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The impacts of land use and climate change on Simiyu river discharge and the riverine sediment dynamics flowing towards lake Victoria

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THE IMPACTS OF LAND USE AND CLIMATE CHANGE ON SIMIYU RIVER DISCHARGE AND THE RIVERINE SEDIMENT DYNAMICS FLOWING TOWARDS LAKE VICTORIA

Renatus James Shinhu

A Thesis Submitted in the Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Hydrology and Water Resources Engineering of the Nelson Mandela African Institution of Science and Technology

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ABSTRACT

This study aimed to trace the dominant sources of riverine sediments and assess climate change's current and future impacts on the river discharge at the critical agroecological region of the Simiyu catchment. Geochemical fingerprinting of the riverbed sediments and potential sediment sources were compared using a Bayesian mixing model (MixSIAR) to attribute the dominant riverine and land-use sources to the Simiyu Mainstem. The mixing model outputs showed that the Simiyu tributary was the dominant sediment source to the Simiyu Mainstem with 63.2%, while the Duma tributary accounted for 36.8%. Cultivated land was shown to be the main land-use source of riverine sediment, accounting for 80 % and 86.4% in the Simiyu and Duma sub-tributaries, respectively, followed by channel banks with 9% in both sub-tributaries. The Soil and Water Assessment Tool (SWAT) under RCPs 4.5, 6.0, and 8.5 were also used to project the impacts of climate change on river discharge throughout 2030–2060. The selected three General Circulation Models (GCMs) predicted an increase in the annual average temperature of 1.4°C in 2030 to 2°C in 2060 and an average reduction of 7.8% in rainfall, which causes a decrease in river discharge. The simulated river discharge from the hydrological model under RCPs 4.5, 6.0 and 8.5 revealed a decreasing trend in annual average discharge by 1.6 m^3s^{-1} from 5.66 m^3s^{-1} in 2019 to 4.0 m^3s^{-1} in 2060. Arbitrary, there will be an increase in frequent flood occurrence in the future (2030–2060) compared to the current period (1990–2019), with extreme discharges of 451.3 m^3s^{-1} and 232.8 m^3s^{-1} at exceedance probabilities of 0.01% and 99.99%, respectively. The demonstrated application of sediment source tracing provides an important pathway for quantifying the dominant sediment sources in the rivers flowing towards Lake Victoria. This information is vital for designing catchment-wide management plans that should focus on buffering the projected decreases in discharge, reducing soil erosion and sediment delivery from farming areas to the river networks, and ultimately supporting food security and water quality in the Lake Victoria Basin.

DECLARATION

I, Renatus James Shinhu, do hereby declare to the Senate of The Nelson Mandela African Institution of Science and Technology that this Thesis titled *"The impacts of land-use and Climate Change on Simiyu River Discharge and the Riverine Sediment Dynamics Flowing towards Lake Victoria"* is my original work and that it has neither been submitted nor being concurrently submitted for degree award in any other institution.

31st July 2024

Renatus James Shinhu	**Date**

The declaration is confirmed by:

31st July 2024

Prof. Kelvin Mark Mtei	Date

31st July 2024

Prof. Karoli Nicholas Njau	Date

31st July 2024

Prof. Joel Nobert	Date

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CERTIFICATION

The undersigned certify that they have read and hereby recommend for acceptance by the Senate of the Nelson Mandela African Institution of Science and Technology a Thesis titled *"The impacts of land-use and climate change on Simiyu River discharge and the riverine sediment dynamics flowing towards Lake Victoria"* in fulfilment of the requirements for the Degree of Doctor of Philosophy in Hydrology and Water Resources Engineering at Nelson Mandela African Institution of Science and Technology.

31st July 2024

Prof. Kelvin Mark Mtei — Date

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DEDICATION

This work is dedicated to my beloved wife, Salome Daniel Fome; my daughters: Gabriella Renatus, Gladness Renatus, Grace Renatus, and Gloria Renatus; and my sons: Elikulumba Renatus, Emmanuel Renatus, and Elikana Renatus. Finally, I would like to extend my dedication to my late mother, Ms. Anastazia Maganga Bayanda, and my father, Mr. James Shinhu Manyenye.

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ACCESS 1.3	Australian Community Climate and Earth-System Simulator
AgMIP	Agricultural Model Inter-comparison and Improvement Project
ALPHA_BF	Baseflow alpha factor
ARS	Agricultural Research Service
BMM	Bayesian Mixing Model
BS	Bushland
CB	Channel Bank
CH_K2	Efficient hydraulic conductivity in the main channel alluvium
CH_N2	Manning n value for the main channel
CMCC.CM	Centre on Climate Change coupled climate model
CMIP5	Coupled Model Inter-comparison Project Phase 5
CN2	Curve number for moisture condition
CNRM.CM	Centre National de Recherches Météorologiques Coupled Global Climate Model
CU	Cultivated land
CRM	Certified Reference Material
DEM	Digital Elevation Model
DL	Detection Limit
DSMW	Digital Soil Map of the World
EDXRF	Energy Dispersive X-Ray Fluorescence
EUROSEM	European Soil Erosion Model
ESGF	Earth System Grid Federation
FAO	Food and Agriculture Organization
FL	Forest Land
FRN	Fallout Radionuclides
GCM	Global Climate Models
GDP	Growth Domestic Product
GHG	Green House Gases
GIS	Geographic Information System
HadCM3	Hadley Centre Coupled Model Version 3
HBV	Hydrologiska Byråns Vattenbalansavdelning
HEC-HMS	Hydrologic Engineering Center's Hydrologic Modeling System

HEC-Hydro	Hydrologic Engineering Center’s Hydrologic model
HEC-RAS	Hydrologic Engineering Center's River Analysis System
HRU	Hydrological Response Unit
HSPF	Hydrologic Simulation Program Fortran
IAEA	International Atomic Energy Agency
IPCC	Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services
LULC	Lund Use Land Cover
LV	Lake Victoria
LVB	Lake Victoria Basin
LVBWB	Lake Victoria Basin Water Board
M.a.m.s.l	Mean Above Mean Sea Level
MCMC	Markov Chain Monte Carlo
MIROC	Model for Interdisciplinary Research on Climate
MUSLE	Modified Universal Soil Loss Equation
NSE	Nash-Sutcliffe efficiency
PBIAS	Percentage BIAS
PCA	Principal Component Analysis
RB	Mainstem River Bank
RCM	Regional Climate Model
RCP	Representative Concentration Pathway
RUSLE	Revised Universal Soil Loss Equation
RS	River bed sediment
RSR	Ratio of the Root Mean Square Error to the Standard Deviation
SADC	Southern African Development Community
SSA	Sub-Sahara Africa
SURLAG	Surface runoff lag coefficient
SWAT	Soil Water Assessment Tool
SWATCUP SUFI-2	Soil Water Assessment Tool Calibration and Uncertainty Programme Sequential Uncertainty Fitting Version 2
TAEC	Tanzania Atomic Energy Commission
TMA	Tanzania Meteorological Agency
USDA	United States Department of Agriculture
USGS	United States Geological Survey

USLE	Universal Soil Loss Equation
WEPP	Water Erosion Prediction Project
WRF-Hydro	Weather Research and Forecasting Hydrological model
95PPU	95 Percent Prediction Uncertainty

CHAPTER ONE

INTRODUCTION

1.1 Background of the Problem

Water quality and quantity deterioration due to nutrient and sediment loading impacts lakes worldwide, leading to eutrophication and siltation (Søndergaard *et al.,* 2003). These impacts are driven mainly by catchment-wide changes in land use through increased fertilizer use in agriculture, soil erosion, and increased downstream transport of eroded sediments and nutrients (Quinton *et al.,* 2010). The interaction of climatic variability, vulnerable soils, distinct topography, and rapid land-use change make the East African region one of the world's hotspots for land and water degradation (Wynants *et al.,* 2019). The succession of droughts, erratic rainfall, and torrential rainfall explains the big inter annual differences in sediment yields observed in the region (Vanmaercke *et al.,* 2014). After a long dry period, high-intensity rainfalls can generate extreme amounts of eroded soil and downstream sediment transport. Hudson (1993) emphasized this in Zimbabwe, where about 50%of the annual soil loss was found to occur in only two storms and that during one year, even 75 % of the erosion took place in ten minutes.

Moreover, a study by Wynants *et al.* (2021) in Northern Tanzania has shown that gully incisions can be triggered by extreme rainfall years, especially if they follow years of progressive soil degradation and drought. Gullying can subsequently cause positive feedback responses by increasing hydrological and sediment connectivity in the catchment, leading to the rapid removal of water, soil and nutrients from hillslopes (Wynants *et al.,* 2021a). This higher hydrological connectivity generally leads to bigger and more rapid differences between the peak and base flows, which increases the risks of both floods and droughts (Rwetabula *et al.,* 2007a; Van Griensven *et al.,* 2013b; Zhang *et al.,* 2020c).

One area of interest is the Lake Victoria basin (LVB), which spans over 250 000 km^2 in four countries and is of major importance for biodiversity, regional water, food, and livelihood security. The LVB is a national, regional and international natural resource asset mutually shared among five riparian countries: Burundi, Kenya, Rwanda, Tanzania and Uganda and a source of the Nile Basin (Zhang *et al.,* 2020b). It is also tremendously important for the national economy, support of local communities and biodiversity conservation. Rainfed smallholder agriculture, fishing and pastoralism are the main economic activities in the LVB. The LVB also provides water for domestic, irrigation and industrial uses in some towns around

Mwanza Region. The water demands in the LVB are rapidly growing and are expected to increase even further due to the growing population that has led to an expansion in agricultural areas (Amasi *et al.,* 2021b; Wynants *et al.,* 2018). However, the LVB water resources are deteriorating both in quantity and quality as a result of erosion, irrigation, poor human waste disposal, unsustainable land-use management practices, wetlands degradation, and sand mining in the rivers (Kimwaga *et al.,* 2012c; Rwetabula *et al.,* 2007c). These major land degradation drivers directly impact socio-economic development and community resilience (Blake *et al.,* 2018). A reconstruction in sediment yield change over the past century in northern Tanzania has shown an exponential increase from 8 to 149 t km^{-2} yr^{-1} in a small lower-sloped catchment, and from 57 to nearly 1600 t km^{-2} yr^{-1} for a larger complex catchment (Wynants *et al.,* 2021b). The importance of event-based sediment export is expected to increase even further in the context of future climatic changes (Borrelli *et al.,* 2020a). The combination of increasing land-use pressures and extreme climatic events thus poses an acute threat to the soil and water resources of East African rivers and lakes.

The population increase in the basin is estimated at 3.5% annually, with about 50 million inhabitants currently (Food and Agriculture Organisation of the United Nations, 2020). The inhabitants of this region are generally resource-poor and heavily dependent on subsistence agriculture, leading to a rapid expansion of agricultural land area (Wynants *et al.,* 2019). A study by Wasige (2013) reported a reduction of forest land from 7% to 2.6%, savannas 35% to 19.6%, and woodland from 51% to 6.9% in the LVB from 1901 to 2010, whereas farmland grew by 60%. Increasing agricultural and deforestation activities in the basin influence surface runoff, evapotranspiration, infiltration, groundwater flow, and river discharge dynamics. This has been shown to make catchments more vulnerable to both floods and droughts (Kimwaga *et al.,* 2012c; Natkhin *et al.,* 2015b; Zhang *et al.,* 2020d).

Moreover, changing runoff and discharge dynamics majorly impact soil erosion and downstream sediment transport dynamics. Increased transport of sediments and associated nutrients has contributed to the eutrophication and recurrent blooms of water hyacinth and cyanobacteria in Lake Victoria (LV), which poses a direct threat to the biodiversity, fisheries, and water security of the communities around the lake (Dutton *et al.,* 2018; Jacobs *et al.,* 2018; Olokotum *et al.,* 2020; Tamatamah, 2003). Increasing erosion following land use and rapid downstream transport of eroded sediment is thus one of the biggest threats to the sustainability of LV (Zhang *et al.,* 2020a), necessitating soil and water management plans. However, sediment control strategies require information on sediment's relative and absolute contributions from different sources (Amasi *et al.,* 2021b; Collins *et al.,* 2017). In the LVB, a lack of water quality monitoring and empirical data on soil erosion prohibits an assessment of the scale of the problem.

In addition, the LVB has experienced flooding in the last decades, which has impacted both human safety and agricultural yields (Cecinati, 2013). In 2007, the study area received intensive rains that culminated into floods, eventually leading to loss of life and property, disruption of the local infrastructure and involuntary resettlement (Amasi *et al.,* 2021b; Byerlee *et al.,* 2014; Foley *et al.,* 2005). Studies in the area assume that the increased flood peaks are caused by increased urbanization, deforestation, and wetland degradation due to livestock keeping and farming (Bamutaze *et al.,* 2010; Bingwa, 2013). Therefore, there is a need to understand the contributions of current land-use change and future climate variability to changes in discharge in the rivers draining towards Lake Victoria (LV).

Although some empirical findings have been reported on the potential impacts of land-use and climate change in LVB (Mulungu & Kashaigili, 2012; Myanza *et al.,* 2005), there has been no monitoring of sediment flux or water quality in the basin river tributaries. Little is, therefore, known about the main sources of eroded sediment to the LV, nor have the effects of land degradation in the catchment been evaluated. In this context, the Simiyu catchment was used as a case study to fill gaps in our understanding of soil erosion and sediment transport dynamics, which are faced in all LV catchments.

Soils and sediments in the catchment were geo-chemically fingerprinted, allowing the comparison of the physical or chemical (dis) similarities (Collins *et al.,* 2017). Sediment tracing techniques are crucial for evaluating the magnitude of siltation problems by elucidating the dominant sediment sources of the main river (Dutton *et al.,* 2019; Wynants *et al.,* 2021a). These techniques evaluate the similarities and dissimilarities between downstream sediments' physical or chemical traits and the potential sediment sources of the catchment (Collins & Walling, 2004; Nosrati *et al.,* 2019). Since eroded sediment carries the parent material's conservative properties downstream, downstream reservoir sediments' geochemical composition depends on the tributaries' relative contributions and geo-chemical properties (Haddadchi *et al.,* 2013; Walling, 2013). Therefore, the proportional attribution of the tributary sources to downstream sediment can be obtained by integrating the multivariate source and mixture of geo-chemical fingerprints within mixing models (Blake *et al.,* 2018a). Integrating geo-chemical tracers within mixing models has proved a robust technique for sediment source tracing because it integrates multivariate tracer signals encompassing various distinctive signatures affected by different environmental factors, thus improving the validity of discrimination of sediment sources (Smith *et al.*, 2018).

In addition, there's currently no empirical evidence about the impacts of land use and climatic variability on the Simiyu River discharge. Also the impacts of future climate change on Simiyu River discharge is not known. Hydrological models can be instrumental in simulating the effects of land-use and climate change using existing hydrological data and subsequently reconstruct and forecast river discharges (Devia *et al.,* 2015; Ullrich & Volk, 2009a). They are based on the water balance equation of the main components of the water cycle (such as precipitation, infiltration, evapotranspiration) and the physical catchment characteristics (e.g., topography, soil type, landuse) that affect runoff (Ullrich & Volk, 2009b).

In this study, the Soil and Water Assessment Tool (SWAT) was used because it has been shown to perform well in semi-arid environments with distinct rainfall seasonality and climate conditions that are characteristic of the Simiyu catchment (Arnold *et al.,* 2012b; Gassman *et al.,* 2007). The model is semi-distributed, wherein the smallest defined sub-catchments are routed using the stream network. The sub-catchments are built on hydrological response units (HRUs), which are classes of overlapping land-uses, soils, and slopes within the sub-catchment. This dissertation aimed to quantify the relative contribution of sediment sources to the Simiyu River using a scientifically robust sediment source tracing technique (Blake *et al.,* 2018a).

Furthermore, the dissertation aimed to assess the current and future impacts of climate and land-use change on the river discharge at the critical agroecological region of the Simiyu catchment. The results on the dominant sediment sources will aid the Lake Victoria Basin Water Board (LVBWB) in designing targeted management interventions for reducing soil erosion and sediment yield in the Simiyu catchment (Owens, 2022). Moreover, the work can be an example of applying sediment source tracing studies in other catchment draining to LV. Furthermore, the study's results will give insights into developing and implementing adaptation and mitigation measures to minimize the impacts of climate change and land use on water resources for sustainable economic development.

1.2 Statement of the problem

The Simiyu catchment in LVB is experiencing rapid land degradation and water resources. The deterioration of water quality and quantity in the LVB restricts sustainable socioeconomic development in the Simiyu catchment. This is hypothesized to be caused by increasing anthropogenic activities in the catchments, which amplifies the effects of climate change and climate variability, affecting the hydrological cycle. For instance, high levels of deforestation and the loss of permanent vegetation through the fast expansion of agricultural land and urban areas have accelerated soil loss rates and downstream siltation (Dutton *et al.,* 2019; Kimwaga *et al.,* 2012d; Mulungu & Munishi, 2007; Ndomba *et al.,* 2005a). The changing demographics in LVB are increasing the demand for land, food, and water, leading to land and water use changes. The lack of agricultural intensification and livelihood options outside of agriculture has resulted in expansion of farming areas in the catchment (Kimwaga *et al.,* 2012d; Rwetabula & De Smedt, 2005). Unsustainable agricultural practices and increased livestock densities in the catchment have led to the degradation of the soils and increased surface and gully erosion. These changes influence surface runoff, evapotranspiration, infiltration, groundwater flow, and river discharge dynamics and making catchments more vulnerable to both floods and droughts (Kimwaga *et al.,* 2012b; Natkhin *et al.,* 2015c; Zhang *et al.,* 2020c). Despite the socioeconomic importance of the Simiyu catchment and LV, there is little or no empirical evidence available on the relative contribution of various sediment sources to the infilling of LV. In addition, there are no studies on how land-use and climatic changes impact discharge and flood regimes in Simiyu river catchment. The lack of these data meant that relatively little is presently known about the scale of the problem.

1.3 Rationale of the study

The lack of adequate and sufficient data on sediment sources in the LVB represents a key restriction for sustainable land use and effective water management practices, especially in vulnerable, arid and semi-arid environments of the Simiyu catchment and for the catchment-wide management plans on mitigation strategies with an emphasis on decreasing soil erosion rates. Data scarcity and limited studies have posed a significant challenge for designing improved water resource management and adaptation strategies to land use and climate change. The sediment fingerprinting technique provides an important pathway for quantifying the dominant sediment sources in the rivers flowing towards LV.

On the other hand, the SWAT model has proved to be a robust tool for predicting the hydrological response of semi-arid tropical catchments to changes in climate and land use. The integration of the ArcGIS-based hydrological model ArcSWAT with the site-specific ensemble of the General Circulation Models (GCMs) under different Representative Concentration Pathways (RCPs 4.5, 6.0 and 8.5) simulated the impacts of land-use and climate change on overland flow and river discharge in the Simiyu catchment. The three RCPs predict how greenhouse gas concentrations in the atmosphere will change due to human activities, whereby the RCP 8.5 (high emission scenario) represents very high emission and low implementation of climate policies. In contrast, RCP 6.0 (medium–high emission scenario) represents moderate emission and medium implementation of climate policies and RCP 4.5 (low–medium emission scenario), represents low to moderate emission with the introduction of strict intervention of implementation of new climate policies. The summary of the major issues that make an annotated bibliography is discussed in the context of the logical framework depicted in Fig. 1.

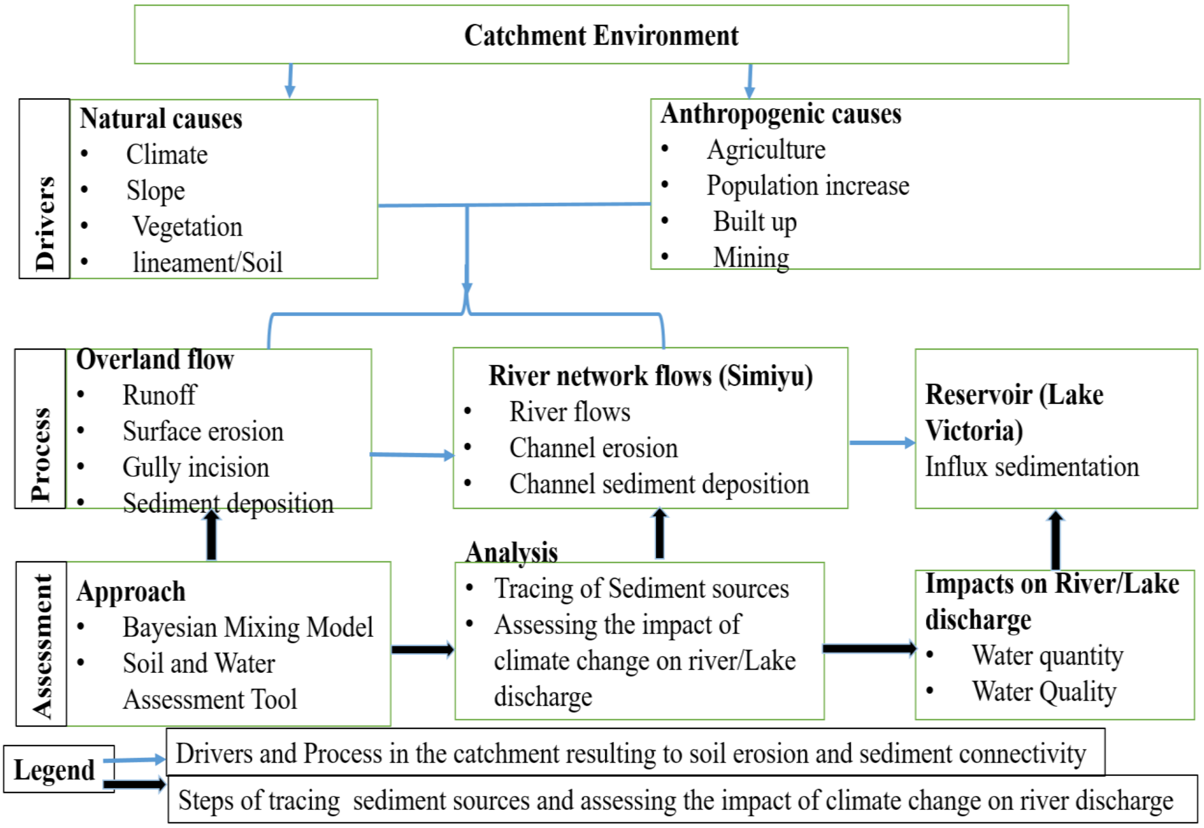


Figure 1: Sediment delivery in the complex catchment and assessment approach for impacts of climate and land-use change

1.4 Objectives of the study

1.4.1 General objective

Assessment of the impact of land-use and climate change on the river discharge and sediment dynamics in the Simiyu riverine sediment flowing towards Lake Victoria.

