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DEPARTMENT OF CIVIL AND ENVIRONMENTAL ENGINEERING

QUANTITATIVE ANALYSIS OF CONTRIBUTIONS OF HUMAN ACTIVITIES AND CLIMATIC VARIABILITY TO STREAMFLOW VARIATION IN RIVER RWIZI CATCHMENT

BY

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DECLARATION

I, **NYESIGIRE RESTY**, hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree of the university or other institute of higher learning, except where due acknowledgement has been made in the text and reference list.

Signed: ….……..**..**

Date: …….…….

APPROVAL

The undersigned confirm that they have read and hereby recommend for submission to Kyambogo University a dissertation entitled "Quantitative assessment of contributions of human activities and climatic variability to streamflow variation in River Rwizi catchment," in fulfilment of the requirements for the award of Master of Science in Water and Sanitation Engineering Degree of Kyambogo University.

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Date: …….……

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In a special way, I want to thank the Almighty God for bringing me this far and granting me the blessing of knowledge and wisdom for the success of this project. It was God from day one! To God be the Glory now and forever!

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May the almighty God bless you all!

DEDICATION

This dissertation is dedicated to my children Desire, Cranmer, Mellissa, Liz and loving husband Kenneth. Your support was colossal. Thank you all for being there for me! God bless you Lots!

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LIST OF ACRONYMS

AWBM	Australian Water Balance Model
CFRs	Central Forest Reserves
CMPs	Catchment Management Plans
CN	Curve Number
DEM	Digital Elevation Model
DWRM	Directorate of Water Resources Management
EE	Earth Explorer
ETM	Enhanced Thematic Mapper
FAO	Food and Agriculture Organisation
GIS	Geographic Information Systems
GoU	Government of Uganda
GR4J	Genie Rural a 4 parametres Journalier
HBV	Hydologiska Byrans Vattenavdelning
HEC-HMS	Hydrologic Engineering Centre-Hydrologic Modelling System
HRUs	Hydrological Response Units
IDLGDP	Isingiro District Local Government Development Plan
LFRs	Local Forest Reserves
LH-OAT	Latin Hypercube-One-factor-At-a-Time
LULC	Landuse and landcover

MWE	Ministry of Water and Environment
NCEP	National Centres f or Environmental Prediction
NDP	National Development Plan
NPA	National Planning Authority
NSE	Nash-Sutcliffe Efficiency
NWSC	National Water and Sewerage Corporation
OPM	Office of the Prime Minister
RGS	River Gauging Station
SCS	Soil Conservation Service
SDG	Sustainable Development Goals
SRTM	Shuttle Radar Topography Mission
SUFI2	Sequential Uncertainty Fitting algorithm
SWAT	Soil and Water Assessment Tool
SWAT-CUP	SWAT - Calibration and Uncertainty Programmes
UBOS	Uganda Bureau of Statistics
UNEP	United Nations Environment Programme
USGS	United States Geological Surveys
WATSAN	Water and Sanitation

ABSTRACT

Climate variability and human activities have an impact on hydrological processes. Human activities influence rainfall runoff generation process while climate variability does not only affect runoff volume but also low and high flows, among others. River Rwizi in Uganda drains over 12 districts in the Western region has been reported on several occasions to be undergoing decline in its flows with subsequent drying of wetlands within the catchment. This study applied SWAT, a semi-distributed hydrological model to analyse response of runoff across River Rwizi catchment to human activities under changing landuse and landcover (LULC) types. Climate variability was assumed to be the residual of the attribution of results of the flow changes to LULC changes. Changes in LULC types were assessed using information based LULC maps for 1997, 2000, 2008, 2014 and 2019. SWAT was calibrated and validated using monthly data over the periods 2002–2008 and 2009–2013 respectively. Model performance was assessed in terms of Nash-Sutcliffe Efficiency (NSE). From 1997 to 2019, changes in LULC types were characterised by increase in cropland, forest and settlement by 26.09%, 0.87% and 0.35%, respectively. However, grassland and wetland decreased by 25.81% and 1.62%, respectively. NSE values for SWAT over calibration and validation periods were 0.50 and 0.71 respectively. These values indicate the acceptability of model results for assessing impacts of human activities and climate variability on River Rwizi flow temporal variation. River Rwizi flows of each month exhibited an increasing trend from 2002 to 2013. Contributions of human activities and climate variability to runoff variation were about 23.5% and 76.5%, respectively. Impacts of human activities on the stream flow were on average found to be larger during dry (14.7%) than wet (5.8%) season. Massive water abstractions especially during dry season and encroachment of wetlands make River Rwizi catchment hydrologically drier than it would be under minimal influence of human activities. These results indicate that climate variability is far much more influential in shaping River Rwizi flow change than human activities. Therefore, human activities which ensure sustainability of River Rwizi such as preservation of wetland and promotion of tree planting should be undertaken over the catchment.

Key words: Human activities, Climate variability, Streamflow, Rwizi Catchment, SWAT

CHAPTER ONE: INTRODUCTION

1.1 Background

The hydrological cycle of a river basin comprises complex processes which may be susceptible to climate variability, human activities and physical characteristics of the catchment (Chen *et al.,* 2013; Zhao *et al.*, 2014). Globally, whereas climate variability is believed to have led to significant changing patterns of precipitation, human activities have influenced temporal and spatial distribution of water resources (Wang *et al.*, 2015; Huang *et al.*, 2016; Tian *et al.*, 2016; Pirnia *et al.*, 2019). It is known that climatic variables especially precipitation and evapotranspiration are the main drivers of streamflow of a catchment. However, human-induced changes in landuse and landcover (LULC) types also affect the hydrological cycle (Zhao *et al.*, 2014). For instance, it was explained by Onyutha & Willems (2018) that anthropogenic influences such as deforestation, overgrazing and significant expansion of urbanized areas over a given catchment can lead to changes in the catchment behaviour by (i) affecting the amount of infiltration into the soil, (ii) altering the amount and velocity of the overland flow, and (iii) modifying the rate and amount of evaporation. Therefore, analysis of the influence of climate variability and human activities on streamflow temporal variation is relevant for water resources management (Zuo *et al.*, 2016).

In the River Nile basin, the extent to which climate variability and human factors impact on the water resources differs from one catchment to another (Onyutha, 2017a; Onyutha & Willems, 2018). Within the Lake Victoria Nile sub-basin in East Africa, one catchment the streamflow of which is deemed to be affected by both human activities and climate variability is that of River Rwizi.

The dwindling water resources of River Rwizi which extends over about 8000 km in length and used by communities in at least 12 districts of Uganda indicates possible scarcity in supply to meet domestic and commercial demands. This dwindling water resources of River Rwizi can be attributed to heavy degradation of the catchment as a result of human activities such as sand mining, brick making, industry and farming within the catchment (Nagawa *et al.,* 2018). These LULC changes have left River Rwizi in a vulnerable state causing streamflow changes and drying of the wetlands and its fringes (Atwongyeire, 2018; Nagawa *et al.*, 2018). Poor farming practices such as bush burning, deforestation and cultivation near the river banks tend to cause soil erosion which in turn leads to silting of the river bed. Deposition of eroded soil might have led to reduced river volume (Nagawa *et al.*, 2018). Additionally, the rapid urbanization, a condition that is leading to irresistible demand for the water resource seems to be putting an enormous strain on the river flow volume (Atwongyeire, 2018; Nagawa *et al.*, 2018). Industrial processes and other commercial activities that rely on the River Rwizi for their water needs are being frustrated. For example, Nile Breweries receives 10 % instead of 75% of the planned water needs. This is likely to discourage potential investors in the region thereby curtailing economic transformation and efforts to improve livelihoods of communities in the River Rwizi catchment (Masinde, 2019)

By the time of conducting this research, no study was found in literature on quantification of the extents to which climate variability and human influence affect the River Rwizi variation. It was deemed compelling to analyse, separate and quantify the effects of climate variability and human influence on the streamflow changes in the River Rwizi catchment.

1.2 Problem statement

The global demand for renewable resources has increased rapidly due to the growing population and economic development. Eventually, many regions in the world have experienced severe water stress (Miao *et al.*, 2011; Bao *et al.*, 2012; Zhao *et al.*, 2014; Tian *et al.*, 2016). Protection and restoration of water related ecosystems including wetlands, rivers, streams, aquifers and lakes is a global strategy aimed at contributing to environmental sustainability. This is in line with Goal number 6 of the Sustainable Development Goals (SDGs), (Ministry of Water and Environment (MWE), 2013).

The Uganda Vision 2040 conceptualizes strengthening fundamentals of the economy to harness the abundant opportunities around the country including water resources (Government of Uganda (GoU), 2015). Climate is characterized by variability a phenomenon (Uganda, 2013) which is being escalated due to anthropogenic activities in the catchments causing significant streamflow changes. According to the landuse policy, strategies to address the growing concern on climate variability were proposed but there is a growing outcry about the dwindling water resources of River Rwizi in Mbarara district (Ministry of Lands Housing and Urban Development (MLHUD) - Uganda, 2006). The water levels go too low hence affecting water supply by National Water and Sewerage Corporation (NWSC), production from different growing industrial and business enterprises (Ojok *et al.*, 2017; Atwongyeire, 2018; Nagawa *et al.*, 2018; Baraza, 2019) which rely on this water resource for their water needs.

Despite some interventions in River Rwizi catchment restoration, increased landuse due to rapid population growth and increased urbanization in the region (Uganda Bureau of Statistics (UBOS), 2014) continue to place an enormous strain on the

catchment. This river is a major source of livelihood for communities within the catchment for agricultural, commercial, industrial and domestic water demand. Unless serious interventions and regulations of water flow are put in place, River Rwizi flow will go way too low thereby increasing famine and poverty (Atwongyeire, 2018).

1.3 Objectives of the Study

1.3.1 Main objective

To quantify the contributions of human activities and climatic variability to streamflow variation in River Rwizi catchment.

1.3.2 Specific objectives

1) To characterise landuse changes in River Rwizi catchment.
2) To simulate River Rwizi flow changes using a semi-distributed model.
3) To quantify the amount of changes in River Rwizi flow attributable to the impacts of human activities.
4) To quantify the effects of climate variability on River Rwizi flow.

1.4 Research questions

1) For *Specific Objective 1*: How did landuse change in the River Rwizi catchment?
2) For *Specific Objective 2*: Are there any statistical changes in River Rwizi flow?
3) For *Specific Objective 3*: To what extent is the River Rwizi flow changes influenced by human activities?
4) *For Specific Objective 4*: To what extent is River Rwizi flow changes driven by climate variability?

1.5 Research justification

Water resources play a pivotal role towards achievement of the Sustainable Development Goals (SDGs) (United Nations Sustainable Development Goals UNSDGs, 2015). Water resources support economic growth and socio-economic transformation of a nation hence the need to increase investment and formulating sustainable policies for water resources management (National Planning Authority (NPA), 2015, 2020; Mugagga & Nabaasa, 2016). The growing industries such as Nile breweries Ltd, Coca Cola Ltd, Akandi herbal drink factory and large commercial institutions such as Lake View hotel among others rely on this water resource for their water needs. These factories and institutions provide employment to communities, provide market for foodstuffs from local farmers and local business enterprises hence the need for sustainable utilisation of this water resource. According to the National Development Plan (NDP III) for Uganda, the environment and natural resources are under threat from both natural and manmade drivers of climate change and variability. Rapid urbanisation, increased industrialisation and rapid population growth have put an enormous strain on the fragile ecosystems (NPA, 2015, 2020).

Several studies conducted on River Rwizi have not been able to quantify and separate the impacts of human influence and climate variability on the flow change (Atwongyeire, 2018; Nagawa *et al.*, 2018) yet this is critical to facilitate informed decision making for the sustainability of the water resources in this catchment. In line with Government of Uganda's commitment to restore the ecosystems (NPA, 2015, 2020), it is important to know the key drivers affecting mainly the hydrology of the River Rwizi catchment. This is because it is a source of livelihood for communities in

at least 12 districts in Western Uganda. Thereafter, make recommendations to stakeholders and policy makers to support sustainable utilisation of the River Rwizi. Lack of scientific research-based information regarding extents to which River Rwizi flow changes are influenced by human activities and climate variability prompted the need to undertake this study.

1.6 Significance of the Study

This study is relevant to yield information to support management decision making and planning, formulation of catchment management plans (CMPs), and guide in formulation and enforcement of improved policy and regulatory frameworks for sustainable water resource utilization in this catchment. If the amount of human activities influence River Rwizi flow is known, it can be possible to plan and put in place measures to control anthropogenic factors across the catchment. Further information on climate variability can enable planning of predictive adaptation.

1.7 Project scope

1.7.1 Content scope

This study made use of precipitation, flow and temperature time series. Spatial information was in form of soil data and LULC maps. This was limited to application of SWAT to simulate rainfall-runoff under changing LULC types.

1.7.2 Geographical scope

This study was limited to the River Rwizi catchment located in the South-Western Uganda. It has River Rwizi which flows through more than 12 districts in the Western region including Mbarara, Kiruhura, Lyantonde, Sembabule, Lwengo, Kyotera, Rakai

Isingiro, Rwampara, Ibanda, Buhweju, Bushenyi, Mitooma and Ntungamo (Ministry of Water and Environment (MWE), 2017). The catchment lies between longitudes of 30.21°E to 30.68°E and latitudes of 0.24°S to 0.87°S. The River Rwizi originates from the hills found in the Western Uganda, has a series of tributaries joining it flowing in the southern direction. The river flows eastwards for about 57 km until the gauge at Mbarara water works before it enters River Kagera. It finally discharges its waters into Lake Victoria. The gauged catchment area (Mbarara) under this study is 2100 km^2 encompassing portions of six districts including Bushenyi, Buhweju, Sheema, Ntungamo, Mbarara and Rwampara in Western Uganda. The distance from West to East and North to South is approximately 53 km and 68 km respectively, with its waters flowing over a 120 km. River Rwizi is the source of water for livelihood to both people and animals covering the Mbarara – Masaka dry corridor. In the south, it takes approximately part of Isingiro and three quarters of Rwampara districts towards Tanzania (Ministry of Water and Environment (MWE) - Directorate of Water Resources Management (DWRM), 2017). On the western side, the catchment covers Ibanda, Buhweju, Bushenyi, Mitooma and Ntungamo districts that mark the origin of River Rwizi that forms part of the prominent Nile basin.

1.7.3 Time scope

This study was conducted from February 2020 to June 2021.

1.8 Conceptual framework

The main dependent variable is rainfall-runoff. Independent variables are categorised under human activities and climate variability. However, when intervening variables

are initiated, the impact of independent variables on the rainfall-runoff, can be controlled.

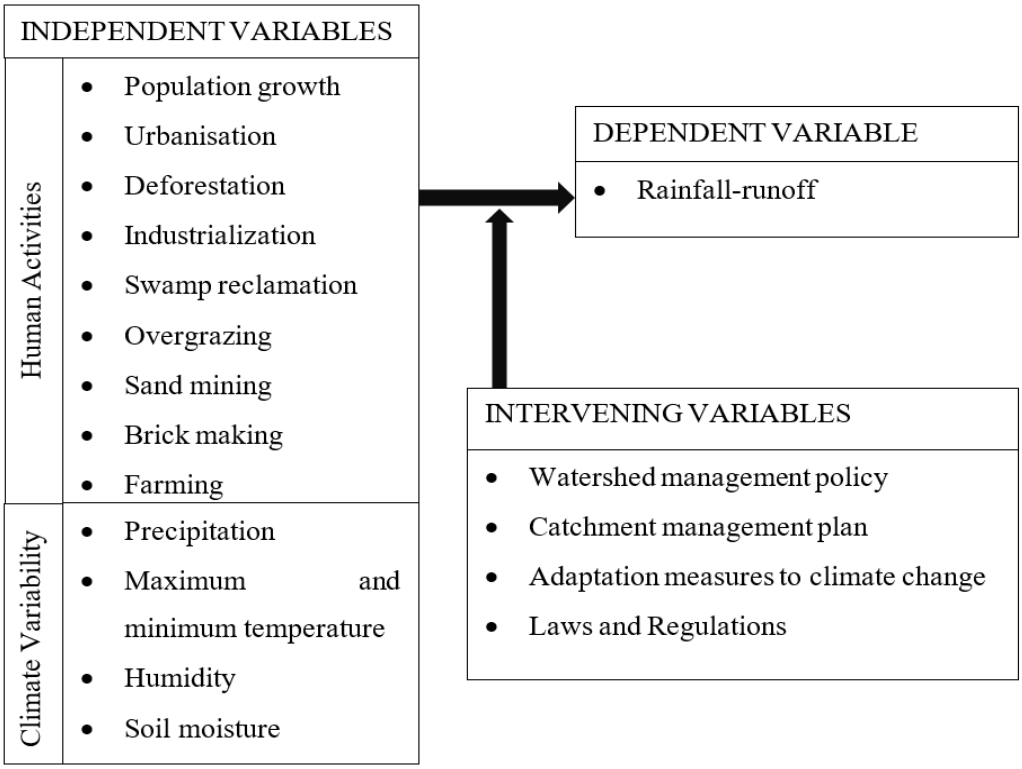

Figure 1-1: Conceptual framework

1.9 Chapter summary

The River Rwizi catchment is currently characterized by significant spatial-temporal changes in its hydrology, which could be attributed to both natural and human influences. Several studies have indicated that human activities and climate variability are the main drivers affecting streamflow. It is important to quantify the extent to which human activities and climate variability impact on the hydrology in this catchment. The results would guide decision making in planning, management and sustainable utilization of the water resources. In summary, this chapter stated the problem and put forward specific objectives to ensure a number of research questions.

CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

Water resources in Uganda comprises ground and surface water. Surface water is that component of the hydrological cycle found in streams, rivers, lakes and wetlands (MWE, 2013). Streamflow statistics such as spatial variations may be explained by the differences in rainfall in both space and time across the country. Runoff coefficients decrease with increasing catchment size. In other words, smaller catchments tend to be in steeper topography with higher storm runoff and they may have almost no wetlands (MWE, 2013).

2.2 Past relevant studies on streamflow attribution

2.2.1 Regions outside East Africa

Several studies have suggested that contribution of human activities as compared to climate variability was the key driver to annual streamflow changes. For instance, human activities contributed 59.11% while 40.89% was attributable to climate variability (Wang *et al.,* 2016). In the Hun - Tai river basin in North East China, climate variability accounted for 43% while human activities were responsible for 57% of the streamflow changes (Zhang *et al.*, 2011). In the Haraz river basin in Nothern Iran, 65.22% of the streamflow changes were influenced by human activities while 34.78% was attributable to climatic variability using a SWAT model (Pirnia *et al.*, 2019). In the Eastern Baltic sea region, Tamm *et al.* (2018) established a strong linear correlation between forest cover change and annual river flow change using a SWAT model. A 3% increase in river peak-flow extremes was attributed to a 10% growth in urban areas for the Grote Nete and Zuunbeek catchments in Belgium (De Niel *et al.*,

2020). Contrary, for streamflow changes in the period from 2000 - 2008 for Chaohe watershed in Northern China, climate variability was responsible for 51% while 49% was attributed to landuse changes (Wang *et al.,* 2013). In the Upper Haihe River Basin, China, 87.15% of the runoff variations was attributed to climate variability while landuse change was responsible for 12.85 % (Samie *et al.,* 2019). As evidenced by several scholars, streamflow changes were more influenced by LULC changes followed by climatic variability (Trang *et al.*, 2017; Guo *et al.,* 2018). On the contrary, for streamflow changes in the period from 2000 - 2008 for Chaohe watershed in Northern China, climate variability was responsible for 51% while 49% was attributed to landuse changes (Wang *et al.,* 2013). In the Upper Haihe River Basin, China, 87.15% of the runoff variations was attributed to climate variability while landuse change was responsible for 12.85 % (Shang *et al.,* 2019). In the analysis of attribution of long-term water level changes in the Taihu Plain in China from 1954 to 2014 to detect an abrupt change, results indicated that climate variables are the dominant driver for annual and seasonal water level changes. However, the contribution of human activities to water level changes in the 2000s was higher than that in the 1990s, indicating that human activities, including the rapid urbanization, are playing an important role in recent years (Wang *et al.,* 2019).

2.2.2 Studies on various catchments in East Africa

2.2.2.1 Outside Uganda

In Nyangores catchment in Kenya, landuse changes accounted for 97.5% of the streamflow change which is attributed to deforestation while climate variability contributed only 2.5% of the change of streamflow (Mwangi *et al.,* 2016). Karamage

et al. (2017) assessed rainfall-runoff response to LULC change in Rwanda. The results showed that Rwanda has experienced a significant conversion of natural forest and grassland to cropland and built-up areas. The increase in the annual runoff depth at a rate of >3.8 mm/year during the past 27 years was a result of severe deforestation (ranging from 62% to 85%) and cropland expansion (ranging from 123% to 293%). LULC changes in the Koga catchment, North Western Ethiopia were attributed to population pressure and landuse policies (Yeshaneh *et al.,* 2013). Guzha *et al*. (2018) evaluated the impacts of LULC changes with focus on discharge, surface runoff and low flows catchments in the East African region. It was noted that a heterogeneity in the changes in hydrological fluxes with LULC exits which calls for the attention Water Resources Managers. Major changes in the hydrological components in the Upper Blue Nile Basin, Ethiopia were mainly driven by growth of cultivation area and reduction in woodland coverage (Woldesenbet *et al.*, 2017). In the Andassa watershed, Ethiopia, LULC changes brought about an increase in wet season flow and a decrease in dry season flow (Gashaw *et al.*, 2018). In the Kilombero catchment in Tanzania, the LULC changes were dominated by conversion of grassland and forestland to cropland particularly rice farming. The reduction in forest land has significant impact on the hydrological processes (Thonfeld *et al.,* 2020).

2.2.2.2 Studies within Uganda

There are a number of studies which quantified the amount of LULC types changes in some catchments across Uganda. Tuyahabwe (2019) assessed the impact of different LULC on the flow of River Mpanga. Luwa *et al.* (2020) focussed on how impacts of LULC responded to different driving forces. In the Murchison Bay Catchment of Lake

Victoria Basin, Kiggundu *et al.* (2018) assessed LULC changes and established that the major change was in built-up land from 20.58% to 49.59% between the years 1984 to 2015. In Kanungu district, Barasa *et al.* (2011) assessed the dynamics of LULC trends. He brought forward interesting findings such as post conflict effects like breakdown of civil laws, social ties and education levels as part of the drivers of LULC type changes. Kizza *et al.* (2017) assessed LULC change patterns in Lake Bunyonyi catchment, Western Uganda. Mugagga (2012) focussed on landuse changes on the slopes of Mount Elgon. In the semi-arid Lokere and Lokok Catchments, North Eastern Uganda, built-up areas increased at a rate of 14.7% between 1984 to 2013 much of which could have been attributed to the disarmament exercise between 2001-2002 under the Office of the Prime Minister (OPM) (Osaliya *et al.*, 2019). In the Malaba River Catchment, Eastern Uganda, streamflow changes were mainly attributed to increased agricultural landuse and high flood frequency re-occurrences (Barasa *et al.*, 2013). Anaba *et al.* (2017) assessed the effects of landuse changes in the Murchison Bay Catchment. The findings indicated an increase in Surface runoff in the upland catchment by 26.7% from the year 1995 to 2003 which is attributed to drastic LULC changes in the catchment.

To note therefore, key drivers affecting LULC changes operate in a combined manner making trade-offs and these consequently influence hydrological processes. For example in the urban catchments, forest cover and grassland were traded off for urbanisation, which was attributed to intense population pressure in the urban centres (Barasa *et al.*, 2011; Kiggundu *et al.*, 2018; Kilama *et al.*, 2020; UBOS, 2014).

2.2.3 Key findings and knowledge gaps

Model performances are quite exclusive. No model is superior under all conditions hence the need to choose from an ensemble of models, a model that is a good representative of the catchment under different spatial and temporal scales to enhance the credibility of the model output. That notwithstanding, the use of lumped models such as Curve Number (CN) method to quantify total runoff relatively limits consideration of catchment physiographical factors. Semi distributed models are able to capture the spatial distribution of the input variables better compared to lumped models (Guzha *et al.*, 2018). Therefore, this study applied the SWAT (semi-distributed model) to quantify the contributions of human activities and climatic variability to streamflow variation in River Rwizi catchment.

Quite a lot of studies have been on several catchments within and outside Uganda including Baraza (2019) on River Rwizi. The study assessed impacts of climate change on hydrological extremes of Rwizi catchment applying conceptual models. It never exhausted the impacts of human activities on streamflow variation in the catchment using semi-distributed models like SWAT. Therefore, this study covered the loophole through application of SWAT model to quantify the impacts of both climatic variability and human activities on Rwizi streamflow.

2.3 Landuse and Landcover types

LULC change within a watershed is recognized as an important factor affecting hydrological processes and water resources. Modelling the hydrological effects of land-use change is important not only for after-the-fact analyses, but also for understanding and predicting the potential hydrological consequences of existing land-

use practices. Records from Uganda's landcover (MWE, 2013) indicate that major changes have occurred to the landcover in the country over 50 years pointing out a great shift in the farming area from 3% to 34% of the total land surface.

Human activities have led to severe land degradation. Land degradation is defined as the reduction of biological productivity that in turn affects ecosystems integrity, including the integrity of ecosystems (Stavi & Lal, 2015). The loss of natural vegetation to built-up areas and farmed ecosystems is also being aggravated by rapid urbanization, poor enforcement of the regulations put in place hence the increase in poor farming practices such as bush burning, deforestation, swamp reclamation, overgrazing (Zhang *et al.*, 2011; Wang, 2014; Pirnia *et al.*, 2019). This has caused increase in soil erosion leading to silting of the river in the lowlands (MWE, 2013). Rapid population growth has led to encroachment of these fragile ecosystems by settling, farming, sand mining and setting up industries near the river banks which are supposed to be gazetted as flood plains or buffer zones (Atwongyeire, 2018; Nagawa *et al.*, 2018).

2.4 Water demand

Whereas surface water is abundant for about 42,000 km² (18%) in Uganda, its demand is increasing rapidly for irrigation, industrialization, commercial and domestic use. Increasing population and the need for food have led to increased demand for water resources. According to MWE (2013), water demand in Uganda was primarily projected to have increased by over 400%. This was because of the irrigation potential that was being promoted as a mitigation, adaptation and resilience to effects of climate

change. This is aimed at enabling farmers avoid over reliance on rainfall which has become very unreliable.

2.5 Climate variability

Climate variability refers to a variation on all temporal and spatial scales beyond individual weather events with key independent variables such as precipitation, temperature, humidity and soil moisture. These influence the dependent variables such as rainfall runoff volumes, low and high flows in a catchment, among others. Therefore, the phenomenon is responsible for extreme weather patterns such as flooding and prolonged droughts (Chang *et al.*, 2015; Musau *et al.*, 2015; Huang *et al.*, 2016). Evidence from communities which entirely rely on the River Rwizi for both domestic and commercial water needs indicates that climate variability has increased with the growing uncertainty of water availability in the river (Uganda, 2013; Atwongyeire, 2018).

Many researchers (Bates *et al.*, 2008; Jung *et al.*, 2012; Hannaford & Buys, 2012; Sonali & Kumar, 2013; Parajuli *et al.*, 2016; Zhang *et al.*, 2011, 2017) have established that climate variability is likely to enhance the severity and frequency of extreme weather events such as severe droughts and floods.

However, in case of intervening variables of climate variability such as watershed management policy, catchment management plan, adaptation measures to climate change and laws and regulations, the results of this phenomena can be minimised.

