx30m) digital elevation model (DEM) from the Shuttle Radar Topography Mission (SRTM) (Fig. 3.2a) was used to set up the SWAT model. Sub basin partitioning and stream networks were computed automatically through the QSWAT interface with the manual configuration of the outlet. A drainage area of 100 ha was chosen as a threshold for delineation of the catchment as they approximately correspond to the Mbarali River sub-catchment size. Data on land use were obtained from USGS Global land cover characterization database with a spatial resolution of one kilometre (http://www.waterbase.org , September 2018).



(a) (b)

Figure 3.2: (a) Stream network and (b): Land cover for the Mbarali River Sub catchment

Land cover is an important factor for computing runoff in the basin. Neitsch *et al.* (2002) described land use as one of the significant parameters used to produce an accurate estimation of evapotranspiration. Mbarali River sub-catchment is a rural area with most of the land use dedicated to agriculture and livestock keeping. Most of the Mbarali River sub-catchment is covered by a mixture of cropland/ woodland mosaic, making 73% of the area, and a mixture of grass, shrub, savanna, forest with pasture and cropland making up about 24%. The remaining 3% of the area is sparsely vegetated, shrubland and water bodies. The land cover map for the Mbarali River sub-catchment is shown in Figure 3.2b. The soil data were obtained from Global soil data that were prepared by the Food and Agriculture Organization of the United Nations, with a spatial resolution of 1 kilometre.

The FAO soil data was used as a working guidance from which essential soil input data such as hydrological soil group, bulk density, water content and water conductivity were adjusted with SWAT editor and employed for simulation. In this study, four dominant soils, namely: Eutric Plano Soils (Bc14-2bc), Chromic Cambisols (Bc18c), Dystric Nitosols (Nd8-2bc), Drystric Regosols (Rd20-2c) were identified (Figure 3.3). The catchment soil is characterized by impervious soil dominated by group C and D that has a tendency of favouring high runoff at the outlet.

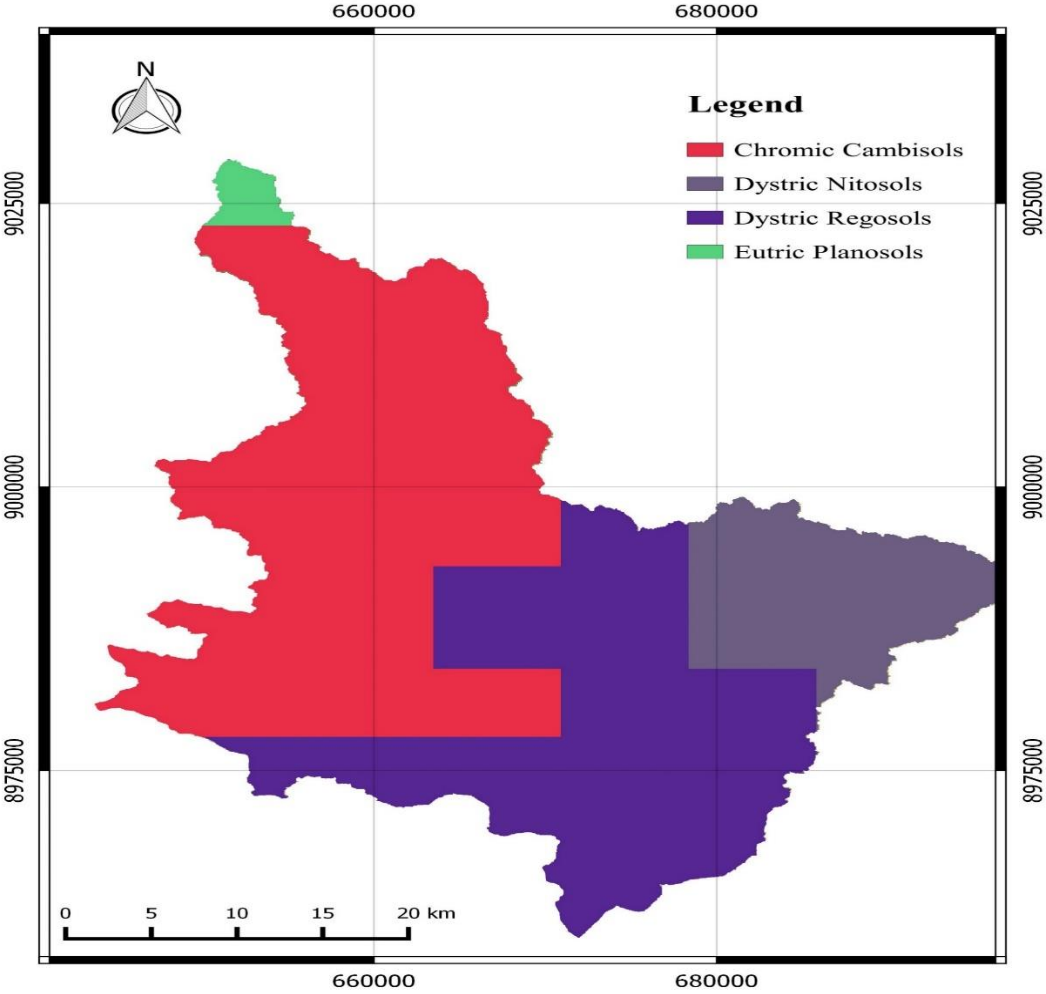


Figure 3.3: Soil map of the Mbarali River sub-catchment

The soil data and land cover were overlapped to define the 70 hydrological response units (70 HRUs) and 23 sub catchments. Splitting the catchment into different parts having individual land use and soil type allows the SWAT model to reproduce changes in evapotranspiration and other hydrological conditions for different soils and land covers. Winchell *et al.* (2009) argued that runoff is generally predicted for each of the separate HRUs and their results give the total runoff for the whole catchment. Therefore, this gives the reality of runoff predictions and the physical meaning of the hydrological water balance.

The SWAT model requires daily data of minimum and maximum temperature, precipitation which were available from the year 1990-2016 and were used to run the model. These data were collected from Tanzania Meteorological Agency (TMA). The rest of the weather data such as solar radiation, relative humidity, potential evapotranspiration and wind speed were generated by the SWAT weather data set using three stations (Refer Figure 3.1). Quality check was examinend on the dataset by assessing reliability and checking for missing data. A stochastic weather generator (WEXGEN) (Neitsch, 2002) is built-in the SWAT and uses it for filling-in missing climate data gaps. The weather generator model uses monthly statistics calculated from daily weather data to account for the missing data in the daily time series and simulate weather based on the statistics (Baker *et al.*, 2013). In this study, 8 years of data were used for calculating the statistics at monthly time scale that were used for building the WXGEN. The daily measured river flows data at Igawa gauge station for the period of 1990-2016 was obtained from the Rufiji Basin Water office in Iringa. In order to ensure that the calibrated and validate data captures well the observed flows, the simulated flows were compared based on the statistical evaluation metrics for model performance.

3.3.3 Hydrological component of the SWAT model

The hydrology of a catchment is simulated based on two different steps. The first one, is the land phase of the hydrological cycle that controls the amount of sediments, water and transport to the big channel in each sub-basin. The canopy storage, infiltration, redistribution, evapotranspiration, lateral subsurface flow, surface runoff, ponds, tributary channels and return flow are hydrological components simulated in land phase of the hydrological cycle. The second step describes the movement of water, sediments, nutrients, and organic chemicals through the channel network of the catchment to the outlet. SWAT simulates the hydrological cycle based on the water balance equation one

(Neitsch *et al.*, 2005). This process increases precision and offers a good description of catchment water balance (Neitsch *et al.*, 2005). Hereafter, the entire procedures that occur in the topography are shown for every HRU inside the basin, depending on its position within the sub catchment (Abbaspour *et al.*, 2011).

$$SW_t = SW_0 + \sum_{i=1}^{t}(R_{day} - Q_{surf} - E_a - w_{seep} - Q_{gw}) \text{ ....Eq (1)}$$

Where; SWt is the final soil water content (mm), SWo is the initial soil water content on day i (mm), t is the time (days), Rday is the amount of precipitation on day i (mm), Qsurf is the amount of surface runoff on day i (mm), Ea is the amount of evapotranspiration on day i (mm), Wseep is the amount of water entering the vadose zone from the soil profile on day i (mm), and Qgw is the amount of return flow on day i (mm). Moreover, various studies on different model components are described by Arnold *et al.* (1998) and Neitsch *et al.* (2005).

In this study, the Sequential Uncertainty Fitting (SUFI2) algorithm of the SWAT Calibration and Uncertainty Program (SWAT-CUP) (Abbaspour *et al.*, 2007) was used for an automatic calibration procedure. The SWAT simulation period was divided into a warming-up period of five year to initialize the state variables of the system, a calibration period (1990-2010), and a validation period (2012-2016). Sensitivity analysis was run for 300 simulations.

3.3.4 Model performance evaluation

The performance of the SWAT model on stream flow simulations was assessed by using three statistical evaluation metrics as recommended by several researchers (Morias *et al.*, 2007, Bennet *et al.*, 2013; Morias *et al.*, 2013). The metrics include the Nash–Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970), the percent of observations bracketed (p-factor) and the average width of uncertainty band to observation standard deviation ratio (r-factor) at 95% or percentage prediction uncertainty (PPU) confidence interval and the coefficient of determination (R^2) (Morias *et al.,* 2013). R-squared values can range from zero to one, where zero indicates no correlation and one represents perfect correlation. NSE values range between negative infinite and one. A NSE value of one indicates a perfect fit between the simulated and observed flow, and negative NSE values mean that use of an average of observed time series is better than the model predictions. These metrics are calculated as follows:

$$NSE = 1 - \left[\frac{\sum_{i=1}^{n} (Y_i^{obs} - Y_i^{sim})^2}{\sum_{i=1}^{n} (Y_i^{obs} - \mathrm{Y}^{mean})^2} \right] \qquad r = \frac{n(\sum \times y) - (\sum \times)(\sum \times y}{\sqrt{[n\sum \times^2 - (\sum \times)^2][n\sum y^2 - (\sum y)^2]}}$$

where Y_{obs} is observed values and Y_{sim} is modelled values at time/place *i*.

x and y are independent variables.

The SWAT model was run on a daily time step for a period of 30 years (1985 to September 2016), including a warm-up period of five years. The model was calibrated using SUFI -2 in the SWAT-Cup. Due to equifinality (non-uniqueness) issues on model parameter estimation and prediction uncertainty, SWAT performance was further evaluated by using the percent of observations bracketed (p-factor) and the average width of uncertainty band to observation standard deviation ratio (r-factor) at 95% or percentage prediction uncertainty (PPU) confidence interval (Abbaspour *et al.,* 2007). Abbaspour *et al.,* 2015 suggested values for the P-factor are more than 0.70 for discharge and R-factor of around 1 and if the measured data are of high quality, then the P-factor should be more than 0.80 and R-factor less than 1.

3.4 Results and Discussion

3.4.1 Parameter estimates and sensitivity analysis

In this research, we have evaluated the relative sensitivity values found in the parameter estimation process. Flow parameters that govern the surface flow and groundwater flow have shown medium to very high relative sensitivity. Ranges of values used during the sensitivity analysis and the calibrated parameter values are shown in Table 3.1. The analysis was performed using observed flow data at the basin outlet. Also, the model provides sensitivity results without flow data. Some parameters show negligible responses with the later approach which is not actually the case when observed flow was used. For example, ALPHA_BF ranked first with mean relative sensitivity of 1.05 when observed flow is used. However, without observed flow it ranked sixth with mean relative sensitivity value of 0.072. The study relied on the sensitive parameters that responded well based on observed flow.

The parameters governing the hydrological processes in the entire watershed in the order of their sensitivity ranking are shown in Table 3.1 (the first is the most sensitive). Ground water flow parameters such as base flow recession coefficient (ALPHA_BF), threshold water level in the shallow aquifer (GWQMN) and aquifer percolation coefficient (RCHRG_DP) were identified as being very sensitive parameters. Also, the soil moisture condition curve number II (CN2), Manning roughness coefficient of channel flow (CH_N2), Effective hydraulic conductivity of the channel (CH_K2) and surface runoff lag coefficient (SURLAG) are found to affect the surface runoff and other basin characteristics. The soil compensation factor was found to be the major determinant parameter for the evapotranspiration process in the sub-basin. More specifically, it has to be noted that the ALPHA_BF which governs the groundwater behaviour and the CN2 that govern surface runoff were found to be the most sensitive parameters for the sub-basin.

This is due to the higher variable nature of the soil water content in the study area which was also reported by Brocca *et al.* (2011). As the area is dominated by low permeable layers, therefore the sensitivity to the base recession factor was also expected. Elevation differences of the sub-basin was also, one of the geomorphologic factors found to affect the catchment response behaviour.

Table 3.1: Best parameters ranges calibrated using SUFI -2

No	Parameter name	Fitted value	Min value	Max value
1	R__CN2.mgt	- 0.119	-0.300	0.300
2	V__ALPHA_BF.gw	0.502	0.000	1.000
3	V__GW_DELAY.gw	78.300	30.000	450.000
4	V__GWQMN.gw	70.000	0.000	2000.000
5	R__SOL_AWC (..).sol	-0.019	-0.800	0.800
6	V__GW_REVAP.gw	0.136	0.000	0.200
7	V__SURLAG.bsn	8.665	1.000	10.000
8	V__RCHRG_DP.gw	0.068	0.000	1.000
9	V__REVAPMN.gw	1830.000	0.000	2000.000
10	V__CH_K2.rte	137.750	0.000	150.000
11	R__CH_N2.rte	0.162	-0.010	0.300
12	V__ESCO.hru	0.572	0.000	1.000
13	R__SOL_BD (..).sol	-0.128	-0.200	0.200
14	R__SOL_K (..).sol	1.099	-0.800	2.000
15	V__CH_K1.sub	97.167	0.000	100.000

* (prefix V-indicates that the parameter value is replaced by a given value, prefix R-indicates that the parameter value is multiplied by (1+ a given value).

3.4.2 Model calibration and validation results

The SWAT model was calibrated using SWAT-CUP program for the period of 1990-2010. Calibration results yielded satisfactory results given NSE and R^2 values of 0.70 and 0.74 respectively. The results gave matching trend between the simulated and observed data set as represented by Figures 3.4 & 3.6. The P-factor (% of measured data bracketed by 95% prediction uncertainty) was 0.93 and 0.90 for the full range and behavioural simulations, respectively. The R factors for the full range and behavioural parameters were 1.94 and 1, respectively. The shaded area represents the 95% predictive uncertainty (95PPU), whereas the blue lines correspond to the observed discharges and the red lines correspond to the simulated flow at the sub-catchment outlet. For the full range simulations (Figure 3.6) it was found that the observations fall within the lower and upper 95% prediction uncertainty in high and moderate flow but with large uncertainty. These results confirm the quite large uncertainty of the simulated discharge due to the large equifinality in parameters and reliability of input data (rainfall and daily temperature data). As reported by Moriasi *et al.* (2007) this result is acceptable for the model performance in terms of the NSE and R^2 during calibration procedure.

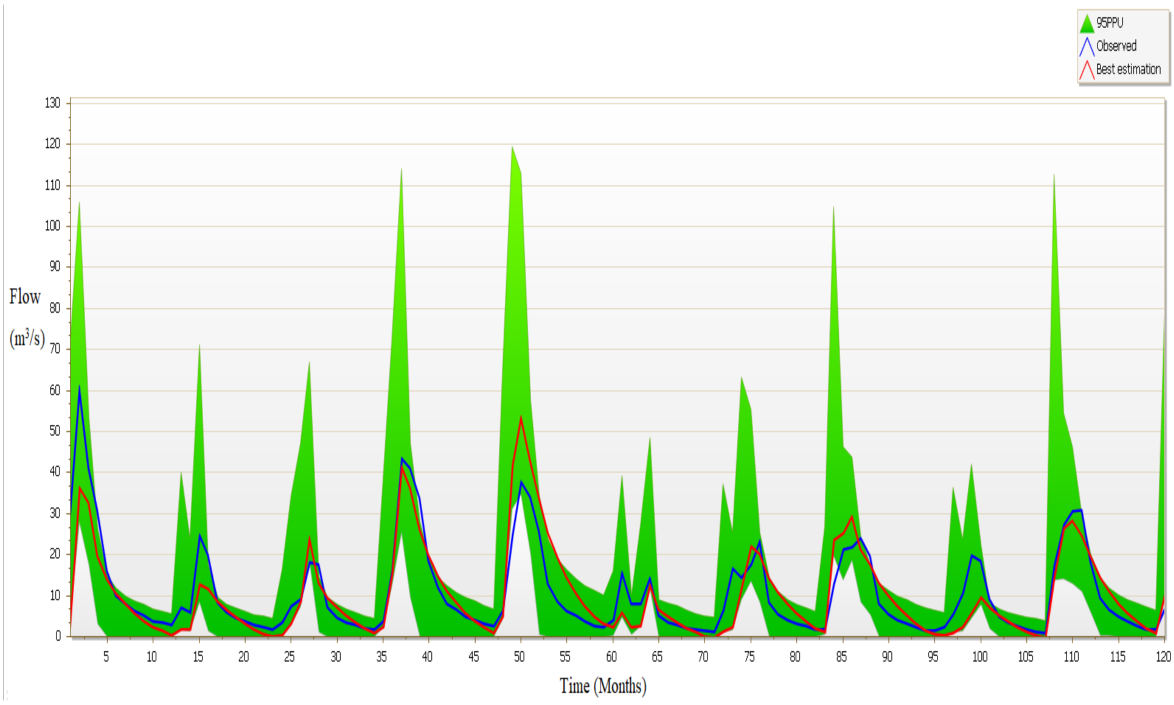


Figure 3.4: Hydrographs of simulated and observed mean flows for calibration period at Igawa.