1.4.2 Specific objectives

(i) To assess the current impacts of land-use and climate change on the Simiyu River discharge.

(ii) To assess the future impacts of climate change on the Simiyu River discharge.

(iii) To assess the dominant sources of the sediments and their relative contributions from the Simiyu River catchment flowing towards Lake Victoria by using geochemical fingerprinting.

1.5 Significance of the study

Although climate change is predicted to cause adverse impacts on freshwater resources, especially in the dry sub-tropical regions (Pervez & Henebry, 2015; Serdeczny *et al.*, 2017), there is a little consideration given to the impacts in the process of planning of future water resource use and management (McCartney *et al.*, 2012). Studies of the impacts of climate change on water resources are encouraged to ensure its sustainability. The findings from this study will improve understanding of different spatial sources of sediments and their relative contribution to the Lake Victoria. The findings from this research will also support the design of improved water resource management and adaptation strategies to climate change. A better understanding of the sediment dynamics will contribute to effective sediment control strategies, including remedial actions for mitigating the impacts of excessive sedimentation in LV and developing soil erosion management plans. Understanding the impact of land use and climatic changes on river discharge dynamics will also support the effective water management practices, especially in vulnerable, arid and semi-arid environments of the Simiyu catchment. Such knowledge will also provide the pre-requisite information to policymakers to mitigate the future risks associated with land-use and climate change river discharge.

Additionally, the result of this study will aid authorities in designing appropriate sustainable land-use and water resources management measures to achieve the following UN Sustainable Development Goals: SDG 3, aiming at improving water quality, SDG 6.6 protect and restore water-related ecosystems, SDG 13.3 build knowledge and capacity to meet climate change, and SDG 15.3 combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world respectively. In addition, the study was aimed to achieve the Tanzania Land Degradation Neutrality (LDN) through reducing soil erosion, soil and water conservation practices, water pollution and deforestation.

1.6 Research questions

(i) What are the current impacts of land-use and climate change on the Simiyu catchment river discharge?

(ii) How will future climate changes affect the Simiyu River discharge?

(iii) What are the dominant sediment sources from the Simiyu River catchment and their relative contribution to the infilling of Lake Victoria?

1.7 Delineation of the study

This study used geochemical fingerprinting to trace the sediments' dominant sources and their relative contributions from the Simiyu River catchment flowing towards LV. The study also assessed the impacts of land-use and climate change on the river discharge. The geo-chemical fingerprints and the Bayesian mixing model (BMM) for source apportionment are discussed. This dissertation is divided into 5 Chapters whereby parts of this thesis are published in peer-reviewed scientific journals:

Chapter one consists of the background statement information, study rationale, objectives, research questions and the significance of the study. Chapter two presents the literature review on which the factors responsible for soil erosion and river discharge processes, sediment connectivity, hydrological models, Global circulation models and downscaling methods are discussed. Chapter three covers the techniques to establish the proportions of the dominant sediment sources (the Bayesian mixing model (BMM) using the geo-chemical tracers and the SWAT model for establishing the current impacts of land use and climate change and forecasting the future impacts of climate change on river discharge. Chapter four presents the results and discussion of the changes in proportional sediment contributions of different land-use and tributary rivers. Chapter five presents the conclusion and recommendations

CHAPTER TWO

LITERATURE REVIEW

2.1 Overview

Soil erosion is a global environmental challenge that threatens human survival and development. It threatens one of humanity's most vital resources, dating back to Cain and Abel (Panagos *et al.,* 2016c). It causes both on-site and off-site problems. The on-site problems include the deterioration of soil's physical, chemical and biological properties (Lal *et al.,* 2000), loss of nutrients (Lal, 2003), reduction of agricultural productivity (Lal, 1999), and even cropland loss (Pimentel, 2006), while the off-site damages include silting of water bodies, deterioration of water quality, loss of reservoir capacity, and damages to infrastructure (Mullan, 2013). Eroded sediment also transports attached nutrients and contaminants such as heavy metals, fertilizers and pesticides, which impact the water quality of rivers and lakes around the world, leading to eutrophication (Søndergaard *et al.,* 2003) and may even negatively affect the global cycles of carbon, nitrogen, and phosphorus (Chen *et al.,* 2010; Quinton & Catt, 2007).

Vegetation, rainfall, soil, and topography are the main factors controlling soil erosion rates. Various studies have asserted that different soil bulk densities are caused by different types of vegetation, which can also lower the soil erosion index, the efficiency of rainfall, and the kinetic energy of raindrops and runoff (Chen *et al.,* 2019; Wang *et al.,* 2013; Wu *et al.,* 2019; Zhang *et al.,* 2019; Zhou *et al.,* 2016; Zokaib & Naser, 2011). When raindrops splash against the soil surface, they can erode the soil's structure by dislodging soil particles (splash erosion) and allowing runoff to move the soil. To understand how water erosion and soil loss occur, it is important to understand how soil properties such as particle size, bulk density, initial water content, and infiltration play a significant role (Defersha & Melesse, 2012; Ekwue & Harrilal, 2010; Fernández *et al.,* 2008; Martinez-Mena *et al.,* 2000; Mathys *et al.,* 2005; Mohammad & Adam, 2010).

Topography impacts soil erosion through gravity, runoff generation and runoff pathways, thereby influencing water erosion and soil loss (Chaplot & Le Bissonnais, 2003; Mathys *et al.,* 2005; Nadal-Romero *et al.,* 2013; Taye *et al.,* 2013). On steep slopes, there is less water infiltration and, thus, more runoff and soil erosion. Moreover, neutral soil detachment processes such as ploughing and rain splash erosion will move the soil particles downhill due to gravity. Apart from natural factors, the main drivers of increased soil erosion are unsustainable land-use, climate changes and climatic variability (Yasir *et al.,* 2014). The most significant factors influencing soil erosion are land-use/cover and management, particularly in the semiarid regions (Li *et al.,* 2015; Mohammad & Adam, 2010; Wilcox *et al.,* 2003; Zhu *et al.,* 2015). Major determinants of land-use/cover and management are land disturbance and restoration (Brunbjerg *et al.,* 2014; Malowerschnig & Sass, 2014; Mohr *et al.,* 2013; Ungar *et al.,* 2010; Vanacker *et al.,* 2014).

2.2 Soil erosion processes and river discharge

The loss of permanent vegetation through the fast expansion of agricultural land (Fleitmann *et al.,* 2007; Kiage, 2013; Maitima *et al.,* 2009; Wynants *et al.,* 2018) has accelerated erosion and downstream sediment transport (Awulachew *et al.,* 2009; Hathaway, 2008). Land disturbance/restoration practices like trampling and ploughing have a significant impact on the vegetation, root system, soil properties, and topography (Dunne *et al.,* 2011; Herrick *et al.,* 2010; Pohl *et al.,* 2012; Vanacker *et al.,* 2014). All these factors are extremely crucial to runoff and sediment yield. Moreover, overgrazing and deforestation reduce vegetation cover and soil organic carbon content in the soil, increasing the likelihood of producing runoff and erosion (Lin *et al.,* 2010; Ludwig *et al.,* 2005; Taye *et al.,* 2013; Zhao *et al.,* 2013). Trampling can increase runoff production by lowering the soil's hydraulic conductivity and macro-porosity (Herrick *et al.,* 2010; McDowell *et al.,* 2003). Additionally, trampling can harm plant roots, reduce vegetation cover, and destroy soil structure, making the soil surface more prone to erosion (Dunne *et al.,* 2011; Pohl *et al.,* 2012).

Land degradation is the human-induced reduction or loss of land's biological or economic productivity and complexity, often attributed to poor land management practices and unsustainable land-use. Land degradation consists of a multitude of processes, including deforestation, soil erosion, drying, and salinization. These processes interact to cause severe environmental impacts such as reducing biomass and biodiversity, nutrient depletion of soils, loss of organic matter in soil, and reduction in soil structure and quality. Land degradation is increasing in severity and extent in many parts of the world, with more than 20% of all cultivated areas, 30% of forests and 10% of grasslands undergoing degradation (FAO, 2008). The effects of land degradation, both onsite and offsite, are widespread and linked. The onsite consequences include loss of productivity, reductions in resilience leading to higher variability in yields and vulnerability to extreme weather conditions, and reduced capacity to adapt to climate change. The off-site consequences are global or regional, such as increased carbon emissions and poor water regulation, resulting in floods, sedimentation and reduced base flow downstream. Land degradation negatively impacts over three billion people, costing the world an estimated loss of more than 10% of the Global Domestic Product (GDP) per annum (IPBES, 2018). Land degradation is a major environmental issue that affects rural livelihoods and the well-being of inhabitants by substantially impacting the sustainability of food production and other ecosystem services, as well as rural infrastructures that are essential to the prosperity of these communities (Kelly *et al.,* 2022).

One of the main causes of land degradation in the pastoral and agricultural landscapes of East Africa is an increase in soil erosion (Wynants *et al.,* 2019). Disruptions to co-adapted agro-pastoral systems in the past have been the source of this wicked problem. Soil erosion is a natural phenomenon which has been accelerated due to anthropogenic factors. Soil erosion is a gradual process that occurs when the impact of water or wind detaches and removes soil particles, causing the soil to deteriorate (Morgan, 2005; Vercruysse *et al.,* 2017). Eroded topsoil is transported by water into streams and other waterways. Sediment is a product of land erosion and derives largely from sheet and rill erosion from upland areas, and, to a lesser degree, from cyclic erosion activity in gullies and drainage ways (Collins & Walling, 2004; Fryirs, 2013; Vercruysse *et al.,* 2017). It reduces crop productivity by limiting water infiltration and loss of nutrients (Pimentel, 2006). A significant amount of the global arable land has become unproductive due to soil erosion, particularly in Sub-Saharan Africa (SSA), where most of the rural population relies on rain-fed agriculture (Kendall & Pimentel, 1994). Most rural residents in SSA won't be able to feed themselves if soil erosion remains unchecked and the pressure from population growth continues to rise (Nearing, 2013). This has already happened in some countries in the African region, where there is a food shortage due to soil erosion and degradation (Kendall & Pimentel, 1994). Soil erosion and sedimentation have been a major challenges facing communities in the LVB for a long time, leading to water quality deterioration and eutrophication of the LV (Rwetabula *et al.,* 2007c).

2.2.1 Climate change and climate variability on soil erosion

The impacts of climate change on soil erosion include direct and indirect impacts which have been noticed since the 1940s (Bryan & Albritton, 1943; Langbein & Schumm, 1958; Leopold, 1951; Raeside, 1948; Ruhe & Scholtes, 1956). The direct impacts are principally affected by changes in rainfall amount (Bangash *et al.,* 2013; Longfield & Macklin, 1999; Nearing *et al.,* 2004; Pruski & Nearing, 2002), rainfall intensity (Bouraoui *et al.,* 2004; Tang *et al.,* 2015; Walling & Webb, 1996; Zhang, 2012) and spatio-temporal rainfall distributional patterns (Maeda *et al.,* 2010). Different patterns of soil erosion are also caused by spatial variation in rainfall. Higher rainfall amount is commonly connected to increased runoff and soil loss

(Zabaleta *et al.,* 2014), because increased rainfall amount may increase soil moisture, soil sealing and crusting, subsequently decrease infiltration capacity, and therefore, increase saturation excess overland flow (Imeson & Lavee, 1998; Nearing *et al.,* 2004). If the soil medium is saturated with water after continued rainfall or snowmelts, excess water will not be able to infiltrate the soil, leading to saturation excess overland runoff. Saturation excess overland flow is more common in temperate regions with lower intensity but longer duration rainfalls and areas with lower evapotranspiration. During high-intensity events, the rainfall can overcome the infiltration capacity of soils, leading to excess overland runoff infiltration. Excess overland flow is common in semi-arid regions with high seasonality and high-intensity rainfall. Overland runoff can transport dislodged particles further downhill but can also join up to form erosive flows that can cut into the landscape.

Land use effects and effects of changing rainfall temporal distributions are frequently combined. For instance, the soil is more sensitive to erosion by heavy rainfall events at the start of the rainy season when vegetation cover is lower, and fields are prepared for planting (Garbrecht & Zhang, 2015; O'Neal *et al.,* 2005; Serpa *et al.,* 2015; Zhang & Nearing, 2005). In addition, prolonged rainfall may decrease or become less predictable, resulting in less vegetation cover and more soil erosion (Wang *et al.,* 2015). A wet year following a dry period might thus disproportionately impact soil erosion dynamics (Wynants *et al.,* 2021).

Water erosion mainly includes rain splash, rill, and gully erosion (McCool & Williams, 2008). Rain splash erosion takes place under erosive raindrops. Rill erosion is caused by overland flows concentrating on fields to erosive energies high enough to dislodge and transport soil particles. Gully erosion occurs when runoff accumulates in depressions and removes the soil from narrow channels to considerable depths (Poesen *et al.,* 2003). Rain splash erosion mainly causes soil detachment within a certain distance of the raindrop, while rill and gully erosion can cause off-site sediment transport and deposition. The close relationship between high rainfall intensity and water erosion is due to the high erosivity of raindrops in convective storms causing detachment of soil particles and subsequently rain splash erosion (Mohamadi & Kavian, 2015) high-intensity rainfall causes infiltration excess runoff that transports detached particles downhill, but also have high enough flow energy to remove the soil from the surface or subsurface, thus leading to rill and gully erosion (Poesen *et al.*, 2003). Infiltration excess runoff, or Hortonian runoff, occurs when high-intensity rainfall arrives at a rate more significant than the soil's infiltration capacity. Areas susceptible to gully erosion caused by Hortonian runoff are generally in semi-arid and sub-humid zones. In these climatic regions, Hortonian runoff is often responsible for the majority of soil erosion (Baartman *et al.,* 2012).

Similarly, Ran *et al.* (2012) compared sediment concentration patterns among three combinations of rainfall durations and reported that erosion was transport-limited for prolonged gentle rainfall while detachment-limited for high-intensity rainfall. Thus, if the rainfall duration is long enough or the rainfall amount is great enough, more soil particles will likely be eroded by saturation excess runoff because of the kinetic energy provided. Also, soil loss tends to be higher from the soil that is shallow or without vegetation cover. More significant soil erosion can be generally expected if the frequency of extreme rainfall events is higher in areas where Hortonian runoff is dominant or if the rainfall duration is longer in areas where saturation runoff is common. Greater rainfall amount can also facilitate runoff generation and lead to higher erosivity. Unfortunately, more intense rainfall and increased runoff events in East Africa are expected at the end of the century (Miao *et al.,* 2023). This result will substantially influence global water security and could worsen the harm brought on by the unequal distribution of water resources (Baker, 2012).

On the other hand, the indirect impacts are associated with the increase in temperature. When atmospheric CO_2 concentration and temperature increase, evapotranspiration rates increase and soil moisture decreases, which increases the soil's infiltration capacity and reduces runoff and soil erosion (Jiongxin, 2003). In addition, in tropical areas of East Africa, increased temperatures will probably decrease plant growth due to increased evapotranspiration and reduced soil moisture (Adhikari *et al.,* 2015). Since vegetation buffers soil erosion by increasing canopy interception and reducing climatic impacts on vegetation growth, it is likely to influence soil erosion (Nearing *et al.,* 2004). The impacts of climate change can either be positive or negative, however, the extent of the impacts and the offset effect of different factors still remain uncertain and problematic to forecast with accuracy.

2.2.2 Land use and climate change on river discharge

Land use/cover and climate changes have a great influence on the hydrological response of a watershed (Kashaigili & Majaliwa, 2013; Kirby *et al.,* 2016) through influencing evapotranspiration, infiltration, surface runoff, groundwater flow and stream discharge regime (Natkhin *et al.,* 2015a). The effects of land use/cover and climate change on hydrological processes are set to increase in the future due to the increased deforestation for agriculture and increased manifestation of the changing climate (Fischer, 2013). Thus, how the future climate will interact with the land use changes and affect the water balance in the watersheds requires more attention. The East-African region is forecasted to be highly impacted by climate change through increased rainfall intensity, runoff, and erosion vulnerability (Borrelli *et al.,* 2020b;

Miao *et al.*, 2023). Further, it is anticipated that the farming sector will experience more impacts, resulting in decreased production of different crops due to reduced water availability and the shift of growing seasons (Kangalawe & Lyimo, 2013; Läderach *et al.*, 2012).

2.3 Catchment soil-sediment continuum from hillslope to river discharge

The passage of water and sediment through different landscape compartments and through the drainage basin is described by the term connectivity, which is increasingly used as a research framework in hydrology and geomorphology (Borselli *et al.*, 2008; Bracken & Croke, 2007; Fryirs *et al.*, 2007; Harvey, 2012). There are three main "types" of connectivity (Bracken & Croke, 2007) or linkages (Fryirs *et al.*, 2007) recognized and broadly categorized as Landscape Connectivity, which refers to how different landforms are physically connected within a drainage basin (e.g., hillslope to channel) (Harvey, 1996; Michaelides & Wainwright, 2002). Hydrological Connectivity, or the movement of water from one landscape area to another, is anticipated to result in some catchment runoff response (Ambroise, 2004; Cammeraat & Imeson, 1999; McDonnell, 2003). Sedimentological Connectivity which is concerned with the movement of sediments and any pollutants they may have attached through the drainage basin (Fryirs, 2013; Fryirs *et al.*, 2007; Harvey, 2001; Hooke, 2003; Wainwright *et al.*, 2011).

Sediment connectivity describes the physical links that sediments have between sources and sinks, the degree to which a system facilitates sediment transfer through the coupling between its components. It is a crucial characteristic when studying sediment redistribution in a catchment (Bracken *et al.*, 2013; Calsamiglia *et al.*, 2018; Cossart & Fressard, 2017). Sediment connectivity reflects the continuity and connectivity of sediment pathways at any given time. Identifying sediment connectivity in the catchments thus helps to locate hotspots or areas particularly susceptible to landform changes (Wohl *et al.*, 2017). Understanding how human activities and land planning affect soil erosion and sediment transport processes can be done with the help of sediment connectivity analysis that includes indices of connectivity (Borselli *et al.*, 2008; Burguet *et al.*, 2018; Gao & Zhang, 2016; Hooke & Sandercock, 2012; Jamshidi *et al.*, 2014; Lisenby & Fryirs, 2017) existing models ranging from empirical to process-based models (Baartman *et al.*, 2013; Cislaghi & Bischetti, 2019; Di Stefano & Ferro, 2018; Liu & Fu, 2016; Medeiros *et al.*, 2010), and graph theory (Cossart & Fressard, 2017; Fressard & Cossart, 2019; Heckmann & Schwanghart, 2013; Heckmann *et al.*, 2015).

Graph theory is used to analyze the spatial fragmentation of the sediment cascade and describe particular spatial assemblages within a catchment (Cossart & Fressard, 2017; Heckmann &

Schwanghart, 2013; Heckmann *et al.,* 2015). Because of their strategic locations closer to both sources and outlets, indices created using the graph theory framework can help pinpoint specific hotspots of geomorphic change on a more local level (Czuba & Foufoula-Georgiou, 2015). Among these techniques, the connectivity index is a well-known method for quantitatively assessing the transfer of sediments between catchment compartments of a terrestrial system (Heckmann *et al.,* 2018). The sediment connectivity index computes the existing linkage scale between sediment sources (e.g. eroded areas on hillslopes) and sink areas (outlets, lakes, hydrologic network). Since sediment redistribution can harm the environment and fluvial systems, geomorphologists and hydrologists have continuously evaluated the variability of soil erosion and sediment transport processes (Gay *et al.,* 2016).

Understanding the concept of sediment connectivity is necessary to account for the flux of sediment particle movement within the catchment. Sediment connectivity addresses the spatio-temporal flexibility in sediment delivery and storage and the potential for eroded soil particles to move through the system (Bracken & Croke, 2007; Croke *et al.,* 2013; Fryirs, 2013; Hooke, 2003). In catchments, hydrological connectivity is one of the main determinants of Sedimentological connectivity and is influenced by the climate, hillslope runoff potential, delivery pathway, lateral buffering, landscape position, and sediment propagation (Bracken *et al.,* 2013; Bracken & Croke, 2007; Wynants *et al.,* 2020). First and foremost, the climate is the most important factor because it affects the catchment's antecedent conditions, including the extent, duration, and intensity of the rainfall. Due to their complex geological, pedagogical, and management histories, hillslopes the primary unit of the landscape-display spatially variable hydrological properties (Fitzjohn *et al.,* 1998). Hillslope runoff is influenced by a number of variables, including slope gradient, soil properties, surface roughness, vegetation type and density, land-use, etc. (Lal, 1990a; Puttock *et al.,* 2013; Singer & Le Bissonnais, 1998; Wynants *et al.,* 2020). Anthropogenic land-use impacts can mutually escalate hillslope connectivity by accelerating run-off as a result of vegetation removal (Guzha *et al.,* 2018) or reduce connectivity by fitting terraces and implanting vegetation strips (Saiz *et al.,* 2016; Wynants *et al.,* 2020).

Furthermore, one factor affecting sediment connectivity is the pathway by which sediment is delivered from a hillslope to a river channel. However, sediment connectivity is non-linear controlled by key variables that must reach thresholds; for instance, in the lateral dimension, disruption of sediment conveyance through floodplain deposition only occurs when thresholds for bank full channel capacity have been exceeded, and floodplain inundation occurs (Croke *et al.,* 2013).