2.6 Water balance

Water availability is based on Internal Renewable Water Resources (IRWR), which represents the annual flow of rivers and recharge of aquifers which are generated from the precipitation of the catchment area. (Zhao *et al.*, 2014). Therefore, it is important to quantify changes in the water balance operating across multiple spatial and temporal scales in a catchment (Mwebaze, 2018). Under hydrologic routines, water balance in a basin aquifer system encompasses several components that include mountain front recharge, surface infiltration and streamflow infiltration, inter-basin flow, and underflow (Shi *et al.*, 2011). Streamflow infiltration is usually the major component and mountain front recharge is the second largest recharge component. Increased evapotranspiration could imply potential effects on the soil water balance leading to occurrence of droughts which consequently bring water stresses (Mubialiwo *et al.*, 2020). According to Sutcliffe (2004), for any given catchment, a long-term hydrological water balance is computed according to the principle of conservation of mass using the relation:

$$P = Q + E + \Delta S \qquad 2.1$$

Where P is Precipitation (mm), Q is runoff depth (mm), ΔS is the water storage change in catchment (mm) and E is the actual evapotranspiration (mm).

In hydrology, rainfall-runoff models are widely used in water resources assessment, regional and global water balance calculation, impacts of climate change and landuse change assessment and streamflow simulation in ungauged catchments (Zeng *et al.*, 2016). Hydrological models range from very simple water balance models to sophisticated watershed models, such as the Soil Water Assessment Tool (SWAT)

model (El-Khoury *et al.*, 2015). However, these models require meteorological data and spatial-temporal watershed characteristics for accurate evaluation, modelling and prediction of the dynamic water balance of a watershed (Tuyahabwe, 2019). Changes in the water balance operate across multiple spatial and temporal scales and the effect of LULC changes can be difficult to isolate from background climate variability (Panday *et al.*, 2015).

2.6.1 Rainfall

Rains in the southern areas of Uganda mostly exhibit bimodal patterns with long rains occurring from March to May and the short rains from October to December. The "short rains" are strongly affected by interactions between the Indian and Pacific oceans (MWE, 2013) and the heavy rainfall during this season being associated with El Niño events. Rainfall variability among other atmospheric variables is the most critical for determining the changes in catchment hydrology attributable to spatial-temporal influence in a particular catchment (Onyutha, 2017b). The spatial variation in rainfall may be influenced by topographical features which may modify the distribution of the rainfall (Déry *et al.*, 2011; Thiery *et al.*, 2015). Rainfall variability drivers can be used to predict future weather events to guide farmers in selection of crops to plant in a particular season (Onyutha, 2017).

2.7 Combined influences of human activities and climate variability on hydrology

Tian *et al.* (2016) and Pirnia *et al.* (2019) indicated that runoff variation has a strong relationship with the impacts of climate variability and human activities and is given equation below;

$$\Delta Q^{tot} = \Delta Q^{hum} + \Delta Q^{clim} \quad 2.2$$

Where; ΔQ^{tot} is the total variation in runoff, ΔQ^{hum} and ΔQ^{clim} are the runoff changes due to human activities and climate variability respectively as in Figure 2-1.

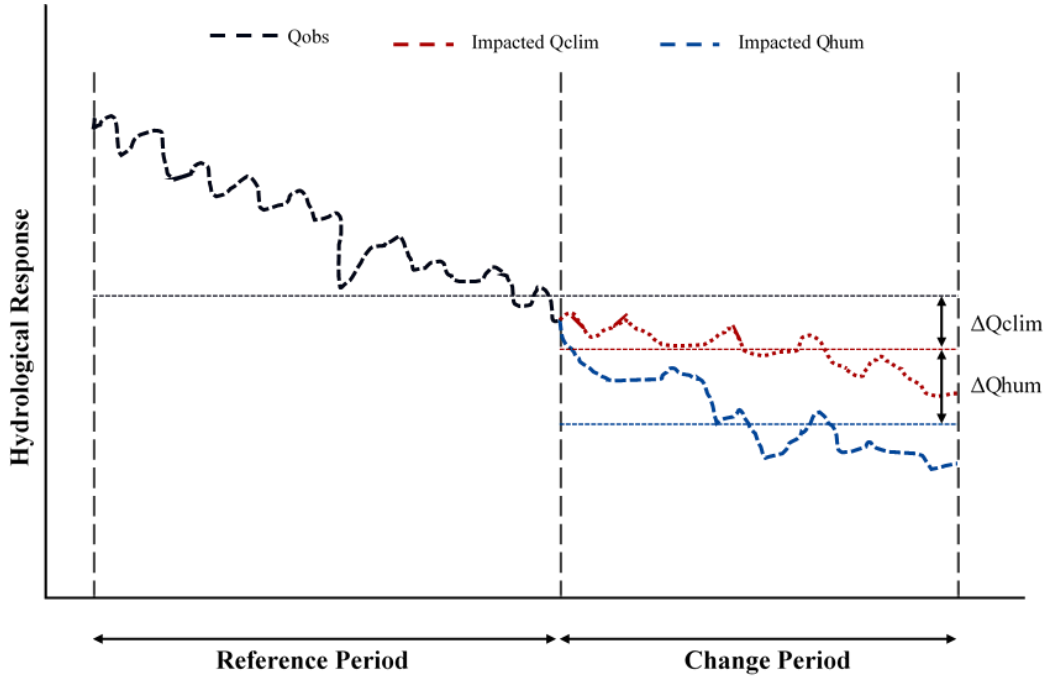

Figure 2-1: Schematic diagram separating impacts of climate and human factors on streamflow changes

Source: (Sutcliffe, 2004; Pirnia *et al.*, 2019)

The methodology schematized in Figure 2-1 can suitably be applied when there is a step jump in mean of the river flow. To apply the said methodology, the LULC types before and after the step jump are analysed for possible attribution of the change. In another method, there can be a number of LULC maps used to simulate river flow over the same period. By keeping the parameters of the distributed model constant while only changing the LULC maps, the differences in the simulations are attributed to the changes in the LULC types.

Another common method which is used to analyse impacts of human activities on hydrology is through the use of hydrological sensitivity elasticity-based approach in which the river flow sensitivities to precipitation and PET are estimated in terms of catchment dryness index and plant available water coefficient. Details and applications of this method can be found in (Koster and Suarez, 1999; Zhang, Dawes and Walker, 2001; Milly and Dunne, 2002; Sun *et al.*, 2005)

2.8 Selection of hydrological model for simulating rainfall-runoff under changing landuse

Hydrological models (both lumped conceptual and physically-based) have become increasingly important tools for quantifying hydrological response to influence of climatic variability and human activities since they are able to give accurate outcomes that are representative of the hydrological processes in the basin (Wu *et al.*, 2017)

2.8.1 Lumped conceptual models

Lumped models generally require fewer inputs compared to distributed models. These models are vital for reservoir management, flood and drought forecasting. However, they have limited capability to predict changes in streamflow attributed to LULC changes (Kunnath-Poovakka & Eldho, 2019). Examples of lumped Conceptual models include; the Australian Water Balance Model (AWBM) (Boughton, 2004), Hydologiska Byrans Vattenavdelning (HBV) model (Bergström, 1976, 2006) NedborAfstromnings Model (NAM) model (Nielsen & Hansen, 2018) and Hydrological Model focussing on Sub-flows' Variation (HMSV) (Onyutha, 2019).

Advantages of Lumped conceptual models include;

- They have few parameters
- They can be easily calibrated
- They take little time to run

Disadvantages of Lumped models include;

- Results are obtained at the end of the catchment, not at every location
- Sometimes the parameters may not possess physical meaning

2.8.2 Distributed models

Unlike lumped models, distributed models require more inputs to evaluate hydrological processes for a given catchment. These can be fully distributed and semi-distributed models. Examples of distributed models include; MIKE Systém Hydrologique Européen (SHE) model (Abbott *et al.*, 1986)**,** Coupled outing and Excess Storage (CREST) (Wang *et al.*, 2011) , Institute of Hydrology Distributed Model (IHDM) (Beven *et al.,* 1987)and Soil and Water Assessment Tool (SWAT) model (Arnold *et al.*, 1998).

Advantages of distributed models include;

- They can give results at all locations

- They take several inputs such as soil, landuse, DEM and Climatic variables. In doing so, they represent catchment hydrology more realistically than lumped conceptual models

Disadvantages of distributed models;

- They have too many parameters to calibrate
- They take a lot of time to run due to several physical processes considered in the model

2.8.2.1 SWAT model

a) Application of SWAT

The Soil and Water Assessment Tool (SWAT) model is a river basin scale model specifically used in predicting the effect of land management practices, over long periods of time, on variables such as water flows, sediment and agricultural chemical yields in watersheds with varying soils, landuse and management conditions over long periods of time (Abbaspour, 2011, 2015; 2017). SWAT, being a physically based, semi-distributed model it operates at daily, sub-daily, monthly and yearly time steps for watersheds of various sizes (Arnold *et al.*, 2012, 2013; Srinivasan, 2012; Leta *et al.*, 2018). The model uses the following water balance equation in the catchment;

$$SW_t = SW_o + \sum_{t=1}^{t}(R_{day} + Q_{surf} - ET_i - W_{seepi} - Q_{gw}) \quad 2.3$$

Where SW_t - is the final soil water content (mm), SW_0 - is the initial soil water content on day i (mm), t is the time (days), R_{day} is the precipitation on day i (mm), Q_{surf} - is the surface runoff on day i (mm), ET_i - is the evapotranspiration on day i (mm), W_{seepi} - is

the amount of water (mm) entering the vadose zone from the soil profile on day i (soil interflow), and Q_{gw} - is the amount of return flow on day i (mm) (Devia *et al.,* 2015) .

b) Data required

It uses readily available inputs, is computationally efficient and enables users to study long-term impacts (Neitsch *et al.,* 2005; Arnold *et al.,* 2012). The model addresses watershed's spatial heterogeneity and connectivity by dividing the watershed into several sub-basins. As such, geospatial data such as DEM, LULC maps and soil maps and temporal data on precipitation, temperature, solar radiation, relative humidity and wind speed are required to develop the model (Abbaspour *et al.,* 2017; Leta *et al.,* 2018)

c) Model build up

The SWAT model application can be divided into five steps: (1) data preparation, (2) watershed delineation and sub-basin discretization, (3) HRU definition, (4) parameter sensitivity analysis, (5) calibration, validation and evaluation (uncertainty) analysis (Arnold *et al.,* 2012; Nasiri *et al.,* 2020).

d) Watershed delineation

Topography of the basin influences the rate of movement and direction of flow over the land surface and is therefore necessary to derive physical properties of the basin (Ha *et al.,* 2017). Sub-basins are the first spatial division of SWAT, which are generated from a DEM data. The accuracy of delineated sub-basins and stream networks by SWAT is highly dependent on DEM resolution (Lin *et al.,* 2013; Goulden *et al.,* 2014; Leong *et al.,* 2015; Leta *et al.,* 2018). Ideally, finer DEM resolution would provide a larger elevation range, accurate sub-basin and streamflow network

representation, smaller sub-basin areas, and realistic model parameterization. Such characteristics would in turn produce accurate model outputs and improve model performance especially for spatially heterogeneous watersheds (Goulden *et al.*, 2014; Tan *et al.*, 2015; Leta *et al.*, 2018).

e) Hydrologic response units

Hydrologic response units (HRUs) are portions of a sub-basin possessing unique landuse, management or soil attributes and are incorporated into the SWAT model to account for the complexity of the landscape within the sub-basin (Neitsch *et al.*, 2011; Leta *et al.*, 2018).

f) Sensitivity Analysis

Sensitivity analysis is done to estimate the rate of change in model outputs in relation to change in the model inputs. It helps to determine which parameters are important for accurate results (Abbaspour, Vaghefi and Srinivasan, 2017). Sensitivity analysis refers to the identification of the most important influence factor in the model. Sensitivity analysis is important from two points of view: First, parameters represent processes, and sensitivity analysis provides information on the most important processes in the study region. Second, sensitivity analysis helps to decrease the number of parameters in the calibration procedure by eliminating the parameters identified as not sensitive. Two general types of sensitivity analysis are usually performed. These are one-at-a-time (OAT) or local sensitivity analysis, and all-at-a-time (AAT) or global sensitivity analysis (Atkinson *et al.*, 2010; Abbaspour *et al.*, 2017).

g) Calibration

Model calibration is the process of changing the model parameters to reduce mismatch between the modelled and observed data. Calibration is a crucial step in creating a hydrologic model that returns results both accurate and realistic in simulating the physical processes occurring in the watershed (Abbaspour *et al.*, 2017). During calibration process, estimation of model values of parameters which cannot be accessed directly from the field data is done. Calibration can be achieved manually or in an automatic manner. Automatic calibration strategies for SWAT can be in the form of tools such as Soil Water Assessment Tool-Calibration and Uncertainty Programme (SWAT CUP). This study adopted auto calibration tool SWAT CUP since it links Sequential Uncertainty Fitting (SUFI2) algorithm to SWAT (Atkinson *et al.*, 2010).

h) Validation

Model validation is the process of determining the degree to which a model or simulation is a correct representation of the observed behaviour from the perspective of the intended uses. It is vital for improvement of the predictive capacity of the model (Barasa *et al.*, 2013; Abbaspour *et al.*, 2017). Validation is used to build confidence in the calibrated parameters. For this purpose, the calibrated parameter ranges are applied to an independent measured dataset, without further changes. The modeller is required to do one iteration with the same number of simulations as in the last calibration iteration. Similar to calibration, validation results are also quantified by the *p*-factor, *r*-factor, and the objective function value (Atkinson *et al.*, 2010; Abbaspour, 2011).

The SWAT model was the ideal choice for use in this study because of major four (4) reasons;

i) It is a physically based model that requires specific information about weather, soil properties, topography, vegetation and land management practices. These inputs aid to simulate the physical processes associated with the catchment hydrology. This enables it to model ungauged watersheds and more importantly, quantify the impact of alternative input data such as changes in landuse, land management practices and climate on water quality and quantity;

ii) Secondly, it uses readily available data. As more inputs can be used to simulate more specialized processes, is still able to operate on minimum data, which is a benefit especially when working in areas with insufficient or unreliable data;

iii) SWAT model is computationally efficient, able to run simulations of very large basins or management practices without consuming large amounts of time and expenses and;

iv) It is a continuous time or a long-term yield model able to simulate long-term impacts of landuse, land management practices and build-up of pollutants (Neitsch *et al.,* 2005). These qualities enable SWAT model to quantify of long-term impacts of LULC changes, variations in rainfall and air temperature on the hydrology of a river basin.

2.9 Chapter summary

LULC change within a watershed is recognized as an important factor affecting hydrological processes and water resources. There are a number of studies that quantified the amount of LULC types change in some catchments across Uganda clearly pointing out the key drivers to LULC changes. Modelling the hydrological effects of LULC change is important not only for after-the-fact analyses, but also for

understanding and predicting the potential hydrological consequences of existing land-use practices. However, most studies in Uganda, have not taken into account, the quantification and recognition of climatic variability impact on hydrological processes and water resources of a catchment using hydrological models. Therefore, because hydrological models have become increasingly important tools for quantifying hydrological response to changes in climate and human activities, SWAT was considered the ideal choice for use in this study.

CHAPTER THREE: METHODOLOGY

3.1 Background

This chapter presents both quantitative and qualitative methods employed for the various specific objectives of the study. This chapter contains description of data including various LULC maps, soil, weather and hydrological data. It also covers the methodology for generation of SWAT model input parameters using basic thematic layers, the procedures for calibration, validation and performance evaluation of the model. Finally, the chapter details steps used to separate contributions of human activities and climate variability on River Rwizi flow change.

3.2 Study Area

3.2.1 Location

The River Rwizi catchment is located in the South-Western Uganda and lies between longitudes of 30.21°E to 30.68°E and latitudes of 0.24°S to 0.87°S. The River Rwizi originates from the hills found in the Western Uganda, has a series of tributaries joining it flowing in the southern direction. It discharges its waters into Lake Victoria hence forming part of Nile Basin. The catchment is gauged at Mbarara covering an area of 2100 km² which encompasses seven (7) districts including Bushenyi, Buhweju, Sheema, Ntungamo, Mbarara, Rwampara and Isingiro in Western Uganda (Figure 3-1)

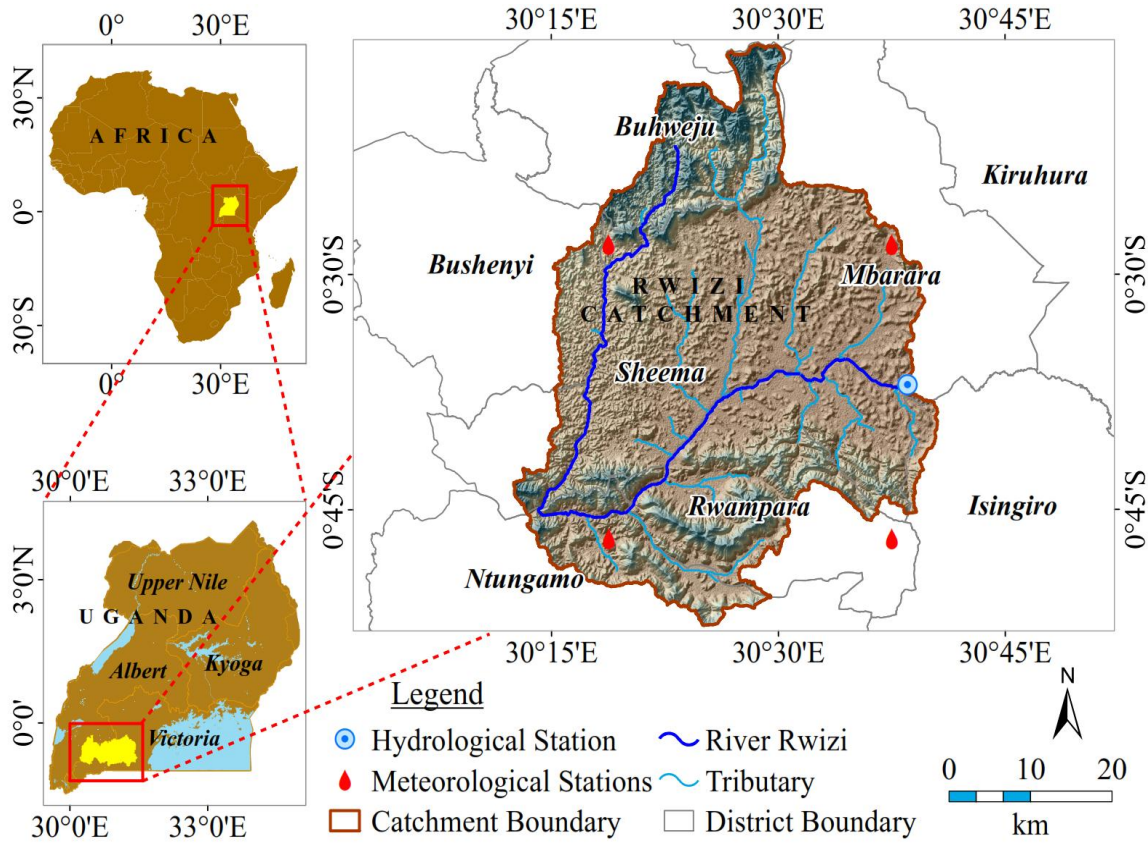

Figure 3-1: River Rwizi catchment areas

3.2.2 Topographic and geophysical features

Figure 3-2 shows the topography of Rwizi Catchment. The altitude varies from 1380 metres above sea level (m.a.s.l) at the outlet to 2171 m.a.s.l. in the northern and southern parts of the catchment. The average elevation is 1776 m.a.s.l. Rwizi catchment is partly flat and sloppy. Rwizi originates flowing southern direction then flows eastwards for about 57km until the gauge at Mbarara water works. The most elevated areas are in Buhweju and Rwampara districts where the altitude varies from 1800 m.a.s.l. to 2171 m.a.s.l. The extreme southern parts of the catchment are in areas of Mbarara where there is a gauging station.

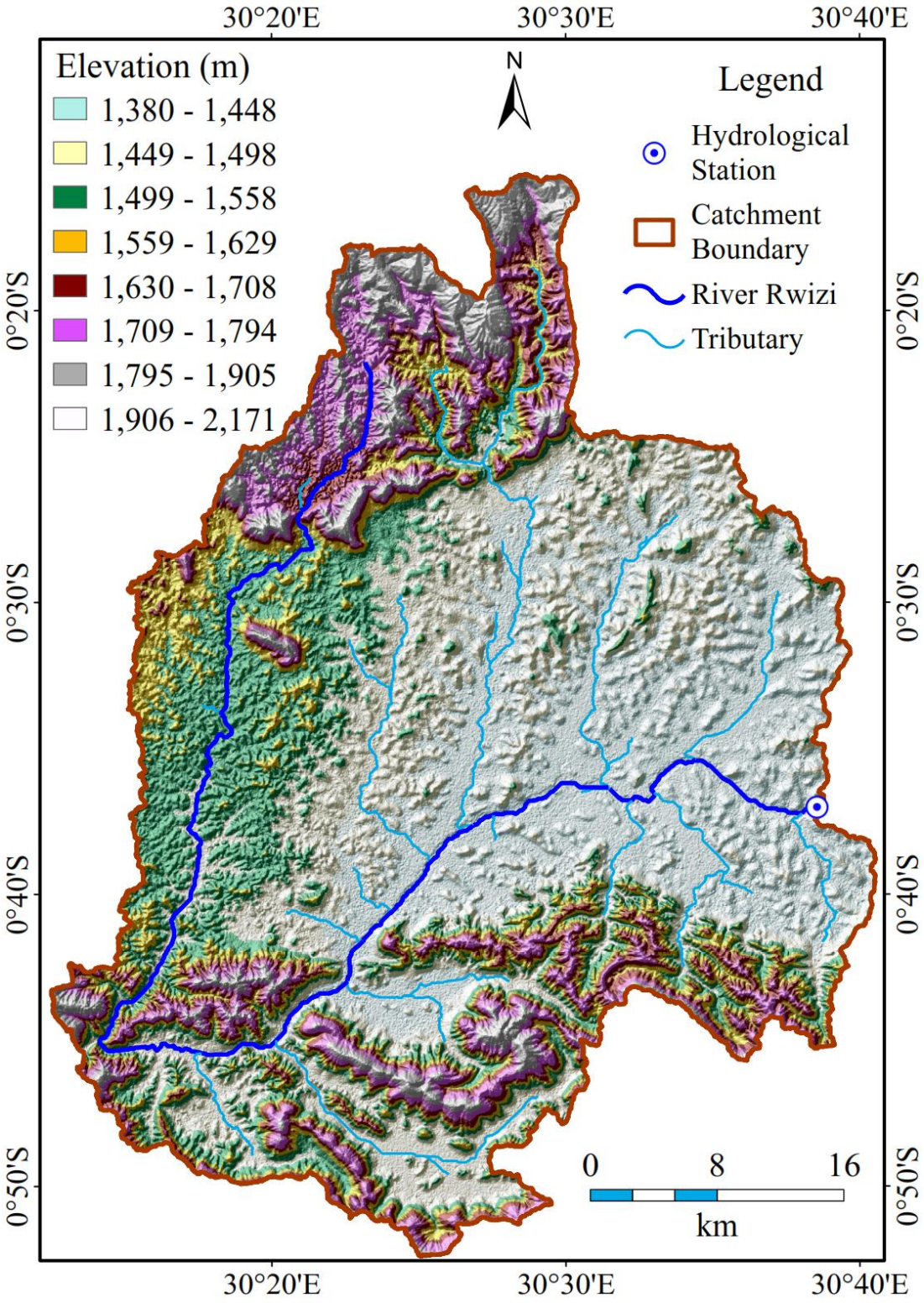

Figure 3-2: Topography of River Rwizi catchment

3.2.3 Landuse and vegetation cover

River Rwizi catchment area has various LULC types highly dominated by agricultural lands (both subsistence and commercial), grasslands due to national parks, forests (natural dense, moderate, sparse and planted forests), settlements (urban and rural setups), wetlands/swamps, and waterbodies (lakes and rivers). Most parts of the catchment are degraded by runoff, deforestation, overgrazing and poor agricultural practices. Based on LULC map 2019, the upper, central and lower reaches of the catchment area are covered by wetlands, which make up about 9.68% of the total land area. Forest covers 4.99%, open water 0.01%, grassland 27.77%, agriculture 56.08% and settlement 1.46%. According to MWE (2017), there are several human activities across River Rwizi catchment and at riverbanks including cattle rearing, brick making, agroforestry (mainly eucalyptus). The main landuses that contribute to sediment production are tillage erosion from the cultivated areas, pathway erosion from the banana groves and cattle tracks. In the study area, landuse changes are primarily determined and triggered by the population dynamics. However, the type of change depends on other factors including position in the landscape, fertility of the soil and economic trends. The catchment has environmental changes and thus provides an opportunity to evaluate its changes in flows (Ministry of Water and Environment (MWE) - Directorate of Water Resources Management (DWRM), 2017).

3.2.4 Climatology

Figure 3-3 shows the rainfall distribution of Rwizi Catchment based on observed data from 1954 to 2016 of six rainfall stations. Rainfall records show that River Rwizi catchment exhibits a bimodal pattern with two wet seasons that occur from March to

May and October to December. This pattern is consistent with the findings in the literature review under Section 2.6.1. Maximum rainfall is recorded during April and November, while the driest months are observed during June - August and January - February. In addition to annual precipitation, temperature is also another indicator of climatic fluctuations and trends. Annual mean rainfall is the mean of the daily temperature in each year. Minimum (maximum) monthly mean rainfall represents the month in which the mean of daily rainfall is minimum (maximum) within a given year.

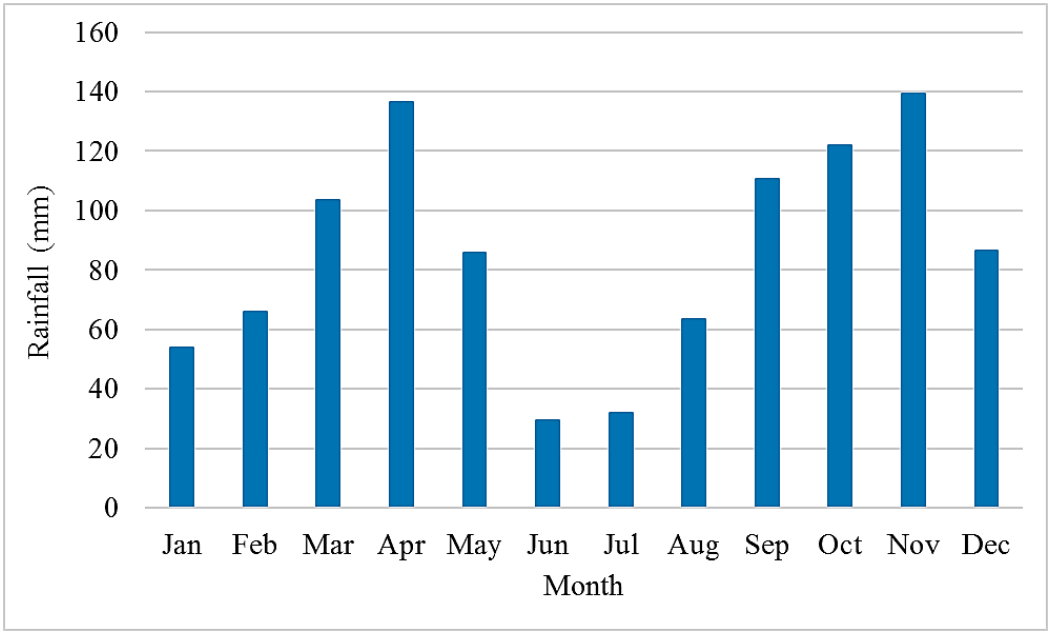

Figure 3-3: Mean monthly rainfall for River Rwizi catchment

3.3 Data collection and processing

To simulate rainfall-runoff using the ArcSWAT model, both spatial and non-spatial datasets were required. The spatial data included the Digital Elevation Model (DEM), LULC map and soil map. Weather data included precipitation, temperature, solar radiation, wind velocity and relative humidity. Observed streamflow data was used for

calibration and validation. The different types of data used were collected from various sources as shown in Table 3-1.