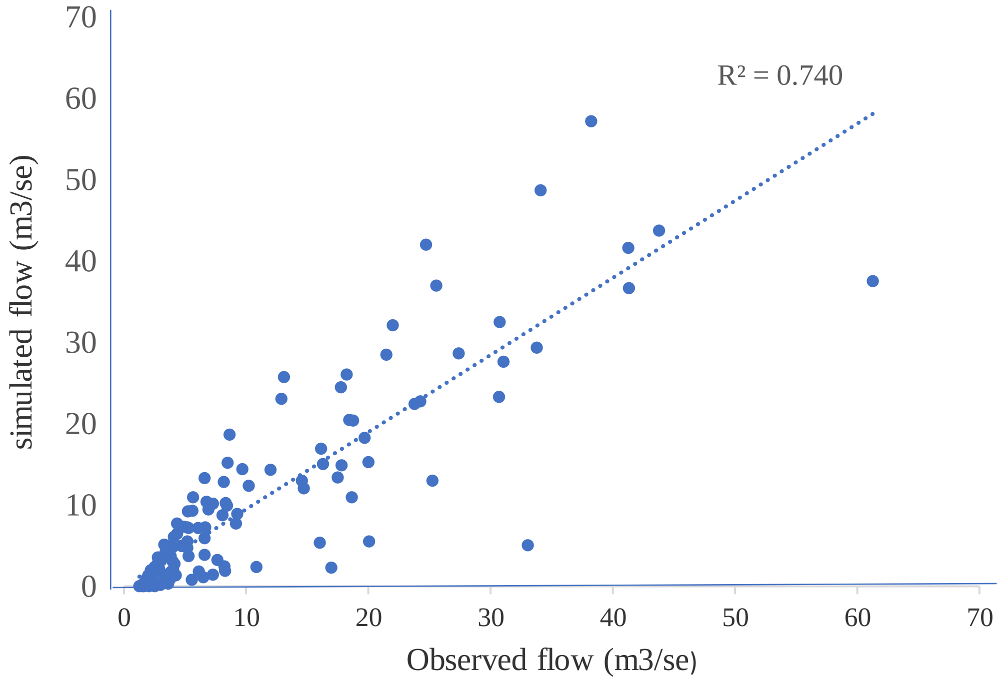


Figure 3.5: Scatter plot of monthly stream flow for calibration period (1990-2010).

Similarly, simulation of stream flows as such, has generally revealed that there is no annual trend disparity between monthly mean observed (11.50 m^3 / sec.) and monthly mean simulated (11.74 m^3 / sec.) stream flow results. This demonstrates that the model was able to simulate stream flows effectively.

The value of R^2 test stands at 0.74 and NSE value of 0.70 for calibration. Which indicate that model estimate a reasonable flow. During the monthly flows' simulations, the model appeared to perform well during the wet seasons and fairly well during the dry period as it is depicted in Figure 3.6. The calibrated model can be considered as a representative tool for further application through validation using an independent dataset at the main outlet of the catchment.

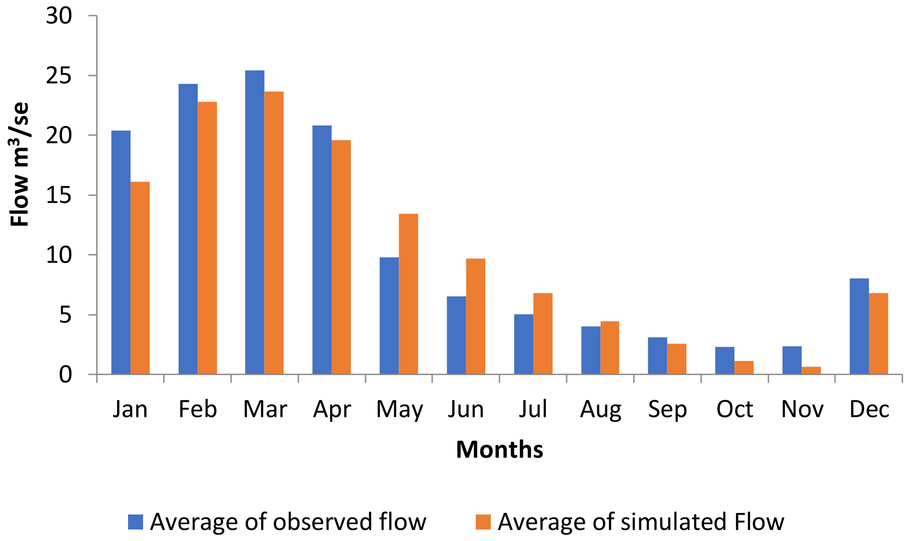


Figure 3.6: Average monthly flow comparison between simulated and measured data for 1990-2010

3.4.3 Model validation

Based on the optimized parameters obtained during the calibration period, a further simulation was carried out to assess the model performance during the period 1/1/2012 to 31/12/2016 which is outside the period when the model was calibrated. Figure 3.7 shows the graphical representation of the observed and simulated flows during this validation period. The hydrographs of stream flow during the period of validation indicate that the simulated and observed flows show a nearly close fit, an indication of improved model performance. There is evidently improved performance of the model with the coefficient of determination, R^2 = 0.76. The NSE value significantly improved to 0.74 while the comparable mean (observed and simulated) flows were also close. This reflects acceptable model performance (Moriasi *et al.*, 2007) which can be considered satisfactory and therefore promising to be applicable in the sub catchment. A summary of calibration and validation results is given in Table 3.2.

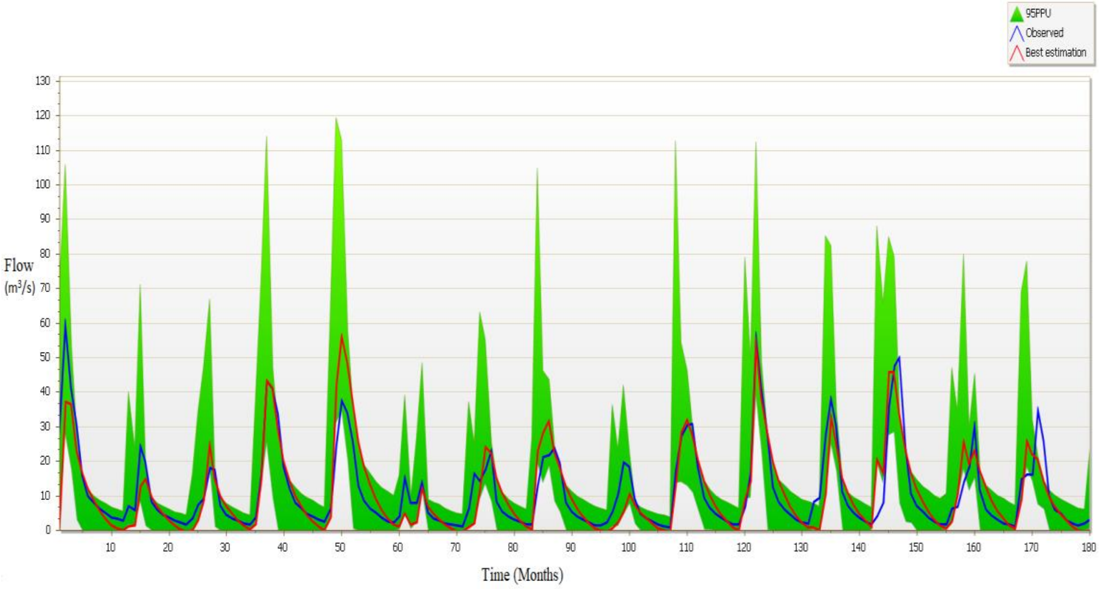


Figure 3.7: Hydrographs of simulated and observed mean flows for validation period at Igawa

Table 3.2: Summary of performance statistics for the best simulation

Station Igawa gauge	**Calibration**		**Validation**		**Calibration**		**Validation**	
	NSE	**R^2**	**NSE**	**R^2**	**Mean Observed Flow (m^3/s)**	**Mean Sim-flow (m^3/s)**	**Mean Observed flow (m^3/s)**	**Mean Simulated flow (m^3/s)**
	0.70	0.74	0.74	0.76	11.01	10.50	11.74	11.56

3.4.4 Water balance estimation

To deal with water resources management issues at catchment scale, it is advisable to quantify and evaluate various water balance components that occur within the study area. The simulations of water balance over the entire Mbarali River sub-catchment were performed using distributed SWAT hydrological model. The model was able to quantify various water balance ratios (Table 3.3) measured in millimetres. As stated by Ghoraba (2015), precipitation, surface runoff, lateral flow, percolation and evapotranspiration are the most important hydrological water balance components of a catchment. Among these, only precipitation needs to be measured while the remaining variables are to be predicted using hydrological models.

The water balance components of the catchment were calculated using SWAT water balance Equation (Eq. 1) and the results from the SWAT Check (Figure 3.8). The simulation of the hydrologic cycle component of the Mbarali River sub catchment revealed to have four subsystems (Figure 3.8): surface soil, intermediate zone, shallow and deep aquifers, and channel flow. Stream flow in the main channel is determined by three sources: surface runoff, lateral flow and base-flow from shallow aquifers. Table 3.3 indicates that much of the stream flow was from the base flow that contributed 87% of the total flow and 39 % of the incoming precipitation was converted to stream flows while 2% of the rainfall recharging the aquifer. The model also projects that there is high evapotranspiration taking place within the Mbarali river sub catchment that accounts for 54% of the total precipitation. The notable evapotranspiration rate projected could be attributed to the type of land cover.

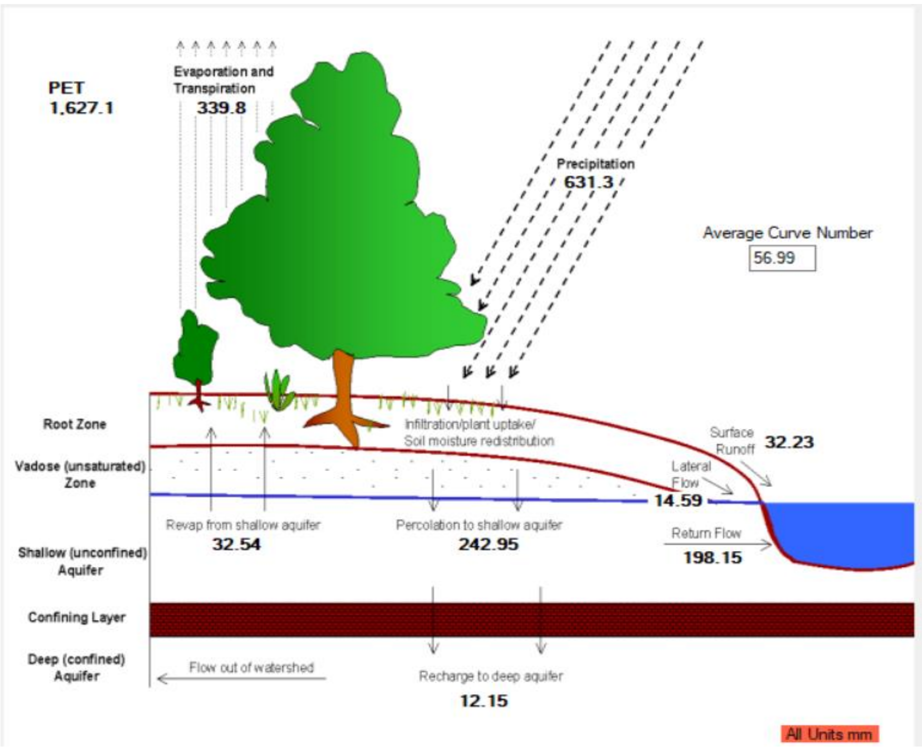


Figure 3.8: Schematic of the hydrologic cycle components

Table 3.3: Water balance ratios

Water balance component	Percentage ratios
Streamflow/ rainfall	0.39
Baseflow/total flow	0.87
Surface runoff/total flow	0.13
Percolation/ rainfall	0.38
Deep recharge/ rainfall	0.02
Evapotranspiration/ rainfall	0.54

3.5 Conclusion and Recommendation

This study presents the assessment of SWAT model performance in simulating stream flow over the Mbarali River sub-catchment, which is part of the Rufiji Basin, Tanzania. The hydrologic response was evaluated using stream flow measurements at 1KA11 – the outlet of the Mbarali river sub-catchment. SWAT model was able to capture all catchment responses through calibration and validation processes. The model revealed that 2% of the rainfall contributed in recharging the aquifer. However, much of the stream flow was from the base flow that contributed 87%.

The hydrography analysis has shown that there is a strong agreement between the observed and simulated flow for high and average flow than the low flow conditions. Therefore, it can be concluded that the model is more sensitive to weather variables than surface dynamics. The SWAT results confirm quite large uncertainty of the simulated discharge due to the large equifinality in parameters and reliability of input data (rainfall and daily temperature data). Thus, further analysis is required to quantify the unexplained uncertainties.

The approach employed in this study represents a major step towards the uncertainty analysis rather than calibration to local observations. The results are encouraging in the sense that the simulated hydrograph ranges bracket the observed curves at the Igawa gauging station. Thus, the uncertainty approach that has been adopted in this study is appropriate for the Upper Great Ruaha Sub Basin, given the available input data and the large spatial and temporal variability in both climate and geology. The results from this study will help in guiding various stakeholders and decision-makers working at this sub catchment level when preparing the Integrated water resources management and development projects. The overall conclusion is that the SWAT model has been satisfactorily established for the main part of the Mbarali River sub-catchment and that it can be used for impact assessment.

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CHAPTER FOUR

4.0 Assessment of the Impacts of Climate Change on Hydrological Characteristics of the Mbarali River Sub-Catchment Using High Resolution Climate Simulations from CORDEX Regional Climate Models.

4.1 Abstract

This study assesses the impacts of climate change on water resources over Mbarali River sub-catchment using high resolution climate simulations from the Coordinated Regional Climate Downscaling Experiment Regional Climate Models (CORDEX_RCMs). Daily rainfall, minimum and maximum temperatures for historical climate (1971-2000) and for future climate projection (2011-2100) under two Representative Concentration Pathways RCP 8.5 and RCP 4.5 ware used as input into the Soil and Water Assessment Tool (SWAT) hydrological model to simulate stream flows and water balance components for the Mbarali River sub-catchment. The impacts of climate change on hydrological conditions over Mbarali river sub-catchment was assessed by comparing the mean values of stream flows and water balance components during the present (2011-2040), mid (2041-2070) and end (2071-2100) centuries with their respective mean values in the baseline (1971-2000) climate condition. Results indicate that, in the future, under both RCP 4.5 and RCP 8.5 emission scenarios, the four main components that determine change in catchment water balance (rainfall, ground water recharge, evaporation and surface runoff) over Mbarali river sub-catchment are projected to increase. While the stream flows are projected to decline in future by 13.33% under RCP 4.5 and 13.67% under RCP 8.5 emission scenarios. It is important to note that simulated surface runoff under RCP 8.5 emission scenario is higher than those obtained under the RCP 4.5 emission scenario.

Key Words: RCP, Regional climate model, General circulation models, SWAT model, hydrological water balance components.