2.4 Modelling of soil erosion and river discharge

Modelling is a common approach and practical method for quantifying the impacts of soil erosion and river discharge under climate change (Li *et al.,* 2010; Salazar *et al.,* 2012). Numerous new modelling techniques have been developed, and more models have emerged, including hydrological and erosional models (Francipane *et al.,* 2015), such as the Universal Soil Loss Equation (USLE) (Wischmeier & Smith, 1978), Revised Universal Soil Loss Equation (RUSLE) (Renard *et al.,* 1997), Water Erosion Prediction Project (WEPP) (Nearing *et al.,* 1989), TETIS model (Francés *et al.,* 2007), erosion 3D model (Schmidt, 1991), Soil and Water Assessment Tools (SWAT) (Neitsch *et al.,* 2011), Hydrologiska Byråns Vattenbalansavdelning (HBV), Hydrologic Engineering Center's Hydrologic Modeling System (HEC- HMS), Hydrologic Engineering Center's River Analysis System (HEC-RAS), Weather Research and Forecasting Hydrological model (WRF-Hydro), MIKE SHE and HEC-Hydro (Devia *et al.,* 2015).

This section provided a concise summary of the models currently used to estimate the impacts of climate change on soil erosion and river discharge. Not all models are considered. The objective is to demonstrate how some hydrological and erosion models can be implemented in their most fundamental forms. In this study, only hydrological model (SWAT model) was used to assess the impact of climate change on the river discharge.

2.5 Hydrological models

Hydrological models simulate water fluxes based on generalized rainfall-runoff responses and water balance equations constrained by the environmental conditions of the catchment. Hydrological models can be used to predict the impacts of land use and climate changes on water fluxes (Abdollahi *et al.,* 2018; Ivezic *et al.,* 2017; Pedro-Monzonís *et al.,* 2015) although each has different underlying assumptions and uses (Horton *et al.,* 2022; Singh & Frevert, 2002). However, based on structural similarities in traits and underlying assumptions, hydrological models can be classified into a number of distinct groups (Devia *et al.,* 2015).

Empirical (black box) models are established from statistically derived relationships between empirically observed climatic inputs and hydrological outputs. Empirical models are simple in application and provide representative estimations within the range of measured observations.

However, the drawback of the empirical model, at watershed level, is the stationary assumption that underlying conditions remain constant throughout the simulation period (Kandel *et al.,* 2004). Moreover, empirical models do not give any information on the individual processes governing the observed response and are considered black boxes. Given complex regional differences in hydrological processes, they are usually only applicable on smaller scales.

Conceptual models (gray box) are considered to be between empirical models and physically based models. They typically consider physical laws but do so in a highly simplified manner. Physically-based models, also called process-based (white box) models, are defined in terms of key governing processes connected to the hydrological cycle and have a logical structure comparable to the real system being modelled (Muleta, 2003). Process-based models can, in theory, be applied on larger scales; however, they require local calibration of parameters based on observations. Hydrological models can be further divided in the way they represent spatial variability. Global models treat the watershed as a single entity and ignore spatial variability. As a result, the outputs are produced without considering the spatial variability of processes, inputs, boundary conditions, and geometric system characteristics (Singh, 1995).

In contrast, distributed models represent the watershed area in small units (raster cells or triangulated irregular networks) so that the environmental factors, parameters, and inputs can vary spatially (Moradkhani & Sorooshian, 2008). However, distributed models require a lot of processing power and, therefore, take a long time to run, which is particularly problematic for large catchments and long-time series. Semi-distributed models such as SWAT have been suggested to combine the advantages of both forms of spatial representation referenced to a specific catchment or sub-catchment where the smallest defined sub-catchments are routed together using the stream network. The hydrological response units (HRUs), which are collections of similar types of slopes, soils, and land-uses within the sub-catchment, serve as the foundation for the sub-catchments. Because of this, these models can accurately capture a watershed's key characteristics while requiring less data and spending less money to run (Orellana *et al.,* 2008).

Unfortunately, these models frequently have significant application-process uncertainties, which primarily consist of the following: (a) Model input uncertainty, (b) Model structure uncertainty, and (c) Uncertainty of model parameters. Model input uncertainty is due to datasets that frequently contain measurement errors and systematic errors during the process of model calibration and uncertainty analysis. In order to improve the results of model simulations, it is necessary to input a significant amount of observation data, such as temperature, relative humidity, precipitation, and soil databases (Beven & Freer, 2001; Nešpor & Sevruk, 1999). The uncertainty in model structure, is mostly caused by the natural systems' assumptions and simplifications while the uncertainty of model parameters are those characteristics that governing the watersheds and hydrological processes, as these parameters are frequently challenging to measure directly (Abbaspour *et al.,* 2015).

As a result, in order to identify the values of the calibrated parameters during the calibration of the model parameters, the empirical methods and literature are frequently referred, though may introduce additional errors (Wu & Chen, 2015). Furthermore, uncertainty, often referred to as equifinality for several parameters, can arise from correlation and interaction between parameters (Atkinson *et al.,* 2010). However, choosing the right algorithm makes controlling the uncertainty of the parameters relatively simple (Beven & Freer, 2001). As computing technology has advanced, more and more optimization strategies have been put forth to address or lessen model uncertainty (Song *et al.,* 2015). The more effective and often used algorithms for uncertainty analysis in hydrological modeling are Sequential Uncertainty Fitting (SUFI-2) (Abbaspour *et al.,* 2015). Parameter Solution (ParaSol) (Duan *et al.,* 1992). Generalized Likelihood Uncertainty Estimation (GLUE) (Beven & Binley, 1992) and Particle Swarm Optimization (PSO) (Eberhart *et al.,* 1995). However, depending on the study region and location, different essential parameters must be identified, and their uncertainties (streamflow simulation uncertainties and parameter uncertainties) must be quantified (Wu & Chen, 2015). Therefore, parameter sensitivity and uncertainty analysis must be done before conducting additional hydrological study, particularly in some watersheds with complex terrain. For methodologies and approaches developed or applied to manage or mitigate uncertainty in hydrological modelling in data scarce environment the readers are referred to studies by (Arnold *et al.,* 2012a).

2.5.1 Soil water assessment tool model for assessing impacts of climate change on river discharge

Soil Water Assessment Tool (SWAT) is a physically based, basin-scale, continuous-time, computationally efficient, spatially distributed model developed for the USDA Agricultural Research Service (ARS) that runs on a minimum daily time step (Gassman *et al.,* 2007; Shawul *et al.,* 2013). The development of SWAT is a continuation of the USDA Agricultural Research Service (ARS) modelling experience that spans roughly 30 years (Arnold *et al.,* 2009). In SWAT, calculations happen on the sub-catchment scale, where the smallest defined sub-catchments are routed using the stream network. The sub-catchments are built on hydrological response units (HRUs), groups of similar land-uses, soils, and slopes within the sub-catchment. The model has proven to be a powerful tool for studying water resources, non-point source pollution problems, and environmental conditions (Arnold *et al.,* 2012a; Gassman *et al.,* 2007). The SWAT model has been used to calculate the long-term effects of various land-use decisions on runoff, sediment loads, and nutrient loss at various scales.

The major model geospatial data inputs include meteorological data such as daily rainfall and minimum and maximum temperature. The hydrological data consists of the daily river discharge records, soil data, and digital elevation model (DEM) and land-use/land cover data. Hydrological processes are represented in SWAT using specific parameters, which govern infiltration, runoff, retention, river discharge, nutrients, and sediment movement (Arnold *et al.,* 2012a). The regionalization approach calibrates the model using observed data, particularly the discharge data, assuming catchments with similar physiographic and climatic characteristics would have comparable hydrologic responses. The model is employed to study climate and land-use land cover (LULC) change impact on water balance components with input data from Global Climate Models (GCMs) and hypothetical LULC change scenarios, respectively.

Generally, the catchment's semi-arid environments, distinct rainfall seasonality and climate conditions made the SWAT the best choice for this study because of its demonstrated performance in such conditions (Arnold *et al.,* 2012a; Gassman *et al.,* 2007; Neitsch *et al.,* 2011). However, a significant barrier to using in situ observations to run the SWAT model is the wide range of data input, parameters, and spatial variability (Moriasi *et al.,* 2015). When simulating ground water systems, the SWAT model performs poorly in geologically heterogeneous basins (Nguyen & Dietrich, 2018). Applying the model to complex catchments with several hydrological response units (HRUs) is time-consuming because of the manual calibration and sensitivity analysis. Global climate models (GCMs) are thus the principal tools that provide information about climate on global, hemispheric and continental scales (Trzaska & Schnarr, 2014). Input data from the downscaled GCMs are commonly used to assess the impact of climate change on the hydrologic cycle.

The SWAT model can quantify the effects of climate and vegetation change on water quantity, water quality or other variables of interest, and physical processes like water flows in soil and groundwater (Arnold *et al.,* 2009; Neitsch *et al.,* 2011). The water balance Equation (1) is the foundation for the hydrologic cycle that the SWAT model simulates (Arnold *et al.,* 2009).

$$S_{wt} = S_{wo} + \sum_{n=1}^{t} \left(R_{day} - Q_{surf} - E_a - W_{seep} - G_w\right) \ldots\ldots (1)$$

S_{wt} is the final soil water content (mm H_2O), S_{wo} is the initial soil water content on day *I* (mm H_2O), *t* is the time (days), R_{day} is the amount of precipitation on day *i* (mm H_2O), Q_{surf} is the amount of surface runoff on the day *i* (mm H_2O), E_a is the amount of evapotranspiration on day *i* (mm H_2O), W_{seep} is the amount of water entering the vadose zone from the soil profile on day *i* (mm H_2O). The Gw is the amount of return flow on day *i* (mm H_2O) (for each HRU). The main water input to the watershed system is rainfall. After entering the HRU, the rainfall is divided into four response categories: Surface runoff (surf), evapotranspiration (Ea), water infiltrating to the vadose zone (W_{seep}), and the volume of water released into the streams as return flows (G_w). The initial soil water content on the day (S_{wo}) plus the amount of rainfall retained after being divided into the other components determine how much water is in the soil at any given time of the day (S_{wt}). Figure 2 shows how rainwater during the SWAT simulation was divided into various water balance components and how it moved through the land phase hydrological cycle.

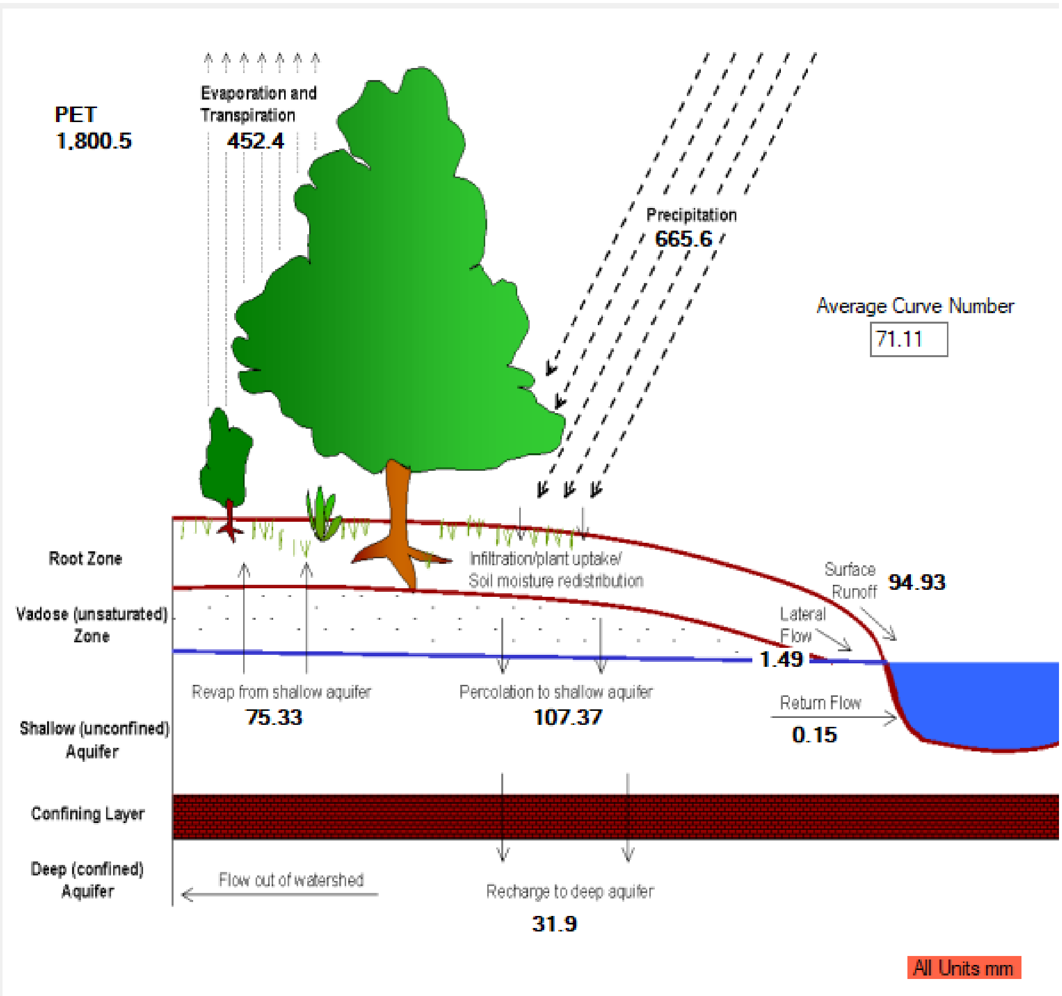


Figure 2: **Schematic presentation of water balance components and movement of water in the land phase hydrological cycle during SWAT simulation (Arnold *et al.*, 2009)**

2.5.2 Hydrologiska Byråns Vattenbalansavdelning model

Hydrologiska Byråns Vattenbalansavdelning (HBV) semi-distributed hydrological conceptual model was developed by SMHI for a comprehensive simulation of the hydrological processes in the catchment with significant snowmelt contributions to discharge (Tibangayuka *et al.,* 2022). The model does not apply to situations that are not predominantly influenced by snowmelt, but it can be modified to meet a variety of needs (Devia *et al.,* 2015). The entire watershed is divided into sub-catchments, and the catchment is further subdivided by altitude and vegetation zone. The required climate model inputs are daily or monthly precipitation, ambient temperature, and evaporation. The model uses water balance Equation (2):

$$P - E - Q = {}^{d}\!/_{dt}\,(S_p + S_m + U_z + L_z + L) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.(2)$$

Whereby, P is precipitation, E evaporation, Q is run-off, S_p snowpack, S_m moisture content, Uz and Lz are the upper and lower ground water area and L is the reservoir (Devia *et al.,* 2015).

2.5.3 Integrated catchment hydrological modelling software: Systeme hydrologique europeen (MIKE SHE) model

The MIKE SHE is a physical hydrological model that comprehensively represents the hydrological cycle, including runoff, subsurface flow and groundwater interactions (Devia *et al.,* 2015). The physically based model permits a comprehensive simulation of fluxes and flood forecasting. The model applies to various hydrological environments and requires substantial data inputs that may be difficult to obtain for catchments or regions with limited data. It is also valuable for assessing the catchment's water quality and climate variability (Keller *et al.,* 2023).

2.5.4 Hydrologic engineering center's hydrologic modeling system model

The Hydrologic Engineering Center's Hydrologic Modeling System model (HEC-HMS) operates within an ArcGIS environment to delineate the catchments and subcatchment and can simulate discharge in a hydrograph (Keller *et al.,* 2023; Pascual *et al.,* 2023). The model's versatility in simulating various hydrological components makes it appropriate for large-scale data analyses. The model offers a vast array of functionalities, which can be a challenge, and requires extensive data inputs and parameter calibration, which can overwhelm basic assessments (Keller *et al.,* 2023). The model concentrates primarily on engineering and planning applications, which may limit its suitability for research or studies requiring an in-depth comprehension of hydrological processes (Devia *et al.,* 2015).

2.5.5 Hydrologic engineering center's river analysis system model

Hydrologic Engineering Center's River Analysis System (HEC-RAS) model is a rainfall-runoff model that simulates river and channel flow responses to rainfall events (Razi *et al.,* 2018). The model incorporates floodplain analysis and river basin management. The model explains river behaviour in response to precipitation, which may limit its capacity to simulate the hydrological cycle (Pascual *et al.,* 2023).

2.5.6 Weather research and forecasting hydrological model (WRF-Hydro) model

Weather Research and Forecasting Hydrological Model (WRF-Hydro) model is a sophisticated modeling system that integrates hydrological and atmospheric processes (Cerbelaud *et al.,* 2022). This integration enables the simulation of surface and subsurface fluxes for flood forecasting and water management, making it a valuable tool for comprehensive assessments. The model requires extensive input data and specialized knowledge, which may limit its applicability in situations with limited data or resources (Nkeki *et al.,* 2022).

2.6 Erosion models

2.6.1 Universal soil loss equation model

The US Department of Agriculture created the Universal Soil Loss Equation (USLE) model in the 1970s as an empirical surface erosion quantification model (Wischmeier & Smith, 1978). Application of the model has since grown exponentially, with several slight modifications added e. g. MUSLE (Modified Universal Soil Loss Equation) (Williams, 1975), and Revised Universal Soil Loss Equation **(**RUSLE) (Renard *et al.,* 1991). The USLE and its modifications have been used in studies at large and complex catchment scales despite being designed for application at simple agricultural catchments with gentle slopes and fine-textured soils (Alewell *et al.,* 2019). The USLE calculates the mean annual soil loss from the following Equation (3):

$$A = R.K.LS.C.P \ldots\ldots\ldots\ldots (3)$$

Whereby, A is the mean annual soil loss (t $ha^{-1}yr^{-1}$); R is the annual rainfall erosivity factor ($MJmmha^{-1}h^{-}1yr^{-1}$); K is the soil erodibility factor (t ha h $ha^{-1}MJ^{-1}mm^{-1}$); LS is the topographical factor (slope length and slope steepness), C is the land management factor (dimensionless), and P represents soil conservation practice factor (dimensionless). The USLE factors are frequently modified in studies because it is often difficult to obtain some data. For instance, Maeda *et al.* (2010) and Segura *et al.* (2014) calculated the *R* factor under future climate change using the Fournier Index (FI) (Fournier, 1960; Renard & Freimund, 1994). Modification to USLE was always performed to be integrated in other models (Mukundan *et al.,* 2010) combined the SWAT and MUSLE models to forecast sediment yield under projected climate change.

2.6.2 Watershed erosion prediction project model

The WEPP model is a physically process-based model capable to simulate erosion areas and sediment amount in a single event. This model incorporates numerous procedures that depict how soil erosion is affected by climate change (Williams *et al.,* 1996). The WEPP model simulates the growth of plants and residue decay when affected by soil and temperature as well as soil consolidation and its impacts on infiltration rate. Due to its sensitivity to climatic variation, WEPP and its modification, is extensively used to assess the impact of climate change on soil erosion (Mullan, 2013; Savabi, 1993) for instance, used the WEPP model to estimate soil loss rates for six hillslopes in Northern Ireland for the 2020s, the 2050s and the 2080s. O'Neal *et al.* (2005) carried out a comparable investigation.

2.7 Model selection

These models differ regarding data requirements and complexity, processes considered and implementation potential (Pandey *et al.,* 2016). Process-based models require large input of data mathematically represented on the set of equations, and calibration routines for different catchments (Fenta *et al.,* 2020). Empirical models demand less geospatial data input, while retaining the majority of factors, such as the physical characteristics (e.g. topography, geology, land-use, and climate) that have an impact on erosion (Fenta *et al.,* 2020; Renard *et al.,* 1997). The accuracy of the estimated soil loss rate using process-based models is also constrained (Fenta *et al.,* 2020; Tamene *et al.,* 2006) but they might more accurately depict process interaction and feedback.

Currently, RUSLE and other empirical methods are extensively used in the East African region, primarily because of their average data demand and ability to integrate with GIS databases, which facilitates the upscaling process (Borrelli *et al.,* 2017; Fenta *et al.,* 2020; Haregeweyn *et al.,* 2017; Tamene & Le, 2015). However, the use of the RUSLE model in East Africa has limitations since it was built for the US temperate climate with gentle systems that are intended to provide the farmers and conservation planners with a tool to estimate rates of soil erosion for different cropping systems and land managements (Alewell *et al.,* 2019; Batista *et al.,* 2019). With the benefits of GIS, the RUSLE model can predict the possible erosion potential on a cell-by-cell basis (Shinde *et al.,* 2010), which is helpful when attempting to identify the spatial pattern of the soil loss present within area (Ganasri & Ramesh, 2016).

The soil loss calculated by the RUSLE model for every pixel predicts the erosion related to runoff as well as the heterogeneity of the landscape factors (soil type, slope, topography, vegetation, geology, land-use, and climate) that have an impact on the soil erosion process (Fenta *et al.,* 2020; Renard *et al.,* 1997). Since the model was created specifically to forecast sheet and rill erosion, the model only fully captures one aspect of the entire erosion spectrum (Fenta *et al.,* 2020) and does not include other important erosion processes, such as gully erosion and stream erosion. Consequently, this model fails to accomplish the desired result in a locality where gully erosion, and streamline incision processes dominate (Blake *et al.,* 2018; Renard *et al.,* 1997), this model fails to accomplish the desired result.

Furthermore, the RUSLE model is less useful for analyzing source-to-sink dynamics in huge and complex catchments and does not predict localized changes in susceptibility to erosion in response to process change (Wynants *et al.,* 2018). Moreover, the model never considers certain essential factors for erosion dynamics, such as sediment supply and overland flow initiation dynamics (Wynants *et al.,* 2018). The conjunction use of the RUSLE model with sediment tracing source techniques will offer complementary evidence to explore the knowledge of source-to-sink dynamics within the catchment. This combination also provides a reciprocal validation of the proportional contribution from areas of high erosion risk (Owens *et al.,* 2016; Wynants *et al.,* 2018).