Table 3-1: List of variables used in the SWAT model and their sources

Data Type	Scale/resolution/ data period	Source (s)	Description
Topography data	30 × 30 m	United States Geological Surveys (USGS) - Earth Explorer (EE) website. Shuttle Radar Topography Mission (SRTM) (.tiff)	DEM map
Land-use information	Data between 1996 and 2020	Landsat Images	Classified LULC maps of 1997, 2000, 2008, 2014 and 2019 (.img).
Spatial soil information	Scale of 1:5,000,000	Food and Agriculture Organisation (FAO)	Soil map characterising soil types or classification and properties
Daily Streamflow (m^3/s) from River Rwizi hydrological station No. 81224	1997 - 2013	Ministry of Water & Environment (MWE) - Directorate of Water Resources Management (DWRM)	Observed data
Daily precipitation (mm/day) Daily minimum and maximum	1997 - 2013	Global Weather Data for SWAT https://globaleather.tamu.edu/	Reanalyses data Reanalyses data

Data Type	Scale/resolution/ data period	Source (s)	Description
temperature (°C)			
Solar radiation (MJ/m^2)			Reanalyses data
Relative humidity (fraction)			Reanalyses data
Daily wind speed (m/s)			Reanalyses data
Administrative boundary maps	2019	Uganda Bureau of Statistics (UBOS), 2019	Shape files(.shp)

3.3.1 Digital Elevation Module (DEM)

A DEM for south-western Uganda at a resolution of 1 arc second (30 m × 30 m) was retrieved from the United States Geological Surveys (USGS) website (https://earthexplorer.usgs.gov/) [Accessed 5th January, 2020]. This was processed in ArcGIS 10.5 environment to clip the area of interest (AOI) with help of current administrative boundary shapefiles of obtained from UBOS. The clipped topographical/terrain data (DEM) was used for; (i) automatic delineation of the catchment, (ii) defining the stream network, and (iii) establishing sub-basin parameters such as stream network, longest reaches, and drainage surfaces and slope (Nasiri, Ansari and Ziaei, 2020).

3.3.2 LULC types

LULC information was obtained from remotely sensed images retrieved from USGS Landsat ETM/TM satellites (https://earthexplorer.usgs.gov/) [Accessed 10th January, 2020] in Path 171 and Row 60 at a spatial resolution of 30 m. The images for the year 1997, 2000 and 2008 were for Landsat 7. However, LULC maps for year 2014 and 2019 were obtained from Landsat 8, which is partially cloud free. The images were classified into six landuse-cover types based on maximum likelihood supervised classification tool in ArcGIS 10.5. The area of interest was extracted with the help of Rwizi Catchment basin watershed boundary polygon using the ArcGIS Spatial Analyst tools. The LULC types included agricultural or cropland, settlement (built-up areas i.e. both urban and rural setups), forests (dense, moderate, sparse and planted), water (lakes and rivers), wetlands (swamps and papyrus) and grasslands. Landsat 7 satellite has high cloud cover content that partially hindered the proper identification of small and minor LULC classes in the catchment hence minimum errors in areas of coverage incurred. The 2019 LULC map clearer than others (based on Landsat 7). This could have been because Landsat 8 is the most recent and cloud free satellite.

3.3.3 Soil map

The soil map was obtained from Land and Water Resource, FAO soil database (FAO, 2009; IUSS Working Group WRB, 2015) at a scale of 1: 5,000,000. The dominant soil associations in the Rwizi catchment are Alisols and Arenics. The soil physical and chemical properties were based on texture, soil hydrologic groups, maximum rooting depth, fraction of porosity, moist bulk density, available water capacity, saturated hydraulic conductivity, organic carbon content, electrical conductivity, Universal Soil

Loss Equation (USLE) for soil erodibility, sand, silt and rock fragment contents. Details can be obtained via http://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/%0Ahttp://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/en/ [Accessed 23rd January 2020].

3.3.4 Climate data

The observed climate data including rainfall and temperature obtained from MWE had several missing values (gaps) for many years that could not allow successful model simulation. Eventually, reanalyses data were used for the hydrological modelling. Hydrological simulation with the SWAT model requires weather data consisting of precipitation, maximum and minimum temperature, relative humidity, solar radiation and wind speed. These daily datasets were obtained from the National Centres for Environmental Prediction (NCEP) (http://globalweather.tamu.edu/) for the period of 1997 to 2013 [Accessed 3rd February, 2020]. The weather datasets were downloaded from eight stations within the study area.

3.3.5 Streamflow (Hydro-meteorological) data

Daily streamflow time series for two hydrological stations (Table 3-2) were obtained from the Directorate of Water Resources Management (DWRM) under Uganda's MWE. The observed streamflow data were from 1997 to 2013. However, in this study, only data from the New hydrological station located in Rwebikoona, Mbarara Municipality along Mbarara – Ishaka road was used. Based on findings from MWE (2017), the old hydrological station measurements were highly disrupted by Kabale road NWSC plant water abstraction.

Table 3-2: River Rwizi River Gauging Station (RGS)

RGS Name	Coordinates	Position
New RGS No. 81224	0°36'56.17"S, 30°38'35.88"E	Before Mbarara – Kabale road (Along Mbarara – Ishaka road)
Old RGS No. 81224	0°37'7.73"S, 30°38'43.42"E	After Mbarara – Kabale road (NWSC Plant)

3.3.6 Data processing

Data processing was done in ArcGIS 10.5, which provides most spatial modelling tools. This was through an Arc SWAT 2012.10.2.19 plug-in interface used to simulate stream discharge from the hydrological model of the catchment. Soil and Water Assessment Tool - Calibration and Uncertainty Programmes (SWAT-CUP) 2012 was used to perform sensitivity analysis, automatically calibrate and validate rainfall-runoff. In addition, Google Earth pro was used to verify streams and LULC based on the year of data acquisition.

3.4 Impacts of climate variability and human influence on River Rwizi streamflow changes

3.4.1 Hydrological modelling

In this research, a semi-distributed hydrological model - SWAT (Abbaspour *et al.*, 2015) was employed for rainfall-runoff modelling. SWAT as a semi-distributed model was used because it takes into account more detailed processes in rainfall-runoff generation than conceptual models. In other words, SWAT allowed the use of spatial information such as LULC and soil maps as spatial inputs thereby giving possibility to assess effects of human activities on rainfall-runoff.

3.4.1.1 SWAT model

The study used SWAT 2012 version via the ArcSWAT interface for ArcGIS 10.5 to model rainfall-runoff. SWAT is developed and refined based on the water balance equation 2.3 in Section 2.8.2.1 which is the base of the hydrologic cycle simulation in SWAT *(*Neitsch *et al., 2005).* Figure 3-4 shows the procedure for setting up, calibration and valuation of SWAT model. The SWAT model application can be divided into five steps: (1) data preparation, (2) sub-basin discretization, (3) HRU definition, (4) parameter sensitivity analysis, (5) calibration and validation (6) uncertainty analysis (Winchell *et al.*, 2010; Nasiri *et al.*, 2020).

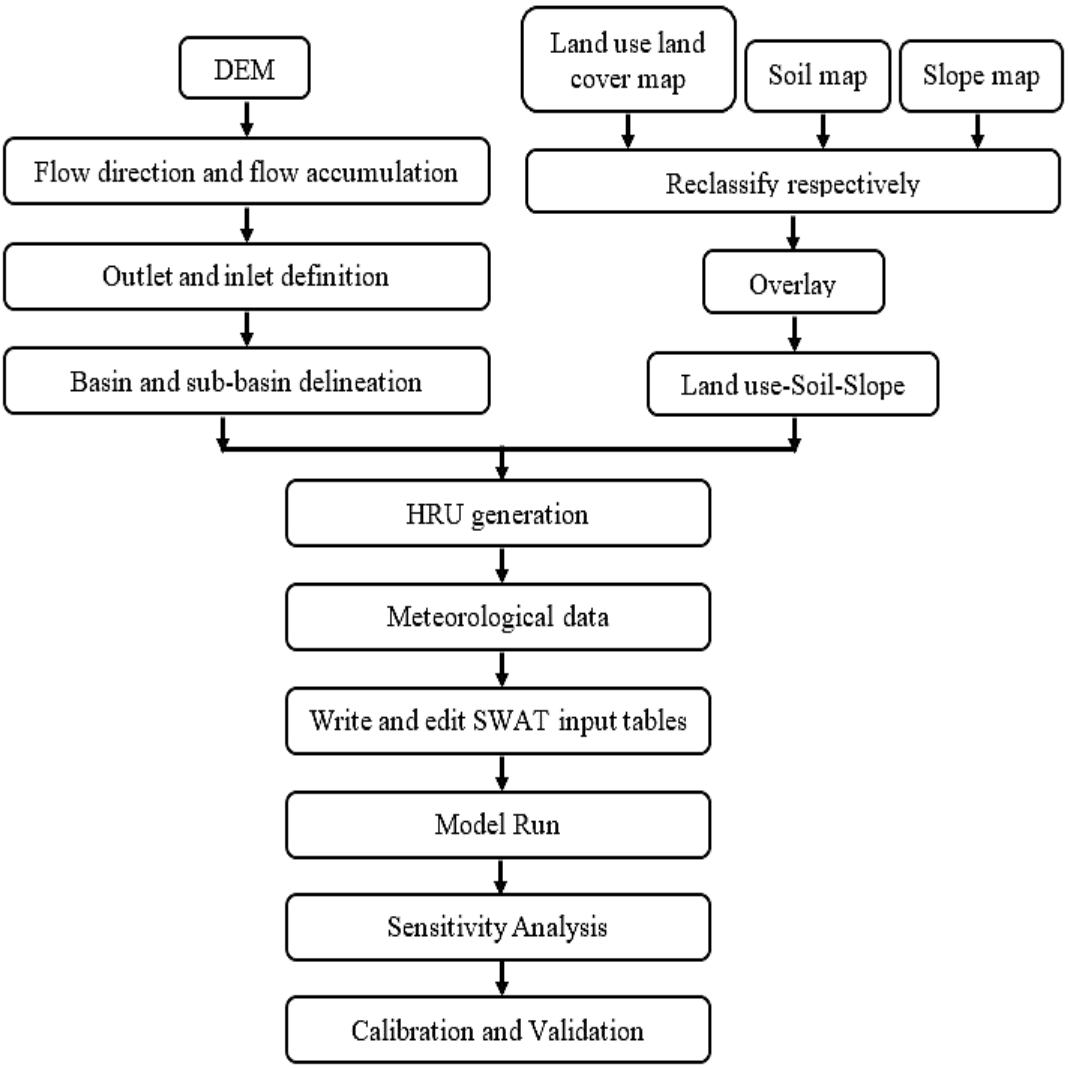

Figure 3-4: Model setup diagram for SWAT model

Source: (Winchell *et al.,* 2010; Nasiri *et al.,* 2020)

3.4.1.2 Watershed delineation and sub-basin discretization

The DEM of 30 m × 30 m resolution for the study area obtained from the Shuttle Radar Topography Mission (SRTM) was used for catchment delineation. It was also analysis of the land surface characteristics and drainage patterns through DEM setup, stream definition, outlet and inlet definition, watershed outlets selection and definition and calculation of sub basin parameters to get flow direction and accumulation.

3.4.1.3 Definition of Hydrologic Response Units (HRUs)

After delineation of watershed, the resulting sub-watersheds were divided into HRUs based on their combinations of landuse, soil and slope combinations under the landuse/soils/slope definition subsection. LULC data for 1997, 2000, 2008, 2014 and 2019 together with their respective look-up attribute tables were imported and used. Also, soil map was imported into the model. During HRU analysis, LULC was reclassified into six classes namely; FRST – Forest, AGRL – Cropland, WATR – Water, URBN – Settlement, WETL – Wetland and PAST – Pasture and Grasslands.

Soils were first grouped as Group A for Arenic qualifier (Swanton), Group B for Loamic qualifier (Benson), Group C for Siltic qualifier (Weider) and Group D for Clayic qualifier (Lyons) which are in ArcSWAT database. This was based on soil properties such as clay content, sand content, loam content and hydrological group.

Five slope classes in number were set each having the lower- and upper-class limit in percentage (%) namely; class 1 (0 – 5%), class 2 (5 – 10%), class 3 (10 – 20%), class 4 (20 – 50%) and class 5 (50 – 9999). The 0% was set as the threshold level for landuse, soil and slope.

SWAT automatically converts the landuse and soil data resolutions to the DEM resolution during watershed delineation and geospatial data overlying processes. To account for the variability of geospatial characteristics and hydrologic processes, sub-basins are further sub-divided into several hydrological response units (HRUs), with each characterized by a unique combination of landuse, soil type, and slope value within a sub-basin. Finally, overlaying landuse, soils and slope led to the definition and creation of multiple of HRUs for River Rwizi catchment.

3.4.1.4 Weather data definition

SWAT simulates hydrologic processes at land and routing phases. At the land phase, the model uses soil water balance approach and equations to independently estimate the water balance elements, such as precipitation, surface runoff, actual evapotranspiration, lateral flow, percolation, groundwater, and deep groundwater loss at the HRUs scale Neitsch *et al.,* 2011; Leta *et al.,* 2018). During the routing phase, the computed surface runoff, lateral flow, and groundwater flow components from different HRUs are summed up per sub-basin and routed to the main river reach. Neitsch *et al. (*2011) provides the detailed approaches for simulating the aforementioned processes are provided.

This study particularly used the Curve Number method of the modified Soil Conservation Service (SCS) (USDA - SCS, 1986) for surface runoff simulation, the Penman - Monteith method (Monteith, 1965) for monthly Potential Evapotranspiration (PET) estimation, and the variable storage routing method (Williams, 1969) for monthly streamflow routing. To facilitate the integration of geospatial and hydro-climate data, the model is interfaced with ArcGIS (Winchell *et al.*, 2010). SWAT uses either locally obtained regional observation/gauge stations or global weather downloaded climate data. In this study, a total of five different daily climate data files was used to simulate SWAT flow for a period of 17 years. These files contained data of the same starting and ending dates for the ease of SWAT simulation and were downloaded from SWAT website. They included the precipitation (pcp), temperature (tmp), relative humidity (rh), wind speed (wind) and solar radiation (solar) together with station geographical location coordinates.

The first 5 years (1997 – 2001) were used as a warm-up period to allow the processes simulated to reach a dynamic equilibrium and decrease the uncertainty of the initial conditions of the model. A longer warm-up period allows buckets in SWAT (reservoirs, wetlands, soil moisture and aquifers) to fill up and reach stable values. This is because flows in the first few years are usually underestimated (Gholami *et al.*, 2016). The model included all dry, wet years and leap years occurring in the historical period as in Figure 3-5.

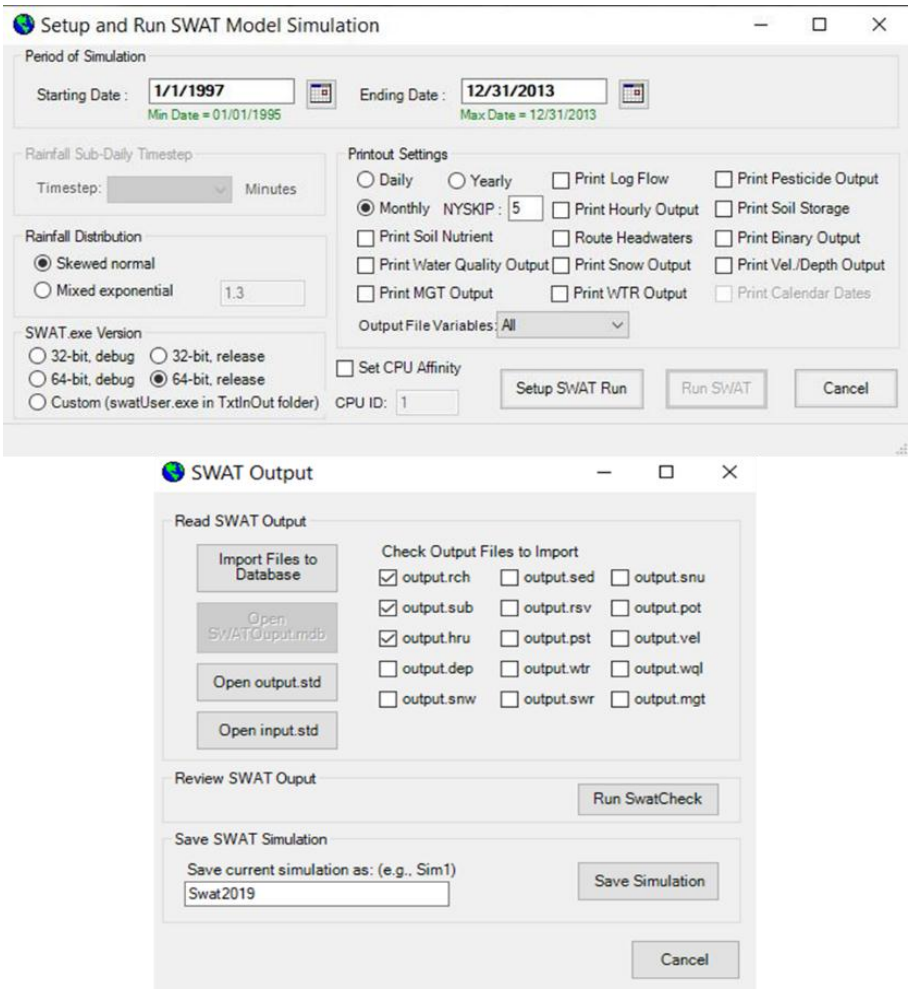

Figure 3-5: SWAT model setup, running a SWAT check and saving simulations

3.4.1.5 Water balance ratios in SWAT

Figure 3-6 shows the schematic of a hydrological system and processes involved during SWAT simulation process. SWAT model applies two methods for calculating the surface retention coefficient. First method, the surface retention coefficient changes with moisture content in the soil profile. Secondly, it allows the surface retention coefficient to change with the cumulative evapotranspiration. Therefore, SWAT model calculates evaporation from soil and plant separately. Being a physically based model, SWAT was used to simulate monthly time step for Rwizi catchment. The required data for calculating potential evapotranspiration by Penman-Monteith method included solar radiation, air temperature, wind speed, and relative humidity. The model uses the water balance equation under section 3.4.1.1.

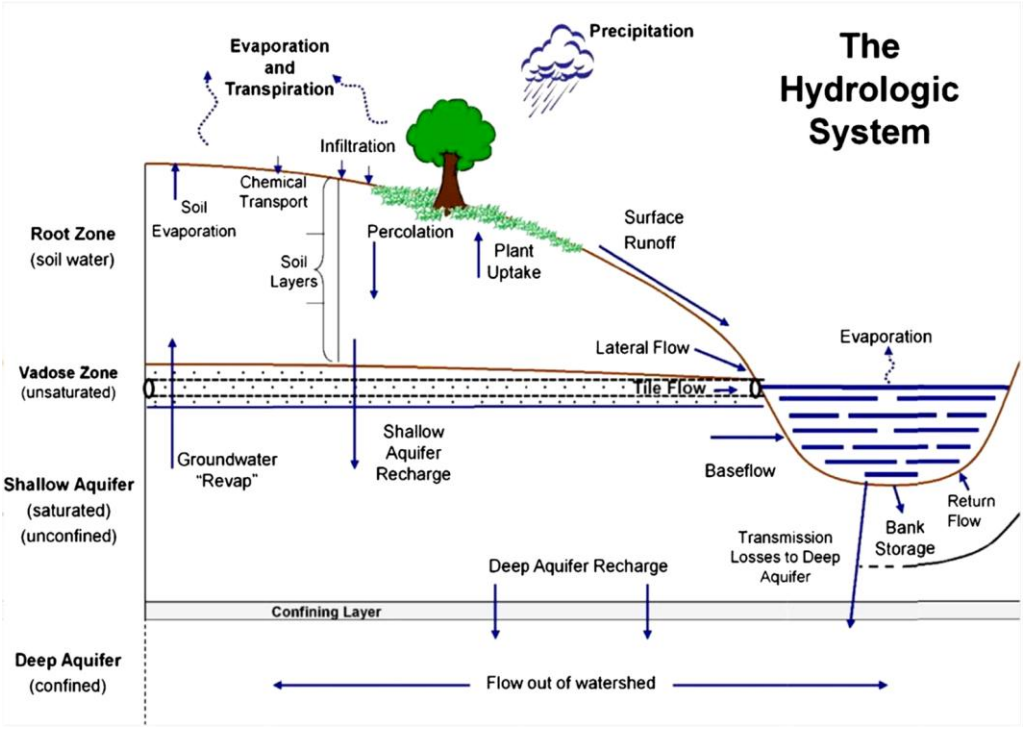

Figure 3-6: Schematic of the hydrological cycle and SWAT simulation processes

Source: (Neitsch *et al.*, 2005; 2011; Nasiri *et al.*, 2020)

3.4.1.6 Sensitivity analysis of model parameters

In this study, the Sequential Uncertainty Fitting (SUFI2) algorithm of the SWAT Calibration and Uncertainty Programme (SWAT-CUP) was used for an automatic calibration procedure. The SWAT simulation period was divided into a warming-up period of 5 years to initialize the state variables of the system (e.g., soil moisture), a calibration period, and a validation period. Depending on the availability of daily-observed streamflow, data that was converted to monthly flows, the calibration and validation periods covered 2002 - 2013 at a single streamflow gauging station. The warm-up period helps to minimize the effect of user estimated parameter values (Neupane *et al.,* 2015).

To facilitate the calibration process, first, the sensitive parameters were identified by using the global Latin Hypercube-One-factor-At-a-Time (LH-OAT) sensitivity analysis technique of SWAT-CUP (Atkinson *et al.*, 2010; Abbaspour, 2011; Arnold *et al.,* 2012; Abbaspour *et al.*, 2015a; Abbaspour *et al.,* 2017; Ha *et al.,* 2017; Leta *et al.,* 2018). For sensitivity analysis, the minimum and maximum values of the SWAT parameters were set based on the ranges given in SWAT and SWAT-CUP guidelines (Arnold *et al.,* 2012; Abbaspour *et al.,* 2017) as well as incorporating our experience of the sites (Leta *et al.,* 2016, 2017 & 2018). It should be noted that the purpose of sensitivity analysis was only to identify the sensitive parameters from 20 flow related parameters of SWAT for the subsequent calibration and validation processes.

Sensitivity analysis was independently run for 500 simulations as in Table 3-3. For some parameters that show spatially different values (heterogeneity) based on landuse, soil type, and slope value, relative global multipliers to the original parameter values

were applied. The *t*-statistics and *p*-values of the parameters were used to rank to the different parameters considered to influence flow and the final selection done based on the significance of the ranked values. In addition, detailed reviews and analyses on SWAT parameters carried out before by various authors were considered (Immerzeel *et al.*, 2008; Ullrich & Volk, 2009; Gitau *et al.*, 2010; Githui *et al.*, 2012; Anaba *et al.*, 2017).

Table 3-3: Sensitivity analysis parameters

Parameter Name	Description	Minimum value	Maximum value
r_CN2.mgt	SCS runoff curve number (dimensionless)	-0.2	0.2
v_ALPHA_BF.gw	Base flow alpha factor (days)	0	1
v_CH_K2.rte	Effective hydraulic conductivity of main channel (mm/h)	0	500
v_SLSUBBSN.hru	Average slope length	0	100
v_HRU_SLP.hru	Average slope steepness	0	1
r_SOL_Z.sol	Depth from soil surface to bottom of layer	-0.2	0.2
r_SHALLST.gw	Initial depth of water in the shallow aquifer (mm)	-0.2	0.2
v_REVAPMN.gw	Threshold depth of water in the shallow aquifer for "*revap*" to occur (mm)	0	500

Parameter Name	Description	Minimum value	Maximum value
r_SOL_K.sol	Saturated hydraulic conductivity (mm/h)	-0.2	0.2
v_CH_N2.rte	Manning's "*n*" value for the main channel (dimensionless)`	0	0.3
r_GW_REVAP.gw	Groundwater evapotranspiration coefficient (dimensionless)	-0.2	0.2
v_SOL_BD.sol	Moist bulk density	0.9	2.5
v_GWQMN.gw	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	0	10
r_EPCO.hru	Plant uptake compensation factor (dimensionless)	-0.1	0.1
v_ESCO.bsn	Soil evaporation compensation factor	0	1
r_SOL_AWC.sol	Available water capacity of the soil layer	-0.2	0.2
v_SURLAG.bsn	Surface runoff lag time (hours)	0.01	24
v_ESCO.hru	Soil evaporation compensation factor (dimensionless)	0	1
v_RCHRG_DP.gw	Deep aquifer percolation fraction (dimensionless)	0	1
v_GW_DELAY.gw	Ground water delay (days)	30	450

Note: (r): Multiplying existing value with (1+ the given value) %; (v): replacing initial value with given value. (Betrie *et al.*, 2011)

3.4.1.7 SWAT model calibration and validation

SWAT was automatically calibrated for those parameters that showed high sensitivity. The Auto -calibration and uncertainty analysis were done using one algorithm, i.e., Sequential Uncertainty Fitting (SUFI-2) (Abbaspour, 2011, 2015, 2017) that is incorporated in SWAT. SUFI-2 algorithm maps all uncertainties (such as those due to inputs and model structures) on the parameters (expressed as uniform distributions or ranges) and tries to capture most of the measured data within the 95% prediction uncertainty (95PPU) of the model in an iterative process. The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling. The SUFI2 algorithm determines the 95% prediction uncertainties (95PPU) generates two indices: the *p*-factor and the r-factor (Abbaspour, 2007). The *p*-factor is the fraction of measured data (plus its error) bracketed by the 95PPU band and varies from 0 to 1, where 1 indicates 100% bracketing of the measured data within model prediction uncertainty i.e., a perfect model simulation considering the uncertainty. The quantity (1 - *p*-factor) could hence be referred to as the model error. The *r*-factor on the other hand is the ratio of the average width of the 95PPU band and the standard deviation of the measured variable. Consequently, (Atkinson *et al.*, 2010; Abbaspour *et al.*, 2015) suggested a *p*-factor $\geq$ 0.7 and *r*-factor $\leq$ 1.5 as acceptable values. However, this depends on the scale of the project and adequacy of the input and calibrating data. These two indices were used to judge the strength of the calibration and validation. Based on these two additional

criteria, the results were considered as acceptable or not (Figure 3-7). According to *(Abbaspour et al.*, 2017), in the all-at-a-time (AAT) or global sensitivity analysis, all parameters are changing; hence, a larger number of runs (500 - 1000 or more, depending on the number of parameters and procedure) are needed in order to see the impact of each parameter on the objective function. Therefore, in this study, SUFI2 was run for 500 simulations, nevertheless, the 95PCI uncertainty was assessed for those simulations that provided a behavioural solution (threshold value) of NSE $\geq$ 0.5.