4.2 Introduction

According to the Intergovernmental Panel on Climate Change (IPCC) assessment reports, climate change is projected to substantially reduce water availability in the watershed (IPCC 2007, 2013 and 2014). In developing countries, Tanzania is included, by the year 2020, between 75 to 250 million people are predicted to be exposed to increased water stress due to climate change (IPCC, 2007).

The only strategy to reduce the impacts of climate change on water resources is to invest in the development of adaptation strategies. However, the development of water resources adaptation strategies to overcome the impacts of climate change on hydrological systems is challenging (Muerth *et al.,* 2014; Piani *et al.,* 2010). The challenges on one hand are attributed to the lack of scientific evidences that shows the projection of how future climate change will impact the hydrological systems. On the other hand, there are high uncertainties associated with the projections.

In Tanzania several studies that address climate change impacts on water resources have been done (e.g., Mwandosya *et al.,* 1998). These research studies have used climate simulations derived directly from the General Circulation Models (GCMs) to evaluate the impacts of climate change on water resource in Tanzania.

However, the GCMs have coarse spatial resolutions (500 or 1000 km) and are designed to simulate global or continent climate characteristics like global or continent temperature or rainfall amount. The coarse spatial resolutions of the GCMs severely limit the direct application of their output in regional and local decision making (Masson and Knutti, 2011; Ramirez-Villegas and Challinor, 2012). This limitation is particularly challenging in a country like Tanzania with high regional heterogeneity of its climate influenced by different topographic features (Mountain Kilimanjaro with an altitude of 5895 m, Lake Victoria in the North, Lake Nyasa and River Ruvuma in the South and Lake Tanganyika in the West). Moreover, the study by Wambura *et al.* (2014) underscored the fact that GCMs climate change projections provide poor simulation of hydrological conditions at catchment scale.

The poor performance of GCMs in estimating hydrological conditions call into questions of the many prior evaluations of climate change impact on water resources in Tanzania. Furthermore, adaptation and mitigation policies developed based on GCMs simulation are not realistic and might pose significant challenges for anticipatory adaptation in the country. Therefore, credible evaluation of climate change impacts on water resources using high resolution downscaled GCM simulations in Tanzania is required. This study evaluates the impacts of climate change on stream flows over Mbarali River sub catchment of the Rufiji basin in Tanzania using high resolution climate simulations from the Coordinated Regional Climate Downscaling Experiment Regional Climate Models (CORDEX_RCMs).

4.3 Data and Methods

4.3.1 Study area

The Mbarali River sub-catchment has an area of 1530 km^2 and is located between latitude 7 °S and 9 °S and between longitude 33.8 °E and 35 °E in the upper Great Ruaha sub basin of the Rufiji basin in the southern highlands of Tanzania (Figure 4.1).

Rainfall pattern over the Mbarali River sub-catchment is mainly driven by the seasonal migration of the Inter-Tropical Convergence Zone (ITCZ). This zone moves southwards in October and reaches the southern parts of the country in January or February and reverses Northwards in March, April and May. This movement makes Mbarali river sub-catchment to receive a Unimodal rainfall pattern that starts in October and continue through April or May. The mean seasonal rainfall and temperature with the sub-catchment ranges between 450 to 650 mm and 25 to 30 °C respectively.

The topography of the Mbarali sub-catchment is dominated by forest, woodland, bushland, cultivated land and grassland (refer Fig.4.2, Land use Map). The sub-catchment is dominated by four soil types, namely (chromic Cambisols, dystric Nitosoils, dystric Regosols and Eutric Planosols) (refer Fig 4.2, soil map).

As the result of favorable climate conditions and fertile soils, the Mbarali River sub-catchment has and is important for agriculture production in the southern highlands of Tanzanian. The main crop cultivated within the sub-catchment is paddy which is the major food and cash crop within the sub-catchment. Despite the high agricultural potential of the Mbarali River sub-catchment, few studies, if any, have analyzed the impacts of climate change on water resources using high resolution climate simulations. Therefore, the study area is best placed in this kind of research study to provide reliable information about the impacts of climate change on water resources that can be used to prepare adaptation strategies by the policy and decision makers.

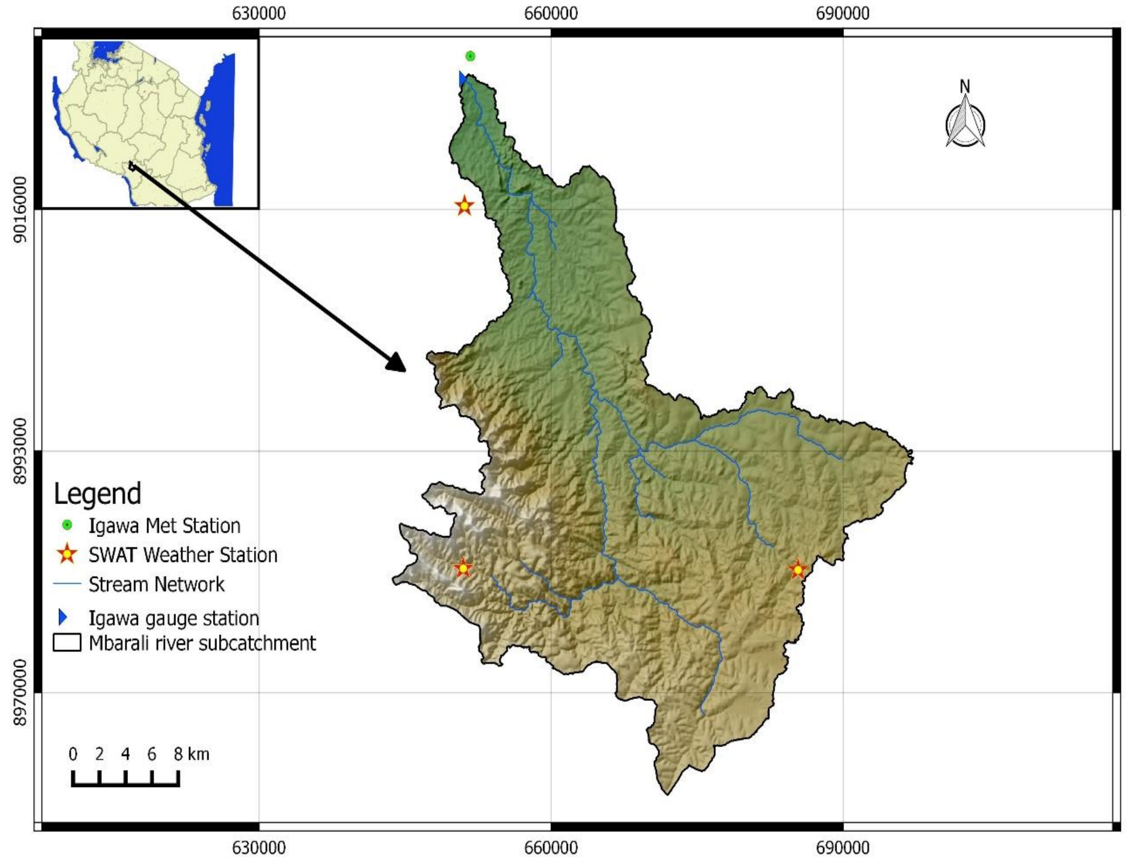

Figure 4.1: Location of the study area

(a)

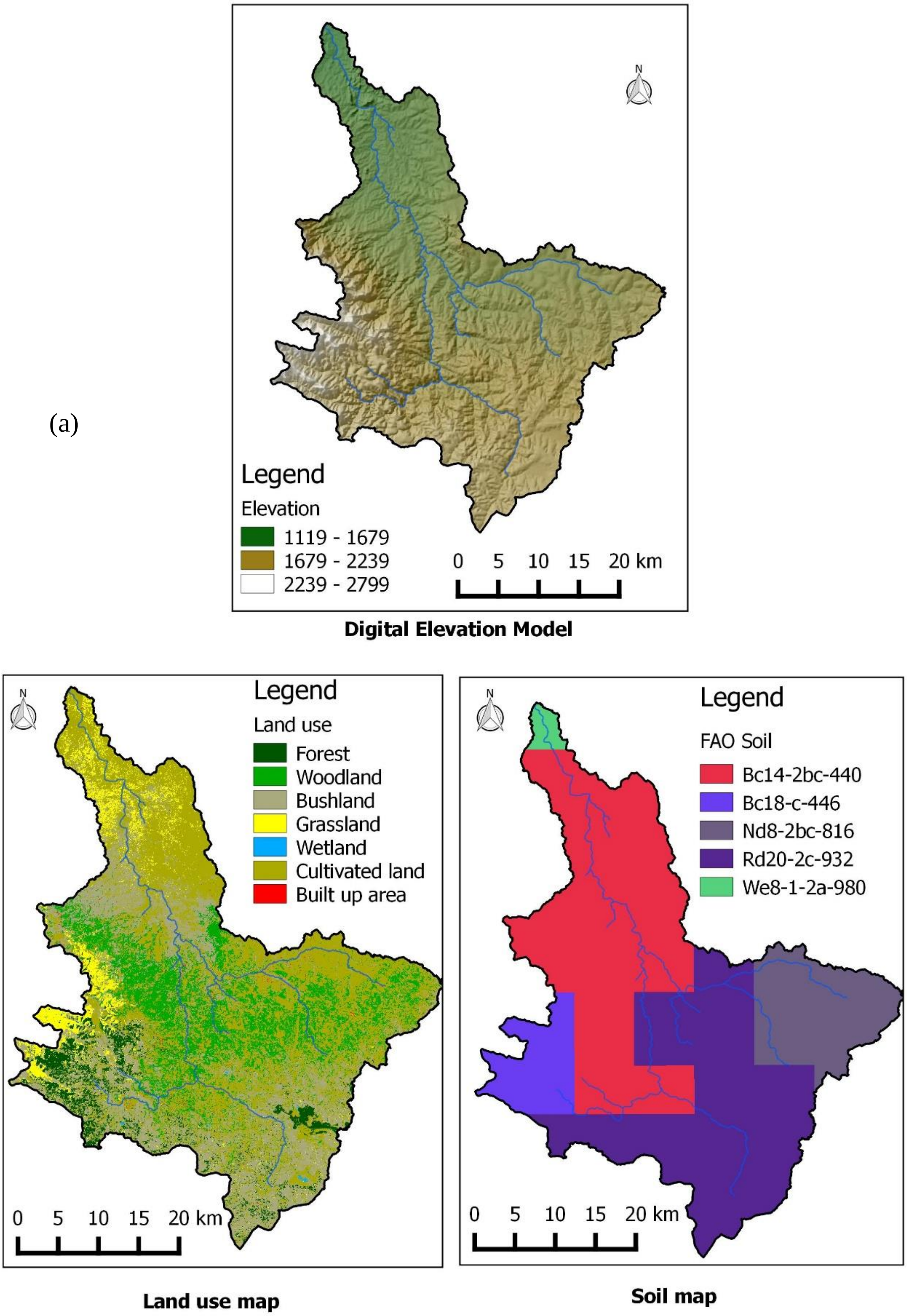

Figure 4.2: (a) Digital elevation (b) Land use and (c) soil maps

4.3.2 Data from Regional climate Models

Climate simulations from three high resolution regional climate models (RCMs) forced by three general circulation models (GCMs) from the Coordinated Regional Climate Downscaling Experiment (CORDEX) initiative were used in this study. It is important to mention here that climate variables (daily rainfall, minimum and maximum temperatures) from the historical (1971-2000) and future (2011-2100) climate projections, under two Representative Concentration Pathways (RCP): RCP 4.5 and RCP 8.5 averaged over the entire sub-catchment were used to drive the SWAT hydrological model to simulate hydrological conditions over the Mbarali River sub catchment.

Table 4.1: Cordex RCMs and the driving GCMs

No	Regional climate model	Model center	Short name of RCM	Short name general circulation Model
1	Rossby Center Regional Atmospheric Model (RCA4)	The Swedish meteorological and hydrological institute (SMHI)	RCA4	MPI CNRM-CERFACS
2	Regional Atmospheric Climate Model, version 2.2 (RACMO2.2T)	Koninklijk Nederlands Meteorologisch Instituut (KNMI), Netherlands	RACMO22T	ICHEC-EC-EARTH
3	The subset of High resolution limited area Model (HIRLAM) (HIRHAM5)	Danmarks Meteorologiske Institut(DMI), Danmark	HIRHAM5	ICHEC-EC-EARTH

The RCMs and the driving GCMs used in this study are listed in Table 4.1. These models were chosen based on their ability to simulate the historical (1971-2000) climate condition over the southern regions of Tanzania with relatively minimum error (Luhunga *et al.*, 2017). For detailed description of the regional climate models and their driving general circulation models used in the CORDEX program the reader may consult (Nikulin *et al*., 2012).

4.3.3 Hydrological model and Model Input Files

To assess the future water resource availability for the Mbarali River Sub- Catchment the soil and water assessment tool (SWAT) model were used. The soil and Water assessment tool (SWAT) is a semi distributed hydrological model that can quantitatively explain the processes and mechanisms that influence the behavior of the watershed (Arnold *et al.*, 1998). This model has been used intensively by different researchers, consultants, hydrologists, policy and decision makers' worldwide (Abbaspour *et al.*, 2007). In this study SWAT v10.4 was used to simulate hydrological conditions over the Mbarali River sub catchment. For detailed description of SWAT v10.4 the reader may consult (Abbaspour, 2009). SWAT require DEM, soil data, and weather information to simulate hydrological conditions. Weather information requested to run SWAT includes daily values of incoming solar radiation (MJ/m^2-day), maximum and minimum daily air temperature (°C) and daily rainfall (mm). The model input files were created using a several levels in SWAT. For detailed description on how to create the model input files using SWAT the reader may refer Abbaspour (2009).

4.3.4 Model calibration and validation

The Soil and water assessment Tool SWAT (SWAT)- hydrological model is incorporated within Arc GIS version 10.4 to simulate hydrological condition as influenced by catchment characteristics. The calibration and validation of SWAT-Hydrological model to obtain reasonable estimates of model evaluation performance was done by comparing simulated and observed stream flows data from 1KA11 Igawa maji gauge station.

Daily rainfall, minimum and maximum temperatures from four CORDEX regional climate models were used to force SWAT to simulate hydrological parameters.

4.3.5 Assessment of the impacts of climate change on water resources

The assessment of the impacts of climate change on water resources was carried out by comparing hydrological parameters simulated in historical climate (1971-2000) against future climate (2011–2040, 2041–2070 and 2071– 2100) under two emission scenarios (RCP 4.5 and RCP 8.5). Since different CORDEX regional climate models simulate climate variables at specific location differently. This may contribute to large uncertainties in the simulated hydrological parameters. To address the issue of uncertainties introduced from the climate models, the ensemble average of four CORDEX regional climate models driven by three different GCMs was constructed. Outputs from the constructed ensemble average for RCP 4.5 and RCP 8.5 emission scenarios were used to force SWAT model to simulate the stream flows and water balance components during historical (1971–2000) and future (2011-2100).

4.4 Results and Discussion

The results are presented in two sub sections. The first sub section presents the climate variables over the Mbarali River sub-catchment as simulated by the climate models. The second sub section presents the hydrological characteristics over Mbarali River sub catchment as simulated by SWAT hydrological model.

4.4.1 Climate variables over Mbarali river sub-catchment

In the Mbarali River sub-catchment, the RCMs from CORDEX simulates historical (1971-2000) climate variables (rainfall, minimum and maximum temperatures) differently (Figures, 4.3 - 4.5). All the RCMs reproduce the unimodal rainfall pattern over Mbarali

River sub-catchment (Figure 4.3). However, all RCMs simulates phase change and the magnitude of rainfall in the historical (1971-2000) climate differently. Moreover, even for the same RCM forced by different GCMs simulates the phase change and magnitude of rainfall in the historical climate differently (Figure.3). For instance, RCA4 forced by different GCM (MPI) and RCA4 forced by GCM (CNRM) simulates rainfall amount of 276.13 mm in November and 275.66 mm in December respectively (Figure 4.3). The different RCMs forced by the same GCM simulates the phase change and magnitude of rainfall over Mbarali river sub-catchment differently. For instance, HIRHAM5 forced by ICHEC and RACMO22T forced by ICHEC simulate rainfall amount of 269.41 mm in January and 222.9 mm in December respectively. These results indicate that there are high uncertainties in simulating rainfall over Mbarali river sub- catchment from individual models. The sources of uncertainties can be analyzed and quantified when the same RCM forced by different GCMs and different RCMs forced by the same GCM simulate rainfall over Mbarali river sub catchment differently. However, the presented results suggest that high variability in simulated rainfall over Mbarali River sub catchment occurs when different RCM are forced by same GCM than when the same RCM is forced by different GCM.