Complementing RUSLE models with other models for plotting susceptibility to other erosion processes (e.g. mass movements, gully, riverine and wind erosion), would enhance the representation of the entire erosion susceptibility (Aksoy & Kavvas, 2005; Wynants *et al.,* 2018). According to Evans *et al.* (2017), not all methods for assessing, monitoring, and estimating erosion are appropriate at all scales. For instance, since each model has unique assumptions and constraints, no model can accurately predict all hydrologic conditions (Ndomba, 2007; Ndomba *et al.,* 2007; Yanda, 1995). Therefore, different methods to monitor, assess and estimate sedimentation will be appropriate at different spatial and temporal scales. Since no models are specifically made for the East African conditions, their critical values for current models are probably outside the bounds of many models' design parameters (Visser, 2003). Most models assume that the catchment outlet sediment flux is in a steady state, with changes in the catchment environment being immediately transmitted to it (Geeraert *et al.,* 2015), but disregard alterations in sediment connectivity over time. Since the amount of sediment entering the river network primarily depends on catchment connectivity, the concept of connection-disconnection between the slopes and the channel network (hillslope-sediment delivery ratio) is crucial (Brosinsky *et al.,* 2014; Vercruysse *et al.,* 2017).

2.8 Global climate models for future climate change modeling

According to the Intergovernmental Panel on Climate Change (IPCC, 2007), the temperature and precipitation patterns will change significantly by the end of the 21st century. As the primary determinants of the global hydrological cycle, precipitation and temperature changes will substantially impact watershed hydrology (Teutschbein & Seibert, 2010). Currently, the GCMs are the primary tools used to simulate the present climate and to project the future climate change. However, the resolution of GCM outputs (usually precipitation and temperature) is too coarse and biased to be used directly by hydrological models for impact assessment. The poor temporal and coarse spatial resolutions limit the effectiveness of GCM model output in providing useful information at the regional scale (Wilby & Wigley, 1997). Thus, there is a need to convert GCM outputs into regional high-resolution meteorological fields required for reliable hydrological modelling, and this process is generally referred to as 'downscaling' (Hewitson & Crane, 1992a, 1992b).

Further, hydrological models forced with regional climate change scenarios downscaled from GCMs are widely used to assess the impacts of climate change on hydrology (Tian *et al.,* 2013). Statistical and dynamic downscaling techniques such as Simple Delta Method were thus established based on dynamic formulations using the initial and time-dependent lateral boundary conditions of GCMs and have therefore being used to fill these gaps by driving a Regional Climate Model (RCM) to produce higher resolution outputs (Caya & Laprise, 1999; Dickinson *et al.,* 1989; Giorgi, 1990).

2.9 Sediment source tracing

Sediment source tracing has been developed to connect upstream erosion measurements with downstream sedimentation measurements (Owens *et al.,* 2016; Walling & Foster, 2016; Walling, 2013). These methods can provide thorough details of source-to-sink dynamics within the catchment, guarantee proportional source contribution, and identify high erosional risk areas (Owens *et al.,* 2016; Walling *et al.,* 2014). Sediment source tracing techniques were developed and established to strengthen the similarities between the physical, geo-chemical, or biochemical properties of downstream sediments with the catchment potential sediment sources (Collins & Walling, 2004; Nosrati *et al.,* 2019; Pulley *et al.,* 2015a, 2015b).

The technique can generate valuable evidence on the relative importance of particular potential sources contributing to the downstream sediment flux of a river and reservoir (Chalov *et al.,* 2017). Such details are essential for bolstering evidence regarding the relationships between upstream potential sediment sources and downstream sediment yield (Walling & Collins, 2008), necessary for precise sediment control measures. Additionally, the method offers crucial details about sediment movement through the landscape at various temporal and spatial scales (Guzmán *et al.,* 2013).

2.9.1 Sediment tracers

Different soil and sediment characteristics can be used as tracers to discriminate between various land-use types and erosion processes at the catchment scale. According to Caitcheon *et al.* (2012) and Walling (2005), fallout radionuclide (FRN) activities are typically greater in topsoil materials and less in subsoil materials, which enables them to be useful in differentiating between surface and subsurface materials as well as between cultivated and uncultivated agricultural surface soils (Smith & Blake, 2014). Consequently, sediment source apportionment using FRNs (Collins *et al.,* 2017; Collins & Walling, 2007; Collins *et al.,* 2001; Smith & Blake, 2014) tends to be at a more generic surface-subsurface level. The most used tracers include the broad spectrum of geo-chemical concentrations (Douglas *et al.,* 2009; Lin *et al.,* 2015), concentrations of fallout radionuclide (FRNs) (Wilson *et al.,* 2012) and biochemical tracers, i.e., specific stable isotope (CSSI) (Laceby *et al.,* 2015; Schindler Wildhaber *et al.,* 2012).

The use of a single component signature in this context has a high degree of uncertainty and can occasionally produce false associations between the source and the sediment (Collins & Walling, 2002). The majority of fingerprinting studies make use of multivariate and composite fingerprints, which include a variety of distinct diagnostic signatures influenced by various environmental factors, improving the validity of discrimination of sediment sources (Walling *et al.,* 2006). A multivariate fingerprint is created when numerous parameters are combined (Walling *et al.,* 1993) that, enables the modelling of a greater number of sources and is thought to be more reflective of the relationships between sediments and their sources (Laceby *et al.,* 2017). This lessens the possibility of unlikely matches, which are predicted to happen with specific tracer properties (Collins *et al.,* 1996; Laceby *et al.,* 2017). Consequently, a quantitative analysis is carried out to determine the relative contributions of all potential sources from collected the target sediment, and these frequently relies on frequentist or Bayesian un-mixing models (Nosrati *et al.,* 2019).

2.9.2 Conservative tracers

For source tracing, these models employ multivariate fingerprints, and they determine the relative importance of various sediment source types under various conditions (Collins & Walling, 2007; Motha *et al.,* 2003; Russell *et al.,* 2001; Walling & Woodward, 1995). These models usually need tracer data that interprets the sources and mixture; these qualities are expected to be conservatively transferred from sources to mixtures through a mixing process (Stock *et al.,* 2018). Tracers need to act independently and conservatively in the environment to directly compare the properties of the sediment samples and those of the potential source materials. This suggests that the tracers' chemical makeup does not change during detachment, transportation, or after deposition. Range test for the tracer screening process is usually performed for source apportionment that only excludes tracers on the basis of non-conservative behavior based on their performance from the model (Smith *et al.,* 2018). Ultimately, the modeler's choice of error assumptions and model structural options will determine whether a mixing model can faithfully represent source contributions to a mixture.

2.9.3 Mixing models

Bayesian methods typically couple parameter optimization with Monte Carlo-based stochastic sampling to represent uncertainties related to source area and target sediment variability (Collins *et al.,* 2013; Wilkinson *et al.,* 2013a); while Frequentist models frequently minimize the sum of squared residuals as described by Collins *et al.* (1997). The representation of uncertainty in these frequentist models is inconsistent, and they lack the structural flexibility needed to incorporate all possible sources of error into model output coherently. Subsequently, Bayesian mixing models have grown in popularity over the past decade as a more reliable substitute for fully incorporating uncertainty into models (Blake *et al.,* 2018a; D'Haen *et al.,* 2012; Dutton *et al.,* 2013; Massoudieh *et al.,* 2012; Nosrati *et al.,* 2014). Its flexible likelihood-based structure, which enables better representation of the inherent variability in source and mixture tracer data caused by environmental processes, is a key advantage of

Bayesian over conventional frequentist models in quantifying environmental fluxes of sediments or nutrients (Cooper & Krueger, 2017; Cooper *et al.,* 2015; Stock & Semmens, 2016).

Additionally, Bayesian models allow for the combination of previously known information in the form of "prior" probability distributions with fresh tracer data to produce "posterior" probability distributions for updated parameter estimates (Stock *et al.,* 2018). Fundamentally, the Bayesian approach is superior to Frequentist methods because it enables all known and residual uncertainties related to the mixing model and the data set to coherently translate into parameter probability distributions in a coherent hierarchical framework. Since the Frequentist optimization lacks the structural flexibility to coherently translate all sources of uncertainty into mixing model results, Bayesian inference is preferred to the more widely used Frequentist approach in sediment fingerprinting studies (Cooper & Krueger, 2017).

CHAPTER THREE

MATERIALS AND METHODS

3.1 Overview

This Chapter describes the study area, sampling strategies, and a comprehensive narration of the analytical methods. The fundamentals of the Bayesian mixing modelling from which the model is draws to quantitatively compare different sources with the river sediments and the assumptions from which the model was built in the MixSIAR framework are given in details. Data analysis that includes geo-chemical and SWAT analysis are also presented in this Chapter.

3.2 Description of the study area

The Simiyu River catchment is located southeast of Lake Victoria, and its altitude ranges between 1100 and 2000 M.a.m.s.l. The catchment covers ca. 11 000 km^2 and receives water from two tributaries, the Simiyu and the Duma Rivers (Fig. 3).

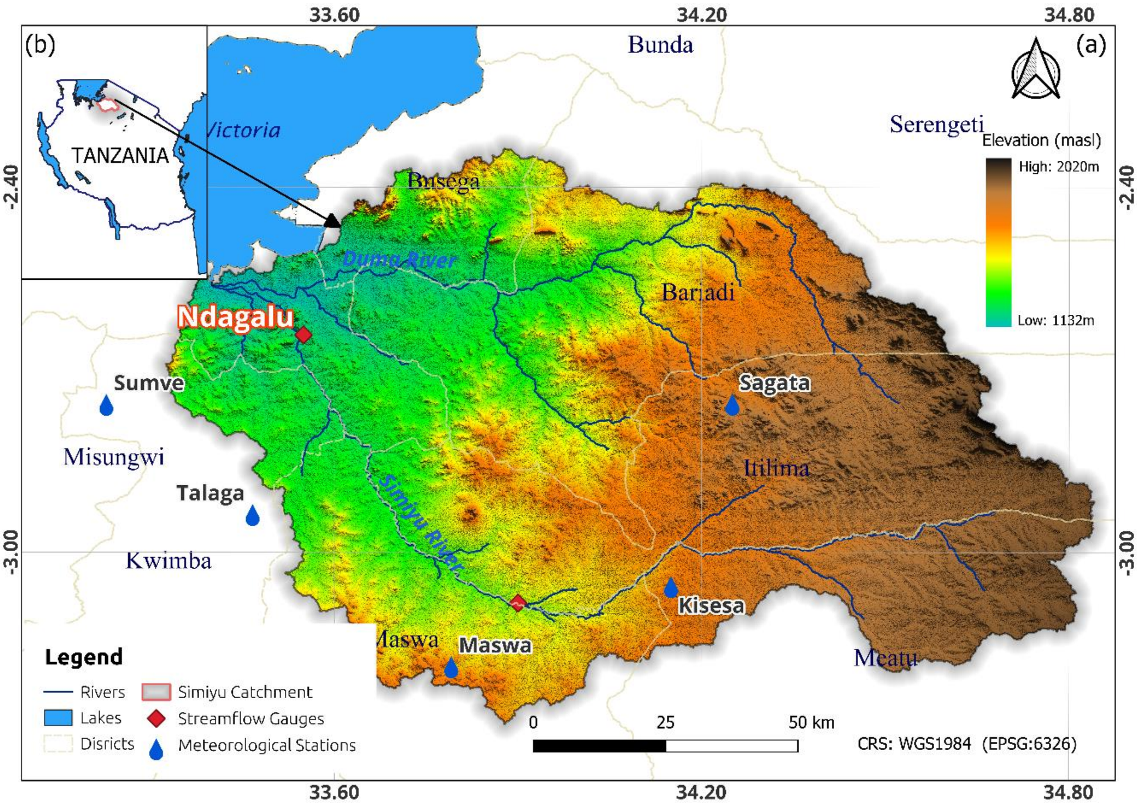


Figure 3: Location of the Simiyu River catchment detailing the elevations, rainfall and hydrometric stations

The Simiyu sub-catchment covers ca. 5540.67 km^{2,} and the Duma ca. 5435.11 km^2 covers the total catchment. The Simiyu and the Duma sub-tributaries drain from the Maswa Game

Reserve and the Serengeti National Park plains, respectively, joining together into the Simiyu Mainstem about 2 km before the inlet in Lake Victoria. The catchment has a semi-arid climate, experiencing seasonal rainfall fluctuations, wherein most rainfall occurs in two wet seasons, with long rains from March through May and short rains from October through December. The dry season occurs between June and September, and the transition period between the two seasons occurs in the intermediate months of January and February (Lubini & Adamowski, 2013). The rainfall also varies spatially in the catchment, wherein the hydrological mean annual rainfall is around 750 mm in the lower parts and 1100 mm in the upper part. The rainfall intensity follows a similar pattern and is shown in Fig. 4a.

Furthermore, the area also experiences high interannual variability in rainfall, with drier and wetter years. For example, in 1988, an annual rainfall of 1312 mm was recorded in one of the climate stations in the catchment, while in 1989, it was only 774 mm. The most distinct slopes are in the northeastern catchment, with other sloped areas spread out more evenly (Fig. 4b). The major land cover types include natural forests, bushland, grassland, wetlands and woodlands that do not form a thickly interlaced canopy (Fig. 4d). Rainfed agriculture, fishing, wildlife tourism, and pastoralism are the main economic activities in the catchment. The Serengeti National Park/game reserve covers the upstream part of the catchment in the east and is dominated by natural grassland and bushland. The geology in the catchment is mainly dominated by granite with smaller intercalations of Magmatite, sedimentary, metamorphic and volcanic rocks (Fig. 4c). The main soil types are sandy loam (63.8%), sandy clay loam (13.5%), clay loam (12.9%), clay (5%), loam (2.9%), and sandy clay (1.9%) (Rwetabula *et al.,* 2007b).

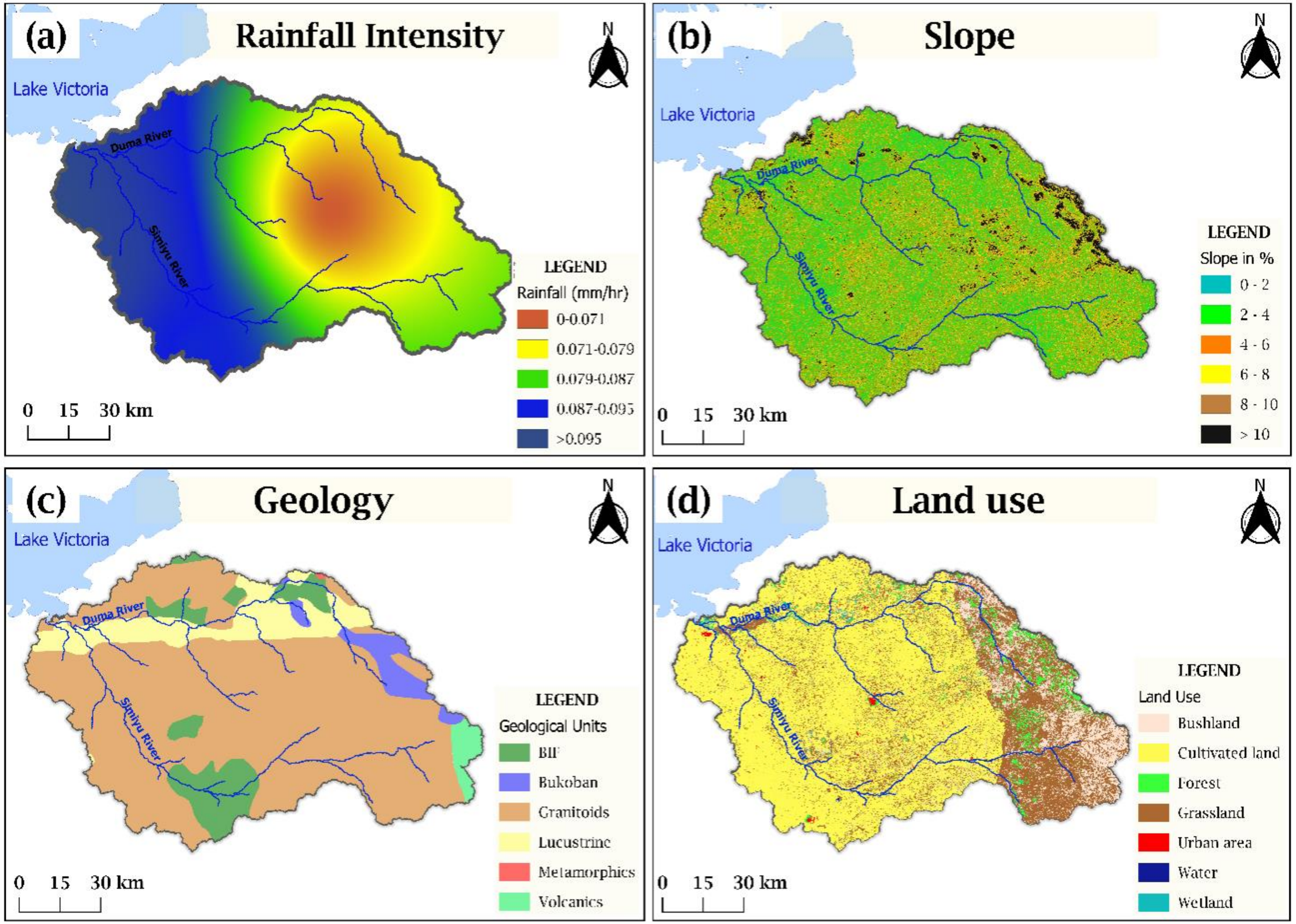


Figure 4: **(a) The rainfall intensity, (b) slope, (c) geology, and (d) land-use distributions of the Simiyu catchment**

Modelling studies of the Simiyu catchment estimated sediment yield between 0 to 38.83 t $ha^{-1}yr^{-1}$ for the period 1980-2009, and between 0.50 to 11.86 t ha^{-1} yr^{-1} for the period 2010-2016 (Kimwaga *et al.,* 2012b; Ndomba *et al.,* 2005b; Van Griensven *et al.,* 2013a). A study by Kimwaga *et al.* (2012b) revealed a dramatic expansion of agricultural land from 19.33% in 1975 to 73.44% in 2006 at the expense of bushland, forests, grassland and woodlands. The Tanzania Participatory Poverty Assessment conducted in 2002-2003 also reported high deforestation rates in the Meatu district to clear land for cultivation (Kimwaga *et al.,* 2012a). The domestic animal and wildlife populations have been increasing since the eradication of rinderpest in the 1960s (Food and Agriculture Organisation of the United Nations, 2020; Ogutu *et al.,* 2016). Anecdotal evidence from the area indicates that the catchment has experienced dramatic changes over the past decades through increased agriculture, livestock-keeping, deforestation, and urban and rural settlement (Zhang *et al.,* 2020a). Several studies also report high densities of gullies in the area (Ndomba *et al.,* 2005b; Zhang *et al.,* 2020a) and this was also observed during the fieldwork campaign at Ng'hanga village a border to Serengeti National Park (UTM arc 1960 658475E, 9667580N) as shown in Fig. 5.

Figure 5: A plate of gully incision in the Simiyu River catchment taken at Ng'hanga village

3.3 Assessing the impacts of land-use and climate change on the stream flow in the Simiyu catchment

3.2.1 Data preparation

The SWAT requires spatial, hydrological, and meteorological data for building, calibrating, and forcing the model. The required input data were collected from different sources and prepared in the ArcGIS 10.2.1 environment to acquire the necessary setup essential for the ArcSWAT12 database. A digital elevation model (DEM) of the Simiyu catchment with a resolution of 1 arc-second (30 m × 30 m) was included in the spatial data and was acquired from the United States Geological Surveys (USGS) website (http://gdex.cr.usgs.gov/gdex/ accessed on 28 March 2020), and was used to delineate the watershed and the stream networks following the procedures by Gassman *et al.* (2007), and Neitsch *et al.* (2011). The land-use/cover map of 1990 and 2019 (Fig. 6a and b, respectively) were downloaded from Earth Explorer in May 1990 with Landsat 5 (resolution 30 m) and Landsat 8 images (resolution 30 m) captured in May 2019 and interpretation, atmospheric correction and geometric rectification performed using impact toolbox software (http://glovis.usgs.gov/accessed on 17 December 2021).

Geotagged photographs and field notes were collected from numerous ground observation operations (through field surveys and interviews with local people) to ensure full documentation of the land cover spectrum. Using these ground observations, supplemented by Google Earth imagery, the main land cover types in the region were mapped into a spectral signature file developed from training samples. According to ArchMap's maximum likelihood algorithm method, the supervised classification uses these signature files to estimate predefined land cover classes from the entire Landsat image database. Visual inspection and comparison with high-resolution aerial images provided by Google Earth were used to remove potentially misclassified features. A raster calculator function was used to determine the appropriate elevation for specific land-use classes based on expert knowledge of the study area as detailed by Taweesuk and Thammapala (2005).

Expert classification aims to improve the classification accuracy used to combine remote sensing data with other sources of georeferencing information such as digital elevation models (DEMs), land-use and spatial texture data. The accuracy assessment was performed to determine the level of agreement between classified images and ground features. Overall accuracy ratings for images observed in 1990 and 2019 were 87.37% and 85.74%, respectively.

This value meets the minimum accuracy threshold of 85% required for effective and realistic land-use/cover change analysis and modeling (Ahmed *et al.,* 2013; Araya & Cabral, 2010). The results of this study are considered acceptable because the accuracy values are greater than 80%, as reported by Jensen (1986).

The Lake Victoria Basin Water Board (LVBWB) provided meteorological data such as daily rainfall (rainfall records for 5 stations Maswa, Sumve, Talaga, Sagata and Kisesa) and minimum and maximum temperature (Neitsch *et al.,* 2011) (Table 1), supplemented by data from Tanzania Meteorological Agency (TMA) (satellite data from the Earth System Grid Federation (ESGF)). The hydrological data included the daily river discharge records from the Ndagalu gauging station (−2.65299° S, 33.541930° E) between 1 January 1972 and 31 December 1996.