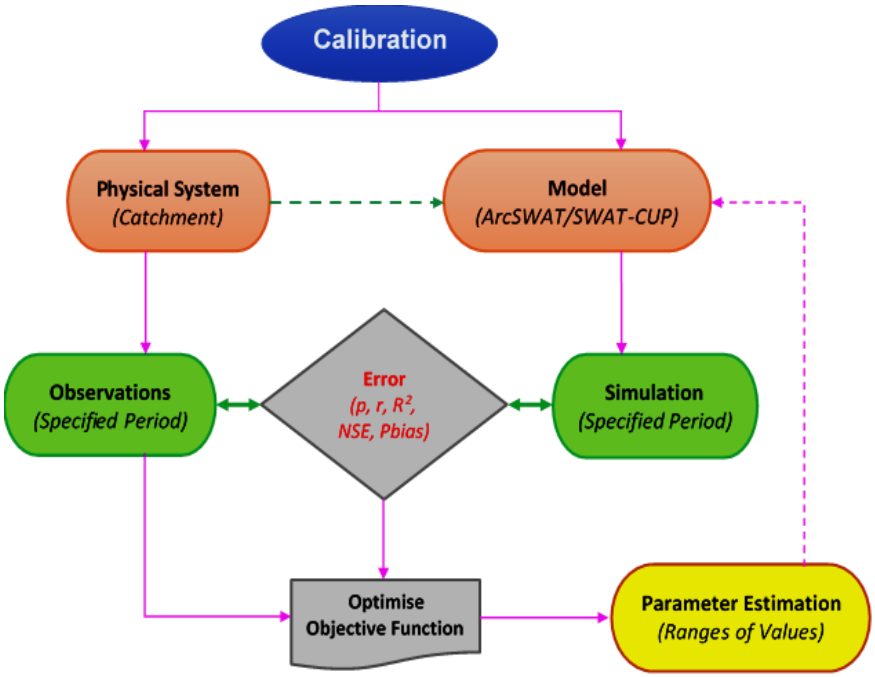

Figure 3-7: Conceptualization of model calibration

Source: (Abbaspour *et al.*, 2017)

Figure 3-8 shows the calibration process of the streamflow in SWAT CUP. The length of the simulations was determined by the availability and length of time series data for discharge, air temperature and rainfall, which are key pieces in the model simulation. For the rain gauge data model, out of that the 17 years of complete time series datasets,

5 years (1997 – 2001) were used warm period, 7 years (2002 – 2008) for calibration and the remaining 5 years (2009 – 2013) were used for validation. SUFI-2 is an iterative procedure and does not require too many runs in each iteration (Figure 3-9). Usually, 3 to 4 iterations should be enough to attain a reasonable result *(Abbaspour et al.*, 2017).

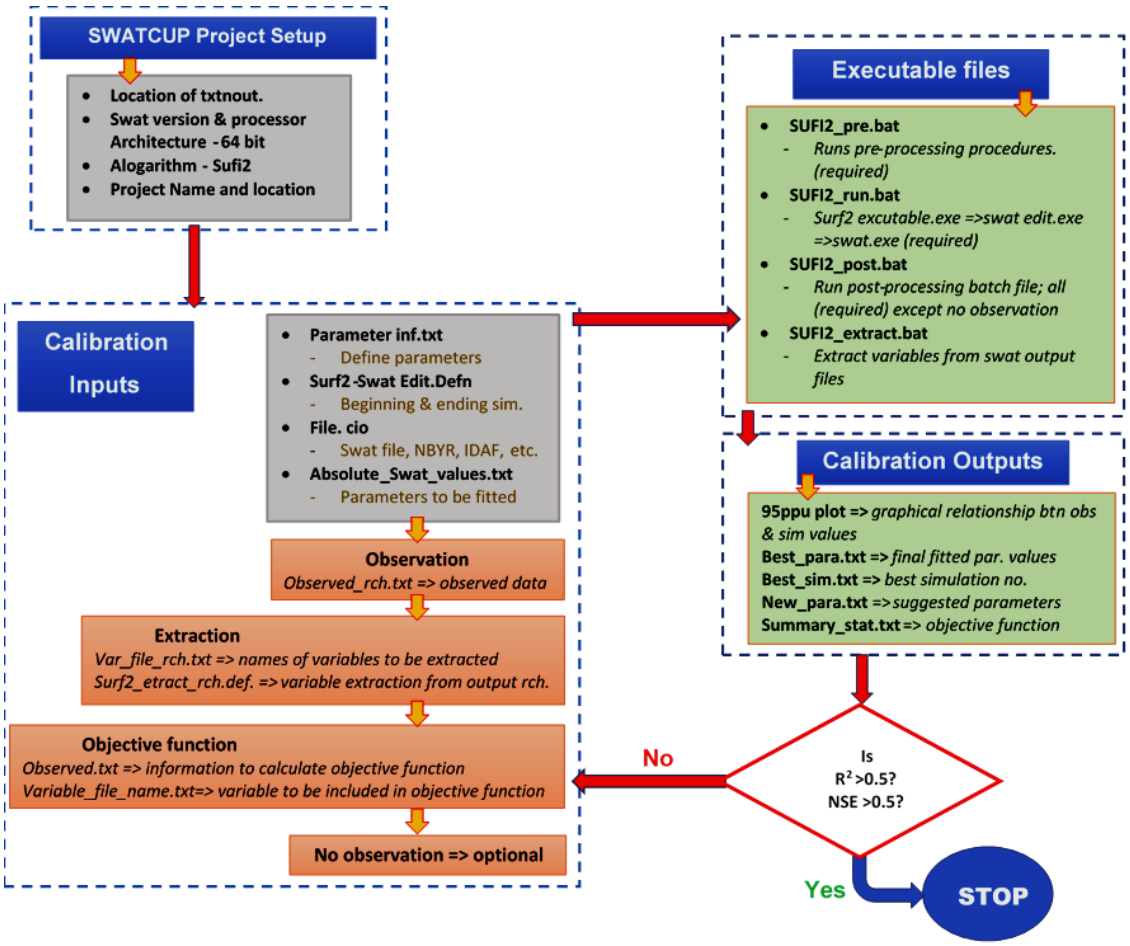

Figure 3-8: Calibration process using SWATCUP

(Abbaspour *et al.*, 2015)

Main assumptions and limitations

According to Abbaspour *et al.* (2007, 2011, 2015), the following assumptions and limitations were defined for the developed SWAT model.

i) Water quality parameters since no water quality data was available.

ii) Regionalisation of the observed rainfall and temperature data in SWAT may introduce large errors in the model during surface runoff simulation.

iii) Due to lack of local water and agricultural management data on reservoirs or dams, lakes, wetland systems and existing irrigation schemes, complete SWAT model proficiencies were not grasped.

iv) Both small and big reservoirs existing in the catchment were omitted from the analysis, assuming it will not change water balance in the study area.

v) The spatial details required to correctly simulate extreme events, as it may occur with spatial variability of the precipitation data within a watershed was a major limitation due to hydrologic modelling of a large catchment.

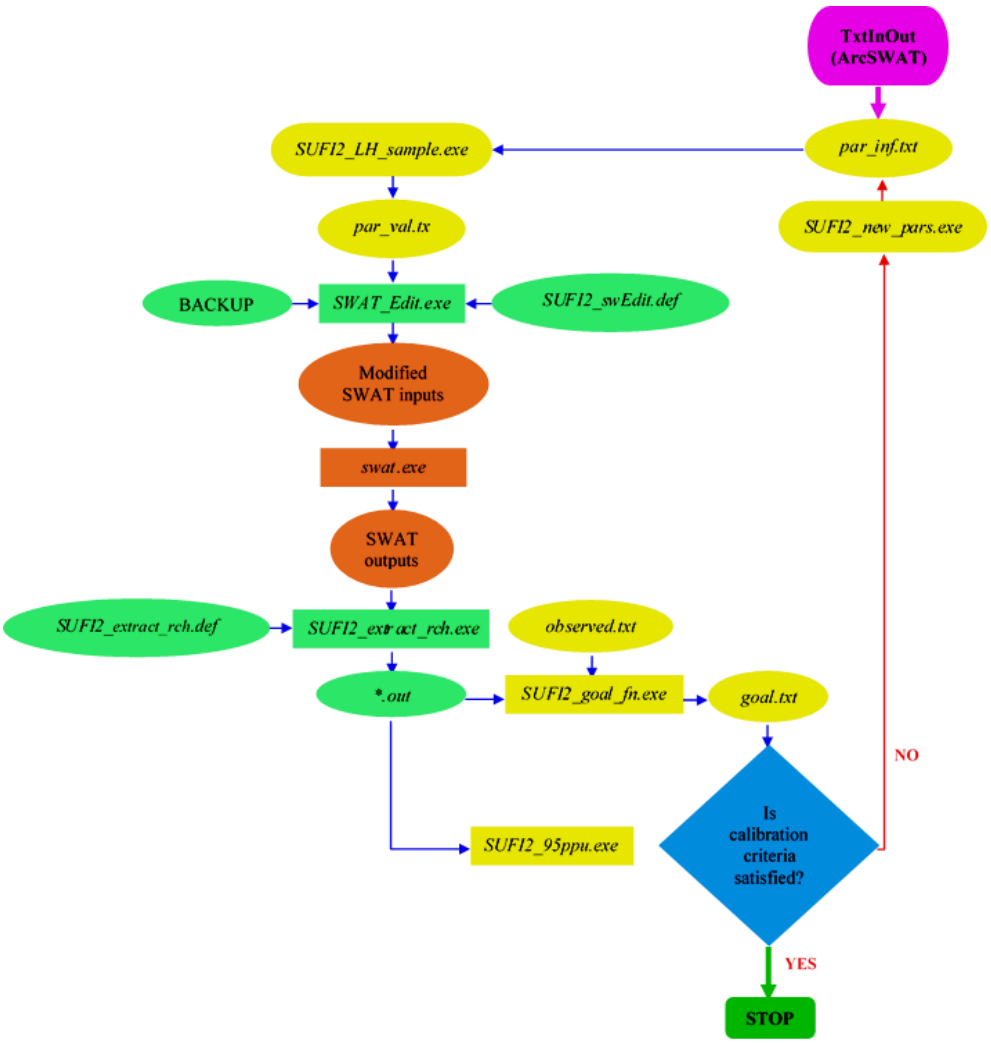

Figure 3-9: Summary of SUFI2 algorithm operation in SWAT CUP (Atkinson *et al.*, 2010; Abbaspour, 2011)

3.4.1.8 Model performance evaluation and uncertainty analysis

To evaluate performance of the model during calibration and validation, statistical measures as well as graphical representations at monthly time step were used. SWAT performance on streamflow simulations was assessed by using three statistical evaluation metrics as recommended by several researchers (Moriasi *et al.*, 2007, 2015). The metrics include the NSE (Nash & Sutcliffe, 1970; Mills, 2001), the percent bias (PBIAS) and the coefficient of determination (R^2) (Moriasi *et al.*, 2007). Liew *et*

al. (2003); Fernandez *et al.* (2005) and Leta *et al.* (2018) also proposed some limits for the classification of these statistical indices. Table 3-4 shows the used limits of the statistical indices. These were employed to confirm the relationship between modelled or predicted values and observed values (Ndulue *et al.*, 2015) and to verify the robustness of the model (Betrie *et al.*, 2011). These metrics are calculated using Equations 3.2 to 3.4 were used to determine NSE, PBIAS, and R^2 respectively.

In addition, Betrie *et al.* (2011); Fukunaga *et al.* (2015) and Ghoraba (2015) also recommended these three quantitative statistics for model performance evaluation in watershed runoff simulations. NSE is a normalized statistic that determines the relative magnitude or strength of the relationship between observed and modelled values or the residual variance compared to the measured data variance (Nash & Sutcliffe, 1970; Mills, 2001). NSE values range between $-\infty$ and 1.0 (1 inclusive). NSE value of one is for an ideal model. Values between 0.0 and 1.0 are generally viewed as acceptable levels of performance, whereas values < 0.0 indicates that the mean observed value is a better predictor than the modelled value, which indicates unacceptable performance (Moriasi *et al.*, 2007).

R^2 is the proportion of the total variance in the observed data that can be explained by the model by fitting a regression line. It measures the degree of collinearity i.e., strength of a liner relationship between modelled and measured data.

PBIAS indicates the average tendency of the modelled data to be larger or smaller than their observed value's. According to Gupta *et al.* (1999), PBIAS can be utilized as an indicator of under or overestimation. Negative PBIAS indicates a slight underestimation of model generated values against the measured values. For PBIAS,

constituent-specific performance ratings were determined based on uncertainty of measured data (Moriasi *et al.*, 2007). PBIAS values for streamflow tend to vary more, among different auto-calibration methods, during dry years than during wet years. This fact should be considered when attempting to do a split-sample evaluation, one for calibration and one for validation (Gupta *et al.*, 1999).

Table 3-4: Recommended statistics and rating of indices for streamflow simulation

Performance rating	NSE	R^2	PBIAS (%)
Inappropriate	NSE ≤ 0.00	$R^2 \leq 0.25$	± 50 ≤ PBIAS
Unsatisfactory	0.00 < NSE ≤ 0.36	$0.25 < R^2 \leq 0.50$	± 25 < PBIAS ≤ ± 50
Satisfactory	0.36 < NSE ≤ 0.60	$0.50 < R^2 \leq 0.60$	± 15 < PBIAS ≤ ± 25
Good	0.60 < NSE ≤ 0.75	$0.60 < R^2 \leq 0.75$	± 10 < PBIAS ≤ ± 15
Very good	0.75 < NSE ≤ 1.00	$0.75 < R^2 \leq 1.00$	PBIAS ≤ ± 10

R^2: coefficient of determination; NSE: Nash–Sutcliffe efficiency; PBIAS: percent bias.

$$NSE = 1 - \frac{\sum_{i=1}^{n}(x_i - y_i)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad 3.2$$

$$R^2 = \frac{\left(\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})\right)^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2} \quad 3.3$$

$$Pbias(\%) = \frac{\sum_{i=1}^{n}(x_i - y_i)}{\sum_{i=1}^{n} x_i} \times 100 \quad 3.4$$

Source:(Liew *et al.*, 2003; Fernandez *et al.*, 2005; Moriasi *et al.*, 2007)

Where x_i is the i^{th} observed streamflow, y_i is the i^{th} modelled streamflow, and $\bar{x}$ is the mean of observed data (m^3/s), $\bar{y}$ is i^{th} the mean of simulated data (m^3/s) and n is the total number of streamflow data points.

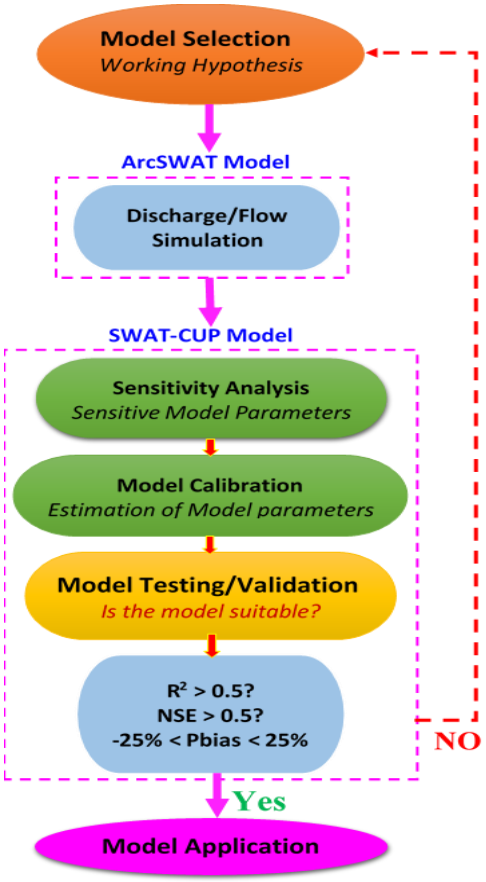

Figure 3-10: Model performance evaluation and analysis process

(Source: Abbaspour *et al.*, 2017)

3.4.1.9 Simulation of River Rwizi streamflow using LULC maps of 2000, 2008, 2014 and 2019

To simulate monthly streamflow for the years 2000, 2008, 2014 and 2019, the optimised parameters values of SWAT were obtained during calibration were maintained. Separate LULC maps of the respective years were used together with

monthly series. Throughout each simulation, other factors like the soil and slope information were maintained spatially the same as that used during calibration.

3.5 Separation and quantification of contributions of human activities and climate variability.

The following procedure was undertaken to quantify contributions of human activities and climate variability;

1) SWAT model was calibrated and validated using LULC map of 1997 to obtain optimal senstive parameters.
2) Maintaining SWAT at its optimal senstive parameters, the model was modelled based on LULC maps 2000, 2008, 2014 and 2019 respectively.
3) Difference in the model results based on simulations and calibration was taken to be due to the difference in landuse reflecting human influence.
4) To the difference between model results in (3), water diverted from the river through other human activities especially that abstracted to supply several towns and industries was added.
5) The difference in (4) was expressed as a percentage of observed flow. This was done for the long-term mean monthly results but for model outputs based on various LULC maps.
6) For each month, the remaining percentage after deducting the contribution from human activities was attributable to climate variability.

CHAPTER FOUR: RESULTS, ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter gives the analysis of LULC changes in River Rwizi catchment using a semi-distributed model (SWAT). It quantifies and separates the changes in the river flow attributable to human activities and climatic variability. It also analyses the behaviour of River Rwizi catchment under combined influences of human activities and climate variability on its hydrology. This was through analysis of LULC change in River Rwizi catchment from 1997 to 2019. It also details the sensitivity analysis, calibration, validation, evaluation of the model and concludes with results of the flows obtained after simulation of different types of landuse in River Rwizi Catchment and possible measures as per the scenario analysis results.

4.2 LULC changes in the River Rwizi catchment

Figure 4-1 shows change of LULC over time. The two dominant LULC types based on all maps were grassland and cropland. From 1997 to 2014, cropland was characterised by an increase at a rate of 194 ha/yr, grassland decreased at a rate of 22 ha/yr and settlement increased at a rate of 33 ha/yr. Forest increased at a rate of 125 ha/yr whereas wetlands reduced at 331 ha/yr respectively. However, from 2014 to 2019, cropland was characterised by a decrease at a rate of 621 ha/yr, grassland continued to decrease at a rate of 3,826 ha/yr and settlement increased at a rate of 417 ha/yr. Forest and wetland rapidly increased at a rate of 1,392 ha/yr and 2,639 ha/yr respectively.

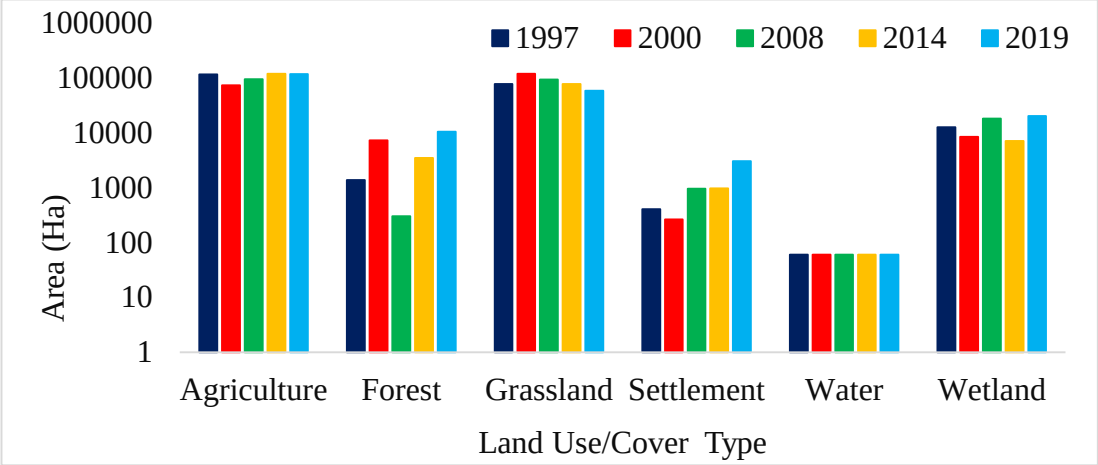

Figure 4-1: LULC of River Rwizi catchment for 1997, 2000, 2008, 2014 and 2019

Table 4-1 shows that in 1997, LULC comprised grassland (37.2%), cropland (55.9%), forest (0.7%), wetland (6.1%), water (0.1%) and settlement (0.19%). In 2000, there was increase in grassland (57.2%) and forest (3.5%) against a decrease in wetland (4.1%), cropland (35.2%) and settlement (0.1%). In 2008, the trend reversed with a decrease in grassland (45.0%) and forest (0.1%) while cropland gained (45.6%), settlement (0.4%) and wetland (8.8%). In 2014, cropland increased to 57.5% thereby dominating the catchment considering that grassland had reduced to 37.0%. Wetland decreased to 3.4%, forest increased to 1.7% and settlement remained at 0.5%. By 2019, grassland had reduced to 29.9% and cropland to 56.0%. However, forest increased to 5.0%, wetland to 9.7% and settlement to 1.5%.

Table 4-1: Proportion of total area under various LULC in different years

LULC	Area (Ha)					Area (%)				
	1997	2000	2008	2014	2019	1997	2000	2008	2014	2019
Agriculture	117275	73769	95611	120581	117475	55.9	35.2	45.6	57.5	56.0
Forest	1381	7302	301	3505	10463	0.7	3.5	0.1	1.7	5.0
Grassland	77995	119920	94513	77618	58487	37.2	57.2	45.0	37.0	27.9
Settlement	404	264	968	973	3059	0.19	0.1	0.5	0.5	1.5
Water	60	60	60	60	60	0.1	0.1	0.1	0.1	0.1
Wetland	12703	8504	18366	7082	20274	6.1	4.1	8.8	3.4	9.7
Total	209818	209818	209818	209818	209818	100	100	100	100	100

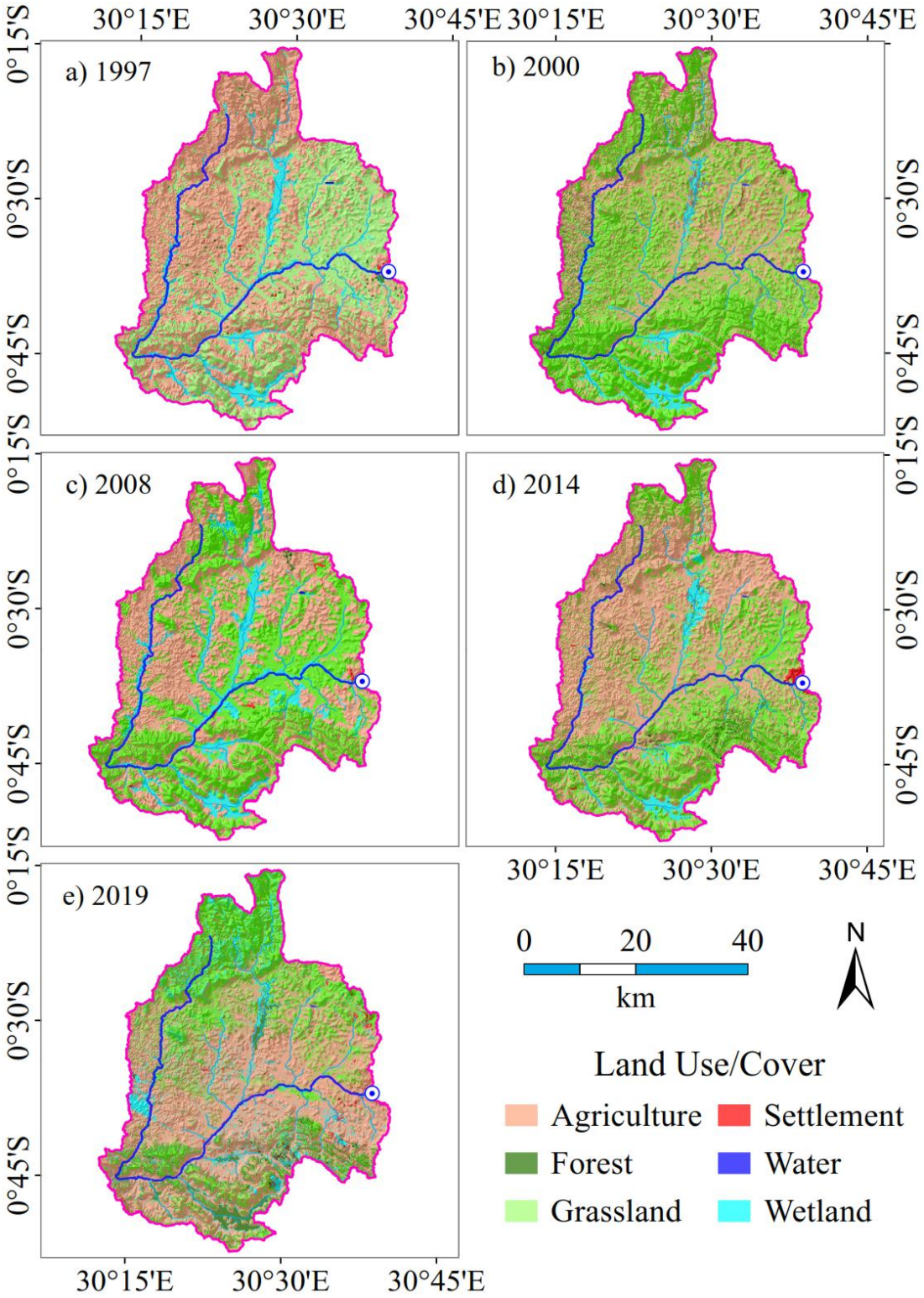

Figure 4-2: LULC maps of River Rwizi catchment for (a) 1997, (b) 2000, (c) 2008, (d) 2014 and (e) 2019.

Figure 4-3 shows how LULC has changed over a period of two decades i.e., between 1997 and 2019. It shows that settlements had a continuous increment than the rest of cover types while water remained constant. Grasslands had a constant decrement however; the rest of cover types demonstrated varying trends. Between 1997 and 2019, the largest increment was in forests (4.33%), followed by wetlands (3.61%), settlement (1.27%) and agriculture (0.10%). However, the greatest decrease was only in grassland by 9.3%.

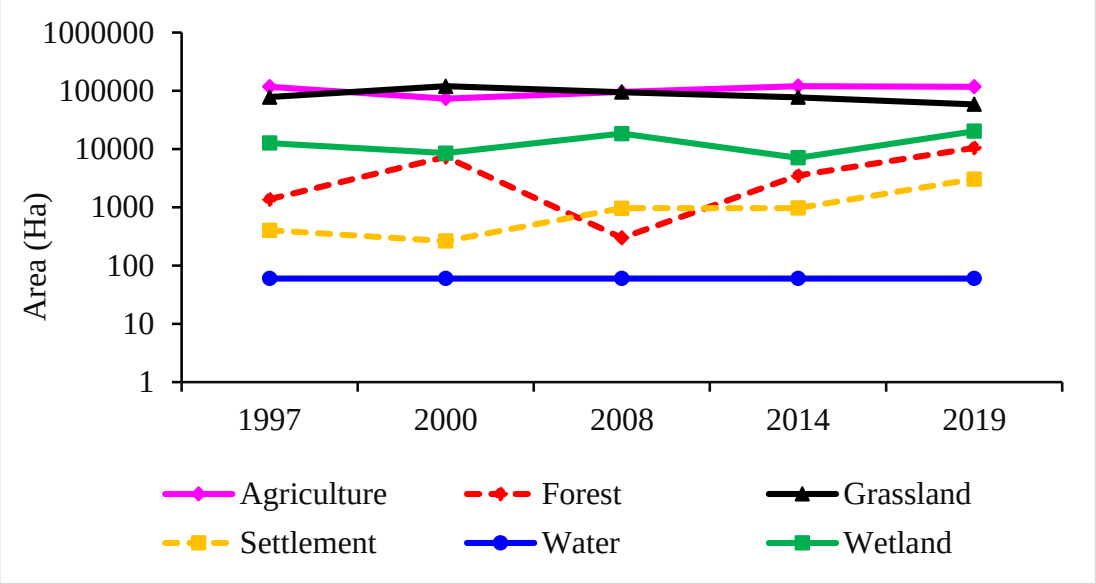

Figure 4-3: LULC variation from 1997 to 2019

Figure 4-4 shows the hectarage increase and decrease of LULC types in Rwizi catchment from 1997 to 2019. According to (Isingiro District Local Government Development Plan-II IDLGDP-II, 2015), most of these changes are attributable to human population pressure mainly in Nakivale refugee camp and weak policies in place. The increased cropland was preciously attributed to increased population growth rate in the region (Isingiro, Mbarara, Nakivale refugee camp and other towns).