In order to reduce the uncertainties associated with the individual RCMs and GCMs, the multi-model approach or ensemble average of simulated climate variables (rainfall, minimum and maximum temperatures) was created and the results can be compared with those from individual models (Figures 4.3 - 4.5). Taking the ensemble average as a reference, it is found that the absolute error (biases) from the RCMs and driving GCMs contribute almost equally in simulating both rainfall and temperatures over Mbarali River sub-catchment. Similarly, during the historical climate (1971-2000) the RCMs simulates the patterns and magnitude of minimum and maximum temperatures better than those of rainfall.

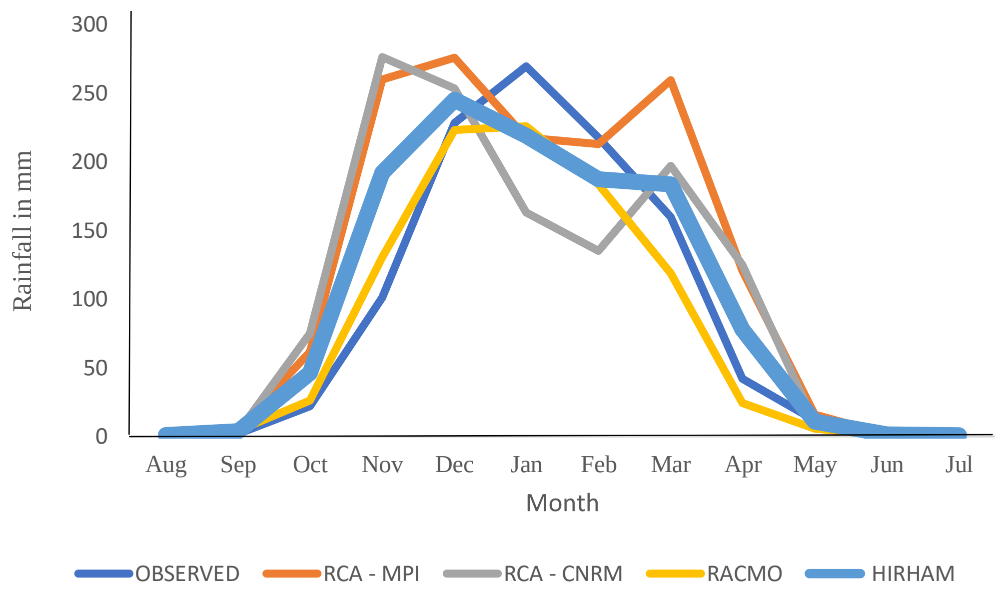

Figure 4.3: Simulated annual cycles of rainfall during the historical climate 1971-2000).

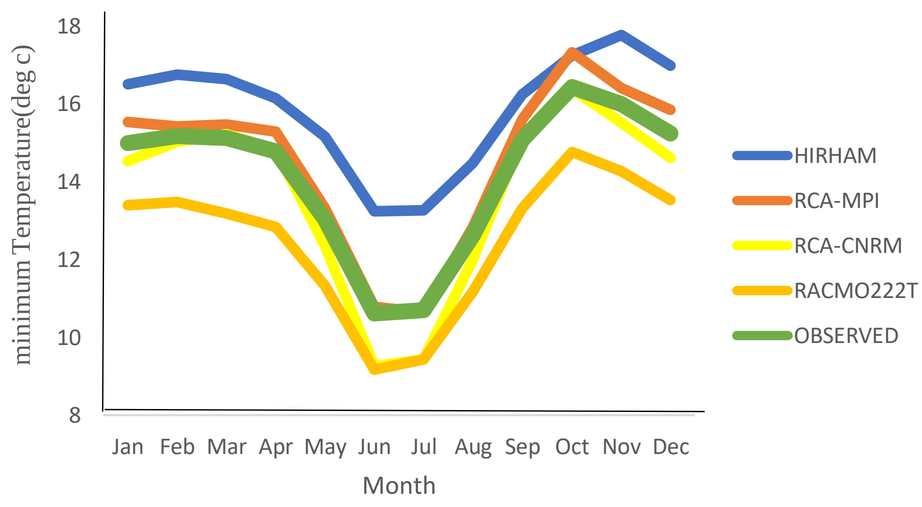

Figure 4.4: Simulated annual cycles of minimum temperature during the historical climate (1971-2000)

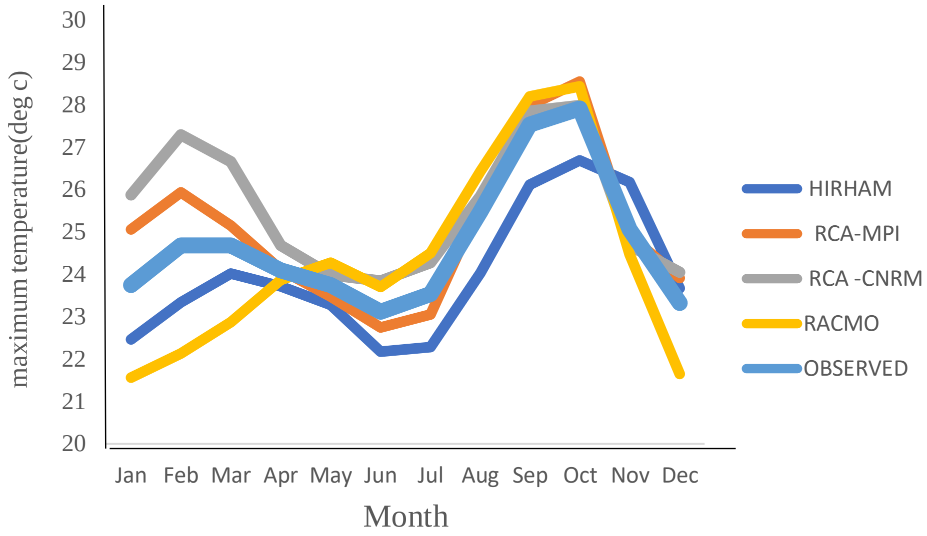

Figure 4.5: Simulated annual cycles of maximum temperature during the historical climate (1971-2000)

Figures 4.6 - 4.8 present the projected annual cycles of climate variables (rainfall, minimum and maximum temperatures) in the Mbarali River sub catchment as simulated by the CORDEX RCMs under two Representative Concentration Pathways (RCP8.5 and RCP 4.5). It can be seen that all the models can reproduce the annual cycles of the historical climate in the future climate condition. However, rainfall is expected to increase in the present century (2011-2040) under both RCP 8.5 and RCP 4.5 emission scenarios. Similarly, minimum and maximum temperatures are projected to increase in present century (2011-2040) under both RCP 8.5 and RCP 4.5 emission scenarios.

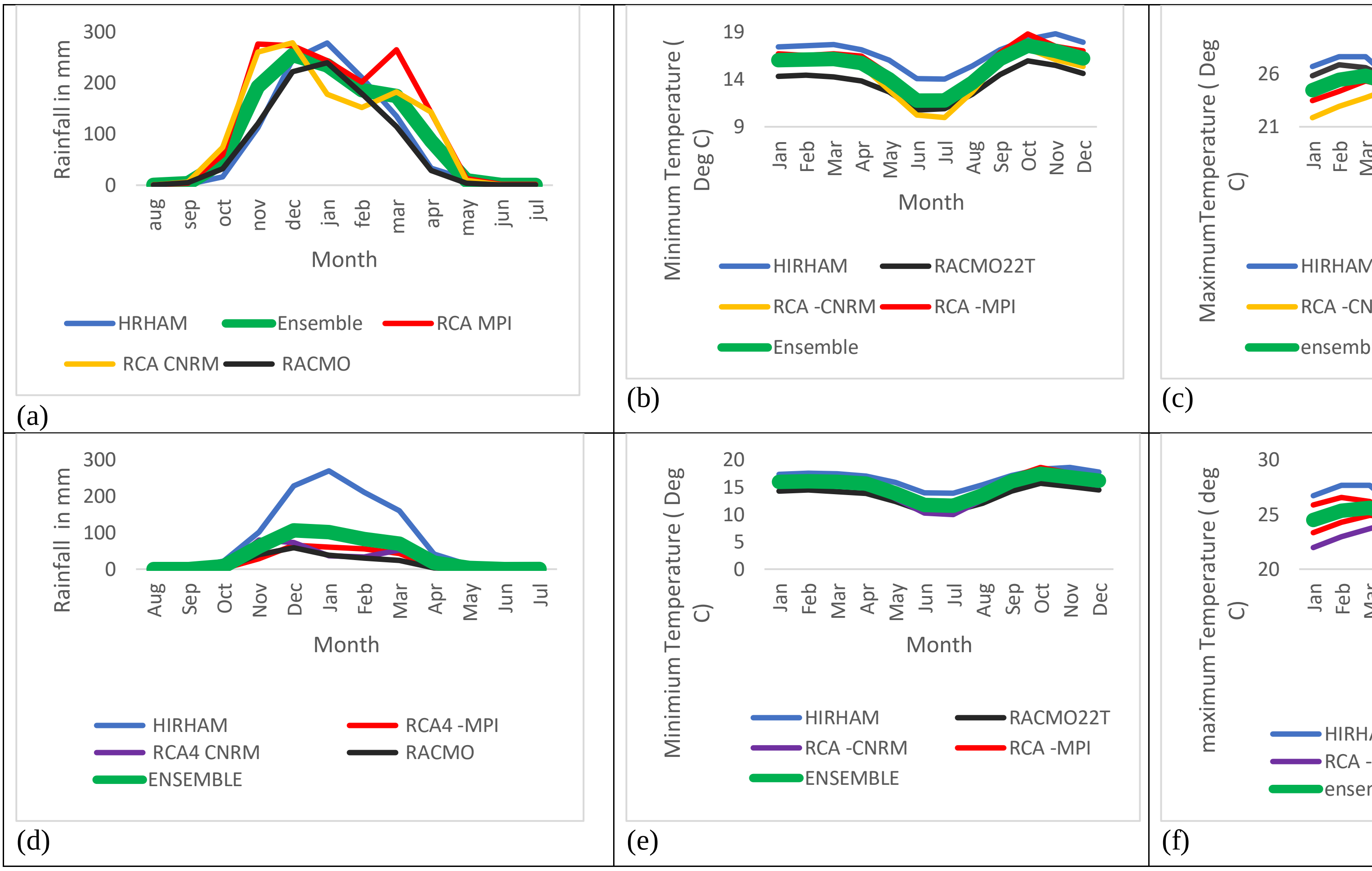
Rainfall in mm
300
200
100
0
aug sep oct nov dec jan feb mar apr may jun jul
Month
HRHAM
Ensemble
RCA MPI
RCA CNRM
RACMO
(a)
Minimum Temperature (Deg C)
19
14
9
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Month
HIRHAM
RACMO22T
RCA -CNRM
RCA -MPI
Ensemble
(b)
MaximumTemperature (Deg C)
26
21
Jan Feb Mar
HIRHAM
RCA -CN
ensemb
(c)
Rainfall in mm
300
200
100
0
Aug Sep Oct Nov Dec Jan Feb Mar Apr May Jun Jul
Month
HIRHAM
RCA4 -MPI
RCA4 CNRM
RACMO
ENSEMBLE
(d)
Minimium Temperature (Deg C)
20
15
10
5
0
Jan Feb Mar Apr May Jun Jul Aug Sep Oct Nov Dec
Month
HIRHAM
RACMO22T
RCA -CNRM
RCA -MPI
ENSEMBLE
(e)
maximum Temperature (deg C)
30
25
20
Jan Feb
(f)

Figure 4.6: Simulated annual cycles of climate variables (rainfall, minimum and maximum temperatures) in the present century (2011-2040): the upper panel is for RCP 8.5 and the bottom panel is for RCP 4.5 emission scenarios.

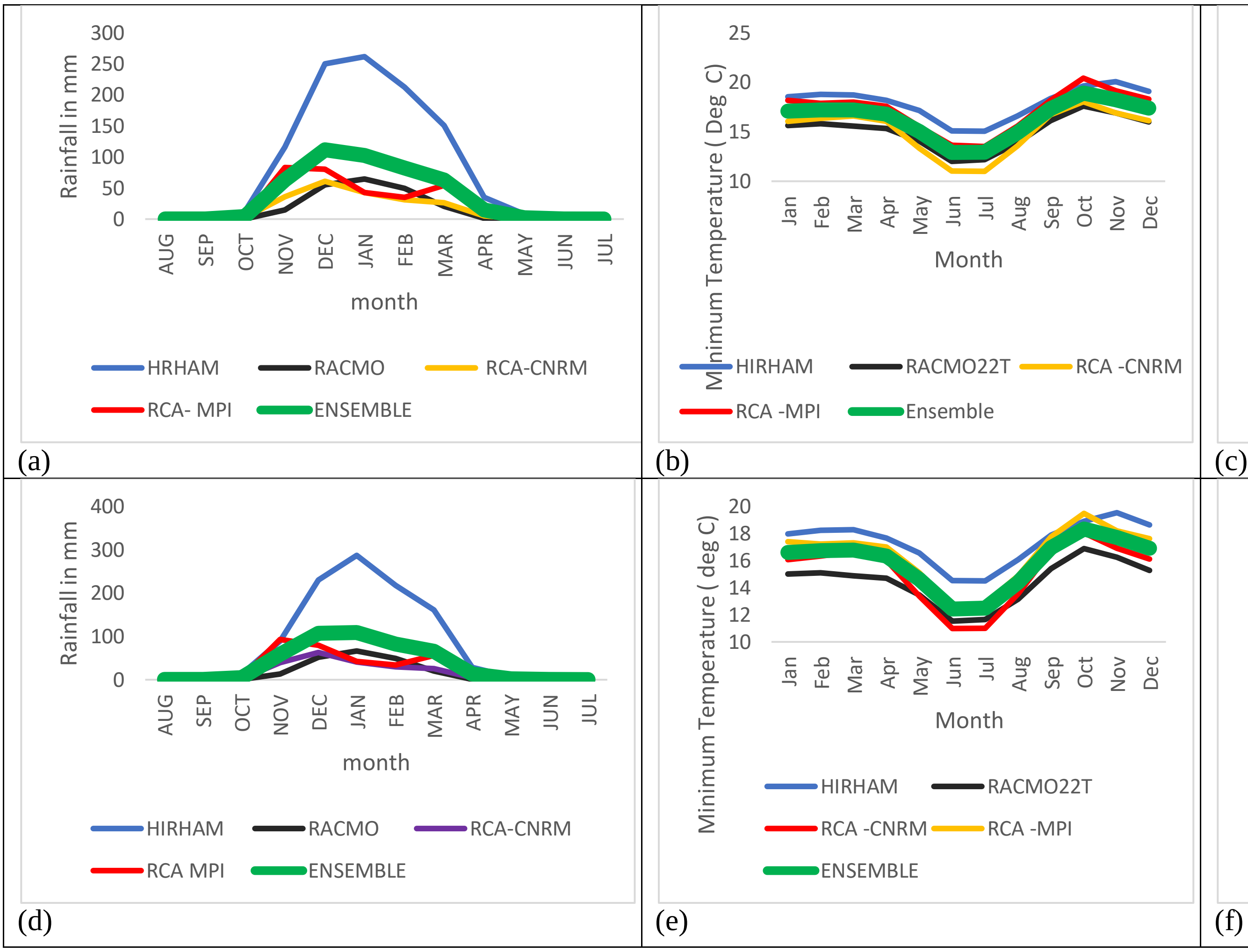

Figure 4.7: Simulated annual cycles of climate variables (rainfall, minimum and maximum temperatures) in the midcentury (2041-2070): the upper panel is for RCP 8.5 and the bottom panel is for RCP 4.5 emission scenarios.