The soil data were obtained from the Harmonized global soils database at http://www.waterbase.org/download_data.html (Digital Soil Map of the World (DSMW) (Dewitte *et al.,* 2013) (Fig. 7). However, there were missing data in the rainfall patterns that could hide true patterns in the data and impede the analysis and interpretation of the flow variability, resulting in complexity and uncertainty in modelling. Encountering data gaps is unavoidable, particularly in developing countries, hence various methods for handling infilling of missing data have been developed. In this study, missing data was filled using the RClimtool software version 1.

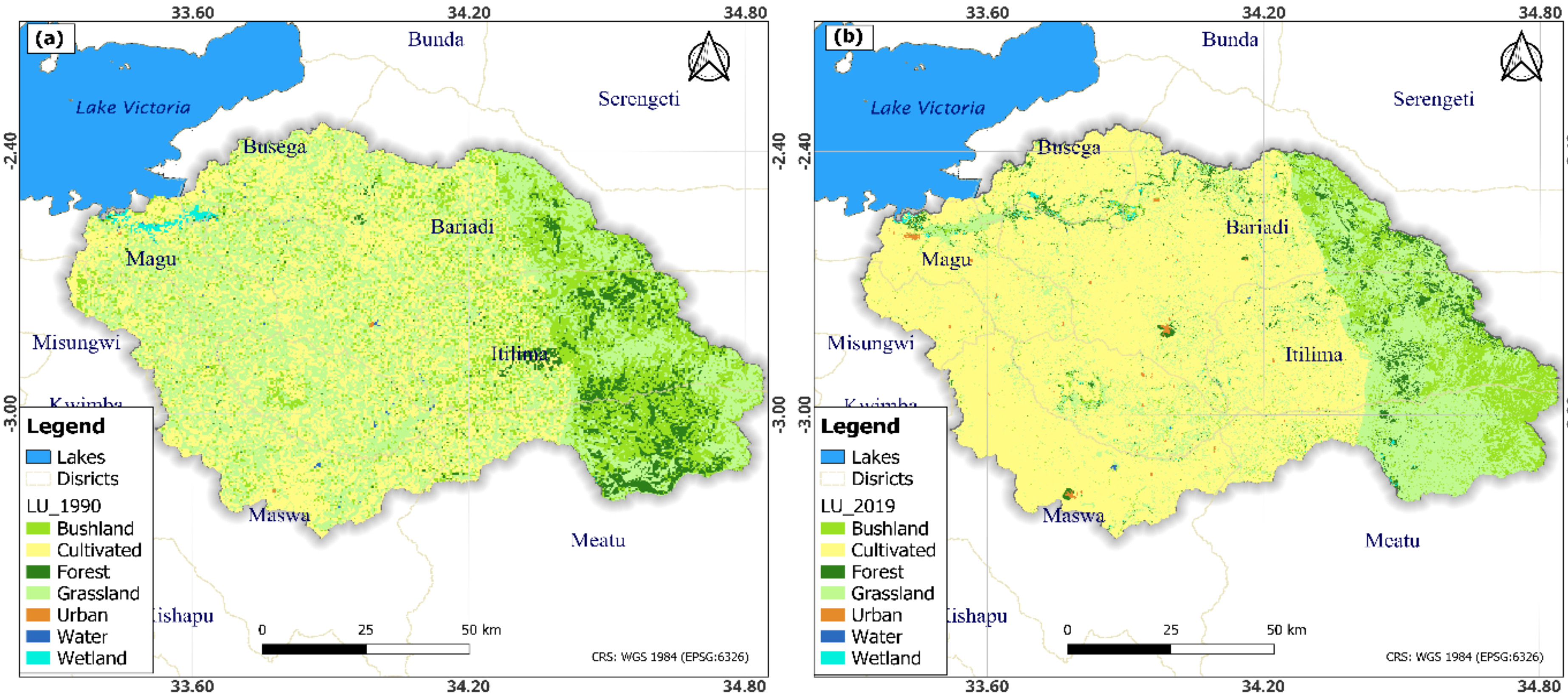


Figure 6: **Land cover maps of (a) 1990 and (b) 2019, detailing the changes in land-use land cover from 1990 to 2019**

Table 1: Meteorological stations in the Simiyu catchment

Station ID	Meteorological Stations	Latitude ° S	Longitude ° E	Elevation	Daily Rainfall	Percentage Missing (NA%)
933305	Maswa	−3.182	33.79098	1334	1971–2019	7.182
923301	Sumve	−2.751	33.2265	1243	1971–2019	30.814
923240	Talaga	−2.932	33.46581	1237	1971–2019	0.691
923401	Sagata	−2.75	34.25	1394	1971–2019	17.227
933406	Kisesa	−3.05	34.15	1343	1971–2019	45.915

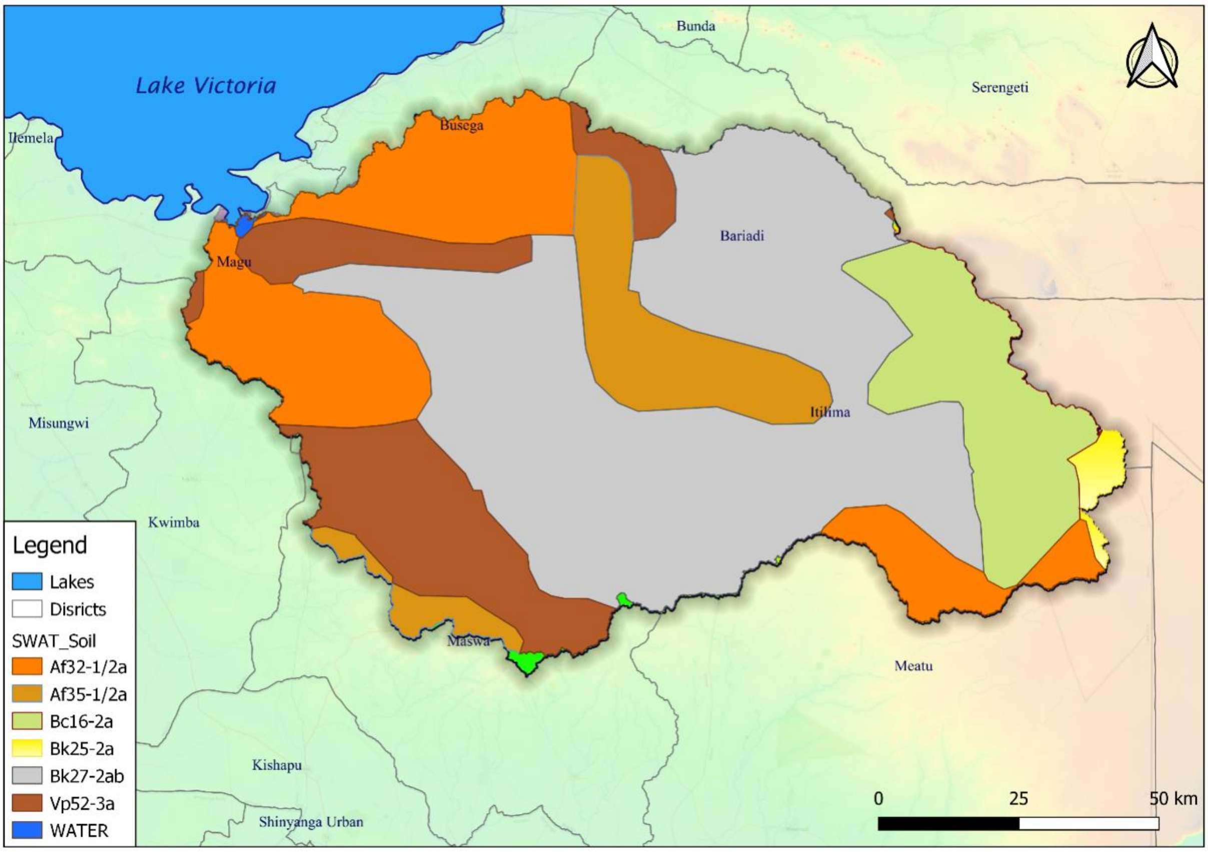


Figure 7: **Soil water assessment tool soil reclassified map of the study area**

3.2.2 Soil water assessment tool model setup, sensitivity analysis, calibration and validation

Two main categories of statistical evaluations are used to assess the performance of the best parameter sets chosen in the sensitivity analysis, i.e., model performance evaluation and uncertainty in model predictions. The statistical analysis parameters proposed by Moriasi *et al.* (2007), such as the Nash–Sutcliffe efficient (NSE), a ratio of the root mean square error to the standard deviation of measured data (RSR) and the percentage bias (PBIAS), were used to assess the model performance in predicting the catchment conditions (Wang *et al.,* 2011). The *r*-factor and the *p*-factor were used for model prediction uncertainty (Arnold *et al.,* 2012a). The *p*-factor is the percentage of observations covered by the 95% prediction uncertainty, while the *r*-factor refers to the thickness of the 95% prediction uncertainty (95PPU) envelope. The *p*-factor value ideally falls between 0 and 100%, while the *r*-factor falls between 0% and infinity (Teklay *et al.,* 2022). An exact simulation of the measured data has a *p*-factor of 1 and an *r*-factor of zero (Abbaspour, 2007). The extent to which model results deviate from these values can be used to assess the model's representativeness and the need for further calibration. A *p*-

factor value of >70% and an *r*-factor value of around 1 are suggested in semi-arid regions (Abbaspour, 2015).

In this study, the catchment's hydrological responses to land-use and climate changes were quantified using the climate scenario and the annual runoff coefficients of each land-use. This enables the evaluation of the water resource dynamics, which are controlled by the succession of wet and dry years in the studied catchment. The multi-decadal climate prediction was analyzed in accordance with (Krysanova *et al.,* 2016) using 30-year average annual and monthly results to obtain river discharge predictions for reference and future scenario periods. All the elements of the water balance in the study catchment were estimated using the hydrological component of the SWAT model. The model was built by partitioning the catchment into sub-catchments that are composed of several HRUs with relatively uniform combinations of land-use/land cover, soil types, and topography. It is assumed that each HRU has similar hydrological processes (Arnold *et al.,* 2012a; Neitsch *et al.,* 2011; Winchell *et al.,* 2013). The required climatic driving variables (daily rainfall, minimum and maximum temperature) were subsequently fed into the model, consequently determining the evapotranspiration rate by using the Hargreaves method (Hargreaves & Samani, 1985).

After completing all the above processes, the model was calibrated, validated, and assessed with historical hydro-meteorological datasets for performance accuracy and efficiency. Validation was carried out using the split sample test, whereby two time periods were selected for this analysis (Santos *et al.,* 2018), a calibration period of 1972–1982 and a validation period of 1988–1992. The daily river discharge data from 1972 to 1982 and 1988 to 1992 from the Ndagalu gauging station were used to calibrate and validate the SWAT model. The SWATCUP SUFI-2, a semi-automatic calibration and uncertainty program, was used for the calibration and validation (Arnold *et al.,* 2012a). Model initialization was carried out during model calibration over a four-year warm-up period from 1988 to 1992. Validation used the same number of calibration iterations as before; however, the sensitivity analysis was first performed then, followed by the calibration process. The number of iterations used for calibration was maintained for validation (Abbaspour, 2013).

According to Mutenyo *et al.* (2015), sensitivity analysis entails identifying the parameters that are most sensitive for a given basin and calculating the rate at which model outputs change as a result of changing model inputs. Sensitivity analysis was performed in ArcSWAT with and without discharge data from gauging stations and in SWAT-CUP using the SUFI procedures by running the model 1000 times. The t-statistic and p-values are used to rank the sensitivity of the parameters. The most sensitive parameters are those with the lowest *p*-value and the highest absolute value of the *t*-stat. Readers can be referred to for the details on the whole calibration and validation of the model (Abbaspour, 2007, 2015).

3.2.3 Simulating the impacts of land-use and climate change on stream discharge

The baseline land-use/cover of 1990 was replaced in the calibrated SWAT model with the 2019 land-use/cover of the Simiyu catchment. The 2019 land-use/cover scenario was then used to simulate the impact of the change in land cover on river discharge without changing the other SWAT input data (soils, slope and weather). The major assumption of this study is that the calibrated parameter set is still valid under changing land-use and climatic conditions. The potential combined effect of land-use and climate change on river discharge was evaluated using scenarios derived from a suite of 3 GCM models under the RCPs 4.5, 6.0 and 8.5 Greenhouse Gas Emission scenarios, which represent a wide range of simulated future (2030–2060) climate conditions. Scenario 1 (S1) is the baseline with land use from 1990 and climate data from 1972 to 1990. Scenario 2 (S2) represented river discharge under land-use change only. Scenario 3 (S3) was climate change only. Finally, scenario 4 (S4) represented the combined effect of land and climate change.

To quantify the impacts of land-use and climate change on river discharge in the Simiyu catchment from 1990 to 2019, the four scenarios (S1) to (S4) were used to run the calibrated SWAT model, and their outputs were compared. For future simulations of climate change impacts to discharge (2030–2060), only S1 and S3 were considered since no predictions were made on future land-use.

3.4 Assessing the impacts of future climate change on the Simiyu river discharge

3.4.1 Calibration and validation of future climate data

General Circulation Models (GCMs) are useful for describing and forecasting future climate change patterns. In this study, the 1990–2019 period was used as the baseline and the near future (2030–2060) was accounted for in climatic projections. Considering expansive numbers of accessible climate models and computational and human resource constraints, detailed climate change impact studies cannot incorporate all projections. In practice, one climate model or a small ensemble of climate models that covers more climatological variables using cluster analysis algorithms (Cannon, 2015; Houle *et al.,* 2012) is usually selected for the assessment based on their skill to simulate the present and near-future climate (Biemans *et al.,* 2013; Pierce *et al.,* 2009). In addition, the poor temporal and coarse spatial resolutions of GCM outputs (usually precipitation and temperature) might be biased, limiting the effectiveness of GCM model outputs in providing useful information at the regional scale (Wilby & Wigley, 1997), and are thus downscaled to convert GCM outputs into regional high-resolution meteorological fields required for reliable hydrological modelling of particular catchments.

For this study, four climate models from the Coupled Model Intercomparison Project 5 (CMIP5), i.e., CMCC.CM, ACCESS 1.3, MIROC5 and CNRM.CM was downscaled and compared to find the most representative of the Simiyu catchment's climatological patterns and spatial variations (Kang *et al.,* 2009) (Fig. 8). The three climate models (MIROC5, CNRM.CM5 and ACCESS 1.3) replicated climate variability of the Simiyu catchment (Northern Tanzania) with high accuracy coefficient correlations of 0.96, 0.97 and 0.98, respectively (Fig. 9); thus, three climate models were assumed to be the most representative in simulating spatial patterns in the decadal change of climate zones (Bodian *et al.,* 2018) in the catchment (Fig. 8). Forecasting climate change impacts on water resources is cumbersome (Hyandye, 2019) and requires using viable scenario changes detailed by the Intergovernmental Panel on Climate Change (IPCC) (Hyandye, 2019). As shown in the Fig. 10, the IPPC's fifth assessment report from 2014 presented four Representative Concentration Pathways (RCPs) emission scenarios: RCP 2.6 (low emission scenario), RCP 4.5 (low–medium emission scenario), RCP 6.0 (medium–high emission scenario) and 8.5 (high emission scenario). In this study, three RCPs (4.5, 6.0 and 8.5) were used to analyze the future (2030–2060) climate change impacts because they assume an increase in GHG emissions until 2080, followed by a decline (Mfwango *et al.,* 2022). The steps outlined in the Guide for Running AgMIP Climate Scenario Generation Tools with R were used to create the near-future climate scenario of precipitation and temperatures (Hudson & Ruane, 2013; Mfwango *et al.,* 2022; Zhang *et al.,* 2020d). The RCPs 4.5, 6.0 and 8.5 with ensemble GCM (ACCESS1.3, MIROC5 and CNRM.CM5) models were subsequently downscaled to the watershed level (Shrestha *et al.,* 2013) using the Simple Delta Method, as it retains the historical patterns of the gridded observations (Zhang *et al.,* 2020d).

To statistically downscale the selected models, the delta change algorithm that was acquired (Hyandye, 2019), along with the CMIP5-GCMs, was used to calculate the change factor or the ratio between a mean value in the future and historical run (Hyandye, 2019). To create a time series that represents the future climate, this change factor was then applied to the observed time series 2030–2060 (Hyandye, 2019). The downscaled and selected 3 GCMs climatic data points under RCPs 4.5, 6.0, and 8.5 were used as forcing data to forecast the river discharge under a future climate.

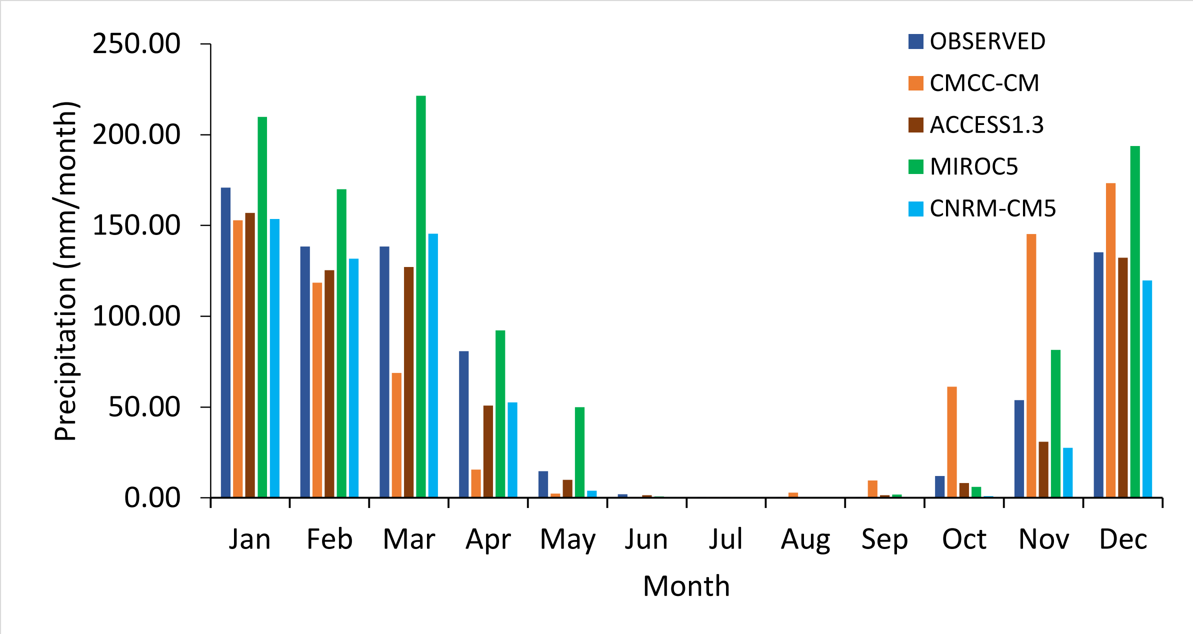


Figure 8: **General Circulation Models (GCMs) were sourced from the Coupled Model Inter-comparison Project 5 (CMIP5)**

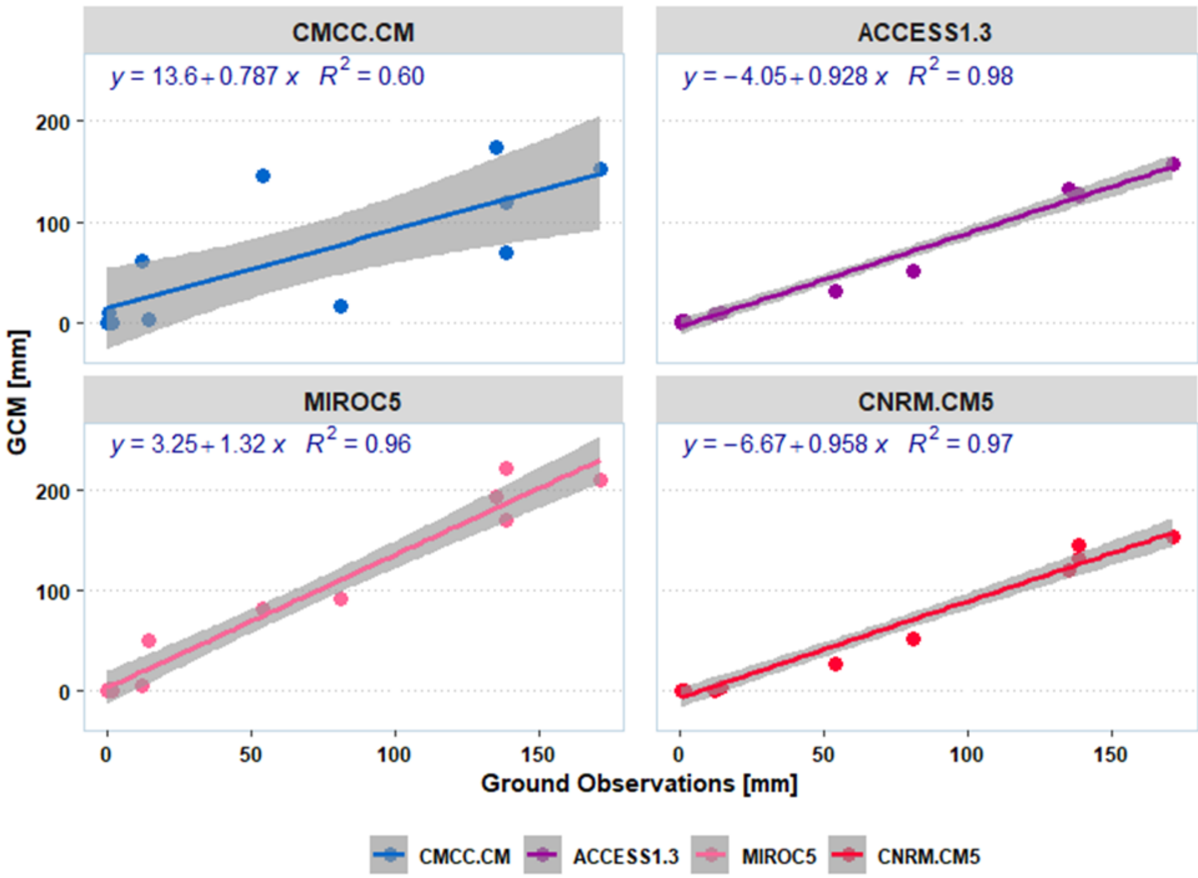


Figure 9: **Correlation of the selected GCMs model used in this study (https://esgf-node.llnl.gov/search/cmip5/)**