Therefore, encroachment on natural resources emanating from population pressures for cropland and bio-fuel has largely challenged the environment. Weaknesses also remain in enforcement of environmental laws and regulations leading to continuous invasion of riverbanks and lake buffer zones. Equally, of concern, over 98% of the district's population depends on biofuel for cooking, which is largely responsible for the depletion of the vegetation and tree cover.

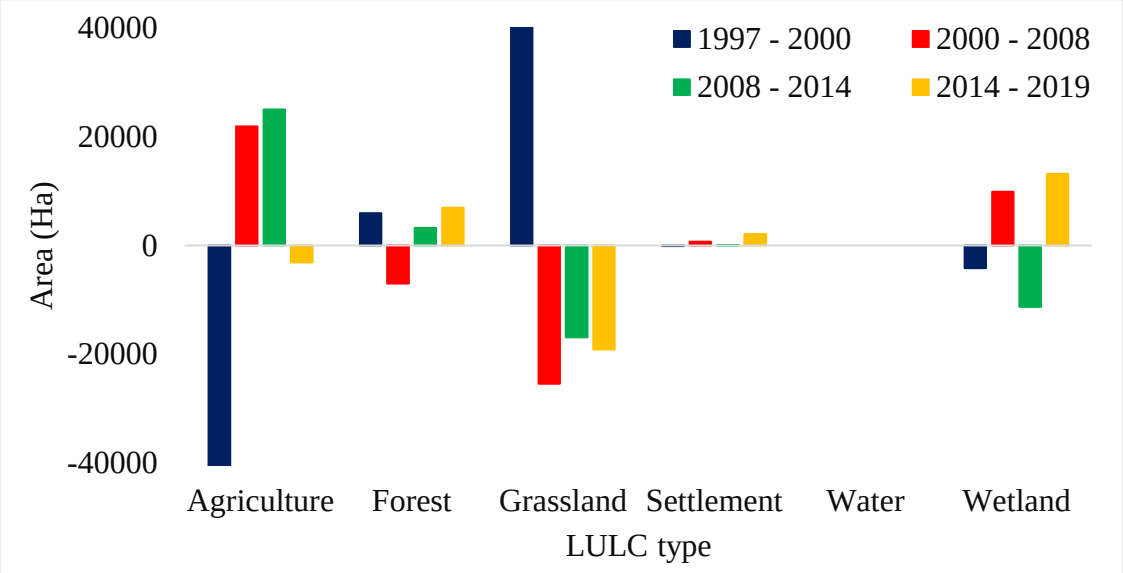

Figure 4-4: LULC changes between 1997 and 2019

According to MWE, (2017); Mwanjalolo *et al.* (2018) and Mugo *et al.* (2020), Rwizi catchment (upper, middle and lower parts) comprises a number of National Parks, Ramsar sites and forest reserves (local forest reserves (LFRs) and central forest reserves (CFRs). These are important areas harbouring the diversity of both fauna and flora. They include Mbarara and Kyahi CFRs located in Mbarara and Isingiro districts respectively. Kabwohe and Kooga LFRs are located in Sheema district while Bwizibwera LFR is in and Mbarara district. The middle part of the catchment has L. Mburo National Park, L. Mburo - Nakivale Ramsar Site reserves in Kiruhura and

Isingiro districts, Kijanebalola and Kyamazzi CFRs in Rakai district. The areas immediate to the main Rwizi catchment outlet around L. Victoria shore include Nabajjuzi Ramsar site, Kigona, Kabira, Tero and Namalala CFRs in Rakai District. These are dominated by wetland vegetation and extensive forest cover.

Atwongyeire (2018) revealed that subsistence and commercial farming, livestock rearing, fish farming and tourism through Lake Mburo National Park are the main economic activities in the catchment. Local industry is also common, particularly brick making, sand mining, motor vehicle washing, motor vehicle repair garages, art craft (making baskets, mats) using reeds, and wide-spread growing of eucalyptus trees (Mugonola *et al.*, 2015; Atwongyeire, 2018).

In addition, a diverse range of small, medium and large water users rely on the catchment's water resources for their supply. This includes ground water and surface water like rivers, lakes, naturally-occurring wetlands and constructed valley dams and tanks (Atwongyeire, 2018).

Most physiographic features in the watershed including both seasonal and permanent wetlands and water bodies (Nakivale, Kachera, Mburo and Kijanebalola) have a major effect on the flow regime in the catchment. These ecosystems sustain livelihoods of the local people and the national economy through fisheries but also the water balance of the basin. Lakes consist of permanently flooded papyrus and grass swamps and are vital sources of fish. However, with the rapidly growing population that is still predominantly rural and agricultural, pressure on these (water resources wetland systems and water bodies) has affected the recovery of water levels (Ministry of Water

and Environment (MWE) - Directorate of Water Resources Management (DWRM), 2017).

Bintoora (2013) also attributed the changes in Rwizi catchment to anthropogenic pressures. The landuse practices around Lake Nakivale Wetland have over the last five decades changed from dominantly cattle keeping to crop farming, human settlement (refugee settlement) and urbanisation. The decrease in grassland cover suggests that other landuse options such as cultivation were encroaching into grasslands. Cutting down of trees for various uses such as firewood and timber has led to the decline on the forest cover.

In 2015, a process of wetlands restoration in Rwizi catchment was executed through an integrated effort by MWE, Local Government and political intervention. This aimed at evicting encroachers out of the fragile systems like bare hills, river banks, lake shores, rangelands; to increase forest cover and its economic productivity (IDLGDP-II, 2015). Buffer zones of 200m from the highest watermark the L. Nakivale were demarcated. The district took 100m (from the lake) and gave locals who had encroached it a 50m width of the buffer from inland. This left a middle gap of 50m as a boundary between the restored buffer zone and private land. Furthermore, a by-law was passed by the district that whoever cultivates the remaining 50m stretch, shall plant there a specific given type of tree. In turn, the local people were defeated by the planted trees leaving a total stretch of 150m belonging to district as a complete buffer zone. This is because they could not cultivate it anymore due to canopy (IDLGDP-II, 2015). Consequently, a decrease in cropland and a rise in forest and wetland more than other covers was noted between 2015 and 2019 (Table 4-2).

Table 4-2: LULC change summary for River Rwizi catchment

	Area changes in LULC (Ha)				Area changes in LULC (%)			
LULC	1997 – 2000	2000 – 2008	2008 – 2014	2014 – 2019	1997 – 2000	2000 – 2008	2008 – 2014	2014 – 2019
Agriculture	-43506	21842	24970	-3106	-20.7	10.4	11.9	-1.5
Forest	5920	-7001	3205	6958	2.8	-3.3	1.5	3.3
Grassland	41926	-25407	-16895	-19130	20.0	-12.1	-8.1	-9.1
Settlement	-140	703	5	2086	-0.1	0.3	0.0	1.0
Water	0	0	0	0	0.0	0.0	0.0	0.0
Wetland	-4200	9863	-11285	13193	-2.0	4.7	-5.4	6.3

4.3 Impacts of climate variability and human influence on River Rwizi streamflow changes

4.3.1 Hydrological modelling

4.3.1.1 Watershed delineation and sub-basin characterisation

Figure 4-5 shows the dendritic delineated River Rwizi catchment covering an area of 2100 km². A total number of 21 sub-basins, reaches (streams) and their monitoring points were obtained from the watershed delineation. Table 4-3 shows the list of Rwizi catchment, its sub-basins and their calculated statistics. The smallest and largest sub-basins in the catchment were 1.32 km² and 410.93 km² respectively. The lowest and highest elevation points in the catchment were 1776 m and 2171 m.a.s.l.

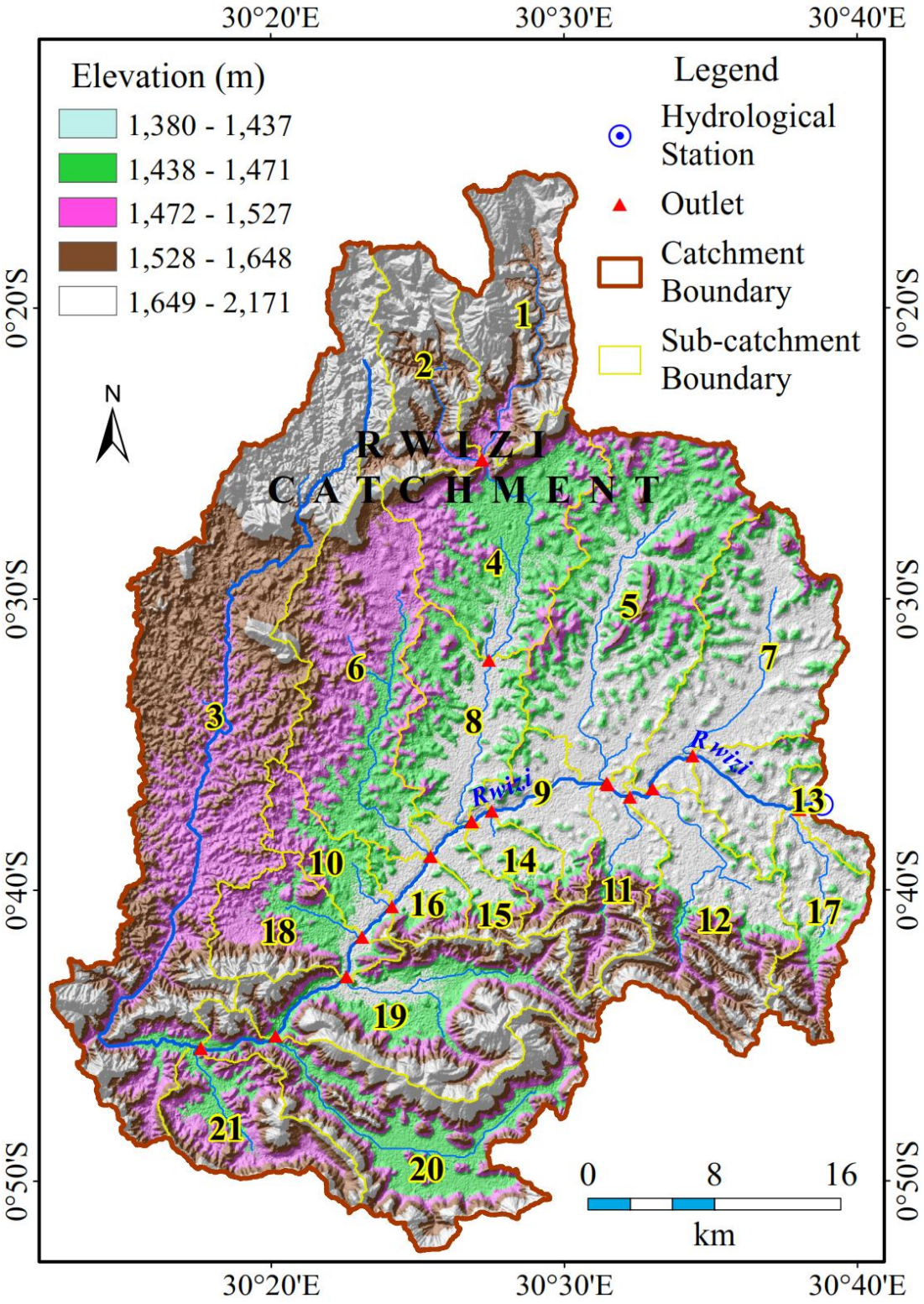

Figure 4-5: A delineated River Rwizi catchment and its features

Table 4-3: Delineated sub-basin and their statistics using SWAT

Sub-basin ID	Area (km²)	Mean Elev (m)	Min Elev (m)	Max Elev (m)
300001	100.25	1472	1750	2171
300002	75.75	1473	1728	2098
300003	410.93	1623	1763	1989
300004	123.33	1427	1465	1526
300005	53.48	1426	1471	1646
300006	149.52	1457	1532	1914
300007	116.65	1392	1428	1636
300008	77.33	1407	1448	1600
300009	41.26	1399	1403	1414
300009	39.79	1383	1418	1533
300010	37.86	1422	1477	1616
300011	53.28	1396	1423	1552
300012	119.18	1391	1410	1510
300013	13.05	1380	1423	1480
300014	1.32	1407	1418	1455
300015	24.77	1407	1480	1780
300016	26.69	1411	1471	1778
300017	53.32	1382	1487	1793
300018	56.21	1426	1529	1913
300019	139.72	1427	1594	1910
300020	156.13	1436	1585	1846
300021	66.61	1447	1551	1825

4.3.1.2 Hydrologic Response Units (HRUs) for Rwizi catchment

Table 4-4 shows the reclassified LULC types, area and percentage coverage out total area. These were obtained after the overlay of LULC map, soil map and slope, HRU definition and analysis in ArcSWAT for 1997, 2000, 2008, 2014 and 2019. As a result, LULC was reclassified into six classes for all scenarios namely; FRST – Forest, AGRL – Cropland, WATR – Water, URBN – Settlement, WETL – Wetland and PAST – Pasture and Grasslands.

Table 4-4: Reclassified LULC types in SWAT

LULC	Area (Ha)					% of catchment area				
	1997	2000	2008	2014	2019	1997	2000	2008	2014	2019
AGRL	79121	46660	83585	100685	64195	38.19	22.52	40.35	48.61	30.99
FRST	114729	16500	183	18317	18847	55.38	7.96	0.09	8.84	9.10
PAST	4535	129896	106350	76436	88930	2.19	62.70	51.34	36.90	42.93
URBN	7881	364	962	1053	9516	3.80	0.18	0.46	0.51	4.59
WATR	557	4105	4403	4358	4271	0.27	1.98	2.13	2.10	2.06
WETL	357	9655	11667	6300	21391	0.17	4.66	5.63	3.04	10.33
TOTAL	207180	207180	207150	207150	207150	100	100	100	100	100

Figure 4-6 shows the reclassified soil using soil types in ArcSWAT database. Based on soil properties such as clay content, sand content, loam content and hydrological group, soil in Rwizi catchment is dominantly clay loam, sandy clay loam, loam, sandy loam and some peat loamy soils. The dominant soil types according to FAO classifications are the Alisol and Arenic with extremely low base saturations. Soils were first grouped as Group A - Arenic qualifier (Swanton), Group B - Loamic

qualifier (Benson), and Group D - Clayic qualifier (Water). Table 4-5 shows the reclassified soil types, area and percentage coverage out total area.

Table 4-5: Reclassified SWAT soil groups obtained in SWAT model

Soil	Area (ha)					% of catchment area				
	1997	2000	2008	2014	2019	1997	2000	2008	2014	2019
Swanton	26813	16743	16812	16743	16816	12.7	7.9	8.0	7.9	8.0
Benson	179573	189663	189574	189663	189570	85.2	90.0	89.9	90.0	89.9
Water	4450	4430	4450	4430	4450	2.1	2.1	2.1	2.1	2.1

Table 4-6 and Figure 4-7 show the slope classes defined for Rwizi catchment for 1997, 2000, 2008, 2014 and 2019. A total of five slope classes were set each having the lower- and upper-class limit in percentage (%) namely; class 1 (0 – 5%), class 2 (5 – 10%), class 3 (10 – 20%), class 4 (20 – 50%) and class 5 (50 – 9999).

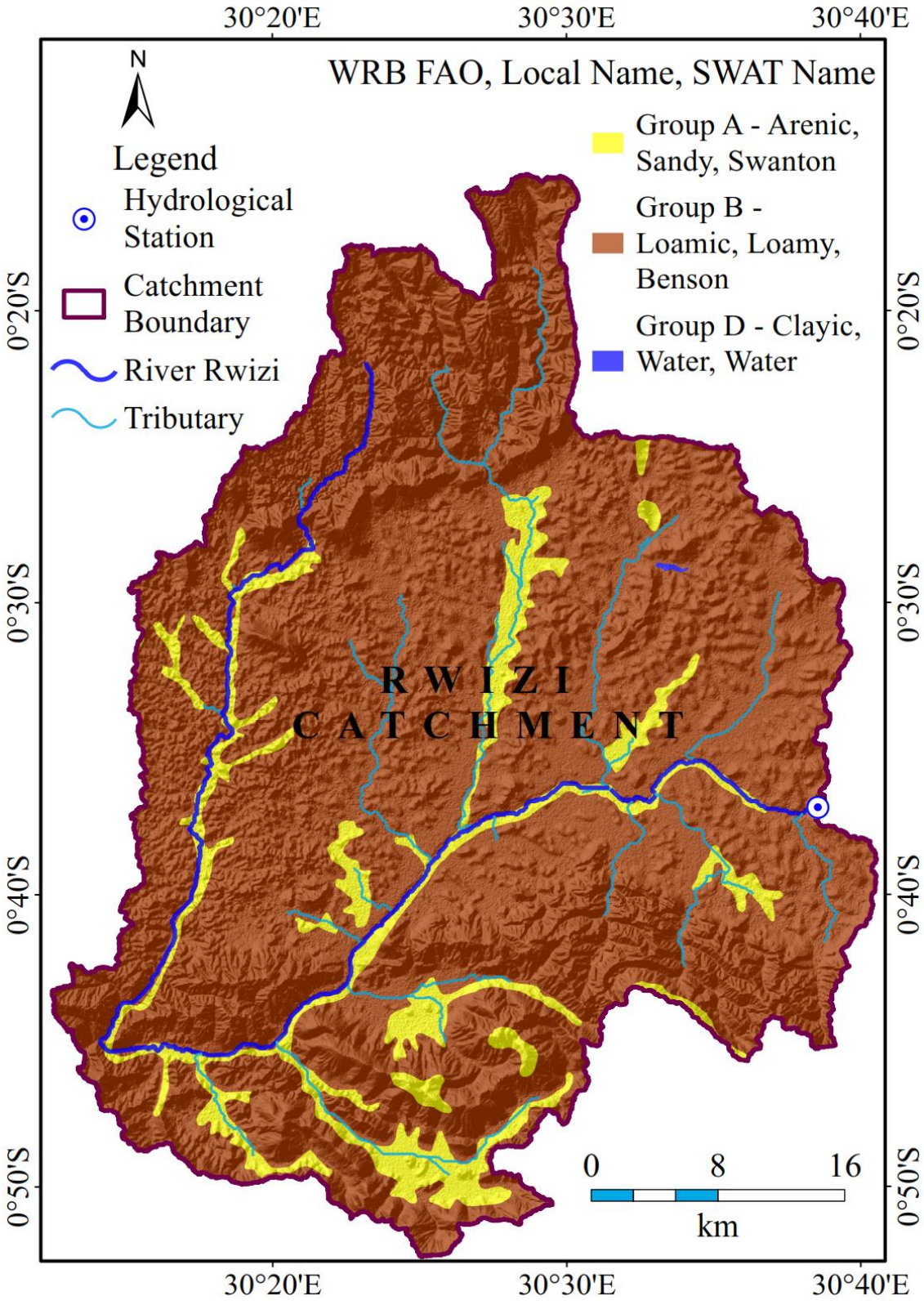

Figure 4-6: Soil map of River Rwizi catchment area

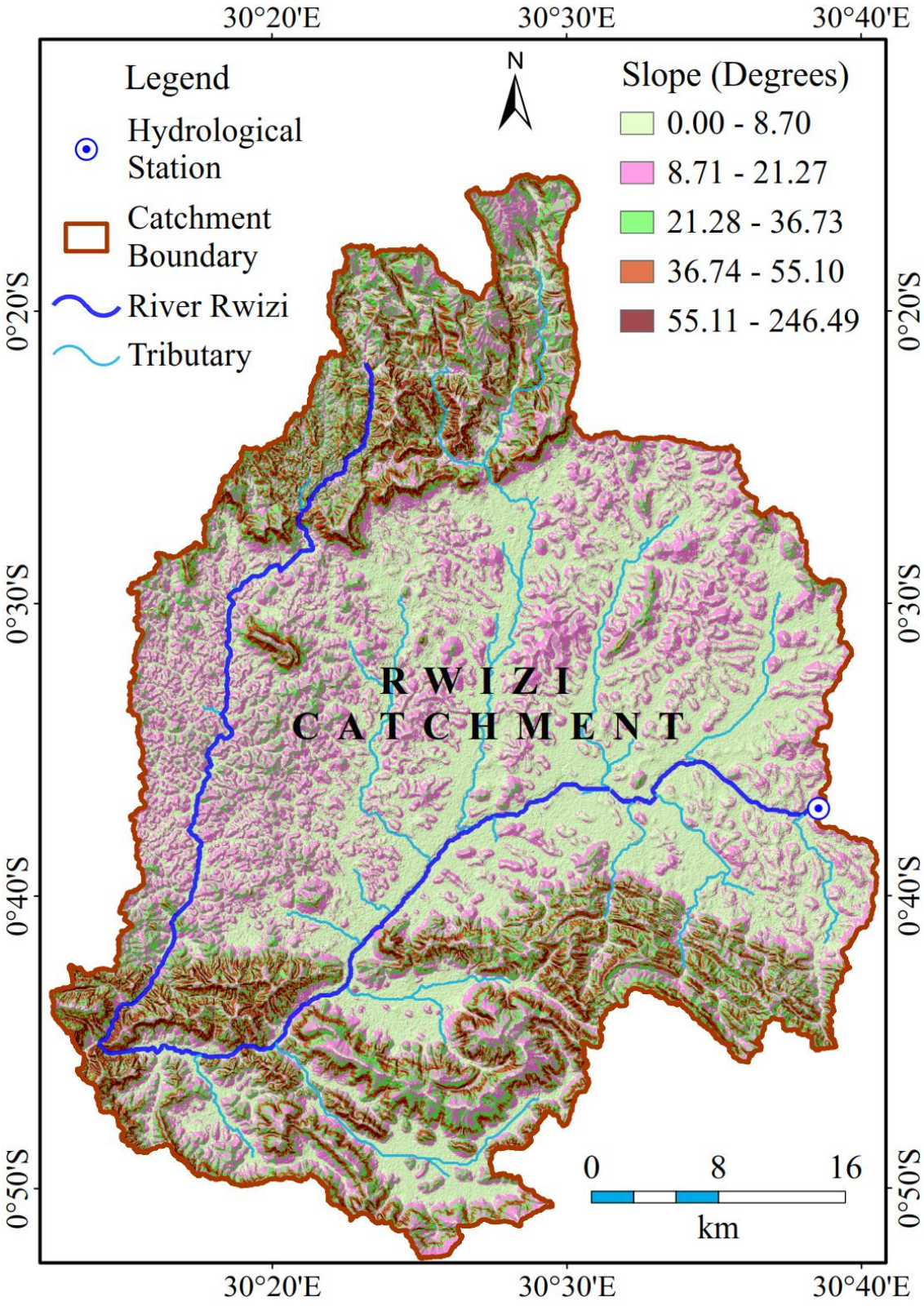

Figure 4-7: Slope map of River Rwizi catchment area

Table 4-6: Slope bands obtained in SWAT

Slope limits	Area (ha)					% of catchment area				
	1997	2000	2008	2014	2019	1997	2000	2008	2014	2019
0 - 5	55540	55474	55540	55475	52212	26.3	26.3	26.3	26.3	24.8
5 - 10	50329	50336	50329	50336	56753	23.9	23.9	23.9	23.9	26.9
10 - 20	58610	58656	58610	58656	55576	27.8	27.8	27.8	27.8	26.4
20 - 50	42289	42312	42289	42312	42234	20.1	20.1	20.1	20.1	20.0
50 - 9999	4068	4058	4068	4058	4060	1.9	1.9	1.9	1.9	1.9

A total of 1145, 1576, 1165, 1577 and 1896 HRUs in 21 sub-basins were obtained covering a catchment area of about 2100 km^2. Different SWAT water balance ratios obtained for different years in Table 4-7 show the influence of LULC on the catch³ent for the past two decades. This shows the trend of stream and surface flows in 1997, 2000, 2008, 2014 and 2019 respectively.

4.3.1.3 Water balance ratios

Table 4-7 shows the LULC types contribution ratios to streamflow in different years. Surface runoff ratios decreased from 0.34 in 1997 to 0.32 in 2000 an indication of increased infiltration as the base flow ratios increased from 0.66 to 0.68. This in turn reduced the streamflow ratios from 0.45 to 0.44.

Table 4-7: LULC contribution ratios to streamflow under different years

Water Balance Ratio	Year of LULC				
	1997	2000	2008	2014	2019
Streamflow/Precipitation	0.45	0.44	0.45	0.45	0.46
Baseflow/Total flow	0.66	0.68	0.66	0.66	0.54
Surface Runoff/ Total flow	0.34	0.32	0.34	0.34	0.46
Percolation/Precipitation	0.16	0.17	0.16	0.16	0.13
Deep Recharge/Precipitation	0.01	0.01	0.01	0.01	0.01
ET/ Precipitation	0.53	0.53	0.53	0.53	0.52
Average Curve Number (CN)	81.25	79.87	81.76	83.07	82.55

The decrease in surface runoff could be attributable to the increase in vegetation cover. Cropland decreased from 38.85% to 22.69% as in Table 4-4. The increased forest cover results in decreased or constant streamflow due to high canopy and soil moisture demand. Forests reduce bare lands and require more moisture. They retard the impact of rainfall droplets on to the ground in terms of falling velocity as the forest canopy allows more moisture holding capacity in the soil. This means, it takes longer to fulfil the soil moisture shortage in forested lands than in agricultural lands generating less runoff in the short run (Mwangi *et al.*, 2016). Also, according to Natural Resources Conservation Service NRCS (1972), more vegetation cover reduces the runoff Curve Number (CN). This is in agreement with results obtained as the value dropped from 81.25 in 1997 to 79.87 in 2000.

The surface runoffs increased from 0.32 in 2000 to 0.34 in 2008, which reflects the decrease in baseflow from 0.68 to 0.66 hence an increase in streamflow from 0.44 to

0.45 as in Figure 4-8. Cropland increased from 22.69% in 2000 to 41.14 in 2008, pasture from 64.89% to 52.30%, and water from 1.69% to 1.78% and wetlands from 3.40% to 4.77%. However, the biggest great vegetation cover loss was due to a 7.33% forest cover loss as more vegetation was cleared to prepare lands for cultivation as in Table 4-4. Also, the CN value increased from 79.87 to 81.76 hence more surface runoff. Baker & Miller (2013) conveyed on how LULC alterations give rise to in increased surface runoff and decreased groundwater recharge for the Njoro watershed located in Kenya's Rift Valley.

Nevertheless, the 0.34 surface runoffs, 0.45 baseflows and 0.45 streamflow between 2008 and 2014 remained constant though the CN value decreased from 81.76 to 79.58. This was because of emergency of forests covering 8.82% of the watershed. However, this was counter balanced with an excessive decrease of pasturelands from 52.30% to 37.93%, wetlands from 4.77% to 1.73%, waterbodies from 1.78% to 1.77%.

Towards the end of the second decade, surface runoff increased from 0.34 in 2014 to 0.46 in 2019. This is indicated by an increase in settlements by 3.85%, forests from 8.21% to 8.14 %, waterbodies from 1.77% to 1.70, increase in pasture lands from 37.93% to 44.67% and wetlands from 1.73% to 9.99%. Settlements and short grasses replaced the lost forests, which increased paved or bare surfaces leading to the decreased infiltration, more runoffs hence higher streamflow during precipitation period but less underground recharge. However, cropland land reduced from 50.36% to 31.65% lost to pasture land.

Rwizi catchment is dominantly composed of Clay loam, Sandy clay loam, Loam, Sandy loam and Peat loamy soils. According to FAO, these dominant soil types are

classified as Alisols that have extremely low base saturations. According to (Ministry of Water and Environment (MWE) - Directorate of Water Resources Management (DWRM), 2017), extensive grazing practices in most parts of the catchment have also compacted the soils, hence decreasing infiltration rates. This is because cropland and skeletal soils diminish the intake rate, increasing the short run runoffs but decrease long run streamflow. Intensive cultivation and negligible use of terraces on the hills in the upper Rwizi catchment makes soils prone not only to the low water intake, but also soil erosion due to forces of the rain.