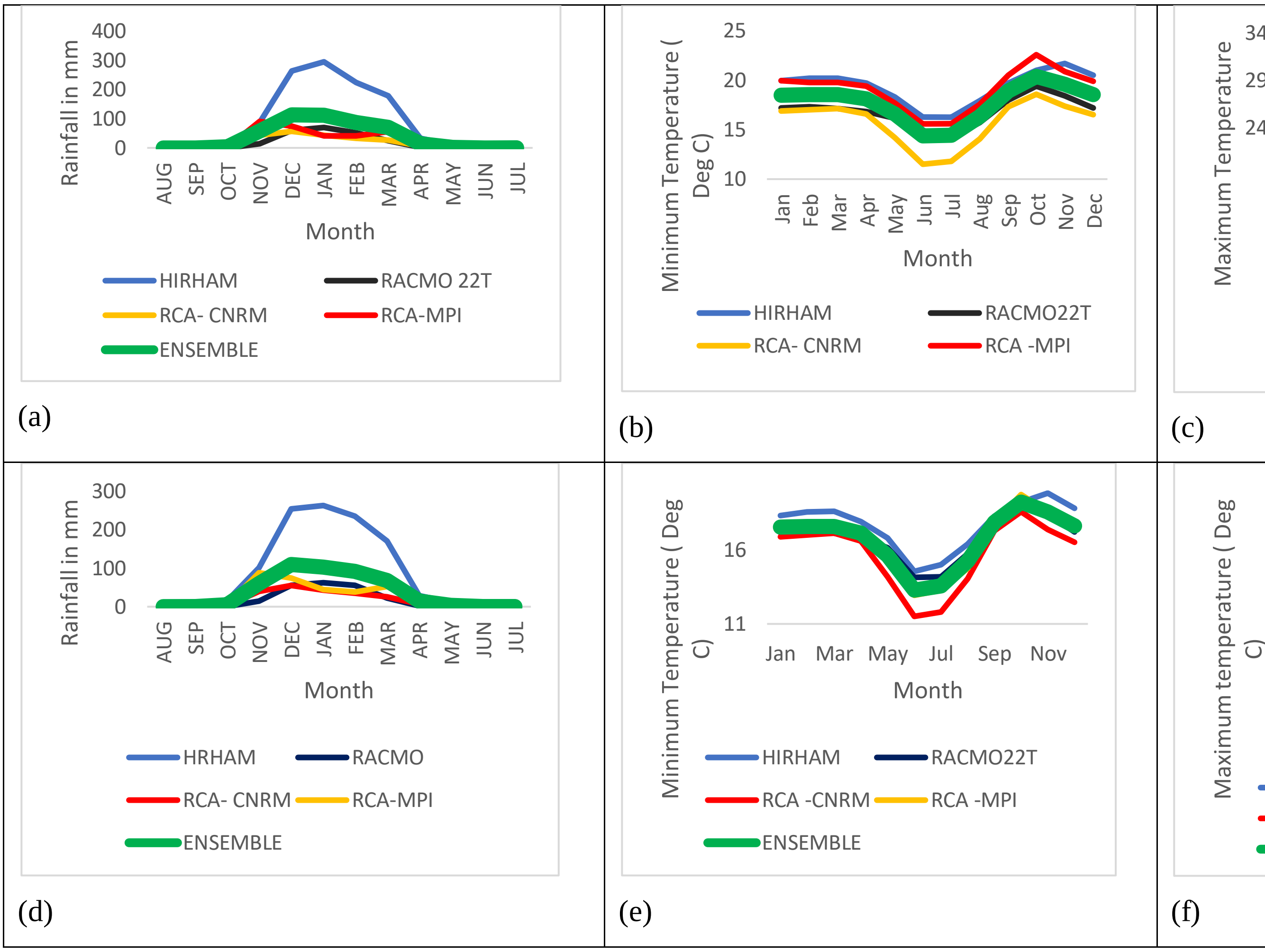

Figure 4.8: Simulated annual cycles of climate variables (rainfall, minimum and maximum temperatures) in the end century (2071-2100): the upper panel is for RCP 8.5 and the bottom panel is for RCP 4.5 emission scenarios.

4.4.2 Impacts of climate change on water resources

The long term means annual cycles of the simulated stream flows in baseline period (1971-2000) and future climate projections (2011-2100) under two emission scenarios (RCP 4.5 and RCP 8.5) for the Mbarali river subcatchment are presented in Figure 4.9. This figure indicates the maximum peak is found in March and the minimum peak is found in December. The figure further shows decline of stream flows during present, mid and end centuries from the month of March to July and from October to January. More declines of stream flows are projected to occur in the end century under both RCP 4.5 and RCP 8.5 emission scenarios. The decline of stream flows in particular during the month of October to January, affects the beginning of the hydrological year of the Mbarali river sub catchment, which starts on Novermber and last on April. The presented results are in agreement with those obtained in the study carried by Rajabu *et al.* (2007) in the Upper Great Ruaha River Catchment (UGRRC). They found decline in the annual stream flow, but with large variations along the year.

Table 4.2 shows the simulated annual stream flow during the baseline period (1971-2000) is 36.74 m^3/sec. These flows are projected to decrease during present (2011-2040), mid (2041-2070) and end (2071-2100) centuries under both RCP 4.5 and RCP 8.5 emission scenarios. More decrease of 15.91% is projected to occur during the mid and end centuries under RCP 4.5. In the present century more decrease of stream flows of 13.99% is projected to occur over Mbarali River sub -catchment under RCP 8.5 emission scenario.

Table 4.2: Mean annual stream flows for the baseline and future period as simulated by SWAT forced by Ensemble RCMs under RCP 8.5 and RCP 4.5 scenario (All values are in m^3/sec)

Baseline	**2011-2040**				**2041-2070**				
1971-2000	RCP 8.5	%	RCP 4.5	%	RCP 8.5	%	RCP 4.5	%	RC
36.74	31.60	-13.99	32.96	-10.28	31.24	-14.96	30.89	-15.91	31.2

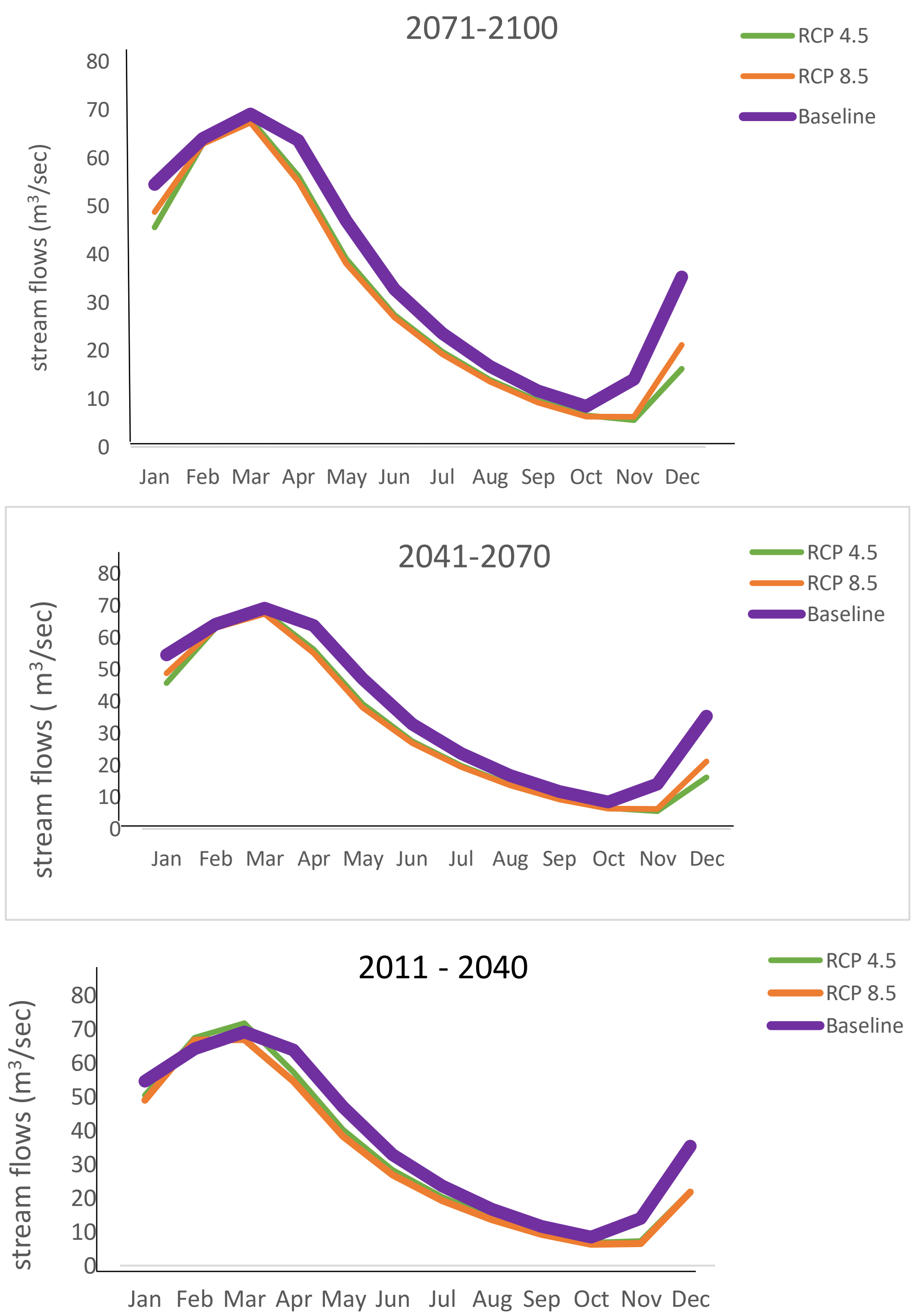

Figure 4.9: Mean monthly stream flows of RCM ensemble under RCP 4.5 and RCP 8.5 for the three future period and baseline period (1971-2000)

4.4.3 The impact of climate change on water balance components

The average annual values of water balance components for the Mbarali River-sub catchment simulated by SWAT hydrological model when forced by climate variables from different RCM-GCM combinations during the baseline (1971–2000) and future (2011-2100) climate conditions are presented in Tables 4.3- 4.7. During historical climate (1971-2000), the highest surface runoff of 13.95 mm is simulated by SWAT forced with HIRHAM-ICHEC and the lowest surface runoff of 0.15 mm is simulated by SWAT forced with RACMO22T-ICHEC. The uncertainties associated with different CORDEX-RCMs can be analyzed. When SWAT is forced by different RCMs but similar GCM it simulates water balance components differently. For instance, in the historical climate, SWAT simulate water yield of 719.72 mm and 614.99 mm when forced by HIRHAM-ICHEC and RACMO22T–ICHEC respectively. Moreover, SWAT forced by similar RCM but different GCMs simulate water yield differently. For instance, water yield of 825.42 mm and 1030.86 mm was simulated by SWAT driven by RCA4-CNRM and RCA4-MPI respectively. The uncertainties from the climate model may be associated with different formulation and parameterization schemes in those models. To account for uncertainties that arise from RCM-GCM combinations, the ensemble averages of four climate models were constructed and used to force SWAT.

Table 4.7 shows average annual basin values for the water balance components simulated by SWAT forced with the ensemble averages. These water balance components differ significantly from that of individual models. This is an indication of large uncertainties involved in climate change impact studies for the Mbarali river sub-catchment. However, results from the ensemble averages that take into account the uncertainties from individual RCMs and driving GCMs are the most estimate of future climate change in the sub basin. Table 4.7 indicate that the ground water and water yield components are projected to decrease under RCP 8.5 during present, mid and end centuries. While surface runoff and Evapotranspiration are projected to increase under the two emission scenarios during present, mid and end centuries.

Table 4.3: Average annual basin values as simulated By Swat model fed with climate data from HIRHAM – ICHEC for Two scenarios RCP 4.5 and RCP 8.5: Note that figures in brackets are % change

		Present century (2011-2040)		Mid century (2041-2070)	
Water balance components (mm)	Baseline (1971-2000)	RCP 4.5 (% change)	RCP 8.5 (% change)	RCP 4.5 (% change)	RCI (% ch
Precipitation	1086.1	1073.2 (-1.18)	1050.0(-3.32)	1040.1(-4.24)	1051.7(
Surface runoff Q	13.95	18.62 (33.47)	15.89(13.9)	16.70(19.71)	17.83(
Groundwater	639.46	631.36(-1.26)	606.68(-5.12)	592.56(-7.33)	598.58
Total water yield	719.72	715.61(-0.57)	685.99(-4.68)	671.70(-6.67)	679.54
Evaporation	339.0	336.5(-0.73)	337.49(-0.47)	343.1(1.20)	347.3

Table 4.4: Average annual basin values as simulated by Swat model fed with climate data from RACMO22T-ICHEC for two scenarios RCP 4.5 and RCP 8.5. Note that figures in brackets are % change

		Present century (2011-2040)		Mid century (2041-2070)	
Water balance components (mm)	Baseline (1971-2000)	RCP 4.5 (% change)	RCP 8.5 (% change)	RCP 4.5 (% change)	RCP 8.5 (% change)

Precipitation	955.8	968.2(1.29)	958.5(0.28)	961.5(0.59)	957.0(0.12
Surface runoff	0.15	0.09(-40)	0.22 (46.66)	0.11(-26.66)	0.08 (-46.66
Groundwater	557.00	554.40(-0.46)	541.63 (-2.75)	592.56(6.38)	514.49 (7.63
Total water yield	614.99	612.29(-0.43)	598.47(-2.68)	671.70(9.22)	569.33 (-7.42
Evaporation	319.2	335.5(5.10)	325.9(2.09)	343.1(7.48)	364.9(14.31

Table 4.5: Average annual basin values as simulated by swat model fed with climate data from RCA – CNRM for two scenarios RCP 4.5 and RCP 8.5: Note that figures in brackets are % change

		Present century (2011-2040)		Mid century (2041-2070)	
Water balance components (mm)	Baseline (1971-2000)	RCP 4.5 (% change)	RCP 8.5 (% change)	RCP 4.5 (% change)	RCP (% char
Precipitation	1223.7	1284.1(4.93)	1284.1 (4.93)	1273.2 (4.04)	1273.2(4
Surface runoff	8.63	12.42 (43.91)	12.42(43.91)	14.04 (62.68)	14.04 (62
Groundwater	740.64	783.20 (5.74)	783.20(5.74)	740.55 (-0.01)	740.55 (-0
Total water yield	825.42	875.87 (6.11)	875.87 (6.11)	831.65(0.75)	831.65 (0
Evaporation	376.0	386.8 (2.87)	386.8 (2.87)	411.1 (9.33)	411.1 (9

Table 4.6: Average annual basin values as simulated by swat model fed with climate data from RCA – MPI for two scenarios RCP 4.5 and RCP 8.5: Note that figures in brackets are % change

		Present century (2011-2040)		Mid century (2041-2070)	
Water balance components (mm)	Baseline (1971-2000)	RCP 4.5 (% change)	RCP 8.5 (% change)	RCP 4.5 (% change)	RCP 8.5 (% change)
Precipitation	1442.8	1446.4(0.24)	1481.4 (2.67)	1497.8 (3.81)	1425.8(-1.17)
Surface runoff	12.48	16.31(30.68)	17.84(42.94)	22.60(81.08)	18.71(49.91)
Groundwater	924.94	93(0.61)	783.20(-15.32)	944.92(2.16)	893.94 (-3.35)
Total water yield	1030.86	1041.07(0.99)	875.87(-15.03)	1063.63 (3.17)	1003.94 (-2.61)
Evaporation	387.5	384.7 (-0.72)	386.8 (-0.18)	408.7 (5.47)	400.9 (3.45)

Table 4.7: Average annual basin values as simulated by swat model fed with climate data from RCM Ensemble average for two scenarios RCP 4.5 and RCP 8.5: Note that figures in brackets are % change

		Present century 2011-2040		Mid century 2041-2070	
Water balance components (mm)	Baseline (1971-2000)	RCP 4.5 (% change)	RCP 8.5 (% change)	RCP 4.5 (% change)	RC (% c
Precipitation	1177.1	11192.97(5.34)	1193.5(1.39)	1188.15(0.93)	1176.925
Surface runoff	8.8025	11.86(34.73)	11.59(31.6)	13.36(51.80)	12.6

Groundwater	715.51	724.89(1.31)	678.67(-5.14)	717.64(0.29)	686.89
Total water yield	797.7475	811.21(1.68)	759.05(-4.85)	809.67(1.49)	771.115
Evaporation	355.425	360.875(1.53)	359.225(1.06)	376.5(5.92)	381.0

4.5 Discussion

The uncertainties observed in a previous study done by Wambura (2015) on the impacts of climate change on stream flows using climate change simulations derived by GCMs offer room for more research to be done on the hydrological responses due to climate change. In this study, we have used the high-resolution climate information from four Regional Climate Models (RCMs) driven by three General Circulation Models (GCMs) and Soil and water Assessment tool embedded in Arc GIS to simulate stream flows over the Mbarali River sub catchment during historical, and future periods under two emission scenarios (RCP 4.5 and RCP 8.5).