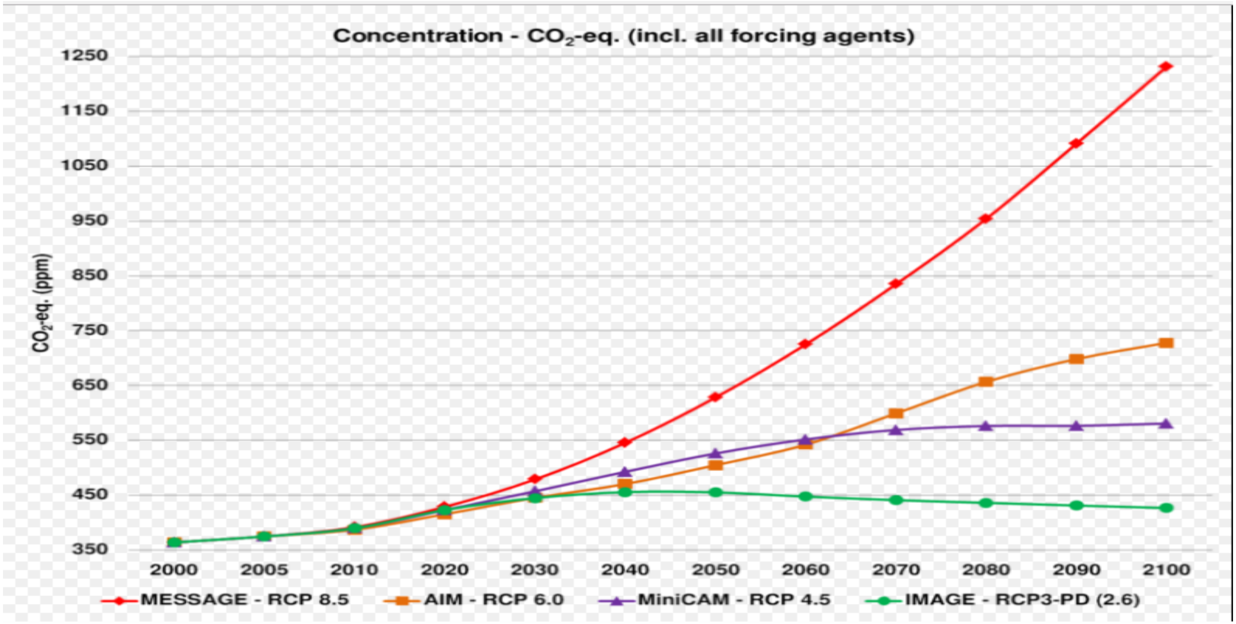


Figure 10: Four Representative Concentration Pathway (RCPs) emission scenarios (IPCC, 2014)

3.5 Assessing the dominant sources of the Simiyu riverine sediment using geo-chemical fingerprinting

3.5.1 Sampling strategy

Due to the challenging environment and logistical constraints, samples could only be taken from the exposed river beds in the dry season, so only deposited river bed sediments (RS) were included in the analysis. The RS samples were taken from the downstream reaches of the sub-tributaries and main rivers (Fig. 11). Because of these logistical constraints, this study works from the assumption that RS samples provide a time-integrated and representative mixture from their respective sources throughout the catchment area (Phillips *et al.,* 2000 & Maarten *et al.,* 2020), implications of this assumption are discussed in Chapter 4.

Thirty-two composite samples of RS, each composed of 10 to 12 sub-samples, were collected from the main Simiyu River over a range length of about 300 m to include potential spatial differences in riverine sediment deposition (Gellis & Noe, 2013; Wilkinson *et al.,* 2013b). The RS samples were collected at the mouth of the inflow, at the point of confluence of the two tributaries. Fifteen and 16 sub-tributary RS samples were also collected from lower reaches of the two major tributaries, Duma and Simiyu, respectively, at points where reciprocal influence through flooding could be excluded. Surface soil samples as potential sediment sources were collected from the catchment's dominant land-use types, which include bushland (BS), agricultural land (CU) and forest land (FL). Subsurface soil as potential sediment sources were sampled from channel banks (CB) and the mainstream river banks (RB). Surface soils from all major land-use types were sampled using composite samples from 0–5 cm depth from areas susceptible to soil erosion based on visual evidence of erosive features and landscape locations. Channel bank materials were sampled in the upstream regions of the catchment characterized by exposed banks devoid of vegetation with actively eroding bank sections. The main river (RB) banks were also sampled further downstream. Sampling locations depended on accessibility, necessary permits and safety. At each site, samples comprised 10 to 15 random scoops pooled into a single composite sample to ensure the representativeness of the corresponding fingerprint property datasets. A total of 69 samples were collected to characterize five main potential sediment sources: (a) Forest (FR, n = 13), (b) Bushland (BS, n = 11), (c) Channel banks (CB, n = 14) (d) Cultivated agricultural land (CU, n = 15) and (e) Mainstream river banks (RB, n = 16), all collected in the same year.

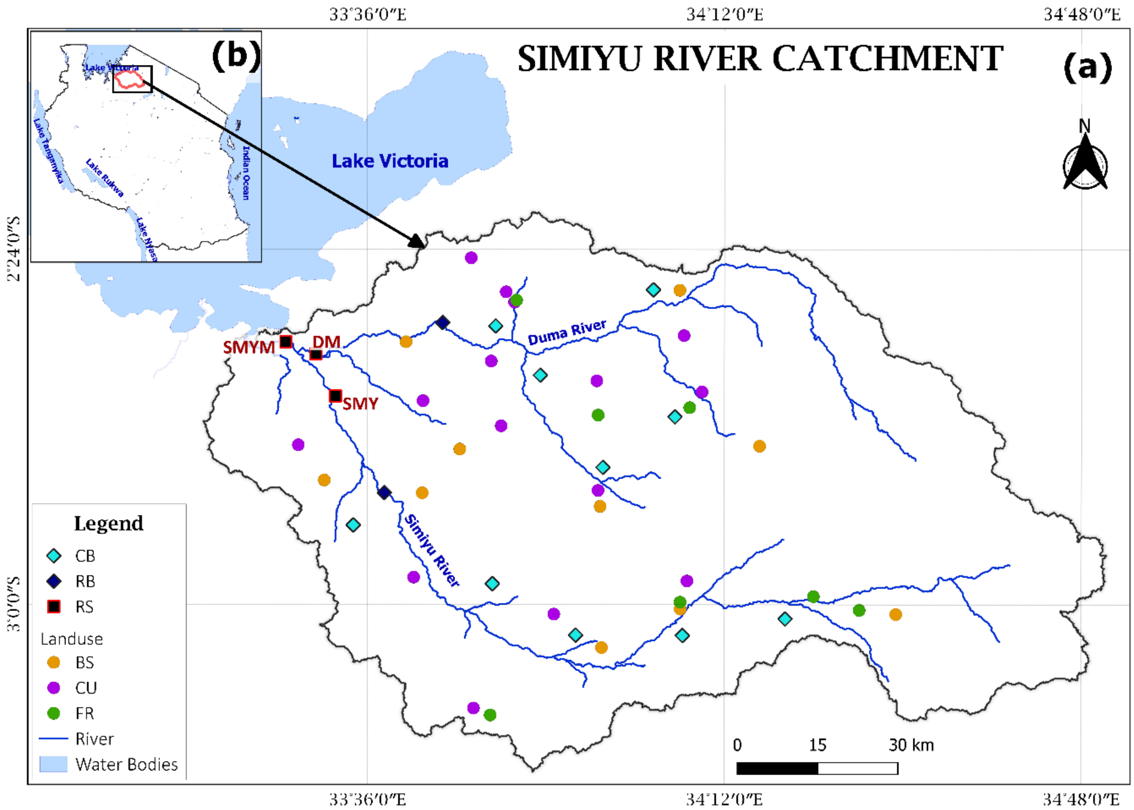


Figure 11: A detailed map of the Simiyu catchment showing locations of sediment sampling and the potential sediment sources from different land-use

3.5.2 Geochemical laboratory sample preparation

Prior to analysis, all dried soil and sediment samples were oven-dried at 55–60°C, disintegrated using a mortar and pestle, and subsequently sieved at < 63 µm fraction to minimize particle size effects on tracer signals that can bias fingerprint property (Laceby *et al.*, 2017). The elemental concentrations are generally enriched in the fine, < 63 µm, particle size fraction compared to the < 2 mm bulk fraction of the soil (Rawlins *et al.,* 2010). Subsequently, about four grams of dried and sieved sample material was mixed with about 0.9 g of cellulose binder (FLUXANA®), homogenized in a pulverizer and pressed into a pellet of approximately 32 mm diameter. The method was validated using the IAEA Soil 7 certified reference materials (CRM) as described in (Amasi *et al.,* 2021b). The dried soil and tributary potential sediment sources were analyzed as pressed pellets for minor and major elemental geochemistry by an energy-dispersive X-ray fluorescence (EDXRF) spectrometer (Spectro Xepos, Spectro Analytical Instruments, Boschstrasse 10, D-47533 Kleve, Germany) coupled with Xlab ProTM software. Triplicates were made from arbitrarily selected samples about once every 3 samples for assessment of the analytical variability and sample homogeneity. Only those elements returning measurements above the detection limit were employed in the analysis. The detection limit varies with the element and depends upon several factors, including the sample matrix. The geochemical analysis of sediment and soil samples was done at the Tanzania Atomic Energy Commission (TAEC).

3.5.3 Data analysis

(i) Bayesian mixing model for source apportionment

The yielded tracer concentrations from the RS mixtures and the potential soil and riverbed sources were represented as multivariate elemental concentration matrices. The Bayesian Mixing Model (BMM) draws upon these matrices to quantitatively compare the multivariate fingerprints between different sources and determine the relative contribution to the sediment mixture. A Bayesian mixing model was built in the open-source MixSIAR framework (Stock *et al.,* 2018), as Blake *et al.* (2018a) first demonstrated for sediment source apportionment in river systems. The MixSIAR methodology was used to unmix the Duma and Simiyu tributary sediment sources and land-use potential sediment sources from the Simiyu Mainstem riverbed sediment mixture after confluence downstream. For accurate use of the BMM model, the following four assumptions must be met: (a) The model includes all dominant sources contributing to the sediment, (b) The value of the tracers is known in both sources and mixture, (c) Tracers behave conservatively throughout the mixing processes and (d) Fingerprint variability between sources is larger than within sources, and the different sources are geo-chemically distinct. In addition, the major advantage of BMM is based on its flexibility in model structure tailored to the following specifications as described by Stock *et al.* (2018). The following specifications were built into the model runs:

In large, complex catchment systems, capturing the entire variability of the sediment flux by time-specific sampling events is difficult, creating a sampling error. In view of this, the "residual error" formulation was incorporated into the model. A "process error" was not included as sediment transport from hillslopes to the river/lake in this river system is not based on targeted processes such as reservoir release (Stock & Semmens, 2016). Uninformative prior: Since there is no empirical information on the dominant sources of sediments contributing to the significant tributary, an uninformative prior was used: (1, 1, 1, 1, 1) and (1, 1) for land-use and tributary sources, respectively.

A mixture of sediment samples was analyzed without fixed or random effects to infer the proportions of the tributaries and land uses to the bed river sediment. The BMM model outputs were evaluated under different scenarios of covariate structure. The following provisions were used for all model runs: A residual error term only and an uninformative Dirichlet prior (= 1). Model convergence was assessed by the Gelman–Rubin diagnostic (variables < 1.05), rejecting model output if >5% of total variables were above 1.05. Model convergence indicates that the model found a singular solution to the problem, decreasing the chances of equifinality. Using the selected 10 tracers the model passed the Gelman–Rubin convergence diagnostic with the parameters of the Markov chain Monte Carlo (MCMC) chain run length set as follows: Chain length = 1 000 000, burn = 700 000, thin = 300, chains = 3.t

(ii) Tracer conservation test and principal component analysis

Comparing the sediment samples' geo-chemical fingerprinting with the potential source materials using the Bayesian mixing model requires tracers to behave independently and conservatively (assumption 3) in the environment (Motha *et al.,* 2002). The tracer conservatism concept implies that the chemical composition of the tracers does not change during detachment, transport, deposition and or after deposition (Belmont *et al.,* 2014). The tracer screening process for source apportionment only excluded tracers on the basis of non-conservative behavior based on their performance from the range test (Smith *et al.,* 2018). Before tracer screening, the samples' elemental concentrations below the detection limit were dropped. Subsequently, Blake *et al.* (2018a) adopted the basic tracer screening approach with additional evaluation of geo-chemical behavior. Furthermore, the tracers found to have higher intra-source variance than inter-source variance were removed. Finally, the normality assessment using the Shapiro–Wilk test for the individual tracer mixtures was done because the model assumes a normal distribution of the mixture tracer data (Stock *et al.,* 2018).

One of the BMM model assumptions is that the inter-source differences in fingerprints have to be larger than the intra-source differences in fingerprints. In this context, a principal component analysis (PCA) was applied to reduce the dimensionality of the entire multivariate tracer dataset, allowing a visual scrutinization of the variance between and within the different sources and the mixture (Blake *et al.,* 2018a). This allows us to evaluate whether the different land-use classes and sub-tributaries are grouped into distinct geochemical groups. A mixture of the sediment at the river confluence point was used to attribute the sub-tributary sediment sources, and soil samples from different land use classes upstream of the catchment.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Overview

This Chapter presents the main findings of the research and a comprehensive analysis of the results. The Chapter detailed assessing the potential sediment sources using geo-chemical fingerprinting integrated within the Bayesian MixSIAR mixing mode. The Chapter further illustrates the necessity of incorporating the methods (geochronology and geo-chemical fingerprints) and stable isotope analysis that explicitly maintain sediment control strategies for sustainable management of food, water and energy security in Eastern Africa. In addition, the chapter illustrates the semi-distributed hydrological SWAT model as a robust tool for evaluating the impact of current land use and climate changes and assessment of the probable future effects of climate changes on the near future 2030-2060 on Simiyu River discharge under RCP6.0. The study revealed that the mutual effect of land-use and climate change is predicted to have increased the chances of extreme discharges more than the singular effects of climate change or land-use change. Furthermore, the study recommends further hydrological modelling with a wider range of representative concentration pathways, such as RCP2.6, 4.5 and 8.5, which would be useful for making more informed decisions by resource managers and water users.

4.2 Assessment of the impacts of land-use and climate change on the current river discharge in the Simiyu catchment

4.2.1 Sensitivity analysis

The parameters' rankings remained relatively stable with and without observed data. A significant difference was observed in CH_N2, Alpha_BF, SURLAG, and CH_K2, which provides insight into the most sensitive parameters. The top 20 parameters were ranked based on sensitivity analysis (Table 2), and the 16 most sensitive parameters (Table 3) were used for calibration. The sensitive parameters show that the catchment seems to be governed more strongly by surface runoff parameters than base flow parameters, which is expected in semi-arid tropical systems (Moriasi *et al.,* 2007).

Table 2: Sensitivity Analysis Parameter Ranking and fitted value after calibration

Parameter	Description	Rank	
		With Obs	Without Obs
Cn2	Curve number for moisture condition 11	1	1
Esco	Soil evaporation compensation factor	2	2
Ch_K2	Efficient hydraulic conductivity in the main channel alluvium (mm/hr)	3	13
Surlag	Surface runoff lag coefficient	4	16
Alpha_Bf	Baseflow alpha factor	5	12
Ch_N2	Manning value for the main channel	6	15
Canmx	Maximum canopy index	7	5
Blai	Maximum potential leaf area index	8	8
Sol_Awc	Available water capacity of the soil layer	9	4
Sol_Z	soil depth(mm)	10	3
Slope	Average slope steepness(mm)	11	7
Revapmn	Threshold depth of water in the shallow aquifer for revap or percolation to the deep aquifer to occur	12	10
Sol_K	Saturated hydraulic conductivity (mm/hr)	13	6
Gw_Revap	Ground water "revap" coefficient	14	11
Gwqmn	The threshold depth of water in the shallow aquifer required for return flow to occur	15	9
Epco	Plant uptake compensation factor	16	14
Gw_Delay	Ground water delay	17	18
Biomix	Biological mixing coefficient	18	19
Slsubbsn	Average slope length	19	20

4.2.2 Model calibration and validation

The most 16 sensitive parameters indicates the catchment to be governed more strongly by surface runoff parameters than base flow parameters (Table 3). The Curve number (Cn 2) being the most sensitive parameter in the catchment with high optimal value, which denotes a low infiltration capacity. The NSE, PBIAS and RSR had values of 0.52, -0.53 and 0.70, respectively, after calibration, which was deemed good/satisfactory for NSE, PBIAS and RSR according to (Cardoso de Salis *et al.,* 2019; Moriasi *et al.,* 2007), while the *p*-factor was 39% and *r*–factor 65%. The *p* factor was 47%, *r* factor was 57%, and the NSE was 0.50 during the validation period (1988–1992) for the daily time step. A poor *p*-factor in validation is attributed to uncertainties in the data and the failure of the model to capture some hydrological catchment processes typical for semi-arid tropical catchments. Moreover, the model simulations for the daily time step slightly underestimated the peak river discharges (Fig. 12 and 13).

Similar results were obtained by Ndomba *et al.* (2008) who validated the poor SWAT performance on accurate estimations of the daily catchment rainfall and lack of spatial distribution in climate data. Nonetheless, the model performed reasonably well since the efficiency performance of the independent parameters RSR, NSE, and PBIAS attained during the calibration and validation period were within the recommended values (NSE > 0.5, PBIAS < ±25% and RSR < 0.7) (Moriasi *et al.*, 2007). To study the impact of future climate data on river discharge, the calibrated models were combined with downscaled future climate data.

The NSE and RSR goodness-of-fit evaluation revealed that the simulated flow fitted the observed flow best, as indicated in Fig. 12 and 13. Precipitation was also positively correlated with simulated and observed flows (Fig. 12 and 13).

Table 3: Sensitive Parameters used in Model Calibration

Parameter Name	Fitted Value	Min value	Max value
R__CN2.mgt	-0.13	-0.13	-0.11
V__ALPHA_BF.gw	0.64	0.60	0.66
V__GW_DELAY.gw	413.55	350.39	492.33
V__GWQMN.gw	1080.60	813.15	1092.62
V__GW_REVAP.gw	0.17	0.16	0.19
V__RCHRG_DP.gw	0.27	0.23	0.31
V__SURLAG.bsn	8.94	8.70	9.56
V__CH_N2.rte	0.16	0.16	0.17
V__CH_K2.rte	71.18	59.67	87.27
V__ESCO.hru	0.37	0.36	0.38
V__CANMX.hru	0.04	0.04	1.67
R__HRU_SLP.hru	0.46	0.40	0.48
R__SOL_AWC(..).sol	-0.12	-0.13	-0.08
R__SOL_K(..).sol	0.51	0.40	0.51
R__SLSUBBSN.hru	0.13	0.12	0.20
V__EPCO.hru	0.79	0.78	0.83

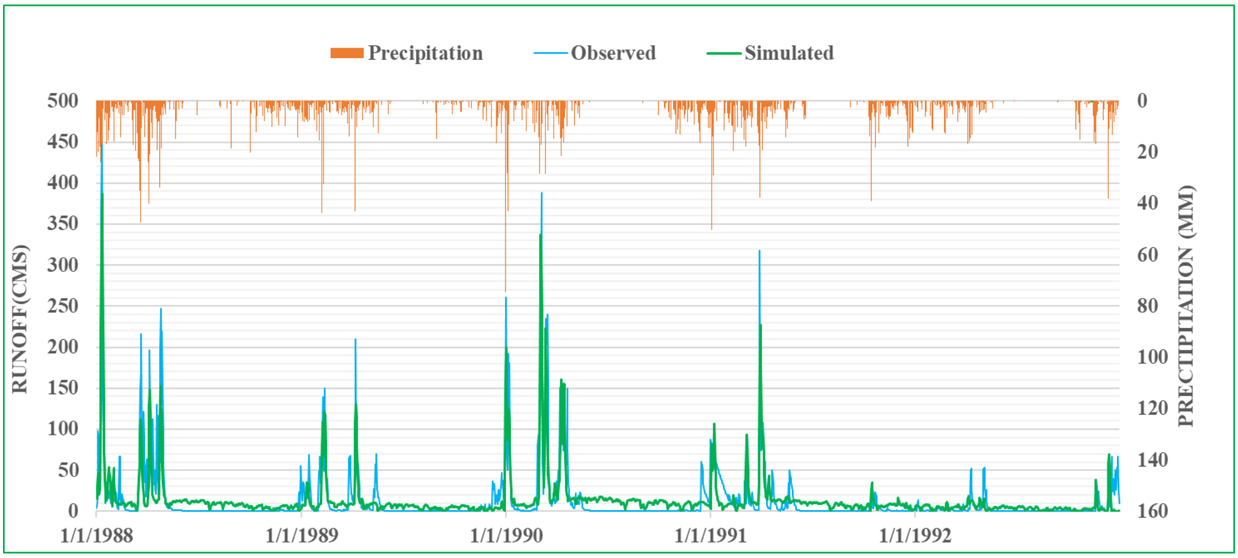


Figure 12: **Observed and simulated daily flows for the calibration period (1988-1992)**

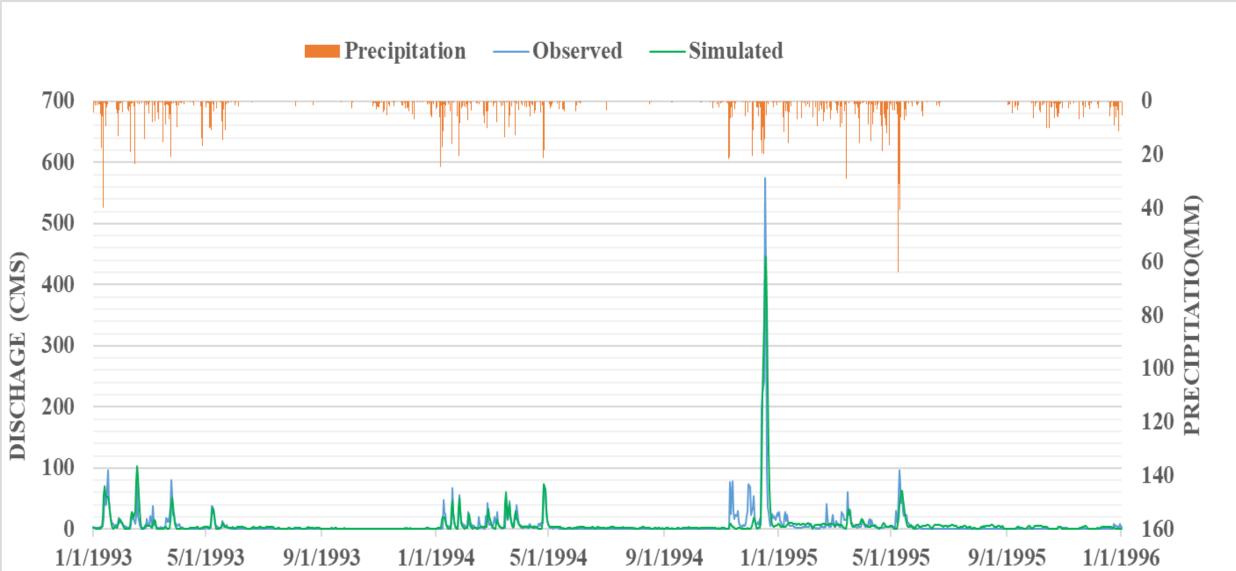


Figure 13: **Observed and simulated daily flows for the Validation period (1993-199**

4.2.3 Impacts of the current Land use and climate change on the river discharge

The World Meteorological Organization's recommendation to use the 18 years as a baseline was adopted to represent the baseline for land use and climate data from 1972 to 1990 (WMO, 2017). The land-use change (S2) was attributed to an increased peak discharge of 0.32% from the baseline. The climate-change-only (S3) scenario showed an increase in peak discharge by 3.72%. The combined impacts (S4) estimated an increase in peak discharge by 6.04%, indicating a synergistic impact of land use and climate change. For the discharges at a return period (T) of 25 years, the baseline discharge (S1) was 294.1 $m^3s^{-1,}$ and S2 increased the discharge by 0.31%, S3 by 2.07%, and S4 by 5.47%. The T = 100 years discharge events demonstrated that S3 had a higher increase (6.55%) compared to S2 (0.29%), while S4 caused an increase of 9.32% (Table 4).