Figure 4-8 shows the relationship between the variations of surface runoffs, baseflows and curve numbers (LULC types). The evapotranspiration ratios were the same between 1997 and 2014 at 0.53 but later reduced to 0.52 in 2019. The decreased evapotranspiration could be attributed to a lot of vegetation has been cleared and replaced with more settlements and pasture or grazing lands with less cover to transpire back to the atmosphere. This is evident with a decrease in forest cover (Figure 4-8). This is also evident with CN variation. A small change in CN value impacts greatly on the runoff (Figure 4-8). A decrease in CN from 81.25 to 79.87 between 1997 and 2000 reduced surface runoff from 0.34 to 0.32, hence a rise in baseflow from 0.66 to 0.68.

Figure 4-8 shows the hydrological cycle relationship between the baseflow (BF) and surface runoff (SF) against the curve number (CN). In 1997, the average CN was high (83.1) which meant low BF (0.66) and high SF (0.34) since more ratio of rainfall was turned into quick flows than slow flows. In 2000, the CN reduced to 82.2 which resulted into reduced SF (0.32) and increased BF (0.68). This was due to land cover changes with an increase in forests (2.0%), grassland (8.6%) wetlands (5.4%) and a

decrease in cropland (15.2%). However, this reversed between 2000 and 2008 as CN increased again to 83.3 resulting into reduced baseflows to 0.66 and increased SF to 0.34. From 2008 to 2014, the changes were not so significant. This later changed course towards 2019 where BF reduced and SF increased. This could be due to increased settlements (4.4%) and decreased grassland (1.2%).

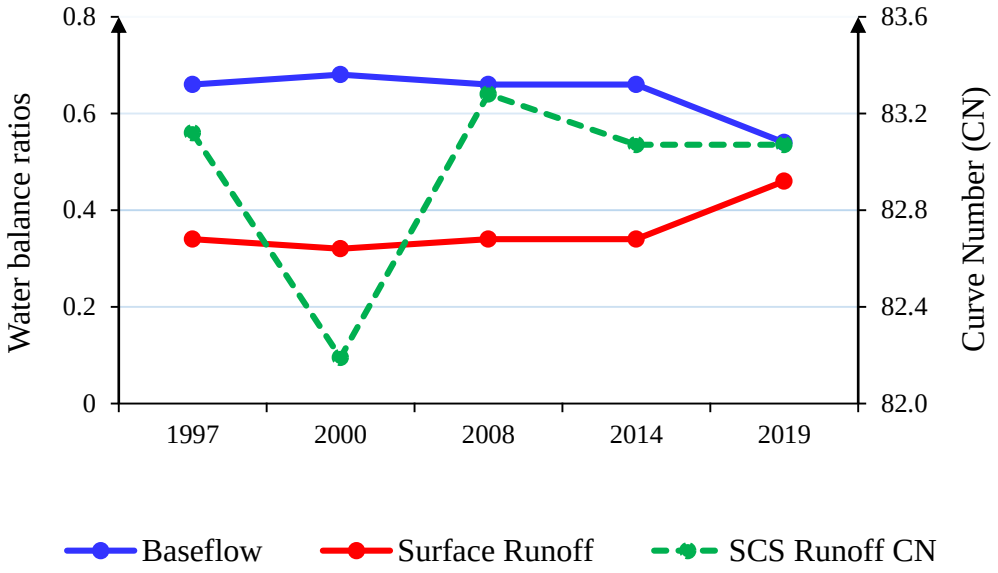

Figure 4-8: Relation variations of surface runoffs, baseflows and curve numbers

Tuyahabwe (2019) assessed the impacts of landuse changes on water resources of River Mpanga catchment and found that surface runoff ratios increased from 0.26 to 0.33 due to vegetation loss to pave way for settlement and cropland. Getahun & Haj (2015) estimated the impacts of historical landuse change on hydrology of the Melka Untie watershed located in Ethiopia using semi distributed hydrological model and revealed that increase in agricultural activities along with deforestation reduces evapotranspiration and increased streamflow during the main rainy season. This implies that when mean annual evapotranspiration, percolation and base-flow

decrease, surface runoff increases since curve number being a function of the soil permeability, LULC and the antecedent soil moisture, affects the rate of surface runoff generation.

Other studies including Zuo *et al.* (2016) have reported that an expansion in forestland and grasslands lead to a decrease in runoff. Although, there is general agreement among researchers that changes in streamflow is attributable to different types of forestry activities. For example, afforestation may lead to lower runoff generation.

4.3.1.4 Sensitivity analysis of streamflow parameters results

Analysis of sensitivity is extremely useful for identifying influential parameters and improving the SWAT model's simulation performance. The sensitivity analysis covered the observed data for entire research period of 1988 to 2013 (Figure 4-9).

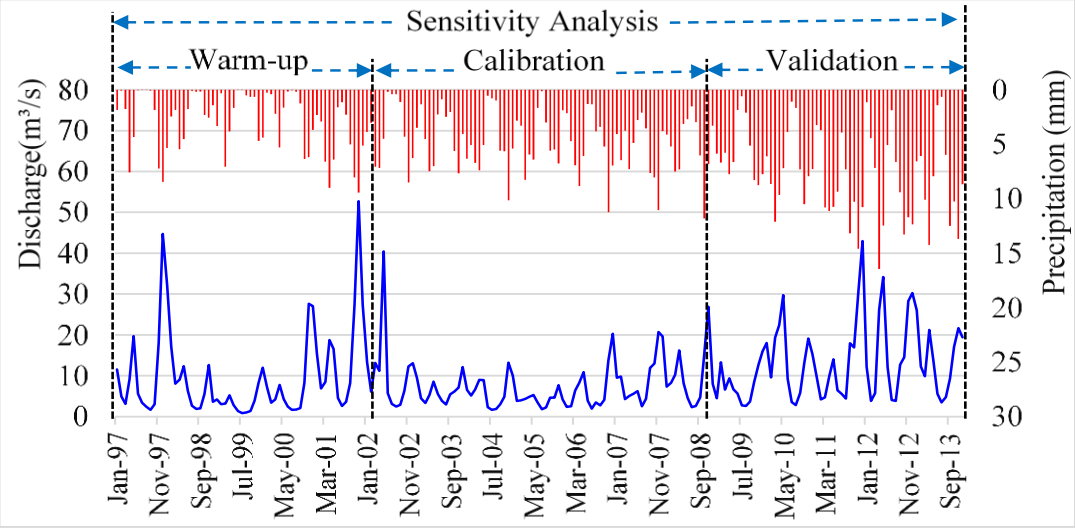

Figure 4-9: Graphical distribution of observed data during sensitivity analysis

The SWAT CUP analysed the relative sensitivity of 20 flow parameters during global sensitivity analysis (Table 4-8). This shows the overall results of global sensitivity of

streamflow parameters in the Rwizi catchment and their rankings after simulations. Figure 4-10 shows a graphical plot of *p*-value and *t*-stat of SWAT-CUP during sensitivity analysis in the order of their sensitivity. In addition, the *p*-value index and *t*-stat of sensitivity analysis are presented in form of scatter dotty plots (Appendix 6). These are representative of relative changes of parameter values versus objective function indicating the distribution of the sampling points in correlation to parameter sensitivity (Arnold *et al.,* 2012; Abbaspour, 2015; Abbaspour *et al.,* 2017). ALPHA_BF.gw revealed the highest level of sensitivity to the objective function by indicating a trend with a sharp and clear peak while EPCO.hru revealed the lowest diffused peak indicating that the parameter was less sensitive.

Table 4-8: Sensitivity rankings of streamflow parameters

S/N	Parameter name	*t*-stat	*p*-value
1	v__ALPHA_BF.gw	10.492544	0.000000
2	v__HRU_SLP.hru	6.435055	0.000000
3	r__CN2.mgt	5.117376	0.000000
4	v__GWQMN.gw	-4.498645	0.000009
5	v__SOL_BD(..).sol	4.074949	0.000054
6	v__CH_K2.rte	-3.325948	0.000949
7	v__SLSUBBSN.hru	-3.143430	0.001773
8	r__SOL_AWC(..).sol	2.481477	0.013426
9	v__REVAPMN.gw	1.656768	0.098221
10	r__SOL_K(..).sol	1.621658	0.105535
11	v__ESCO.hru	1.405752	0.160446
12	r__GW_REVAP.gw	-1.246388	0.213231
13	v__CH_N2.rte	-0.925218	0.355318
14	r__EPCO.hru	-0.920351	0.357852
15	v__RCHRG_DP.gw	-0.689056	0.491122
16	r__SOL_Z(..).sol	0.512072	0.608837
17	v__SURLAG.bsn	-0.453376	0.650484
18	v__GW_DELAY.gw	-0.179320	0.857762
19	r__SHALLST.gw	0.173588	0.862263
20	v__ESCO.bsn	0.167120	0.867346

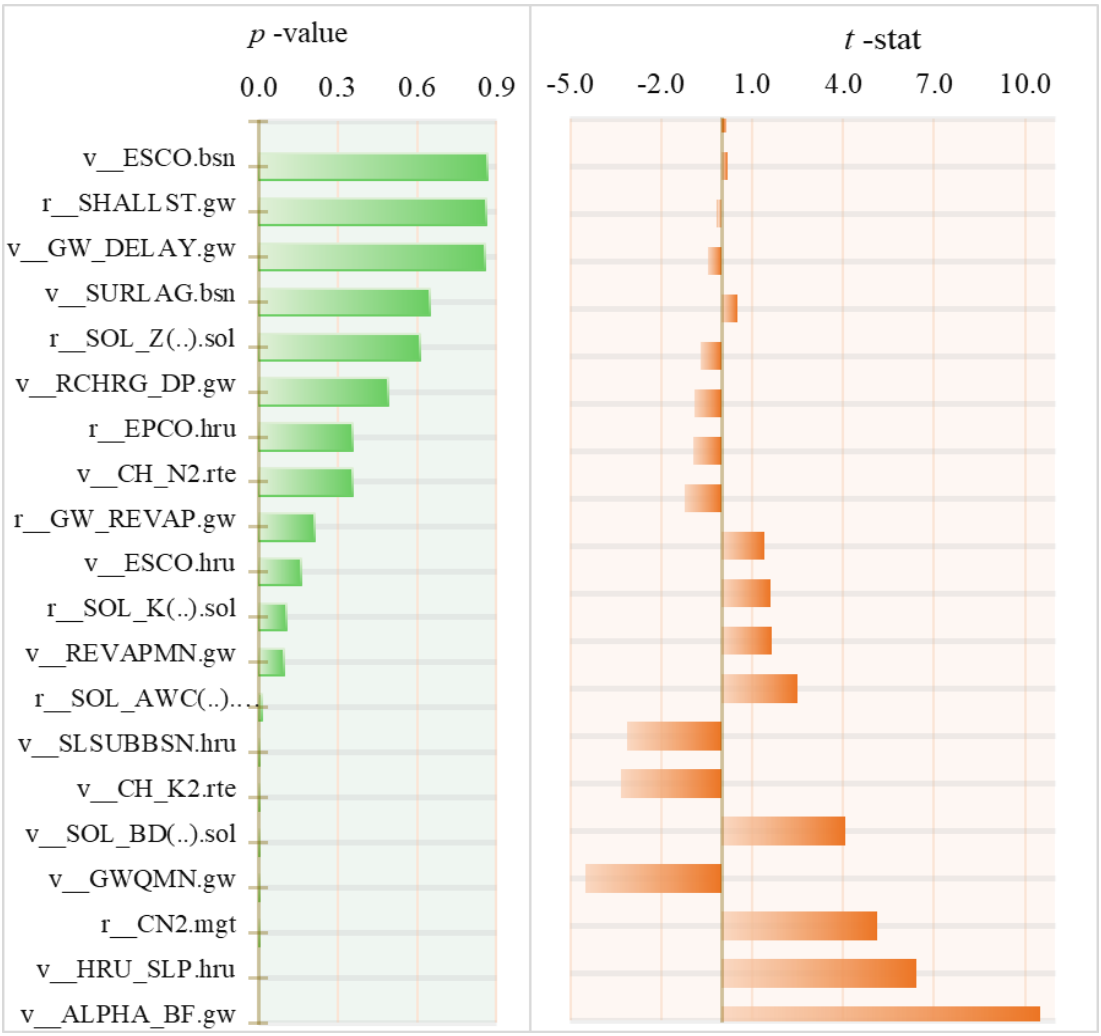

Figure 4-10: Indicator chart of *p*-value and *t*-stat during sensitivity analysis

Table 4-9 shows the 13 sensitive parameters detected by SUFI-2 and considered during calibration of River Rwizi catchment. A total of 8 most parameters had *p*-values less than $\alpha \leq 0.05$. The top four sensitive most sensitive parameters were initial baseflow alpha factor (ALPHA_BF), average slope steepness (HRU_SLP), SCS CN II value (CN2) and the threshold depth of water in the shallow aquifer required for return flow to occur (GWQMN). These were followed by the moist bulk density (SOL_BD), effective hydraulic conductivity in the main channel alluvium (CH_K2), average slope length (SLSUBBSN) and available water capacity of the soil layer (SOL_AWC) were

also very sensitive. These have the $p \leq 0.05$ (Abbaspour *et al.*, 2017). The threshold depth of water in the shallow aquifer for "revap" to occur (REVAPMN), saturated hydraulic conductivity (SOL_K), soil evaporation compensation factor (ESCO.hru), groundwater evapotranspiration coefficient (GW_REVAP) and Manning's n value for the main channel (CH_N2) were the least sensitive with $0.09 < p < 0.35$ range. This shows that variation in streamflow in the Rwizi catchment was strongly influenced by ground water, LULC types and soil properties.

Table 4-9: Most sensitive parameters considered during calibration

S/N	Parameter Name	*t*-stat	*p*-value
1	v__ALPHA_BF.gw	10.492544	0.000000
2	v__HRU_SLP.hru	6.435055	0.000000
3	r__CN2.mgt	5.117376	0.000000
4	v__GWQMN.gw	-4.498645	0.000009
5	v__SOL_BD(..).sol	4.074949	0.000054
6	v__CH_K2.rte	-3.325948	0.000949
7	v__SLSUBBSN.hru	-3.143430	0.001773
8	r__SOL_AWC(..).sol	2.481477	0.013426
9	v__REVAPMN.gw	1.656768	0.098221
10	r__SOL_K(..).sol	1.621658	0.105535
11	v__ESCO.hru	1.405752	0.160446
12	r__GW_REVAP.gw	-1.246388	0.213231
13	v__CH_N2.rte	-0.925218	0.355318

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

It is interesting to note that the CN2 parameter did not show the expected sensitivity, since it is related to direct surface flow however. This fact may be related to the characteristic of the relief, being flatter to a great extent in the lower part of the basin; as well as by the predominant soil having greater permeability. These characteristics favour the component related to water infiltration in the soil and consequently, the formation of the flow from the base flows. The curve number estimates runoff based on the relationship between precipitation, hydrologic soil group and landuse. Therefore, ALPHA_BF.gw was considered as the primary source of uncertainty when dealing with streamflow simulation.

Principe (2012) on exploration of climate change effects on watershed sediment yield and landcover-based mitigation measures using SWAT in Cagayan river basin, Philippines found that CN2 was not sensitive to the catchment. Almeida *et al.* (2018) also obtained the same result in the study; calibration and validation of the SWAT hydrological model for the Mucuri river basin. However, other researchers like Getachew & Melesse (2012); Mutenyo *et al.* (2013); Gyamfi *et al.* (2016); Zuo *et al.* (2016) found CN2 to be the most sensitive streamflow parameter in modelling hydrology in their studies. Tuyahabwe (2019) while assessing the impacts of landuse changes on water resources of River Mpanga catchment also found out that the CN2 was the most sensitive streamflow parameter in modelling hydrology.

Even if the rest of the parameters were not found to be sensitive to flow in the catchment as their *p*-values were greater than 5%, other studies; Betrie *et al.* (2011); Qiu *et al.* (2013); Fukunaga *et al.* (2015) and Gamvroudis *et al.* (2015) have found some of them to be sensitive in their study areas. This is likely as conditions such as LULC, soil characteristics and climatic factors vary from one catchment to the other.

4.3.1.5 SWAT model calibration, validation and uncertainty results

i) Calibration and Validation

Table 4-10 shows the most sensitive parameters and their calibrated values. A total of 13 parameters were calibrated for SWAT model under LULC scenario 1997. Reducing ALPHA_BF slows the aquifer response to recharge, causing a reduction in the annual runoff peak but making more water available for streamflow later in the year. CN2 is usually the most important parameter in calibration of SWAT because it is highly associated with LULC changes and SOL_K or saturated hydraulic conductivity relates soil water flow rate to the hydraulic conductivity. It represents soil moisture parameters in the calibration process.

Table 4-10: Methods, adjustment intervals and parameter calibrated values

Parameter Name	Min Value	Max Value	Calibrated value
r__CN2.mgt	-0.2	0.2	-0.110
v__ALPHA_BF.gw	0	1	0.422
v__HRU_SLP.hru	0	1	0.995
v__GWQMN.gw	0	10	1.146
v__ESCO.hru	0	1	0.933
r__SOL_K(..).sol	-0.2	0.2	-0.337
v__CH_N2.rte	0	0.3	0.476
v__CH_K2.rte	0	500	704.179
r__GW_REVAP.gw	-0.2	0.2	0.189
v__REVAPMN.gw	-0.2	0.2	-118.475
v__SLSUBBSN.hru	0	100	39.564
r__SOL_AWC(..).sol	-0.2	0.2	0.043
v__SOL_BD(..).sol	0.9	2.5	1.967

Table 4-11 shows both observed and modelled average flows for the calibration period (2002 - 2008) and validation period (2009 – 2013). The flows were obtained using the LULC map of the year of 1997. The average modelled flows obtained during both periods were less than the average observed flows for the same periods. However, during validation, the pattern of the modelled streamflow appeared to be in a better agreement with the observed streamflow values than during calibration period.

Table 4-11: Modelled and observed average flow during calibration and validation

Period	Observed Flow (m^3/s)	Modelled (m^3/s)
Calibration	7.46	6.08
Validation	12.82	11.08

According to results in Table 4-12, for the year 1997, the R^2, NSE, *p*-factor, *r*-factor and Pbias values for calibration period were 0.41, 0.50, 0.54, 0.31 and 19.8% respectively. Whereas for the validation period, the results for the same indices were 0.61, 0.71, 4.00, 0.50 and 0.34 respectively. A *p*-factor of 1 and *r*-factor of zero indicates a simulation that exactly corresponds to measured data which was relatively true for the simulations obtained from Rwizi SWAT model. The *p*-factor indicated the percentage of observations bracketed by the 95% prediction uncertainty (95PPU), brackets (%). The performance for the calibration and validation periods was satisfactory. This was because the model clearly captured the observations very well during both periods for the catchment with $0.50 < R^2 \leq 0.60$ and $0.36 < NSE \leq 0.60$ (Liew *et al.*, 2003; Fernandez *et al.*, 2005; Moriasi *et al.*, 2007). In addition, based on the narrow 95PPU bands obtained, it shows that the uncertainty for streamflow simulation was also acceptable with $\pm 15 < PBIAS \leq \pm 25$. Thus, model simulation performance was considered satisfactory.

Table 4-12: Model performance during calibration and validation

Index	Calibration	Validation
Coefficient of determination *(R^2)*	0.41	0.61
Nash and Sutcliffe Coefficient *(NSE)*	0.50	0.71
Pbias *(%)*	19.80	4.00
p-factor	0.54	0.50
r-factor	0.31	0.34

Figure 4-11 shows graphical results (visual and statistical evaluations of model performance) of the comparison of observed versus modelled series. The time series plot shows that the variation in observed flow was well captured by that in modelled series for the hydrological station No. 81224 of River Rwizi while considering the LULC of 1997. However, it is noticeable that there was a large mismatch between observed and modelled flow especially at the beginning of the calibration period especially before 2003. This could be due to a number of reasons. Firstly, such a large mismatch could be due to low quality of hydrometeorological series especially precipitation and evaporation. If this is the case, it means capability of the CFSR data in reproducing observed climatic conditions across the study area was better after than before 2003. The second explanation is that the model might have required more than the selected 2-year period. Perhaps, a 3-year period could have been selected. Nevertheless, this could not have substantially changed the modelled results especially over the period after 2003.

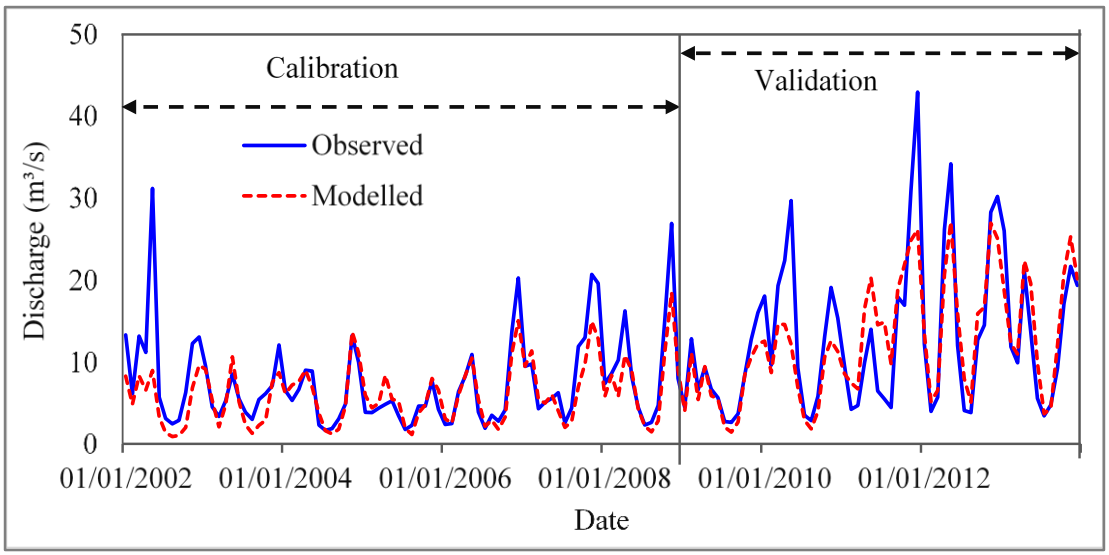

Figure 4-11: Observed versus modelled streamflow

In conclusion, the model performance was better during validation than calibration. The R^2 of 0.61 and NSE of 0.71 were obtained during validation compared to R^2 (0.41) and NSE (0.50) for calibration. There was flow underestimation during both calibration and validation periods indicated by a positive Pbias of 19.8% and 4.0% respectively. In addition, the *p*-factor values for both periods were better satisfactory with $0.50 \leq p\text{-}factor \leq 0.54$. This indicates that in both periods, $p \geq 0.5$ (50%) was obtained. Similarly, the *r*-factor ranges for calibration and validation ranging between $0.31 \leq r\text{-}factor \leq 0.34$. According to Abbaspour *et al.* (2004; 2007 & 2015), both the *p*-factor and *r*-factor values were acceptable since the recommended ranges are $p \geq 0.5$ and $0 < r < 1.5$ respectively.

According to Liew *et al.* (2003); Fernandez *et al.* (2005); Moriasi *et al.* (2007), the model clearly captured the observation data very well during the calibration period for catchment ($R^2 = 0.41$). The narrow 95PPU bands obtained shows that the uncertainty for streamflow simulation was with Pbias ≤ 25% in both periods.

Underestimations during both calibration and validation could be attributed to existence of wetland processes, quality of input data and wastewater discharge from point sources in the catchment. These could not be accounted for during the simulation. These plausible reasons including the limitations of using the SCS CN2 to compute estimate water budget components have also been noted by Abbaspour *et al.* (2007, 2015) and Betrie *et al.* (2011) to be the cause of over and under prediction of flow. This is in agreement with Mutenyo *et al.* (2013) and Qiu *et al.* (2013) who recorded an underestimated streamflow by the SWAT model. However, Qiu *et al.* (2012) suggested that underestimation or overestimation of streamflow by the SWAT model is partly due to the use of CN2, which cannot give accurate prediction of runoff for days with several storms. Mutenyo *et al.* (2013) attributed inaccurate simulation of streamflow to insufficient rain data. It is obvious that, if all these uncertainties are minimised, a well-calibrated SWAT model can efficiently predict flow in the catchment for any management purpose.

In Rwizi catchment, the problem coupled with the values of R^2 during calibration period are associated with large fluctuations in observed flows compared to the past and current observed flows. For the overall low NSE value, it indicates errors in input data such as rainfall and temperature. However, this may also be due to rainfall, temperature and construction of infrastructure in the upstream of the watershed which also affects model performance.

In addition, upstream diversions for water supply and irrigation as well as other unknown activities in the sub-basins affected model performance. With a current population projection of 1,890,802 people based on the 1,687,468 people and average

growth rate of 2.5% (UBOS, 2014) for the districts in Rwizi catchment, most water abstractions are not accounted for. These include water for domestic, industrial, agricultural (livestock, fisheries and crop irrigation) purposes. According to MWE (2017), the dominant water withdrawals include domestic use (56%), industrial (22%) and irrigation (5%). Main industrial water abstraction points in the Rwizi catchment are Century Bottling Company Ltd (Kashari), Grape Winery and Processing (Nyakayojo) and Shumuk Factory (Nyamitanga). The principal abstractors for domestic water include NWSC-Mbarara (4,500 m^3/day), Rakai water supply (384 m^3/day) from L. Kijanebalola, Nakivale Refugee camp (120 m^3/day), Hotel Canan (100 m^3/day). Additionally, a total potential irrigable area of 771,801ha is currently operating in the catchment with estimated current irrigation water demand of 3.5 Mm^3/annum (MWE, 2017). However, this does not have a specific breakdown of any of the abstraction point locations to be incorporated in the model setup.

More still, the catchment engulfs most gazetted areas in western and central Uganda including National Parks, Ramsar sites and forest reserves (both local and central) harbouring a lot of fauna and flora. It also has many main wetlands including Kashara, Kachera, Kijanebalola and Kisoma wetland systems located along the main water bodies like Lakes Nakivale, Kachera, Mburo and Kijanebalola, which play a big role in the water balance of the basin. The small water bodies also consist mostly of permanently flooded papyrus and grass swamps like Kashara River, L. Kachera, L. Kijanebalola, River Katonga, and Kisoma River. The data unavailability of reservoir or lake management makes it difficult to separate the impact of reservoir on streamflow from the recorded streamflow data. This implies all these features have not

been captured and managed to realise their influence on the catchment hydrology hence increased uncertainties during River Rwizi catchment modelling. However, this cannot rule out the possibility of an error in the type of soil and the corresponding soil properties in the area. Another issue could be related to the soil erosion that affects the structure, infiltration capacity and other properties of the soil.

ii) Evaluation of SWAT

Simulating streamflow at the watershed-scale is challenging for many reasons: an array of possible uncertainties may exist in the form of input parameter inaccuracies, processes not accounted for by the model, and processes in the watershed that are unknown to the modeller (Abbaspour *et al.,* 2017). Hydrological modelling is even more difficult in small mountainous watersheds because of irregular topography and complex hydrological processes such as snowmelt (Rahman *et al.,* 2013). In this research, SWAT was used to simulate streamflow at the monthly time step in a watershed in the Rwizi catchment.