This work aimed at assessing, how climate change will affect hydrological characteriscs of the Mbarali River Sub-catchment in the Upper Great Ruaha sub basin of Rufiji Basin. This River sub-catchment is an agricultural watershed which produce food and cash crops in the country (Milder *et al.*, 2013). As a result, assessment on how climate change will impact future water availability within Mbarali River sub-catchment is of great important. The study revel that temperatures are projected to increase throughout the sub-catchment.

The ensemble average revealed that, in the future period, the minimum temperature will increase by 14% (1.9^{0}C) under RCP 8.5 and maximum temperature will increase by 7.68% (1.8^{o}C) under the same scenario RCP 8.5. These increases in temperatures will rise the evaporation within the sub-catchment and hence contributed to the decrease in the stream flows, particularly in warmer low altitude areas.

The hydrological model SWAT simulate water balance ultimately differently when two different RCMs forced by same GCM, the differences are related with the design of the RCMs themselves. For the case of, RACMO22T and HIRHAM5 forced by the same

GCM(ICHEC-EARTH) different amount of stream flows, surface runoff, water yield and Ground water yield in both historical climate (1971–2000), present climate (20110–2040), mid (2041–2070) and end (2071–2100) centuries are simulated.

Likewise, different amounts of water balance components are simulated when the same RCM is forced by different GCMs. For instance, SWAT simulate different amounts of stream flow, surface runoff, water yield even through only one RCM (RCA4) is driven by different GCMs (CNRM, and MPI). The annual Rainfall projections show a significant increase in the averages for the three projected periods relative to the baseline period under both RCP4.5 and RCP8.5 scenarios. These projections agree those of temperatures in the River sub -catchment. Moreover, as with the temperatures, the increase under the RCP8.5 scenario is higher than that obtained under the RCP4.5 scenario.

The projected decrease of the stream flows in the Mbarali River sub-catchment may result in decrease in the amount of water availability. This may have negative impacts on the aquatic biota, water quality and agriculture. The projected increase in the surface run-off may cause serious environmental problems such as soil erosion and floods.

It is important to note the uncertainties related to the current assessment, which is based on the downscaling of the high-resolution regional climate model driven by three members of the GCM (ICHEC, MPI and CNRM) simulations of the RCPs emission scenario. Therefore, the simulations included are the most and the least climate sensitivity member of the GCM runs, and have been somewhat considered in these simulations, therefore some insight into the possible future changes in the river flow under future climate change were provided in this work. Despite the uncertainties of the projections, the results showed some level of agreement with other works and therefore they contain some level of confidence to the hydrological impacts in the Mbarali River sub catchment, which makes the information useful as guidance for local adaptation measures.

4.6 Conclusion

In this study we assessed the impact of climate change on stream flows and hydrological condition of the Mbarali River sub-catchment which is located in the Upper Great Ruaha sub basin of Rufiji basin, Tanzania. SWAT, a semi distributed hydrological model was employed to simulate the stream flows and hydrological condition of the River sub-catchment. The Present climate variable for the period of 1971-2000 and future climate variable for the period of 2011-2100 under two representative concentration pathways (RCP 4.5 and RCP 8.5) was used as in put to the SWAT for the purpose of simulating stream flows and hydrological conditions of the Mbarali river sub-catchment. In order to assess the impact of climate change on stream flows and other hydrologic conditions, the simulated results between two periods ie historical and future were compared.

The future annual rainfall and temperature are projected to increase while the annual stream flows are projected to decrease. The significant decrease of projected monthly streamflow during the year might cause drying up of the Mbarali River sub-catchment. and hence decrease the environmental condition of the aquatic organisms in the future.

Additionally, the decreases of monthly streamflow during March and April would lead to water shortage problems that have been occurring in previous years. The climate of the study area is becoming hotter in both wet and dry seasons. To cope with this situation, the basin water users and other stakeholders should apply integrated water resources management at all level.

4.7 References

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CHAPTER FIVE

5.0 Assessing the Impacts of Land Use and Land Cover Changes on Hydrology of the Mbarali River Sub-Catchment.

5.1 Abstract

Intensification of agricultural activities and population growth for the year 1990-2017 has caused changes in land cover and land use of the Mbarali River sub-catchment in the Upper Great Ruaha Sub basin, Tanzania. This has affected the magnitude of the surface runoff, total water yield and the groundwater flow. The study at hand have attempted to use a combination of remote sensing techniques as well as modeling by the Soil Water Assessment Tool (SWAT) for analyzing impacts of LULC on hydrology of the Mbarali River Sub-catchment. The land use and land cover (LULC) maps for three window period snapshots, 1990, 2006 and 2017 were created from Landsat TM and OLI_TIRS. Supervised classification was used to generate LULC maps using the Maximum Likelihood Algorithm and Kappa statistics for assessment of accuracy. SWAT was set up and run to simulate stream flows and hydrological water balance components, the calibration was done from 1990-2005 and Validation from 2006-2010. The assessment of the impacts of land use and land cover changes on stream flows and hydrological water balance component was performed by comparing hydrological parameters simulated by SWAT using land use scenarios of 2006 and 2017 against the baseline land use scenario of 1990. Accuracy of LULC classification was good with Kappa statistics ranging between 0.9 and 0.99. There was a drastic increase in areal coverage of cultivated land, for periods 1990-2006 (5.84%) and 2006-2017 (12.05%) compared to other LULC. During 2006 and 2017 surface runoff increased by 4% and 9% respectively; however, water yield increased by only 0.5% compared to 1990 baseline period. This was attributed

by the increasing proportion of cultivated land in the sub-catchment which has a high curve number (59.60) that indicates a higher runoff response and low infiltration rate.

Keywords: Geographic Information system (GIS), Mbarali River sub-catchment, Land use and cover change, Soil and Water Assessment Tool (SWAT), Water balance, Stream flow.

5.2 Introduction

Many studies in African countries have revealed decline in availability water and agricultural productivity within the catchments (IPCC 2014). This decline is partly caused by changes in land use and land cover changes (IPCC, 2014). Land use and land cover are key variables in managing most of the hydrological models for large and even smaller river catchments.

A study conducted by Piao *et al.* (2007) revealed that land use and land cover changes (e.g., change of forestland to agricultural land or built area) have a serious effect on the rate of surface runoff, groundwater recharge, erosion and sediment transport. Since land use change has a significant and profound effect on water quality and quantity, there is an urgent need to understand the interaction between the land use change, hydrology and water resources management (Balthazar *et al.*, 2015, De Fries and Eshleman, 2004.

Several studies (e.g. Schulze 2000, and Zhang *et al.*, 2001) have revealed that deforestation or afforestation can cause decrease or increase in total water yield. This has been detected in catchments with wide-ranging size spreading from smaller than 1 km^2 to more than 1000 km^2 (Brown *et al.*, 2005).

Tanzania, like other countries, has been experiencing frequent alteration of land use/ cover as a result of several factors such as population growth, climatic variability, and national policies. In previous years, land cover and land use changes induced by human population pressure and rainfall variability have adversely affected the condition of water resources in the Great Ruaha Sub- catchment of the Rufiji Basin (Kashaigili, 2008).

A study done by Kashaigili (2008) found that land modifications in the Upper Great Ruaha River Catchment resulted in decreased base flows, high peak stream flows, increased width of river channel, and sediment accumulation along the riverbed. The study used remote sensing as the only technique to investigate the hydrological impacts of land-use and land-cover changes on flow regimes of the Great Ruaha River. Further the study was unable to integrate hydrological modeling and land use land cover change detection technique to evaluate the impacts of land use and land cover change on the hydrology and water balance of the catchment. The present study used a combination of remote sensing techniques as well as modeling by the Soil Water Assessment Tool (SWAT) for analyzing impacts of LULC on hydrology of the Mbarali River Sub-catchment.

Likewise, the Mbarali River Sub-catchment experiences rapid population growth, with an annual growth rate of 3.1 % compared to the national annual growth rate of 2.7% (NBS, 2013). This has resulted in expansion of built-up area and agricultural land (Mbarali District Profile, 2017). This has impacted the water balance of the river sub catchment by changing the magnitude and pattern of the hydrological components such as surface runoff and ground water flow, resulting in increased extent of the water management problems. Regardless of what is so far known about threats on Mbarali River Sub- catchment, little effort has been made to understand the effects of land use and land cover change on the hydrology and water balance in this river sub-catchment. This calls for the need to understand the extent to which alterations of the land use land cover have impacted on water availability in this river sub catchment. Assessing the impact of land use and land cover changes on hydrology is very important for current and future management of Mbarali River sub-catchment and other catchments in Tanzania.

5.3 Materials and Methods

5.3.1 Description of the study area

The Mbarali River sub-catchment (Figure 5.1) is located between latitudes 7 °S and 9 °S and between longitudes 33.8 °E and 35 °E in the upper Great Ruaha sub basin of the Rufiji basin in the southern highlands of Tanzania. The population of Mbarali depends mainly on subsistence agriculture and livestock keeping for their livelihoods. The River catchment has a total area of 1530 sq km, of which 321 500 hectares. are arable land that is potential for agriculture production and currently 187 600 hectares have been developed. Paddy production becomes the main food/cash crop which makes Mbarali to become one of the main paddy producers and exporters in Tanzania and neighboring countries. Other crops which are also grown include maize, sweat potatoes, sorghum, sunflower, onions, cassava, beans, groundnuts and vegetables. Apart from rain fed agriculture the River Catchment also undertake irrigated agriculture farming with paddy being the main crop cultivated on large scale under irrigation. The district has the total of 44 000 (ha) cultivated under irrigation which is equivalent to 13.7% of the total arable land potential for agriculture. The River Catchment is at an altitude ranging from 1000 to 1800 meters above sea level. Average temperature ranges between 25^0C and 30^0C. The mean annual rainfall is about 450 to 650 mm.

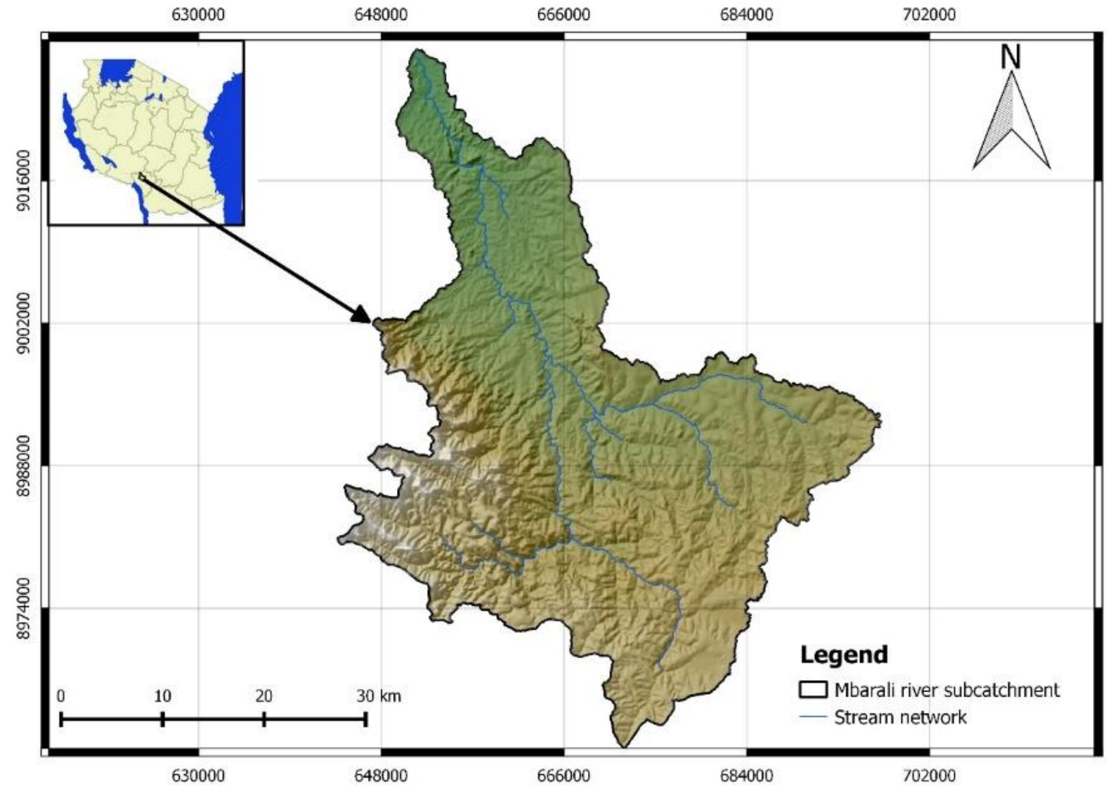

Figure 5.1: Map of the study area

5.3.2 Method

Data collected and used in this study included spatial data, Hydrological data and Meteorological data. Spatial data included satellite images and 30 m resolution digital elevation model (DEM) downloaded from USGS – GLOVIS (www.glovis.usgs.gov) and NASA reverb (https://reverb.echo.nasa.gov) respectively. Meteorological data comprised rainfall, relative humidity, solar radiation, wind speed and minimum and maximum temperature data, were obtained from Tanzania Meteorological Agency and Rufiji Basin Water Office, Iringa. River discharge data, recorded from Igawa maji gauging station (IKA11A).

5.3.3 Data analysis

The land cover change detection analysis was conducted to assess and quantify spatial and temporal changes in land use and land cover in Mbarali sub-catchment.

To ensure accurate identification of temporal changes and geometric compatibility with other sources of information, images were pre-processed whereby geo-correction was conducted to rectify precisely matching of images. Band stacking and Images enhancement was performed using different color composite band combinations and its contrast was stretched from minimum to maximum to reinforce the visual interpretability of images. Images were registered to the UTM map coordinate system, Zone 36 South (Latitudes of Mbeya), Datum Arc 1960. Image Mosaic was conducted to merge together images of the same year with same path and different row so as to create a single image that covers the entire catchment. Supervised image classification using Maximum Likelihood Classifier (MLC) was conducted to create base map. Data from ground truth were used to formulate and confirm different cover classes existing in the study area. Training sites were identified by inspecting an enhanced color composite imagery. Areas with similar spectral characteristics were trained and classified. Supervised classification by using Semi-automatic Classification Plugin (SCP) available in GIS 2.12.1 was conducted and maximum of seven distinct land cover classes were identified.

Table 5.1: Land use/cover classification scheme

Land cover class	Description
Forest	Land covered with naturally regenerated native tree species with no clearly visible indications of human activities
Wetland	Land area that is saturated with water either permanent or seasonally
Woodland	Area of land covered low density trees forming open habitat with plenty of sunlight and limited shade
Grassland	Land area dominated by grasses
Bushland	Area dominated with bushes and shrubs
Cultivated land	Farm with crops and harvested cropland
Built up area	Man-made infrastructure (roads and buildings) and settlement

5.3.4 Image classification and accuracy assessment

User accuracy, producer's accuracy and Kappa coefficient statistics was used to assess the accuracy of final image classification.

The kappa coefficient is expressed as:

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \quad \ldots\ldots (1)$$

Where N is the total number of sites in the matrix, r is the number of rows in the matrix, xii is the number in row i and column i, x_{+i} is the total for row i, and x_{i+} is the total for column.

Post classification comparison was used to quantify the extent of land cover changes over the period 1990, 2006 and 2017. Post classification comparison bypasses the difficulties associated with the analysis of the images that are acquired at different times of the year, or by different sensors and results in high change detection accuracy (Li *et al.*, 2007). The estimation of the rate of change for the different land covers was computed based on the following formulas (Kashaigili and Majaliwa, 2013).

$$\% \, Cover \, change = \frac{Area_{i\, year\, x} - Area_{i\, year\, x+1}}{\sum_{i=1}^{n} Area_{i\, year\, x}} \times 100 \ldots\ldots\ldots\ldots\ldots \quad (2)$$

$$Annual \, rate \, of \, change = \frac{Area_{i\, year\, x} - Area_{i\, year\, x+1}}{t_{years}} \ldots\ldots\ldots\ldots\ldots \quad (3)$$

$$\% \, Annual \, rate \, of \, change = \frac{Area_{i\, year\, x} - Area_{i\, year\, x+1}}{Area_{i\, year\, x} \times t_{years}} \times 100 \ldots\ldots\ldots\ldots \quad (4)$$

$Area_{i\ year\ x}$ is the area of cover i at the first date,

$Area_{i\ year\ x+1}$ is the area of cover i at the second date,

$\sum_{i=1}^{n} Area_{i\ year\ x}$ is the total cover area at the first date,

t_{years} is the period in years between the first and second scene acquisition dates

5.3.5 Hydrological model

The study used Soil and Water Assessment Tool (SWAT) model to simulate the effects of land use and land cover change on stream flow. The calibrated SWAT model was run with the input data including digital elevation model (DEM), soil map, land use map, rainfall and stream flow. The following steps were conducted during SWAT model set up.