Table 4: Scenario results for the highest discharge at return periods 5, 25 and 100

Flow Index	Peak Discharge (m^3s^{-1})	Difference	
		Value	%
Q5			
Baseline	206.8		
LULC-Change (S2)	207.5	0.74	0.36
Climate Change (S3)	212.2	5.36	2.59
Combined Change(S4)	213.7	6.91	3.34
Q25			
Baseline	294.1		
LULC-Change (S2)	295.1	0.92	0.31
Climate Change (S3)	300.2	6.09	2.07
Combined Change (S4)	310.2	16.08	5.47
Q100			
Baseline	366.2		
LULC-Change (S2)	367.3	1.06	0.29
Climate Change (S3)	390.2	24.01	6.56
Combined Change (S4)	400.4	34.13	9.32

4.3 Assessment of the impacts of future climate change on the Simiyu River discharge under RCPs 4.5, 6.0 and 8.5

4.3.1 Projected future temperature and precipitation changes

The downscaled ensemble of GCM (ACCESS1.3, MIROC5 and CNRM.CM5) models predicted the change in the mean annual temperature from 21.8°C in 1990 to about 22.2°C at the end of 2019, an increase of about 0.4°C over the past 30 years. The temperatures of the period between 2030 and 2060 under RCPs 4.5, 6.0 and 8.5 were predicted to increase by 0.6°C from 22.6°C in 2030 to 23.2°C in 2060 in response to increasing greenhouse gas (GHG) concentrations and a reduction in the rainfall amount (Fig. 14 and 15). The future temperature increases are mainly concentrated from December to August, while in September, October and November, the future temperature is predicted to decrease very slightly.

According to IPCC (2021), the projection for high to moderate emission scenarios shows that by the middle and end of this century, the maximum and minimum temperatures over equatorial East Africa will rise, and there will be warmer days compared to the current situation. In the Simiyu catchment, this trend has begun to emerge because the first nine months of the year showed an increasing trend, and the final three months showed a very slight decreasing trend. Increasing soil evaporation and plant transpiration due to rising temperatures due to climate change may impact the soil–water balance, impacting crop growth and agricultural productivity

(Kang *et al.*, 2009). According to these results, the rainfall will decline over time (Fig. 20). The ensemble of GCMs (ACCESS1.3, CMCC.CM, MIROC5 and CNRM.CM5) under RCPs 4.5, 6.0 and 8.5 predicted that from 2030 to 2060, rainfall over the Simiyu River catchment will be reduced by 7.75% on average, according to the climate change models that are currently available.

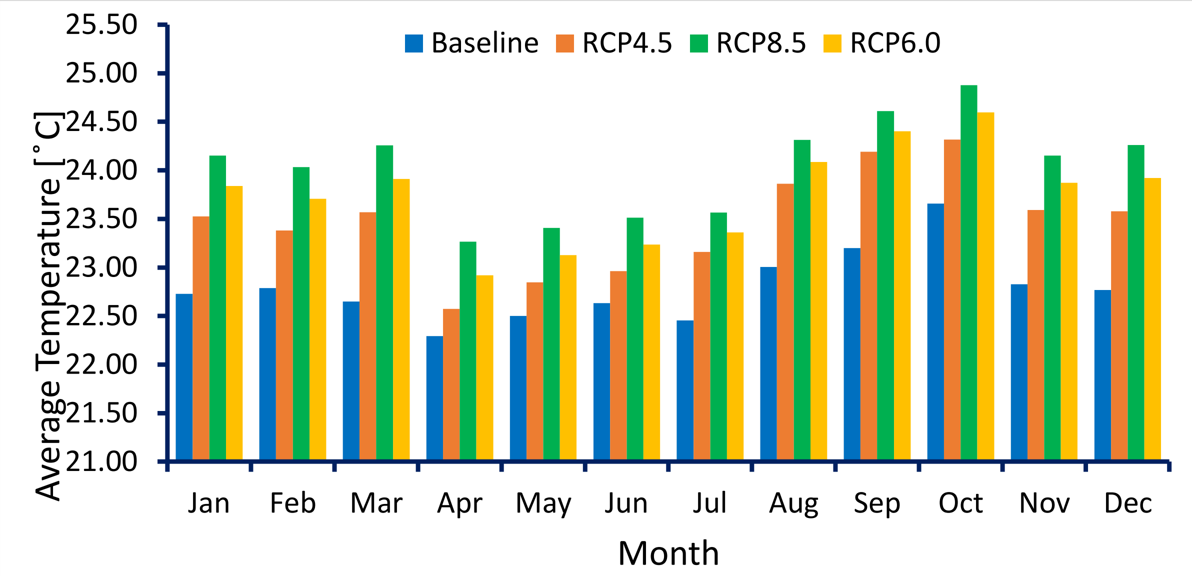


Figure 14: Comparison between the current 1990-2019 (baseline) and future temperature (2030-2060) at Simiyu catchment

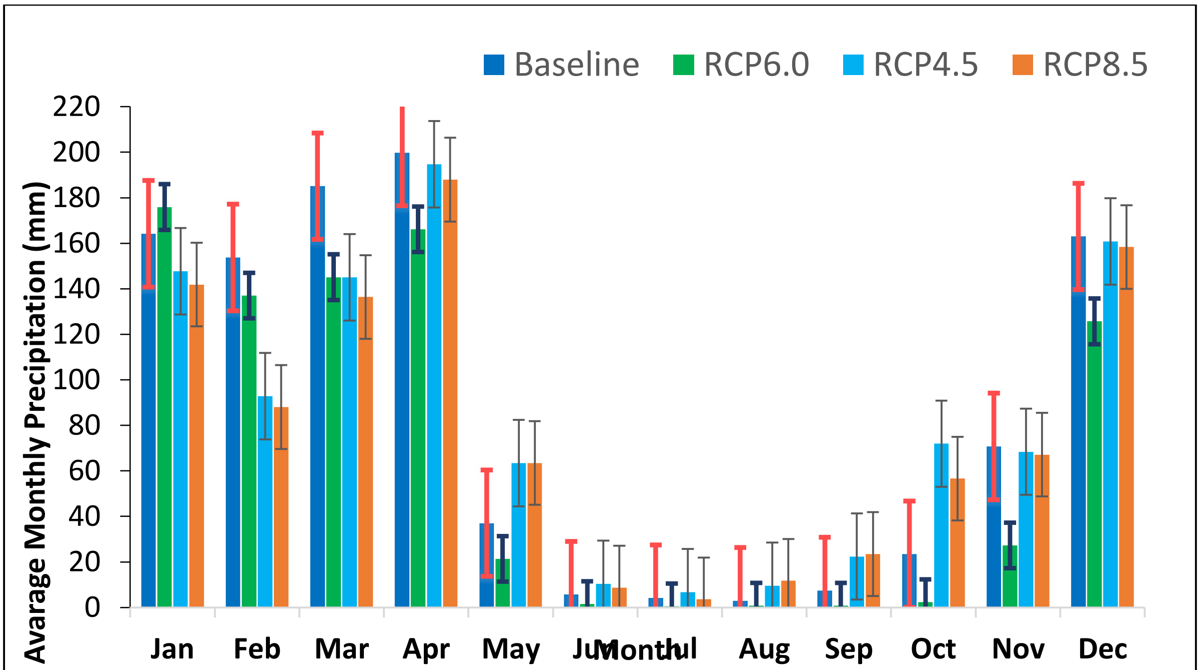


Figure 15: Comparison between the current 1990-2019 (baseline) and future rainfall (2030-2060) in the Simiyu catchment

4.3.2 Projected future annual and seasonal river discharge

The results showed that the river discharge varies across the months following the spatial and interannual variability in rainfall across the two wet seasons, with long rains from March to May, short rains from October to December and two intermediate dry seasons (James *et al.,* 2023). In general, the discharge increased from October through January, decreased afterwards up to March and then started increasing again until May, reaching its peak in April (Fig. 16). Seasonal precipitation and temperature changes drive these large differences between seasons. Mean monthly discharge forecasts during 2030–2060 under RCPs 4.5, 6.0 and 8.5 showed the maximum in April, which is consistent with the timing of the observed mean monthly discharge in the current period (1990–2019). In addition, predicted average monthly discharges are lower in the months from June to September, which is in line with the historical data. According to the model, the annual average river discharge of the Simiyu will significantly decrease (Fig. 16) due to projected decreasing rainfall and increasing temperature in the catchment. Under RCPs 4.5, 6.0 and 8.5, the average annual river discharge decreased from 5.7 m^3s^{-1} in 1990–2019 to 4.0 m^3s^{-1} in 2030–2060, which is equivalent to a 29% decline (Table 5).

Table 5: Comparison of the extreme discharges at exceedance probabilities of Simiyu catchment at Ndagalu gauging station (5D1)

Exceedance Probability (%)	Extreme Discharge (m^3s^{-1}) (Baseline)	Extreme Discharge (m^3s^{-1}) (RCP4.5)	Extreme Discharge (m^3s^{-1}) (RCP6.0)	Extreme Discharge (m^3s^{-1}) (RCP8.5)
0.01	379.6	466.0	451.3	413.2
1	232.8	276.9	214.3	239.7
5	102.2	136.5	72.3	129.3
10	34.2	65.5	32.	62.6
20	14.8	16.8	10.9	16.8
25	10.6	10.9	8.0	11.1
50	6.5	3.9	5.3	3.8
75	5.1	2.8	3.9	3.0
90	4.0	2.0	2.8	2.6
95	3.2	1.9	1.9	2.7
99	1.4	0.1	0.2	0.1
100	1.2	0.00	0.0	0.00

The predicted low discharge in the dry season between June and September under all the land-use and climate change scenarios is due to low rainfall and warm temperatures that lead to higher evapotranspiration, which often decreases runoff and discharge. The single peak discharges are frequently linked to vastly heavy rainfall events and likely occur on timescales smaller than the daily time step of the simulation period (Fig. 16). The catchment is likely to experience longer and more pronounced droughts in the future, which has also been highlighted by the IPCC (2021) in the East Africa region. However, changes in precipitation are also predicted to drive changes in flood regimes (Patterson *et al.*, 2012). The ensemble GCM models (ACCESS1.3, MIROC5, and CNRM.CM5) under RCPs 4.5, 6.0, and 8.5 predict higher incidences of extreme discharge as shown in Table 5 and in the flow duration curve at Ndagalu gauging station (Fig. 17), which indicates frequent flood occurrence in the future (2030–2060) compared to the current period (1990–2019), with extreme discharges of 451.3 m3s−1 and

232.8 m3s−1 at exceedance probabilities of 0.01% and 99.99%, respectively. This might be attributed to the mutual effects of increased land use and climate change.

Intense precipitation events are predicted to produce a larger fraction of runoff, increasing the probability of Hortonian overland flow in the catchment. The higher incidence of high-intensity rainfall is thus predicted to cause both more intense flood and drought events. In addition, extreme events will occur more frequently and also intensify, with large discharge events (floods) generally increasing in magnitude and frequency in the wet months of March and April and low flows (droughts) occurring in the dry months of June to September in particular (Fig. 14). These findings show less extreme discharge events (Kay *et al.*, 2020) from 1990 to 2019 compared to the future projected river discharge (2030–2060), which shows increased extreme events in the catchment because of higher intensity rainfall events following dry periods due to land degradation and short spells of heavy rainfall and prolonged dry spells (Fig. 12).

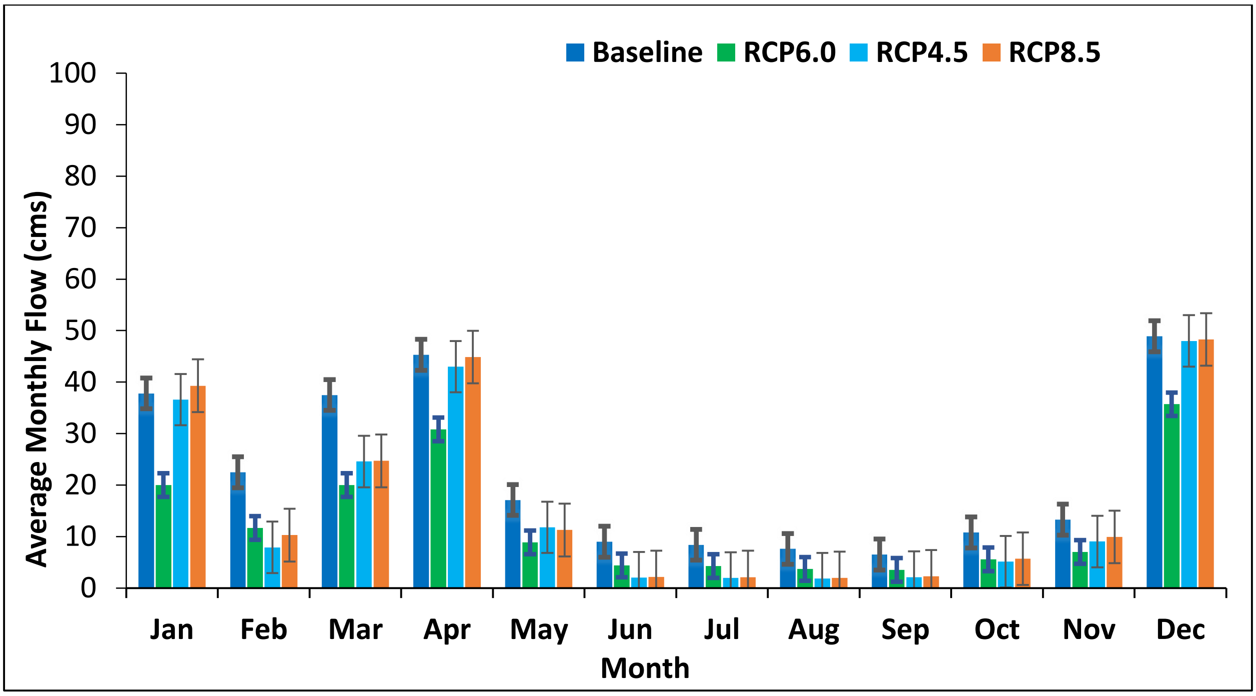


Figure 16: Comparison of the current/baseline (1990-2019) and future (2030-2060) Monthly River discharge in Simiyu catchment

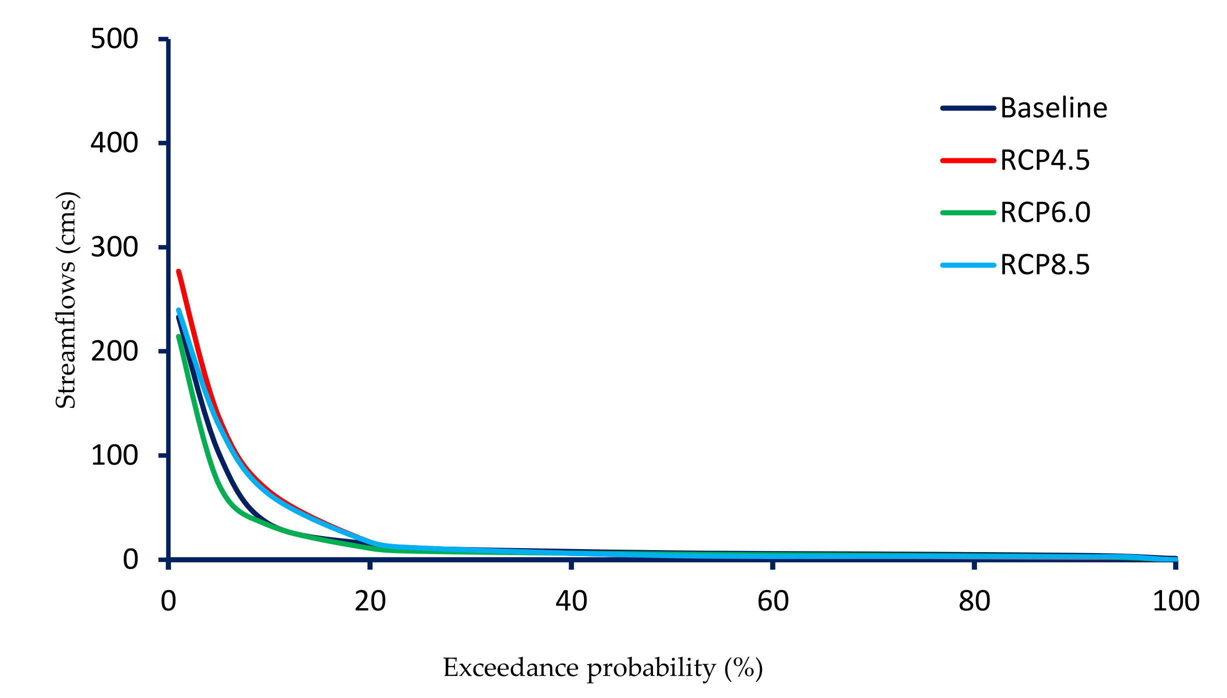


Figure 17: Flow duration curves at Ndagalu gauging Station (5D1) for current and future flows

The present climate-change-only scenario (1990–2019) caused the highest increase in discharge at different return periods compared to the land-use change-only scenario. The mutual impacts of climate and land-use changes showed a disproportional increase in discharge compared to the single contributions, which indicates synergistic effects of land cover and climate change. However, the contribution ratio of climate change was larger than that of land-use change. The model simulations under projected climate change (2030–2060) showed a significant decrease in the discharge at different return periods. The dominant factor for the decrease in discharge was the decrease in precipitation. The observation that discharge dynamics were mainly controlled by precipitation variability rather than temperature is realistic due to the smaller relative differences in temperature between the seasons and future climate scenarios compared to those in rainfall. These results align with the IPCC (IPCC, 2011, 2021) projected impacts of climate change in developing countries.

According to the IPCC (IPCC, 2011, 2021) developing countries are the most vulnerable to climate change and variability (Santos *et al.*, 2018). As such, the availability and variability of fresh water will be greatly impacted by climate change in response to global warming, thus significantly affecting developing countries' economies that heavily depend on agricultural production (Parry *et al.*, 2007; Worqlul *et al.*, 2017). Most likely, the anticipated changes in the rainfall patterns and intensity in the river discharges will impact crop growth and put farmers at risk from floods, soil erosion and drought. These findings underline the vulnerability of river discharge to rising greenhouse gas concentrations resulting from alterations in the climate system and stress the significance of global emission reduction strategies and measures to protect future water resources. Since 80% of the Tanzania population is largely dependent on agriculture (Kassie *et al.,* 2018; Kassie *et al.,* 2015) anticipate further increases in water demand due to population increases. It is, therefore, important to establish adaptation and mitigation measures to minimize the impacts of climate change on water resources.