Most modelling efforts involving SWAT were done on large-scale agricultural watersheds, the SWAT model has been tested in Rwizi catchment. Moriasi *et al.* (2007), introduced model evaluation guidelines where NSE values between 0.50 and 0.65 conclude that the model performance is “satisfactory” and NSE values less than 0.50 are considered “unsatisfactory”. These guidelines can dictate when a model is suitable to predict outcomes and when it is suitable for decision-making operations. Nevertheless, with all the generic data challenge and issues involved including all the uncertainties in the catchment, the SWAT model performance was good in simulating streamflow at a monthly time step during both the calibration validation period, with

an NSE values between 0.50 and 0.71. This implies that the sensitive parameters captured most of the hydrological processes within the watershed hence validating the use of the SWAT model in Rwizi. Therefore, the model results were deemed satisfactory for further simulation and analyses of the impacts of human activities and climate variability on runoff across the study area.

4.3.1.6 Simulated flows for 2000, 2008, 2014 and 2019

Figure 4-12 and Table 4-13 shows the SWAT modelled streamflow results against precipitation under various LULC scenarios (maps) of 2000, 2008, 2014 and 2019. Some high peak flows were underestimated. However, low flows of some years were over estimated. Nevertheless, it is noticeable that the differences among the simulations from the various LULC maps were not large. This was an indication that contribution of human activities to the runoff variation in the study area was not large. Precipitation is plotted alongside the streamflow. It is noticeable that precipitation especially for rainy season was characterized by an increasing trend over the study period. Streamflow also exhibited an increase over time. This also suggested that the increasing trend in stream could be due to the increasing precipitation.

What cannot escape a quick notice is that differences between low flows and high flows in most of the data years were large. These results indicate that River Rwizi is characterized by large intermittency in river flows. In other words, the difference between flows during rainy and dry seasons in each year is large.

Figure 4-12 shows response of runoff to impacts of human activities based on the various LULC maps. Amount of influence of human activities on runoff varied from one month to another. This reflected the variation in the human activities, for instance,

with rainfall season. For instance, some activities such as planting of crops are done during rainy season.

Table 4-13: Average modelled streamflow results under various LULC scenarios

Year of LULC	Modelled flow (m³/s)
2000	11.67
`2008	11.67
2014	11.39
2019	11.56

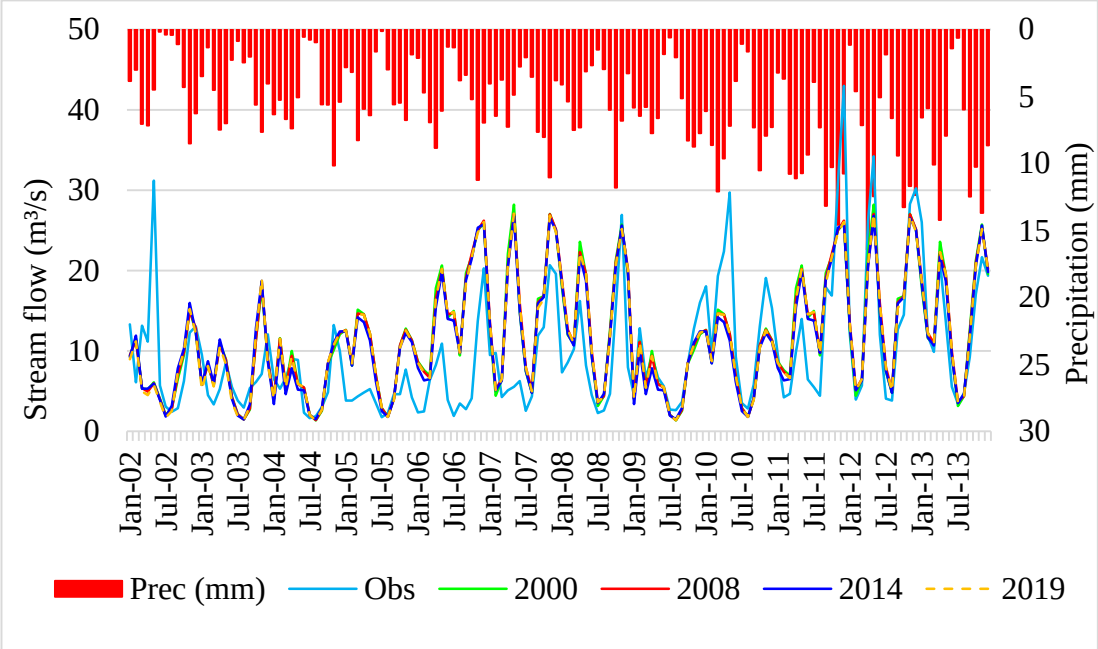

Figure 4-12: Monthly modelled streamflow against precipitation under various LULC scenarios

Table 4-14 and Figure 4-13 show the proportion and variation of total land area (%) under various LULC scenarios in different years. There was a decreasing trend in forests (FRST) from 7.96% up to 0.09% in 2008 whereas settlements (URBN) were

increasing. Pasture and grasslands (PAST) were also lost to cropland (AGRL) since it was increasing before and after the change point. This effect of decreased forests and increased urban lands resulted in the increase of streamflow since it increases chances of average SURQ, WYLD and decrease of average ET, PERC and ratios of percolation in a catchment.

Otherwise, with established root systems and high organic matter, forests improve soil physical properties, increase infiltration, and ultimately reduce surface runoff (Zhang *et al.*, 2017). In case of forest cover increase, the litter layer of plant matter is also effective in reducing surface runoff because it absorbs and stores water and decreases evaporation from soil surface. Due to canopy interception of precipitation and increased evapotranspiration rates in forested lands, more water will return to the atmosphere. Therefore, decreased forest in an area will result in decreased water percolation past the root zone ultimately resulting in lower groundwater recharge.

Meanwhile, less water will transport back into the atmosphere and more precipitation will generate surface runoff and WYLD (Zhang *et al.*, 2017). With limited water infiltration, the hard surface of urban land prevents infiltration into the ground and minimizes the evaporation losses. This increased average SURQ, WYLD, and decrease in average PERC were due to increase in urban land. In addition, forests and grasslands have similar impacts on the hydrologic cycle in this region (Zhang *et al.*, 2011, 2015; Wang *et al.*, 2013; Karamage *et al.*, 2017).

Table 4-14: The proportional area (%) under various LULC in different years.

LULC type	Year					Average
	1997	2000	2008	2014	2019	
AGRL	38.18	22.52	40.35	48.61	31.00	36.13
URBN	0.17	0.16	0.46	0.51	4.60	1.18
FRST	0.27	7.96	0.09	8.84	9.10	5.25
PAST	55.38	62.71	51.34	36.90	42.92	49.85
WATR	2.19	1.98	2.13	2.10	2.06	2.09
WETL	3.81	4.66	5.63	3.04	10.33	5.49

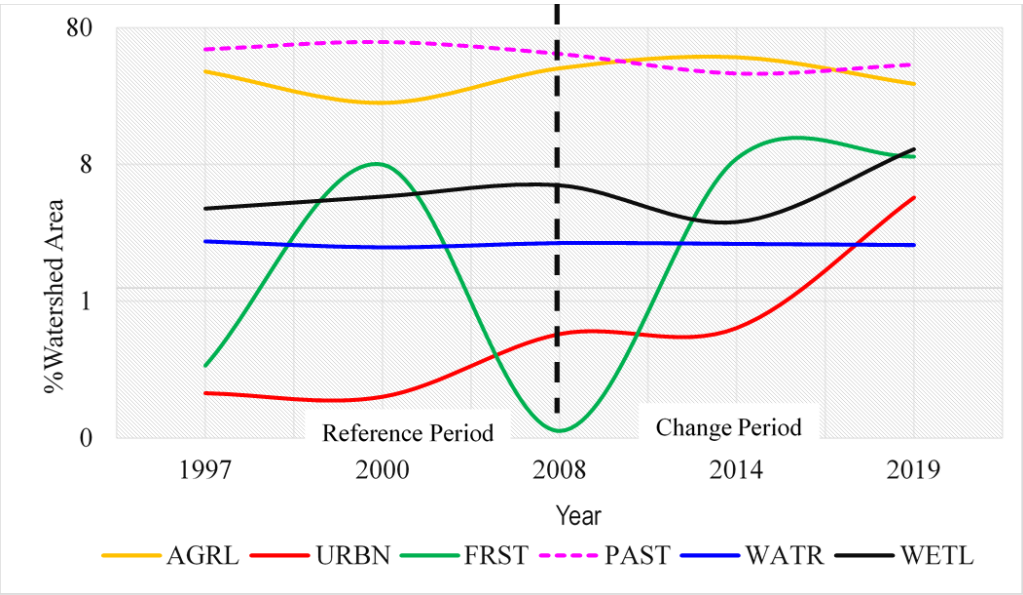

Figure 4-13: Variation of land area size (%) under various LULC scenarios.

4.4 Separation and quantification of the impact of climate variability and human activity on streamflow

Figure 4-14 show the contribution of human activities and climate variability to River Rwizi flow change. Generally, contributions of human activities to runoff variation goes up to about 23.5% in August. For wet seasons (March, April, May, October,

November and December, amounts of contributions of human activities to streamflow variation remained low. Results show that the largest amounts of contributions (at least 76.5%) to variation in mean runoff across the study area came from climate variability which indicates that it is far much more influential in shaping River Rwizi flow change than human activities. Human activities are expected to account for more of this reduction in mean annual streamflow than climate variability (Zhao *et al.*, 2014); however, this prediction is not true with River Rwizi catchment.

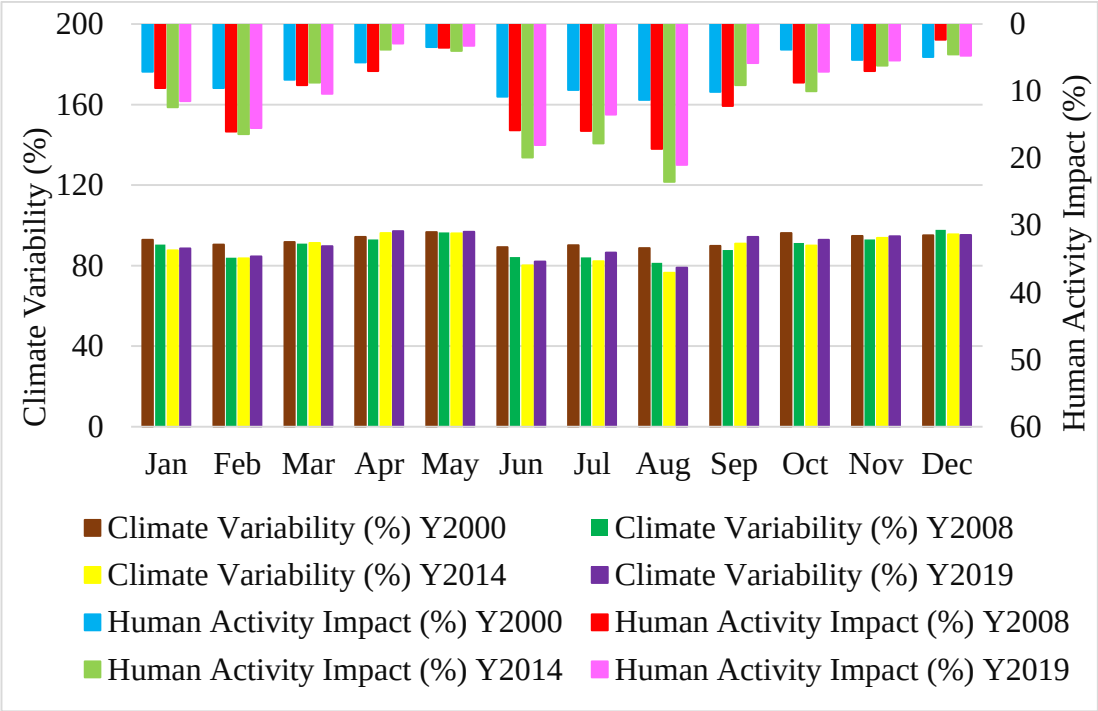

Figure 4-14: Human activities and climate variability contribution on monthly streamflow variation in River Rwizi

Figure 4-14 (top plot) shows response of runoff to impacts of human activities based on the various LULC maps. Quantity of influence of human activities on runoff varied from one month to another. This reflected the variation in the human activities, for

instance, with rainfall season. For instance, some activities such as planting of crops are done during rainy season.

River Rwizi has been reported to be dwindling due to impacts of human activities on the hydrology of the catchment (Atwongyeire, 2018; Nagawa *et al.*, 2018; Masinde, 2019). Question to answer is whether the impacts of human activities could be as substantial as reported by the media. Our study indicates that the mean River Rwizi flow over the study period exhibited an increasing trend. At least 76.5% if the variation in the mean runoff across the study area could be attributable to the impacts of climate variability on hydrology. The amount of contribution of human activities was about 23.5%. However, the impacts of human activities on the streamflow were on average found to be larger during dry (14.7%) than wet (5.8%) season. The increasing pressure from the rapidly growing population in terms of activities such as, encroachment of wetlands (through planting of eucalyptus in wetlands and sand mining), and massive water abstractions especially during dry season is responsible for making River Rwizi catchment hydrologically drier than it would be if allowed to exist under natural condition.

Furthermore, it can be seen that the impacts of human activities on the runoff variation was lager based on LULC map of 2014 than that of 2019. This suggests that that there was some reduction in the rate of vegetation and wetland degradation. This could have followed the constant concerns on the need to stop further degradation and wetland encroachment along River Rwizi. One example of such concerns in 2017 can be found online via https://ugandaradionetwork.net/story/nema-on-the-spot-over-delayed-restoration-of-rwizi-river-protection-zone- (accessed: 24th March 2021). In response

to the concerns, drastic measures were taken against encroachers. For instance, the National Environment Management Authority (NEMA) in liaison with the police gave the wetland encroachers ultimatum in 2017 to voluntarily desist from activities that were detrimental to the normal functioning of the River Rwizi system. Further details on such ultimatum can be read via https://archives.visiongroup.co.ug/vision/NewVisionaApi/v1/uploads/NV061217pg14.pdf (accessed: 24th March 2021). We think that such drastic steps in line with the need for restoration of River Rwizi especially after 2014 could have reduced the negative impacts of human activities on the hydrology of the catchment.

Notably, since the results in this study are based on flows aggregated to monthly scale, probably, more realistic results could be obtained by modelling runoff using data of high temporal resolution such as, daily or hourly series. This requires high quality data for the study area and this was found still a challenge during this study.

Regulations on water abstractions especially during dry season should be carefully enforced to ensure sustainability of the water resources in the catchment. One way would be to set and maintain a water abstraction threshold that ensures the catchment hydrology supports functionality of the various water-related or water-based systems. Currently, the MWE regulation ensures that Q90 or Q95 is used as the environmental flow especially in absence of a relevant study. Q90 is the flow which is exceeded 90% of the times the flows is recorded over a stipulated period. The question would be whether the threshold is respected given the disproportionate volumes of water abstracted by the various permitted and unpermitted water users. As opposed to the use of Q90 or Q95, the threshold for water abstraction could be set while taking into

account (i) the dynamics of runoff generation in the various sub-flows (baseflow, interflow, and overland flow) given the variation in precipitation and evapotranspiration across the study area, and (ii) level of adherence to the environmental flow by the various water abstractors.

4.5 Discussion

Climate variability and anthropogenic activities are widely regarded as the two main drivers of streamflow change (Wang, 2014; 2015, 2016, 2018; Zhang *et al.*, 2014, 2017; Pirnia *et al.*, 2019). Climate variability comprises the changes in precipitation and potential evaporation, which together affect catchment runoff (Fan, Shibata and Wang, 2016). Human activities, including soil and water conservation projects, operation of dams and reservoirs, and water consumption are found to be the dominant factors responsible for the significant decline in the hydrological alteration (Zhang *et al.*, 2011, 2014). However, this was not the case with Rwizi catchment since the biggest influence is probably due to climate variability. Therefore, what is the major driving factor for streamflow changes? This is answer a very important query for future water resources planning and management decisions to ensure sustainable water resources utilization (Wang *et al.*, 2016).

Comparing the streamflow simulations of different scenarios of various LULC i.e., 2000, 2008, 2014 2019 (Figure 4-14), it can be concluded that the biggest influence on streamflow was attributable to climate variability since LULC in the Rwizi catchment a very small influence on streamflow variations. Taking into account changes in irrigational water use and available water abstractions along river Rwizi, landuse changes influenced streamflow with an average of 7.5%, 10.47%, 11.36% and 9.92%

for 2000, 2008, 2014 and 2019, which was a very small contribution compared to climate variability.

This is consistent with Zhang *et al.* (2017), landuse changes increased streamflow between 2.2 and 3.9%, while the change of climate variability made the streamflow declined by 39.1%. More still, it is consistent with the conclusions of Legesse (2003); Zhao *et al.* (2014); Zhang *et al.* (2017). However, several researches indicated that human activities were the major causes for streamflow decrease; for instance, in the Haihe Basin, and their contribution rate was more than 50% (Bao *et al.*, 2012). For the streamflow decrease in Luan River, Wang *et. al.,* (2016) suggested that 57% - 67% of the change was attributable to human activities while climate variability was responsible for only 33% - 43%. According to (Zhang *et al.* (2011), climate variability accounted for over 43% of the change, which can mainly be attributed to the decrease in precipitation. Human activities were found to be liable for about 57% of the change in the annual streamflow in Hun–Tai River basin (Zhang *et al.,* 2011). This is further consistent with results of other several studies (Gao *et al.,* 2013; Zhang *et al.,* 2014; Wang *et al.,* 2016; Pirnia *et al.,* 2019; Mu *et al.,* 2020; Zeng *et al.,* 2020).

Numerous studies show that the variations of streamflow are strongly related to regional climate especially precipitation and generic human activities including this research, but this may be insufficient to explain all the changes in detail (Wang *et al.,* 2016). The construction of water conservancy facilities (reservoirs), wetland degradation, irrigation and domestic water abstraction among others in the catchment are other important factors altering the catchment hydrograph and increasing the water utilization (Zhang *et al.,* 2011; Wang *et al.,* 2015, 2016). It is important to highlight

that there remains a lot of uncertainty in this statistical assessment of climate variability and human activity on water yield.

CHAPTER FIVE: CONCLUSION, RECOMMENDATIONS AND LIMITATIONS

5.1 Conclusions

This research analysed and quantified the influence of human activities and climatic variability on streamflow changes in the River Rwizi catchment. In order to investigate whether the flow variation was attributable to LULC changes, different landuse maps i.e., 2000, 2008, 2014 and 2019 were evaluated at catchment scale. SWAT was driven by monthly hydro-meteorological data over the period 2002-2013. After quantifying the human influence ratio, the reminder was attributable to climate variability.

5.1.1 LULC changes in River Rwizi catchment

The predominant changes in the period between 1997 and 2008 were expansion of forest (2.08%), grassland (8.59%) and wetland (4.57%) at the expense of cropland which reduced by 15.23% while settlement and water did not change much. Between 2000 and 2008, the areas under cropland increased with a 16.15% and settlement (0.27%) which led to a decrease in forest (2.47%), grassland (11.00%), water (0.05%) and wetland (2.90%). From 2008 to 2014, cropland gained 12.47%, forest (2.46%), settlement (0.03%) and water (0.01%) whereas grassland reduced by 14.48% and wetland by 0.50%. Lastly, between 2014 and 2019, the biggest addition was in wetlands which increased by 10.91%, followed by forests at 6.05% and settlement at 4.33%. Conversely, the greatest decline was in cropland at 18.1% followed by grassland at 1.21%, and finally water at 0.10%. Despite the increasing population pressure on the catchment environment River Rwizi becomes wetter and drier during wet and dry seasons over the years, respectively.

5.1.2 Simulation of River Rwizi streamflow changes using SWAT

In order to assess the effect of human activities and climate variability on streamflow in River Rwizi catchment, a SWAT model was used to simulate flows. Changes in LULC types were characterized using maps of 1997, 2000, 2008, 2014, and 2019. SWAT was driven by CFSR-based hydro-meteorological series including precipitation, maximum and minimum temperature, relative humidity, solar radiation and wind speed. SWAT was built-up using LULC map of 1997. Calibration and validation of SWAT were performed on monthly time scale over the periods 2002-2008 and 2009-2013, respectively. Model performance was assessed in terms of Nash-Sutcliffe Efficiency (NSE). NSE values for SWAT over calibration and validation periods were 0.50 and 0.71 respectively. These values indicate the acceptability of model results for assessing impacts of human activities and climate variability on River Rwizi flow temporal variation. To depict the transition in landuse changes, SWAT was parameterized using optimal parameter values obtained during calibration and this was followed by simulation based on LULC maps of 2000, 2008, 2014, and 2019.

5.1.3 Separation and quantification of impacts of human activities and climate variability on River Rwizi streamflow

In Rwizi catchment, it was found that the hydrological processes were mainly influenced by two key drivers with climate variability playing a primary role in the variation of flows in River Rwizi than human activities. Impacts of human activities on the streamflow were on average found to be larger during dry (14.7%) than wet (5.8%) season. Massive water abstractions especially during dry season and encroachment of wetlands make River Rwizi catchment hydrologically drier than it

would be under minimal influence of human activities. Up to 23.5% of the variation in runoff across the study area could be explained in terms of the impacts of human activities on the hydrology of River Rwizi. The impacts of human activities on the streamflow variation were larger during dry than wet season. However, at least 76.5% of the variation in the monthly flow of River Rwizi could be attributed to climate variability.

5.2 Recommendations

5.2.1 Policy

According to this research, the changes in LULC have caused a low impact on the hydrology of Rwizi catchment. Therefore, it is so vital to strengthen the existing policies and laws concerning resource use and management to reduce encroachment on the river and its resources. Control mechanisms like reducing the degree of deforestation and managing increasing settlement patterns in the catchment reduce surface run off and facilitate infiltration and ground water recharge which should be implemented. Policies on human activities which ensure sustainability of River Rwizi such as preservation of wetland and promotion of tree planting should be implemented over the catchment.

5.2.2 Water resources

Largely, the catchment lies within the Uganda's dry corridor which implies strong seasonal variations of river discharge. It is thus prudent to work towards establishing and sustaining sufficient minimum flows that would mitigate the effects of reduced baseflows and put in place measures to maintain adequate sustained River Rwizi flows to the benefit of the stakeholders such as proper land and water management practices.

Therefore, current and future water resource management and planning in the Rwizi catchment if well implemented as an integrated water regulation system, could reduce the overall impact of human activities on the catchment hydrology to ensure a healthy ecosystem of the river. Thus, the planning of ecological restoration and conservation projects, evaluation of the ecological engineering and the spatial structure of the project together with climate change aspect should be put into account.

5.2.3 Future research

Given that this study considered mean flow, it is recommended that future study quantifies impacts of human activities on streamflow of dry season while taking into account the level of adherence (by water users across the River Rwizi catchment) to the water abstraction regulation.

The results of this study can better inform water resources management practices throughout the basin and also at the sub-watershed scale. Therefore, an investigation of climate variability and LULC change effects on streamflow based on seasonal time series (dry and wet seasons) to reveal seasonal effects of LULC changes should be conducted. This should especially be conducted under constant climatic conditions and varying individual LULC changes. This will help develop greater confidence and less uncertainty in the results when individual impacts of landuse changes are considered as being among the most important human activities contributing to variations in streamflow. This is because the contribution of constructing storage and regulative dams, irrigation activities, wetland degradation among others as a part of human activities, also have an important role on the magnitude, frequency and duration of flows on the river downstream.

This study made use of CFSR series for hydrological modelling. There are several other reanalysis or satellite data which can be tested to investigate if they can be adequately applied in hydrological modelling for data scarce regions especially in developing countries like Uganda.

It is also recommended that further research should be conducted on the impacts of climate change on River Rwizi especially using the latest generation climate models from phase 6 of the Climate Model Inter-comparison Project (CMIP6). Comparison of various models at local scale should be conducted in future studies since simulating efficiency of the models varies depending on uncertainty introduced by calibration approach, model input, structure and parameterization among other factors.

5.3 Relevancy of this study for water resources management

This study provides knowledge on attribution of River Rwizi variation. Such information allows predictive planning of the River Rwizi catchment management under the impacts of human activities and climate variability on hydrology. For instance, it was found that impacts of human activities are more pronounced during dry than wet season. This calls for stringent measures in regulating water abstraction during dry season to ensure sustainability of the River Rwizi.

5.4 Limitations

Lack of observed long-term hydro-meteorological data affected the accuracy of the simulated flow. Historical records of the existing human developments and river water abstraction for competing needs were over a short period.

The landuse maps had some inaccuracies due to a coarse spatial resolution of Landsat 7 and 8 (30m × 30m), cloud cover content in space and knowledge of the classifier about the catchment cover and hydrological processes.

This study focused on the contributions of climate variability and human activities to River Rwizi flow variation. Other factors such as bias in hydrological model simulations were included in the residual part.