First step was to delineate the sub catchment by splitting the catchment into sub-basins according to the terrain model and river channels. SWAT 2012, a GIS interface, was used to delineate the sub catchment. HRUs were generated based on user-defined threshold percentages (Arnold *et al.*, 1998). Before defining the HRUs, the Land use data were reclassified to match with the SWAT land use classification. Land use and soil data were required in SWAT model to determine the area and the hydrologic parameters of each land-soil categories simulated within each sub catchment Input data (climatic data) were prepared, edited and saved into delimited format so that can be read in SWAT.

5.3.6 Sensitivity and uncertainty analysis

To understand how closely the model simulates the hydrological processes within a sub catchment, it is critical to examine the influence of different parameters. Sensitivity analysis is the computation of the most sensitive parameters for a given sub catchment. In this study a sensitivity analysis using the Sequential Uncertainty Fitting (SUFI-2) within the SWAT-CUP model (Abbaspour *et al.,* 2007) was used. The advantage of using SWAT-CUP relies on the possibility of using different kinds of parameters including those responsible for surface runoff, water quality parameters, crop, parameters, crop rotation and management parameters, and weather generator parameters (Arnold *et al.,* 2012).

5.3.7 Most sensitive parameters and their fitted values

SWAT CUP 2012 software was used sensitivity analysis, calibration and validation. This software has been applied in a number of studies and is gaining popularity worldwide. Its advantageous features are a user-friendly interface, linkage with the SWAT model run results, simplicity regarding execution, and semi-automated process for the selection of best basin parameter ranges. Before calibration, a sensitivity analysis was performed for the selection of the most sensitive hydrological parameters. The best parameters which give the best value of the objective function was used for the current study. The average monthly stream flow data of 15 years from 1990 to 2005 of the Igawa Maji gauging station were used to compute the sensitivity of the stream flow parameters.

5.3.8 Model calibration and validation

Calibration was conducted for daily and was done for 15 years from 1990 to 2005; Five years prior to 1990 were used for warm up period which was intended to allow the model parameters to reach a stable state condition. Validation period was set for 5 years period from 2006 to 2010. The calibration and validation processes were carried out using the Sequential Uncertainty Fitting (SUFI-2).

5.3.9 Simulation analysis

The calibrated model was then used to simulate stream flows under changed land-use/cover condition for the year 1990, 2006 and 2017, while maintaining the same weather data that was used previously when SWAT model was setup. The influences of the land use land cover change on stream flows were quantified by comparing output of the SWAT hydrological model (Observed and Simulated) for the time period 1990, 2006, 2017. The differences between observed and simulated discharge under changed land use land cover representing the effects of land use and land cover changes on hydrological responses in the catchment.

5.4 Results and Discussion

5.4.1 Land use and land cover changes over the Mbarali River sub-catchment

Figure 5.2 below present the variations in land use and land cover maps of the Mbarali River Sub-catchment during the year 1990, 2006 and 2017, while the Table 5.2 show the comparison of classification of the Land use/cover from Landsat 1990, 2006 and 2017. i.e. a complete number of pixels and percentage number of all pixels. Forest, woodland, Bushland, Grassland, Wetland, cultivated land and Built up area are the major land covers classes. In 1990, 36.65% of all image pixels were classified as Bushland, 25.69% as cultivated land, 23.13% as woodland, 7.54% as forest, 6.89%. As Grassland and the Built-up area was 0.03%. In more than 15 years later, the land cover classes had changed as follows: 5.23% forest, 16.26% woodland, 28.36% bushland, 6.13% grassland, 43.57% cultivated land and 0.36% built up area.

Table 5.2: Comparison of the LULC of the year 1990, 2006 and 2017

Year	**1990**		**2006**		**2017**	
	(Ha)	**(%)**	**(Ha)**	**(%)**	**(Ha)**	**(%)**
Forest	11348	7.54	8292	5.51	7871	5.23
Woodland	34791	23.13	35327	23.08	24453	16.26
Bushland	55132	36.65	46279	30.77	42657	28.36
Grassland	10367	6.89	12532	8.33	9224	6.13
Wetland	92	0.06	53	0.04	125	0.08
Cultivated land	38648	25.69	47426	31.53	65547	43.57
Built up area	45	0.03	514	0.34	547	0.36
Total	**150424**	**100**	**150424**	**100**	**150424**	**100**

1990 **2006**

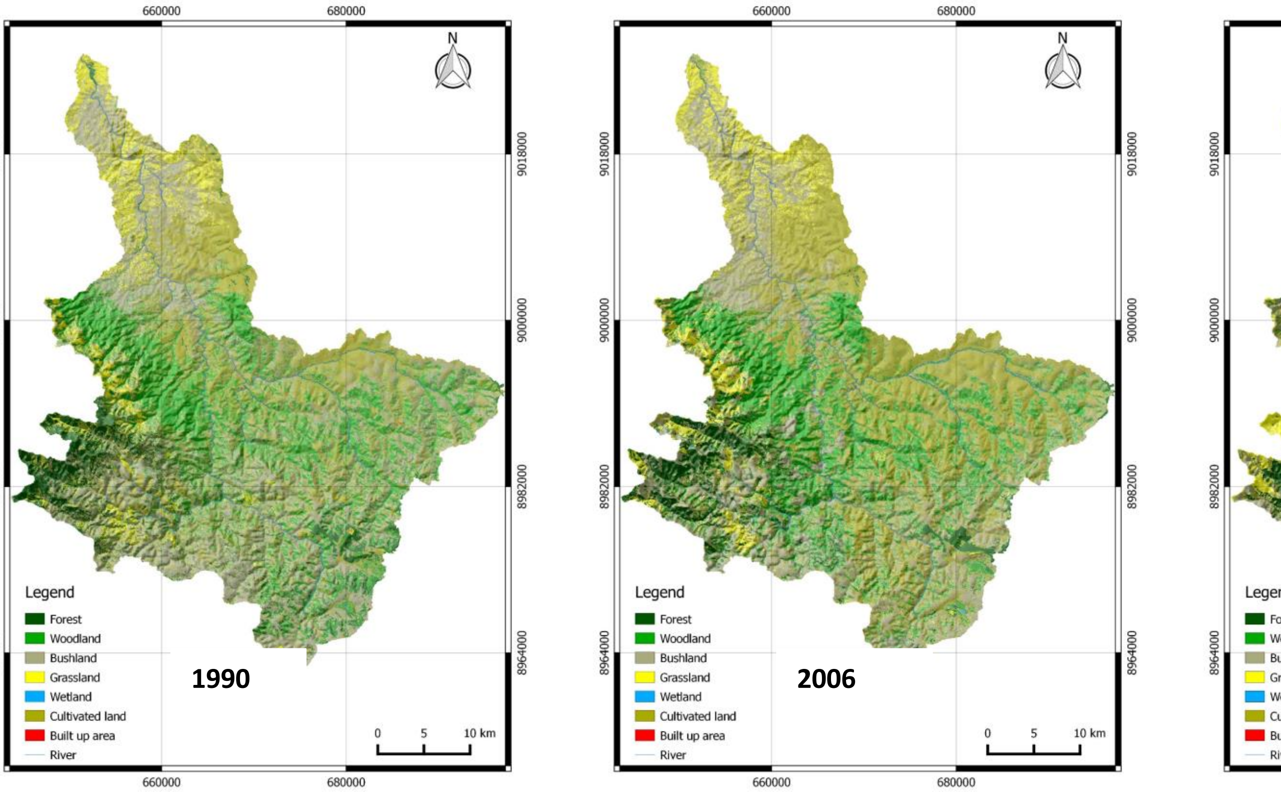

Figure 5.2: Land use/cover maps for 1990, 2006 and 2017

5.4.2 Change in Land use and land cover for the year 1990-2006, and from 2006- 2017

Table 5.3 presents the land use and land cover area distribution for the window period 1990-2006 and 2006-2017. From that table it is shown that, the land use and land cover area within the Mbarali River sub-catchment are most occupied by cultivated land, in the year 1990 it was found to occupy 38 648 ha, in 2006 it had 47 426 ha while in the year 2017 had 65 547 ha, the cultivated land has been increasing for more than 10 years. The results also indicate that, for the two-window period between 1990 – 2006 and 2006-2017 the area under natural forest was found to decrease by 3056 ha (2.03%) and by 421 ha (0.28%) respectively, Bushland decreased by 8853 ha (5.89%) and 3622 ha (2.41%) respectively during the two periods. The decrease in hectares in forest for the two-window periods is due to the demand of land for agriculture activities, since agriculture is the most activities undertaken within the study area.

Similarly, built-up area shows an increase of 469Ha (0.31%) for the period 1990-2006 and an increase of 33Ha (0.02%) for the period 2006-2017. The built-up area was found to increase at a rate of 29 ha/year (0.31%/year) and 3 ha/year (0.02%/year) for the two-window periods ie 1990 -2006 and 2006- 2017 respectively. Cultivated land had shown to increase by 549 ha/year (5.84%) for the period 1990-2006 and by 1647 ha/year for the period of 2006-2017. This fast increase could be due to the expansion of agricultural land and settlement to accommodate local people’s livelihoods including the need for firewood.

Table 5.3: Land use and land cover area distribution

LULC	1990	2006	2017		1990 - 2006		
	Ha	Ha	Ha	Area change (Ha)	Percentage change (%)	Annual Rate of Change (Ha/year)	Area change (Ha)
Forest	11348	8292	7871	-3056	-2.03	-191	-421
Woodland	34791	35327	24453	536	0.36	33	-10874
Bushland	55132	46279	42657	-8853	-5.89	-553	-3622
Grassland	10367	12532	9224	2165	1.44	135	-3308
Wetland	92	53	125	-39	-0.03	-2	72
Cultivated land	38648	47426	65547	8778	5.84	549	18121
Builtup area	45	514	547	469	0.31	29	33
Total	**150424**	**150424**	**150424**				

5.4.3 Change detection and Post -classification of different land use/cover

Table 5.4 & 5.6 present change detection of different land cover maps. A confusion matrix method was used to map the land cover changes for the two-window periods 1990-2006 and 2006-2017. The results for the change confusion matrix of the LU/LC (Table 5.4 and 5.5) shows an increase in the cultivated land by 60.85%, grassland increased by 23.2% and there was no increase in built up area. Also, the results revealed decrease in the forest (16.2%) and the woodland (13.5%). The Figure 5.3 also depict the number of hectares occupied by the LU/LC for the two-window periods. Its revealed that cultivated land has changed significantly in both study period which resulted in formation of wetlands (water bodies) as compared to year 1990-2006 there were no wetlands.

Table 5.4: Land use/land cover - confusion matrix method

LULC (1990 - 2006)	Forest	Woodland	Bushland	Grassland	Wetland	Cultivated la
Forest	**4347**	1753	2829	1173	25	13
Woodland	736	**17995**	6981	1424	5	75
Bushland	1640	8352	**23990**	4197	4	166
Grassland	207	701	3105	**4175**	0	21
Wetland	12	38	34	3	**0**	
Cultivated land	1526	6473	9282	1529	19	**196**
Builtup area	2	4	8	2	0	
Total	8470	35317	46229	12502	53	473

Table 5.5: Land use/land cover - confusion matrix method

LULC (2006 - 2017)	Forest	Woodland	Bushland	Grassland	Wetland	Cult
Forest	3642	388	1590	1166	22	
Woodland	1097	15560	8357	433	40	
Bushland	2119	2455	21047	3203	34	
Grassland	480	634	2943	3189	17	
Wetland	1	0	23	20	2	
Cultivated land	501	5359	8551	1198	10	
Builtup area	31	57	147	16	0	
Total	7871	24453	42657	9224	125	

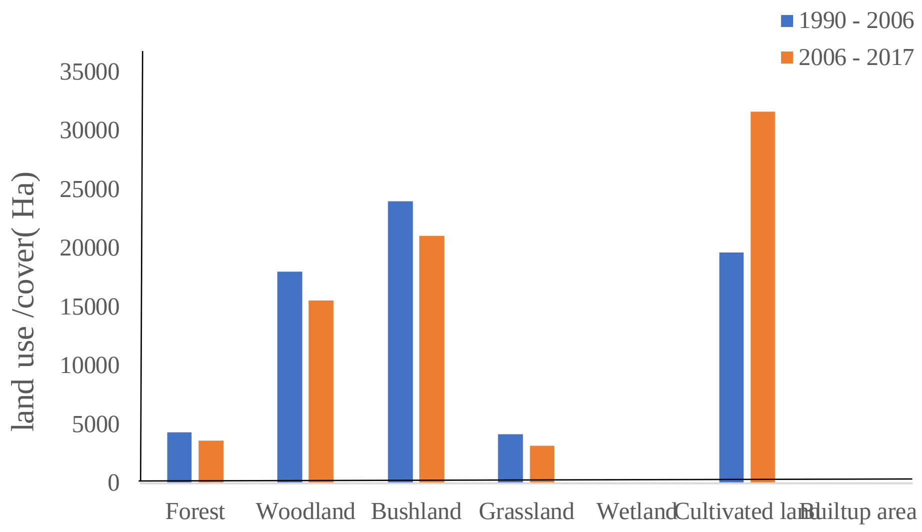

Figure 5.3: Comparison between land use and land cover changes for 1990-2006 and 2006-2017

5.4.4 Change detection accuracy

Results of supervised classification of ETM and satellite imagery were evaluated for the study area. Overall classification accuracy and Kappa Coefficient were computed to provide measures of the accuracy of the classification. The producer's and user's accuracy were calculated to assess error patterns of the respective classification.

Table 5.6 shows the result of supervised classification of ETM data for the year 1990, 2006 and 2017. The Kappa Coefficient took a value of 0.9, 0.95 and 0.99 and overall accuracy was found to increase as 91.98%, 95.92% and 99.31% for the respective years 1990, 2006 and 2017. The forest and cultivate land showed a sensible user's and producer's accuracy, The producer's accuracy was relatively low for grassland (73.64) in the year 1990 and confusion may be result from the presence of low height forest stands in the forest as well as in the class boundaries. Built up sample data appeared to be well defined with producer's accuracy of 100% and also with a user's accuracy of 100%.

Table 5.6: Accuracy classification of ETM data for the years 1990, 2006 and 2017

LULC	1990		2006		
	Producer accuracy (%)	User accuracy (%)	Producer accuracy (%)	User accuracy (%)	Pro accurac
Forest	90.17	95.05	100	100	9
Woodland	95.87	96.55	96.67	92.95	
Bushland	93.74	87.49	86.38	96.79	9
Grassland	73.64	93.11	98.24	98.82	9
Wetland	96.88	100	100	100	
Cultivated land	95.69	89.83	100	88.05	
Built up area	91.67	100	100	100	
Overall accuracy (%)		**91.98**		**95.92**	
Kappa statistic		**0.9**		**0.95**	

5.4.5 Model Sensitivity analysis

SWAT CUP 2012 was used for sensitive analysis. Table 5.8 present the list of the parameters and their ranking with fitted values for the flow measurements at the 1KA11 Igawa maji gauge station. The curve number which indicates the runoff response of a catchment was found to be the most sensitive parameter followed by base flow alpha, groundwater delay and threshold depth of water in the shallow aquifer required for return flow (Table 5.7). The curve number and the base flow alpha are related to ground water, runoff and soil process and thus influence the stream flow in the watershed. The ALPHA_BF is a direct index of ground water flow response to changes in recharges. The Mbarali River sub catchment is geological soils dominate with chromic Cambisols, dystric Nitosoils, dystric Regosols and Eutric Planosolsl that contributes to the ground water recharge.