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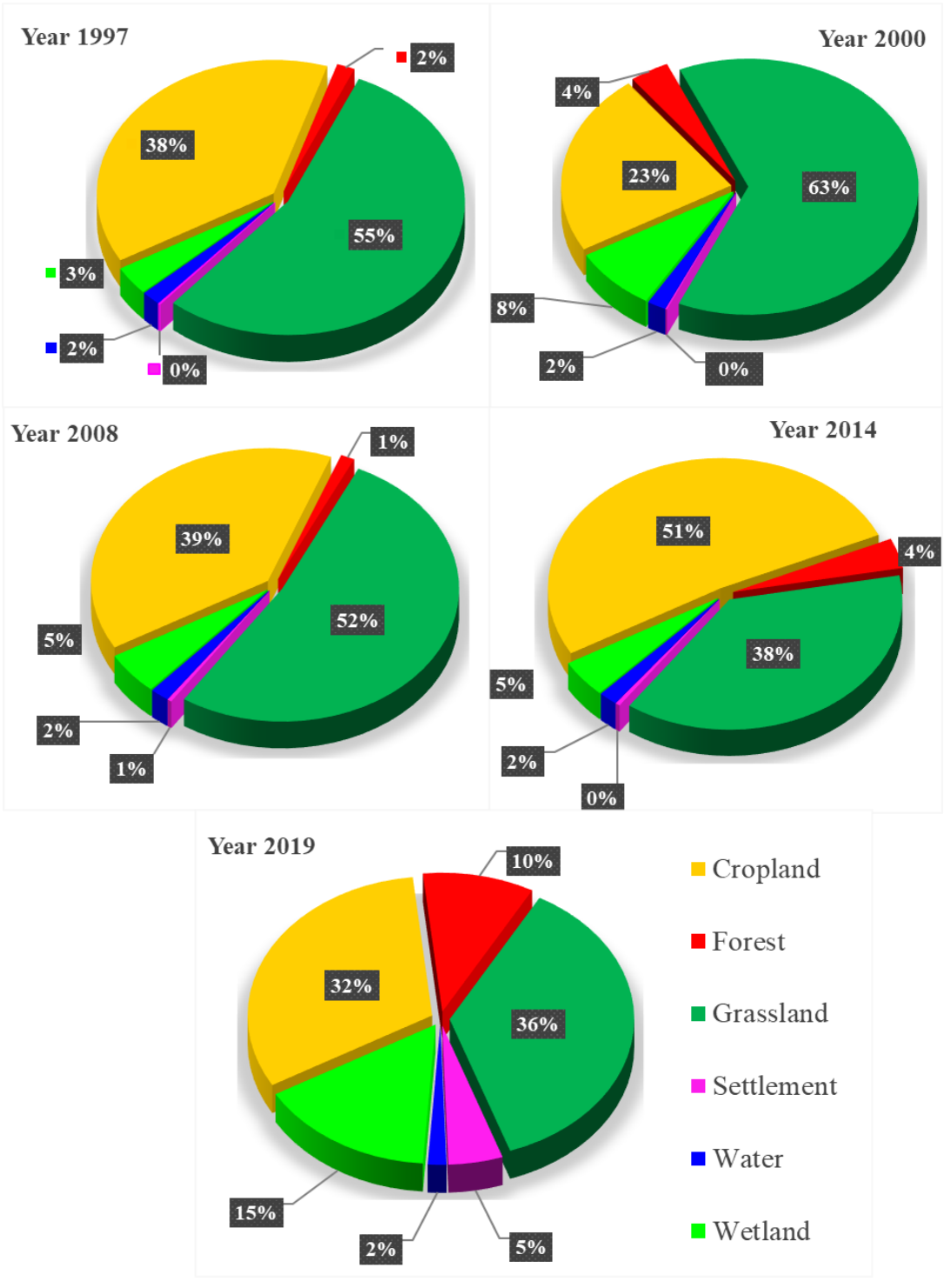
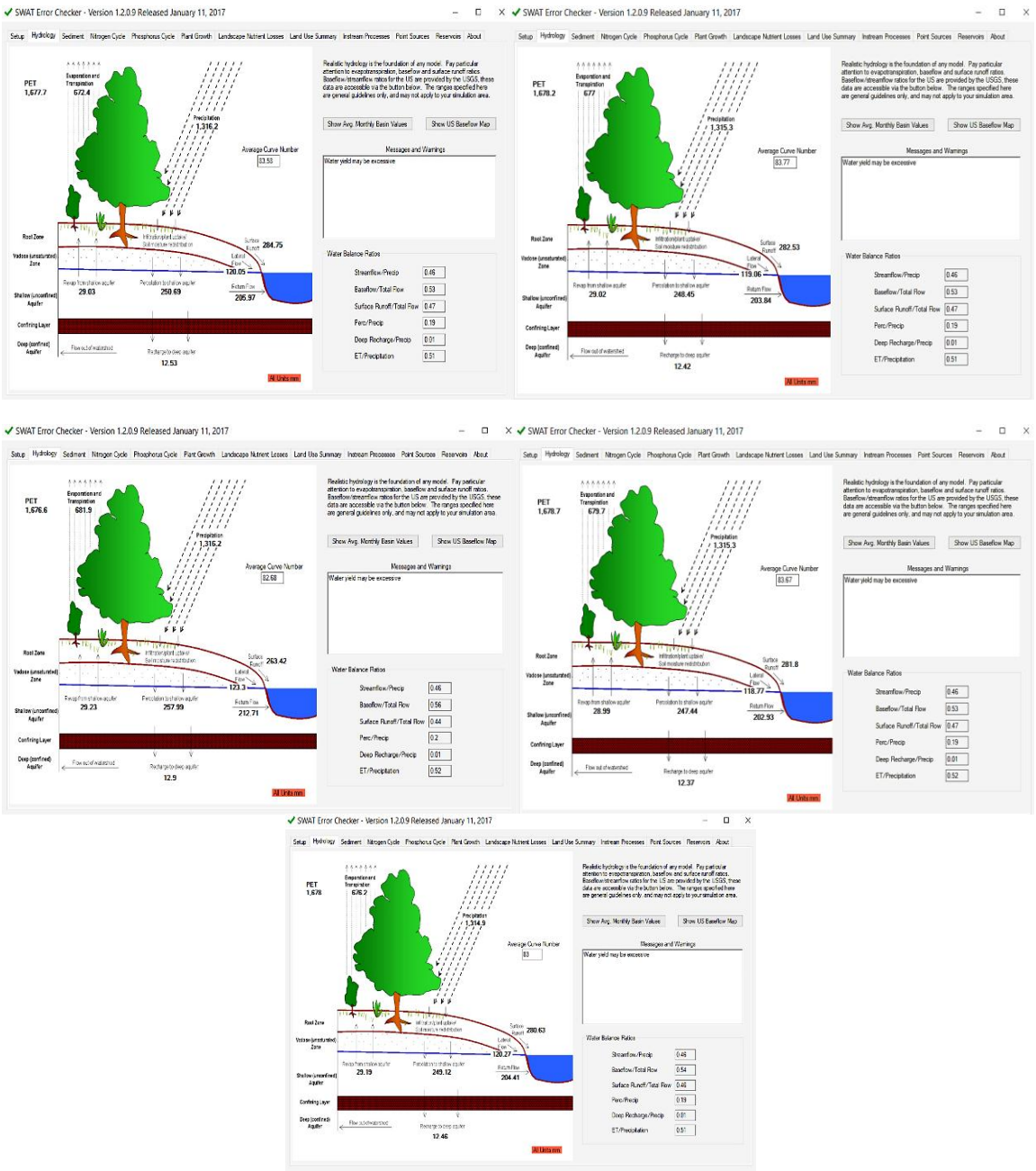
APPENDIX

Appendix 1: LULC for 1997, 2000, 2008, 2014 and 2019



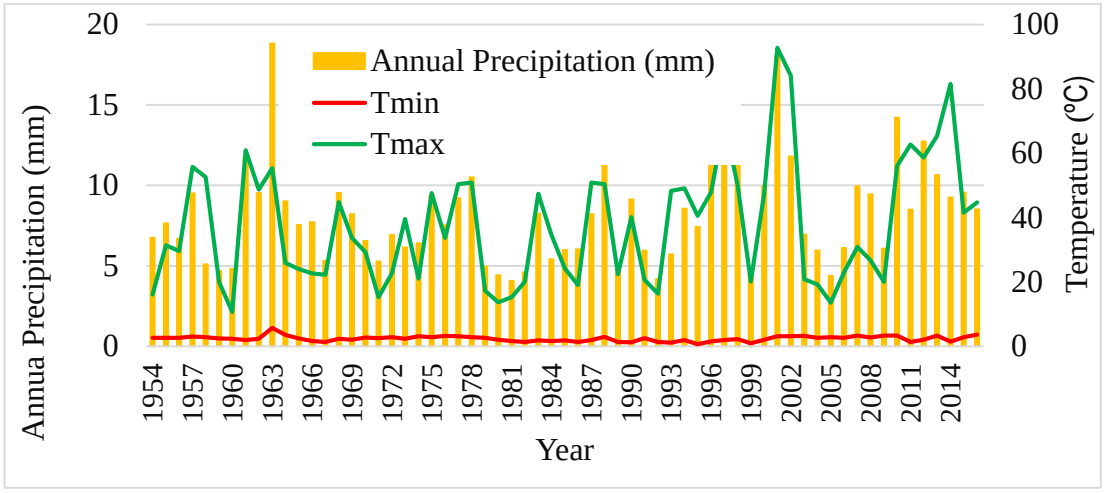
Appendix 2: SWAT model-running process, reading output and error checker



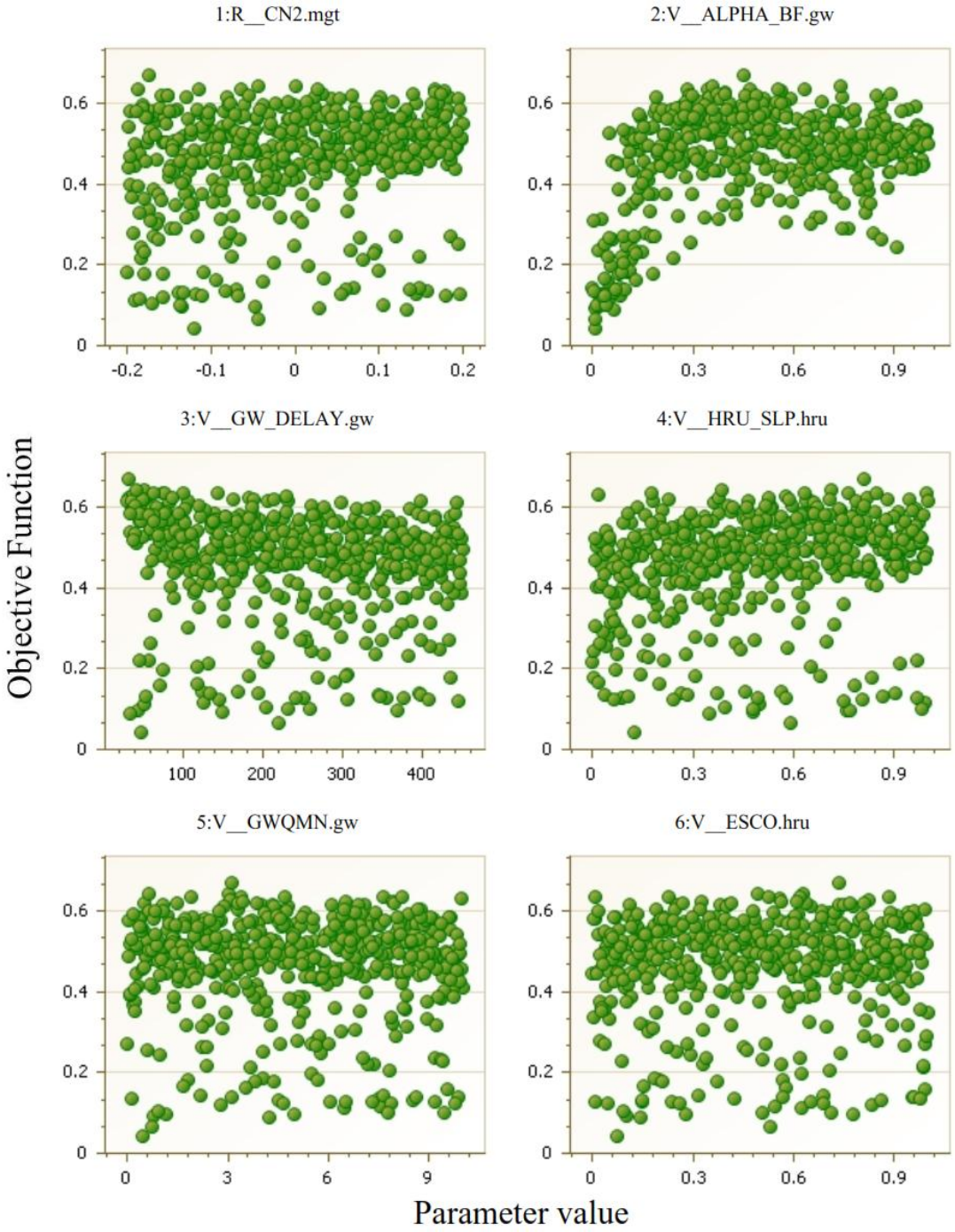
Appendix 3: LULC Summary after SWAT simulation

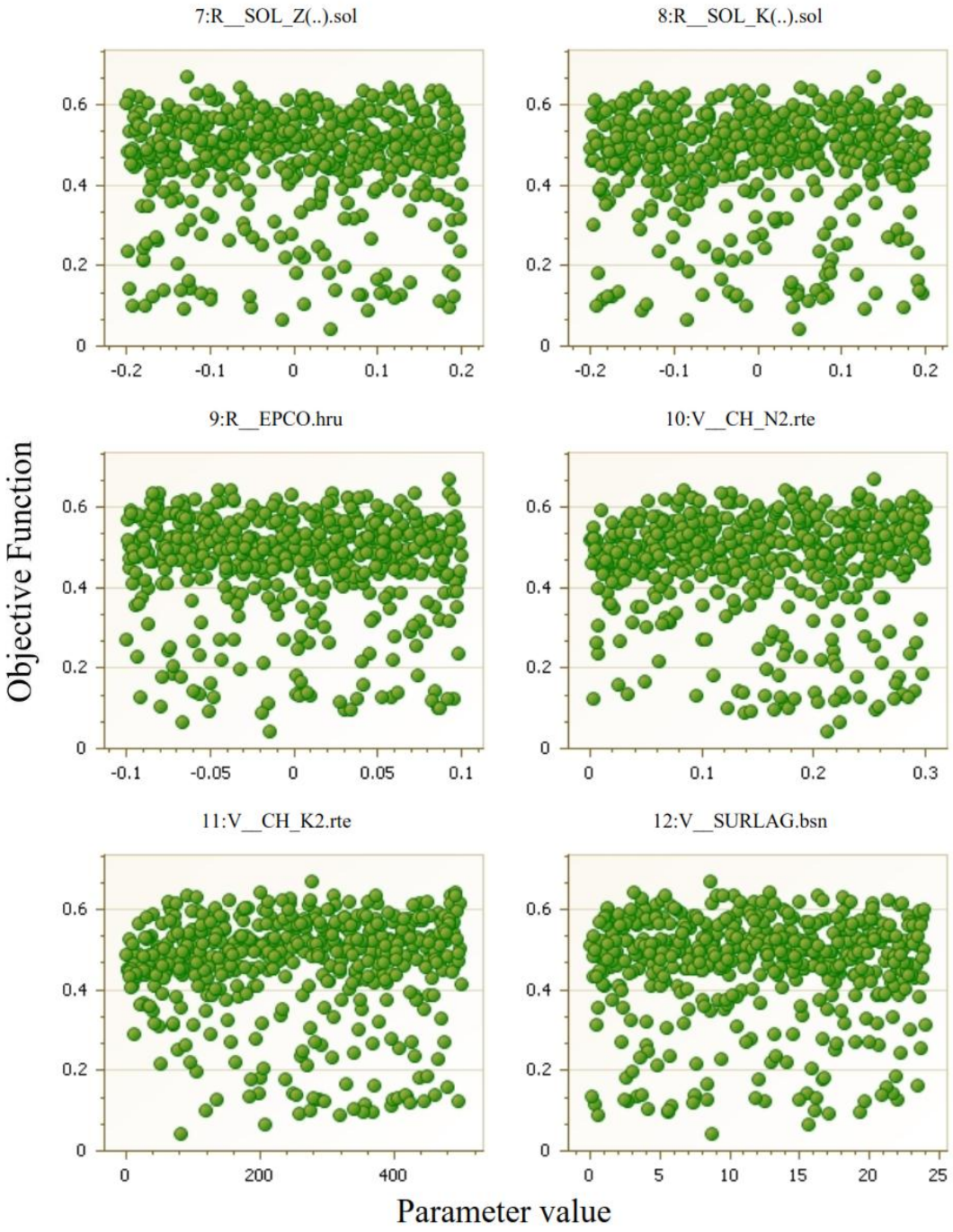
	LULC	Area (km^2)	CN	AWC (mm)	USLE (LS)	PREC (mm)	SURQ (mm)	GWQ (mm)	ET (mm)	YLD (th)
1997	AGRL	2618	86.2	71.3	2.4	2139	282.9	1059	712	6.6
	BERM	12	85.8	66.2	1.4	2563	447.0	1213	808	15.0
	FRST	18	77.1	91.9	1.3	2462	151.2	1403	794	4.9
	PAST	3797	81.3	85.0	2.0	1990	114.6	996	797	0.7
	WATR	150	92.0	35.3	0.4	1492	0.0	0	1759	0.0
	WETL	261	74.3	107.1	0.8	2070	93.5	1148	725	1.9
2000	AGRL	1545	86.1	70.5	1.9	2201	292.0	1102	715	6.7
	BERM	11	86.1	56.6	1.4	2634	469.5	1257	811	14.4
	FRST	546	75.7	82.7	1.9	1952	63.7	1031	773	4.1
	PAST	4301	81.7	81.8	2.3	2029	135.6	1021	790	0.7
	WATR	136	92.0	38.4	0.2	1496	0.0	0	1759	0.0
	WETL	320	76.8	102.1	0.9	1842	67.8	975	710	2.1
2008	AGRL	2767	85.8	77.0	2.1	2075	247.6	1025	718	6.7
	BERM	32	85.6	69.0	1.4	2318	355.2	1066	807	14.4
	FRST	6	78.5	55.5	1.5	2829	179.6	1717	806	3.1
	PAST	3521	81.7	81.3	2.3	2023	129.7	1019	792	0.7
	WATR	146	92.0	30.4	0.3	1496	0.0	0	1758	0.0
	WETL	386	76.3	100.1	0.9	2141	131.1	1163	745	1.8
2014	AGRL	3333.0	86	73.8	2	2081.4	253	1031.2	712	6.5
	BERM	34.8	86	58.6	1	2645.4	472	1262.5	813	13.7
	FRST	606.3	76	95.3	2	1862.1	48	955.9	777	4.1
	PAST	2530.3	81	83.0	2	2072.2	133	1055.8	799	0.6
	WATR	144.2	92	42.6	0	1493.3	0	0.0	1759	0.0
	WETL	208.5	76	107.3	1	1883.4	82	989.2	720	2.1
2019	AGRL	2125	85.8	69.3	1.8	2409	337.3	1248	727	6.4
	BERM	315	85.0	73.8	2.5	1901	190.1	852	787	15.2
	FRST	624	75.3	81.7	2.8	1835	49.1	945	763	5.2
	PAST	2944	81.3	87.9	2.2	1880	107.9	912	782	0.6
	WATR	141	92.0	40.5	0.2	1493	0.0	0	1760	0.0
	WETL	708	81.2	83.6	2.1	1955	128.1	994	747	1.9

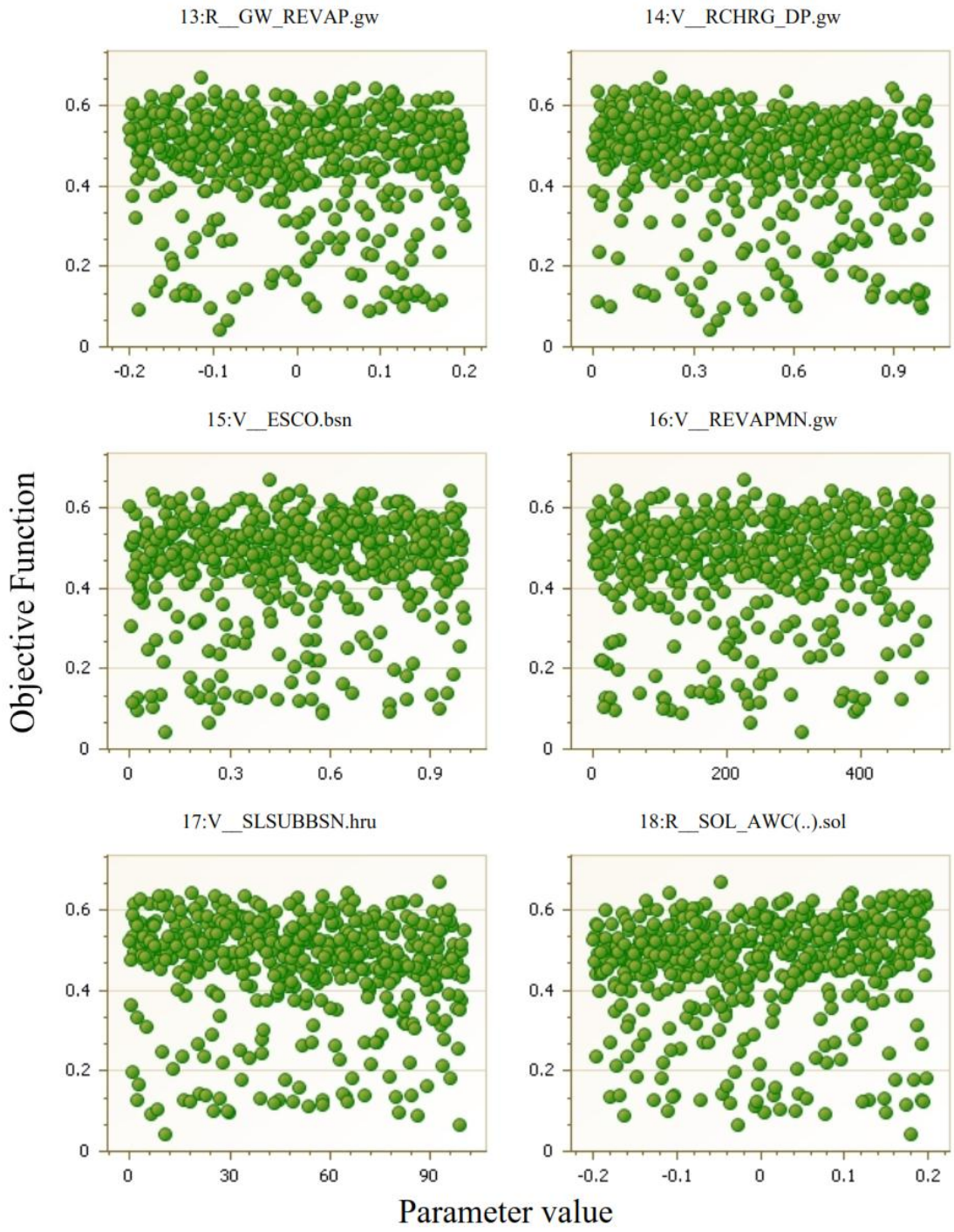
Appendix 4: Variation of streamflow and catchment precipitation from 1950s to 2016.

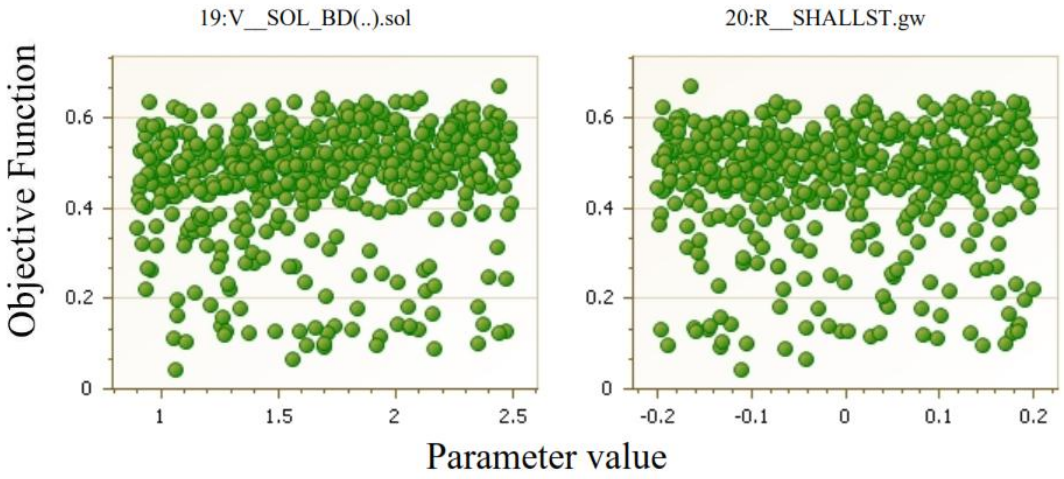


Appendix 5: Scatter plots of parameters during sensitivity analysis phase with SUFI2

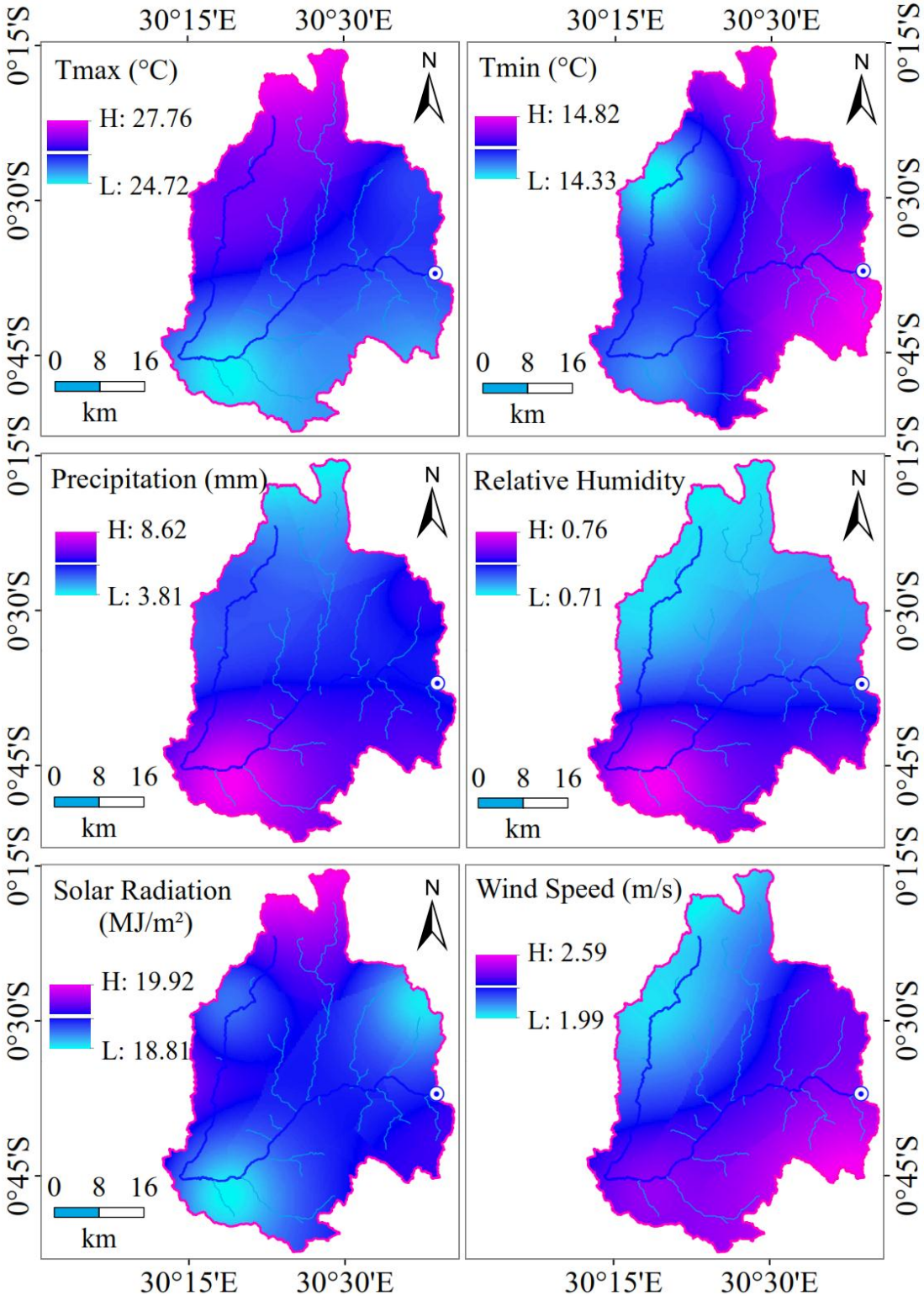



7:R__SOL_Z(..).sol
8:R__SOL_K(..).sol
9:R__EPCO.hru
10:V__CH_N2.rte
11:V__CH_K2.rte
12:V__SURLAG.bsn
Objective Function
Parameter value


13:R__GW_REVAP.gw
14:V__RCHRG_DP.gw
15:V__ESCO.bsn
16:V__REVAPMN.gw
17:V__SLSUBBSN.hru
18:R__SOL_AWC(..).sol
Objective Function
Parameter value


19:V__SOL_BD(..).sol
20:R__SHALLST.gw
Objective Function
0
0.2
0.4
0.6
1
1.5
2
2.5
-0.2
-0.1
0
0.1
0.2
Parameter value

Appendix 6: Maps of interpolated weather data for River Rwizi Catchment



Appendix 7: Photos of some of the human activities along River Rwizi

<table>
<tr>
<td> 
Water pollution with plastic waste and waste water of Rwizi tributary in Kiswahili slums - Mbarara city (2019)</td>
<td> 
River Rwizi pollution with waste water (detergents) while washing motorcycles in the river – November 2019</td>
</tr>
<tr>
<td> 
Gardens including banana plantations cultivated along River Rwizi banks (rainy season) – November 2019</td>
<td> 
Vegetation clearance along the banks of River Rwizi for cultivation (dry season) – August 2020</td>
</tr>
<tr>
<td> 
Increasing built-up areas along the buffer zones of river Rwizi</td>
<td> 
Open/bare land being cultivated without any tree or vegetation over in vicinity</td>
</tr>
</table>

Sand mining along the river banks which increase erodibility

Cattle rearing in the catchment grasslands

Source: The Independent, 20th March, 2019
President Yoweri Museveni looks at what remains of River Rwizi and directs efforts towards its restoration

Source: New Vision,10th September, 2019
Outcry from the community on the extinction of River Rwizi

Deforestation and farming along the buffer of River Rwizi

Sand mining along the River Rwizi banks

Evidence of receding water levels at the River Rwizi gauging station

Brick making on the River Rwizi banks