Table 5.7: List of parameters and their ranking with fitted values for monthly flow

Parameters		Min_value	Ma
Name	**Description**		
R__CN2.mgt	SCS runoff curve number (%)	-0.300	0.3
V__ALPHA_BF.gw	Base flow alpha factor (days)	0.000	1.0
V__GW_DELAY.gw	Ground water delay (days)	30.000	45
V__GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow (mm)	0.000	20

5.4.6 SWAT model Calibration and Validation results

The SWAT model was run for a period 20 years from 1990 to 2010, with the first 5year being used for warming up the model. Calibration was performed for 10 years from 1990 to 2000. The Table 5.8 shows comparison between the simulated and measured flows during the calibration and validation period. It shows that there is a good agreement between the measured and simulated average monthly flows with Nash-Sutcliffe simulation efficiency (NSE) of 0.74, Percentage Base (PBIA) 1.5 and coefficient of determination (R^2) of 0.76 during calibration and Nash-Sutcliffe simulation efficiency (NSE) of 0.74, Percentage Base (PBIA) 1.5 and coefficient of determination (R2) during validation. The observed mean monthly streamflow for the calibration period (1990 – 2000) at Igawa Maji station was 11.01 m^3/s while the simulated was 10.5 m^3/s. The difference was not significant for the validation period (2001 – 2016) which show that the observed mean monthly stream flow was 11.74 m^3/s and simulated mean monthly flow was 11.56 m^3/s. 95 Predictive Probability Uncertainty (PPU) plots derived from running SUFI-2 within the SWAT CUP for 100 simulations are presented in Figure 5.4 and Figure 5.4, both are at monthly time step.

Table 5.8: Comparison of simulated and observed monthly flow for calibration and validation phases

Period	**Average monthly flow (m^3/s)**		**R^2**	**NSE**	PBIA
	Simulated	**Observed**			
Calibration(1990 – 2000)	10.5	11.01	0.72	0.70	4.6
Validation (2001 – 2016)	11.56	11.74	0.76	0.74	1.5

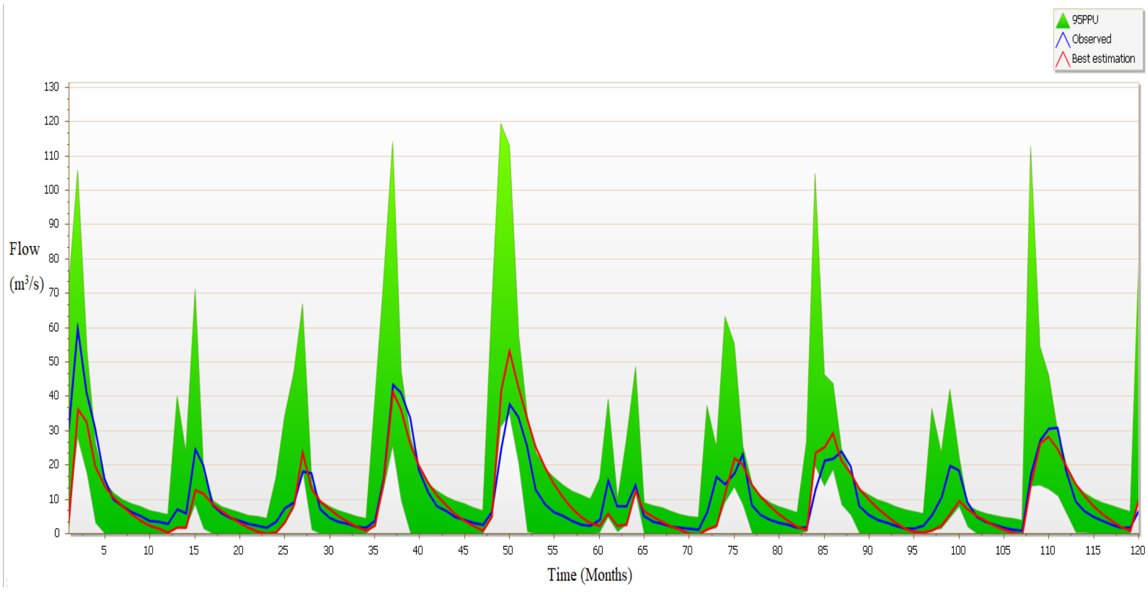

Figure 5.4: 95% prediction uncertainty calibration hydrograph at Igawa station

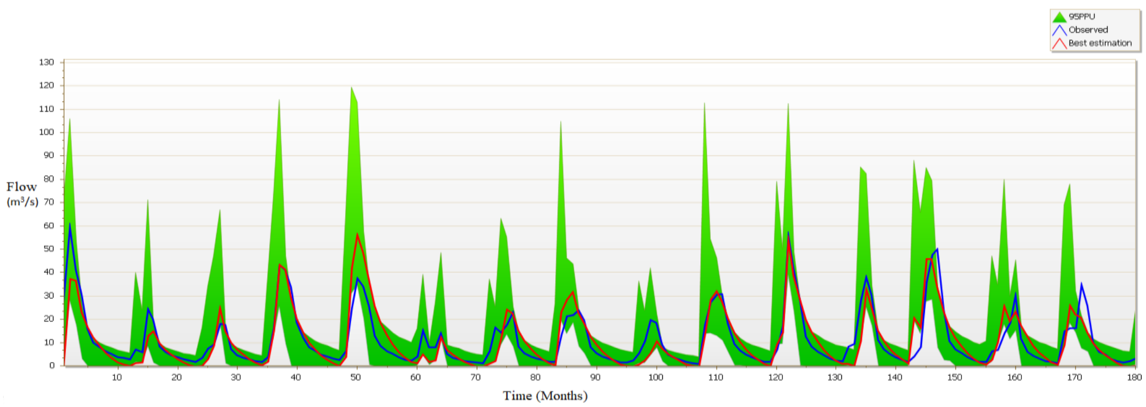

Figure 5.5: 95% prediction uncertainty validation hydrograph at Igawa station

Table 5.8 shows the results of the model performance that are adequately satisfactory during the calibration and validation periods. This indicates that the model captures well the stream flows generated from the watershed. Therefore, the model results can be used to assess the impacts of land use and land cover changes on stream flows.

5.4.7 Assessment of land effects of use and land cover change on stream flow

The main aim of this study was to assess the impact of land use and land cover changes on stream flows of the Mbarali River sub-catchment. The assessment was done in terms of the impact of land use and land cover changes on the seasonal stream flow and variations on the major components of stream flow including water balance components during the period 1990, 2006 and 2017. Land use and land cover has a great influence on the rainfall-runoff process.

Table 5.9 present the mean monthly flows for the seasonal cycle. The model was calibrated and validated using three land use and land cover maps for the periods of 1990, 2006 and 2017, SWAT was run using the three land cover maps (1990, 2006 and 2017 maps) for the period of 1990 to 20017 and other remaining variable were kept the same for both simulations to quantify the variability of stream flow due to the modification of land use and land cover. This technique presented the flows for both land use and land cover forms. Then, the results were compared and the discharge change during the seasonal cycles ie the wettest months of stream flows taken as Jan, Feb, March, April while the driest stream flows are well-thought-out in the months of Jun, July, Aug, and September. The means of these flows were used for estimating the effect of land use and land cover change on the stream flow as shown in Table 5.9. The mean monthly stream flow for wet months had increased from 27.68 m^3/s to 28.09 m^3/s while the dry season flow decreased from $0.24 m^3/s$ to 0.20 m^3/s between 1990 and 2017 due to the land use and land cover changes. Table 5.9 shows the mean monthly wet and dry month’s stream flow for 1990, 2006 and 2017 land use and land cover maps.

Table 5.9: Mean monthly wet and dry month's stream flow and their variability

Mean monthly flow (m^3/s)					
Land use/cover map of 1990		**Land use/cover map of 2006**		**Land use/cover map of 2017**	
Wet months (Jan, Feb, March, April)	Dry months (Jun, July, Aug, sept)	Wet months (Jan, Feb, March, April)	Dry months (Jun, July, Aug, sept)	Wet months (Jan, Feb, March, April)	Dry months (Jun, July, Aug, sept)
27.68	0.24	27.82	0.21	28.09	0.20

Table 5.10 present the water balance components as simulated using the land use and land cover map for the respective three-land use land cover scenarios. The impacts of different land-use land cover scenarios on the water balance components were analyzed at the catchment scale. The results indicate a positive change in three water balance components(surface runoff, soil water content and water yield) and negative change in the other three water balance components (ground water contribution , percolation in water shed and actual evaporation in watershed) land cover map from the year 1990- 2017 as result of increase in surface runoff by 4.14 mm in the year 2006 and 5.29 mm in 2017 while the total water yield has shown to decrease by 0.07 mm in the year 2006 and decrease by 0.93 mm in the year 2017. The increase and decrease in both surface runoff and water yield associated with changes in land use between 2006 and 2017 of an increase in built-up areas (urban areas) by 17.88% and an increase in cultivated land by 5.84%. The increase is due to the fact that built-up areas feature has high portion of impervious surfaces which hamper or sturdily decrease water percolation and groundwater contribution to streamflow and enable an increase in surface runoff.

This finding is in an agreement with the study done by Kashaigili (2008) on Impacts of land-use and land-cover changes on flow regimes of the Usangu wetland and the Great Ruaha River. In that study, it was observed that, change in land use and land cover within the catchment causes an increase in runoff, decrease in base flow, increase in sediment deposit on the river bank and decrease of the width of the river channel.

Similarly, Table 5.10 show that the decrease in evapotranspiration and groundwater contribution to stream flows are associated with the increasing trend in built-up areas for the entire Mbarali River sub-catchments. It is revealed that for the study area, there is an increase in built-up area of 0.31% between 1990 and 2006 and further increase of 0.02% between 2006 and 2017. This corresponds well with a declining trend of groundwater contribution to streamflow of 3.88 mm between 1990 and 2006 and 4.02mm between 2006 and 2017, which lead to a decrease in actual evapotranspiration. The increase in surface runoff (Table 5.10) in the Mbarali River sub-catchment could be attributed to an increasing portion of built-up areas, which corresponds with a decreasing trend of percolation within the sub-catchment. This is physically sound due to the hydrological effect of impermeable surfaces on runoff and percolation.

Increase in agricultural activities is associated with transformation on the land use and increase in water abstraction for irrigation purposes. This can be explained by the crops that demand soil moisture for their growth. Crops need less water than forests; therefore, the rainfall satisfies the soil moisture deficit in agricultural lands more quickly than in forests there by generating more surface runoff where the area under agricultural land is extensive. And this causes variation in soil moisture and groundwater storage. The expansion of land for agricultural activities also results in the reduction of water infiltrating in to the ground. Therefore, discharge during dry months (which mostly comes from base flow) decreases, whereas the discharge during the wet months increases. These results demonstrate that the land use and land cover change have a significant effect on infiltration rates, on the runoff production and on the water retention capacity of the soil, these results are also supported by studied done by Kashaigili and Majaliwa 2013 and Balthazar *et al.*, 2014. The present study has, shown that the flow characteristics within Mbarali river sub catchment have changed, with increase in surface flow and reduction of base flow.

Table 5.10: Impacts on water balance components under different land use /cover scenarios: note that, figures in brackets are percentage change

YEAR	SURQ (mm)	GWQ (mm)	PERCQ (mm)	ET (mm)	SW (mm)	WYLD (mm)
1990	104.63	61.41	91.79	293.78	377.13	178.97
2006	108.77(4.0)	57.53(-6.3)	88.25(-3.9)	292.98(-0.3)	378.34(0.3)	178.9(0.0)
2017	114.06(9.0)	53.51(-12.9)	83.95(-8.5)	290.67(-1.1)	383.93(1.8)	179.83(0.5)

SURQ: Surface runoff contribution to stream flow from HRU (mm)

GWQ: Ground water contribution to stream flow in watershed on day, month, year (mm)

PERCQ: Percolation in watershed (mm)

ET: Actual Evapo-transpiration in watershed (mm)

SW: Soil water content (mm)

WYLD: Water yield (mm)

4.5 Conclusions and Recommendation

In this study, satellite data and GIS were integrated with a hydrological model to assess the impacts of land use and land cover changes on the hydrology of the Mbarali River Sub-catchment, Upper Great Ruaha sub basin Tanzania. Remote sensing and QGIS were used to map different land cover classes and to analyses spatial-temporal land cover appearance. These techniques were applied to assess the land cover change effects on the hydrology of the River sub catchment. The impacts of the land cover change on hydrology was further analyzed using the hydrological model, SWAT and kappa statistics. The land use and land cover changes for the three-window period 1990, 2006, 2017 were identified suing TM and OLI_TIRS satellite images, respectively. The land use and land cover maps for the year 1990, 2006 and 2017 were produced and the accuracy assessments of the three maps were checked using the confusion Matrix. Based on the results, the following conclusions are drawn: From the land use land cover analysis, it revealed that, there is a sbstantial change in land cover classes for the three-window period 1990, 2006 and 2017.

The cultivated land area substantially increased from 25.69 % in 1990 to 31.53% in 2006 and 43.57% in 2017 compared to other land classes. The extension of cultivated land and built up area has an effect on the sustenance of forest land. As such, the forest land which constituted 7.54 % of the total area in 1990 was reduced to 5.51 % in 2006 and 5.23% in 2017. This could be the result of an increase in population which has triggered need for land. As a result of scarcity of cultivated land being a major problem for farmers in the study area.

Model calibration and validation have shown that the SWAT model simulated the flow reasonable. Model performance during both the calibration and validation phases for the Mbarali River sub-catchment was acceptable with Nash-Sutcliffe coefficient (ENS) values of 0.70 and 0.72 and coefficient of determination (R^2) values of 0.74 and 0.76 for the calibration and validation respectively. The curve number was found to be the most sensitive parameter followed by base flow alpha, ground water delay and threshold depth of water in the shallow aquifer required for return flow.

The simulation results indicate that during the wet season, the mean monthly flow for 2006 land cover was increased to 27.82 m^3/s relative to that of 1990 land cover period while the mean monthly flow decreased to 0.21 m3/s during the dry season. With regards to water balance components, it was revealed that surface runoff increased by 3.96% in the 2006 and 9.01% in the year 2017, while the ground water contribution to stream flow decreased by 6.3% and 12.86% in 2006 and 2017 respectively. Similarly, the total water yield increased by 0.5% in 2017with no change in 2006.On the other hand both the actual evapotranspiration and percolation below the root zone commonly known as groundwater recharge (PERC) which could be an inflow further downstream of the sub-catchment have been shown to decrease.

Within the Upper Great Ruaha sub basin of the Rufiji basin, further studies are recommended to investigate different catchment management options, that will conserve the water resource base whilst upgrading the socio-economic status of the population. Hence, various development scenarios be investigated and the best alternative effected for the Upper Great Ruah sub basin. A proposed management approach should be planned to conserve the natural vegetation. This is suggested to improve the supply of water for the whole mbarali River sub river catchment during both dry and wet periods.

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CHAPTER SIX

6.0 CONCLUSIONS AND RECOMMENDATION

6.1 Conclusions

The following conclusions can be drawn from this study:

i. It was found that the CORDEX RCMs and the ensemble average reproduced well the annual and inter-annual cycles of rainfall over Mbarali River sub-catchment. The ensemble average reproduces better the magnitude and the trends of rainfall compared with the individual models.

ii. The mean annual precipitation, annual minimum and maximum temperature for the Mbarali river sub-catchment are likely to increase in the future. However, the SWAT model predicted that stream flow, ground water recharge, total water yield, evapotranspiration will increase in the future suggesting that the whole of Mbarali River sub-catchment will be drier in the future.

iii. The average annual runoff in Mbarali River subcatchment increased by 3.9% in the year 2006 and 9.01% in 2017. The increased runoff was attributed to farming practices where during land preparation much of the vegetation was cleared, hence decreasing canopy interception and litter surface water storage, allowing water to drain off. Poor farming practices like cultivation on slopes or hilly areas are also reported to increase runoff.

6.2 Recommendations

The following are recommendations from this study:

i. The study recommends the use integrated of remote sensing data, bias corrected regional climate models and hydrological model for impact studies on other river catchments, that help in understanding uncertainties in modeling aspects of water resources, climate change and land use land cover.

ii. In the future, the research recommends to predict land use and land cover changes scenario in terms of magnitude and direction, based on past trend in a hydrological unit for minimizing uncertainties and necessary for designing adaptations strategies that will enhance dynamics of the future stream flow.

iii. In assessing the impact of climate change on water resources for Mbarali river sub- catchment of Rufiji Basin, it was assumed that all agricultural management practices were constant. Research is needed to see how the impact of climate change will affect the stream flows of other river catchment under different agricultural management practices.

iv. Furthermore, it is recommended that in preparing integrated water resources management (IWRM) plans, adaptation plans, policy and decision -making processes at all basin levels various stakeholders should consider applying Ensemble of CORDEX RCMs rather than individual models for climate change impact assessment.

v. Policy and decision-making processes should take into account catchment management options when addressing sub-catchment related issues that will help to conserve the water resource base while upgrading the socio-economic status of the population.