4.3.3 Limitations of the methods and robustness of the model

While the model performance was decent, there remained some challenges and weaknesses. The model's underestimations of high-flow events are the main cause of uncertainty and have an impact on the simulations of land use and the climate. The most significant source of uncertainty is due to the model underestimating high-flow events, which affects land use and climate simulations. This underestimation can partly be explained by the absence of enough gauged hydrometric and rainfall stations in the catchment to capture the high spatial and temporal variability in rainfall, affecting simulated flow. Moreover, the discharge was simulated on a daily scale, but rainfall in the study area often comes in high-intensity torrential rains. The high intensity of the rainfall in real life often passes the soil infiltration threshold, leading to Hortonian overland flow. However, in the daily setting, the model might assume that the rainfall is distributed evenly during the day, predicting that more rainfall infiltrates.

In this context, stream discharge models in the East African region could be improved by rehabilitating non-operating rainfall stations and collecting rainfall data on a higher spatial resolution. Discharge and rainfall monitoring should also aim to increase the resolution to hourly time steps for capturing high-intensity rainfall events. Herein, future modelling exercises can follow suit and model stream discharge on hourly time steps, allowing a better representation of Hortonian overland flow. This will enhance the model's performance during calibration and hydrological simulations in upcoming studies. Choosing the GCM model(s) and defining the emission scenarios is also expected to impact future simulations significantly (Cannon 2015; Pierce *et al.,* 2009; Biemans *et al.,* 2013).

This study used an ensemble of GCM models (ACCESS1.3, MIROC5 and CNRM.CM5) and three representative concentration pathways (RCPs 4.5, 6.0 and 8.5) to understand the impact of future climate change on the Simiyu River discharge (Fig. 3 and 20). Different GCM models have shown discrepancies over regional climate change (Amasi *et al.,* 2021), e.g., due to differences in the spatial domains and predictor variables, downscaling with dynamic and statistical downscaling methods (Wilby & Wigley, 1997; Zhang *et al.,* 2019) or even within different statistical downscaling methods. However, this was overcome by locally validating the models and selecting the one with the lowest inaccuracies for discharge modelling. A further area of uncertainty relates to the hydrological model, which interprets how future climate data will affect hydrological responses (e.g., influence on streamflow). The model structure, parameter uncertainty, and a lack of data contribute to the hydrological model uncertainty (Bracken & Croke, 2007).

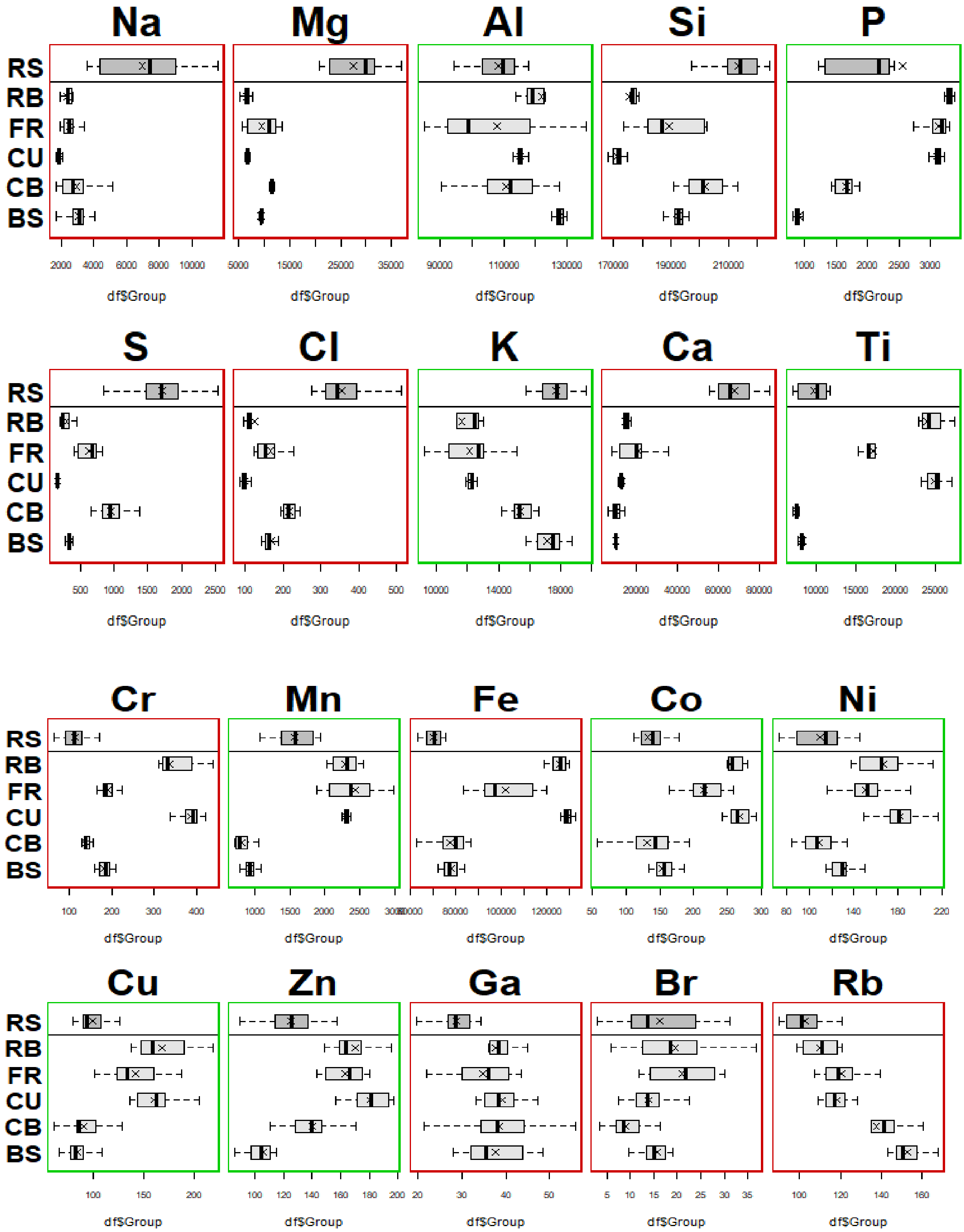
The average performance of SWAT model when simulating specific peaks was probably due to errors in the estimation of daily catchment rainfall, spatial variability in rainfall in the catchment, and inadequate representation of Hortonian overland flow in the model. Other reasons might be water abstractions for domestic and socioeconomic activities (e.g., irrigation practices and mineral processing) that are not included in the modulation. Earlier studies reported that the SWAT model underestimates the discharge peaks (Taylor *et al.,* 2016). However, this was partly overcome with local calibration using a semi-automatic calibration and uncertainty program, SWATCUP SUFI-2 (Arnold *et al.*, 2012). While the parameters are calibrated for a specific climate and environment, these settings are not guaranteed to remain optimal when climate and land-use changes occur. Despite the model's limitations, this study made every effort to reduce the degree of uncertainty in the model's prediction to reasonably comprehend the feasible impact of climate change on the stream flow in the Simiyu catchment.

This study has revealed that the SWAT model is a robust method for predicting the hydrological response of semi-arid tropical catchments to changes in climate and land use. The model is thus an important tool for informing soil and water management strategies in these data-poor regions. Nevertheless, these findings should be hypothesized as best available simulations, not as empirical observations, because of the temporally and spatially simplified representations of the catchment environment and hydrological processes

4.4 Assessing the dominant sources of the Simiyu riverine sediment using geo-chemical fingerprinting

4.4.1 Tracer conservation test and source discrimination from the principal component analysis

Boxplots were produced for each set of sources and associated mixtures for all tracers, and the means of the mixture data were assessed to see if they largely fell within or outside the mean concentrations of the different sources (Fig. 18). The mean of the mixture of the tracers that fell outside the mean of the source ranges was removed.



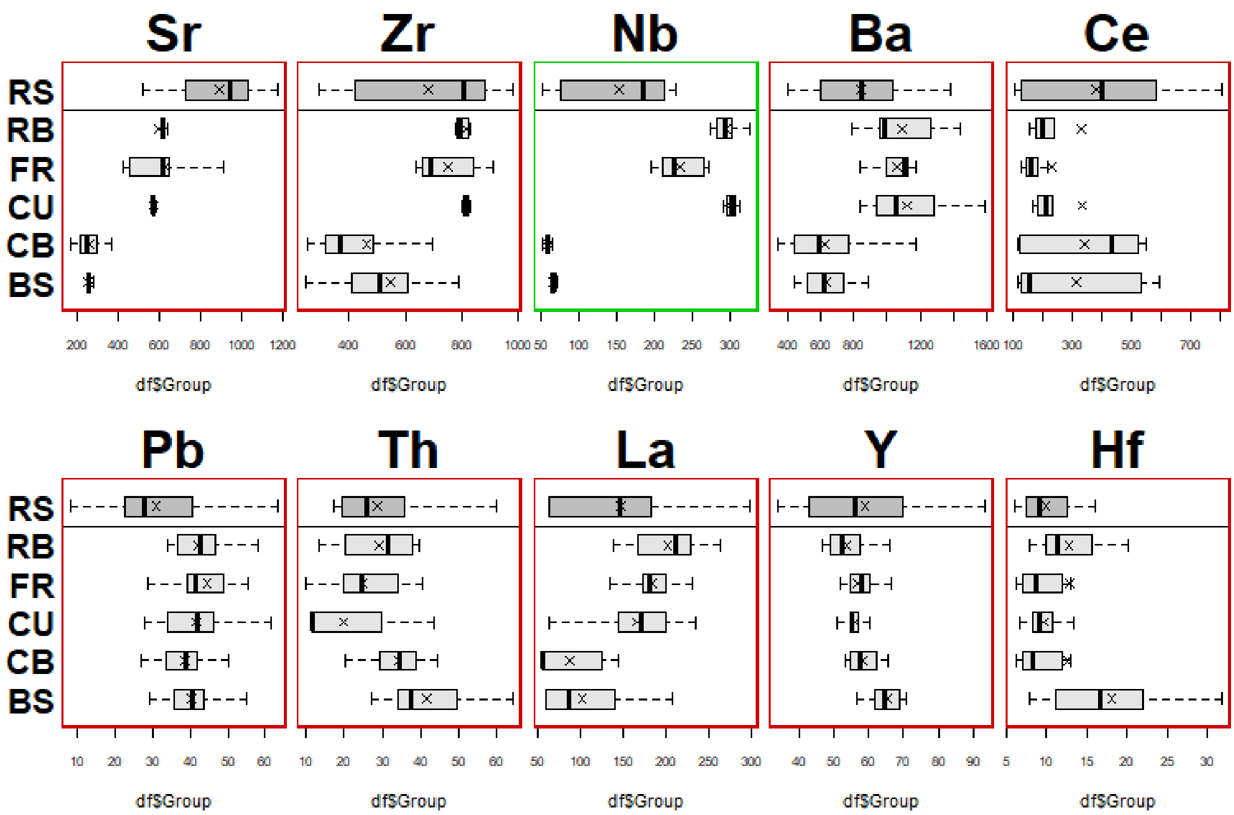


Figure 18: **Boxplots for tracer selection of the potential sediment sources and riverine sediments (mixture)**

Ten tracers qualified the range test (Al, P, K, Ti, Mn, Co, Ni, Cu, Zn, Nb), while 21 tracers (Na, Mg, Si, S, Cl, Ca, Cr, Fe, Ga, Br, Rb, Sr, Zr, Ba, Ce, Pb, Th, La, Y, Hf, Sn) were excluded from the analysis based on their indication of non-conservative behaviour or high intra-source variability (Fig. 6). The elimination of tracers requires some geo-chemical clarification. The non-conservative behaviour of soluble salt elements such as alkali metals, e.g. Na, Mg, and Ca and halogens such as Cl, F and Br is probably due to their tendency to enrich their concentration driven by evaporation (Wynants *et al.*, 2021a). Several elements, such as Si Cr, Y, Pb and Zr, are identified to undergo alterations in medium to long-term storage elements such as floodplains, lakes and wetlands due to changes in redox, pH, salinity and other environmental conditions (Owens *et al.*, 1999; Pulley *et al.*, 2015a). Changes in concentrations of Sr and Rb may have resulted from their irregularity in the soil depth as a function of weathering processes and mixing of soil horizons by cultivation (Tyler, 2004). The Ce, La and Th were removed because of the observed high intra-source variability potential artefacts of analytical challenges due to low abundance or high variability in the terrestrial source concentrations (Wynants *et al.*, 2020). Concentrations of Si and Zr may be due to wider fluvial sorting, e.g., textural controls on mineral composition, i.e., changing proportions of silt versus clay minerals in mixtures, which has been shown to exert a strong influence on sediment concentrations (Cuven *et al.,* 2010).

The first PCA was performed to check the differences between sediment gathered from the main river and tributaries and showed distinct fingerprint clusters between the two tributaries (Fig. 19). The sediment mixture of the main river occupies a larger cluster compared to the sub-tributaries. The second PCA comprised the sediment from the main river and the soils from the different land-use types (Fig. 20a). The land-use PCA highlighted a complex soil system wherein some overlap was observed between the topsoil land-use sources, mainly between forest and bushland. The forest cluster was very small and distinct. The agricultural cluster occupied the largest space on the PCA, and seemed to exist out of two subclusters, wherein the lower cluster was clearly driven by higher values in phosphorus (P). There was some overlap between the upper agriculture and bushland and forest clusters. The subsurface soil samples (Riverbank and Channel Bank) occupied a significantly different space on the X-axis, indicating a distinct difference in surface and subsurface geochemical fingerprint. The surface soil samples generally have higher concentrations in the metal tracers, except for K.

The PCA of the tributaries highlights distinct differences between both tributaries, indicating a strong geo-chemical basis on which the model can draw. On the PCA of the land-use sources, the soil samples also form distinct clusters that seem to be mainly driven by geo-chemical differences between catchment zones and soil depth (Fig. 20a). It is important to highlight the differences in both principal components, wherein the X-axis represents 63% of the variance and the Y-axis 14%. Differences along the Y-axis, therefore, get conflated, while the main differences in fingerprints are along the X-axis. The forest cluster is relatively small, which is unsurprising and can be explained by the more constrained locations of forests in the uplands and their relatively undisturbed soils. The forest cluster was partly overlapped by a larger bushland cluster between forest and bushland, which is probably because there is no distinct border between those land cover types, and bushland tends to transition into forests gradually. However, when a third principal component is plotted, bushland and forest differences are still evident, showcasing the more nuanced geo-chemical difference between those two groups (Fig. 20b).

The forest fingerprint seems to have slightly higher concentrations of Cu and Ti, while the bushland is more characterized by higher concentrations of Cu, Ti, Zn and Co tracers (Fig. 20a, and Fig. 18). Therefore, the overlap between forest and bushland is due to surface tracers Ti and Cu, which are probably indicative of highly weathered soils typical for East African hillslopes (Wynants *et al.*, 2021a). The agricultural cluster was larger and seemed to consist of two subclusters. This can be explained because agriculture is spread over the catchment on hillslopes and wetter areas closer to the river. Differences in underlying geology, soil type, soil management, redox conditions and climate can further explain the bigger size of the cluster. The hillslope agricultural soils seem more driven by Al concentrations, while the wetter areas seem more driven by P concentrations. Applying mineral fertilizers can explain the strong driving effect of P on agricultural soils. The overlap between agricultural soils and bushland/forest soils may be due to similarities in location, but also due to legacy effects of previous land cover wherein bushland/forest is converted to cultivated land and some cultivated land was abandoned and developed back to bushland/forest. The clear difference shown between the surface (FR, CU and BS) and subsurface materials (RB and CB) on the PCA plot can be attributed to weathering and pedogenic processes. As shown by the range tests, CB soils were higher in K (Fig. 18), which might be due to evaporation enrichment or lack of weathering (Wynants *et al.*, 2021a). Generally, the distinct clustering between the source groups on the PCA plot shows that the mixing model is a robust tool for sediment attribution from selected land-use types (Smith & Blake, 2014).

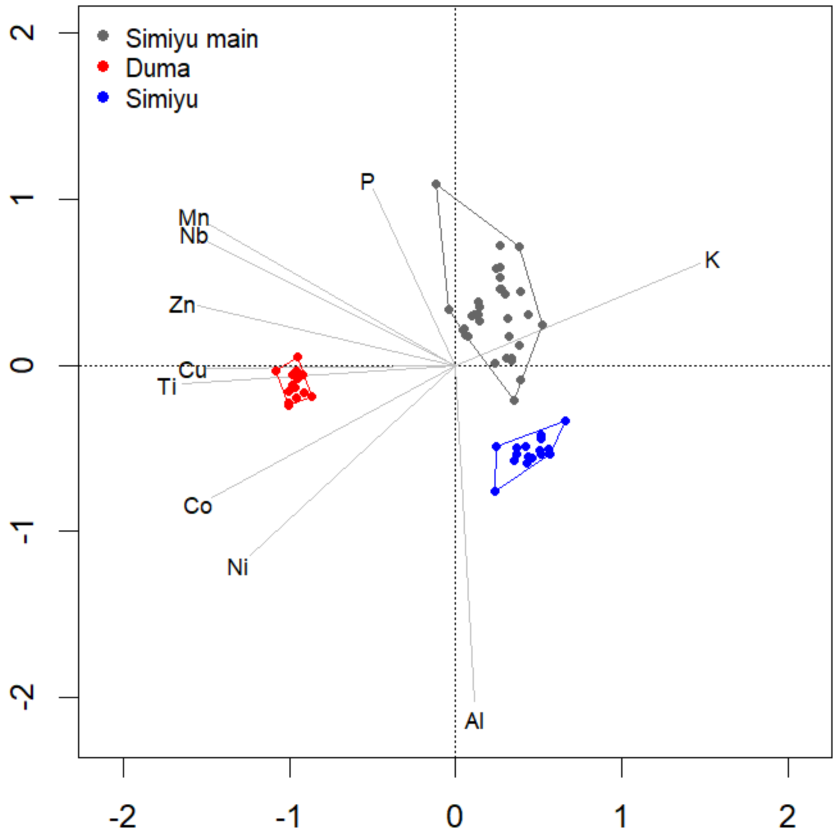


Figure 19: Principal component analysis plot highlighting variability in geo-chemical fingerprints of the Duma and Simiyu tributaries and the Simiyu Mainstem sediment

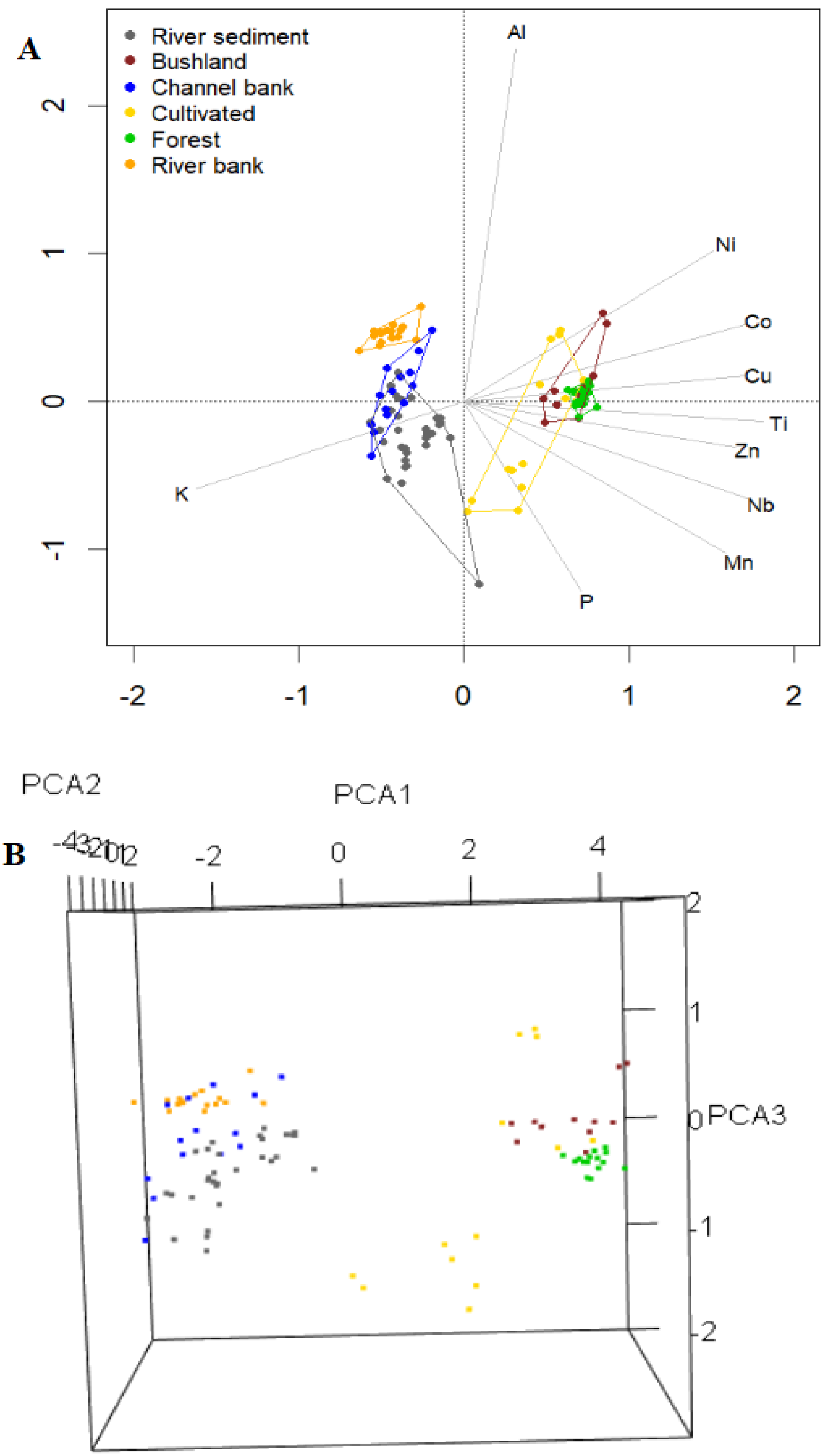


Figure 20: (A) Principal Component Analysis & (B) 3D Principal Component Analysis plots highlighting variability in geo-chemical fingerprints of the land-use sources and mixture pool of Simiyu Mainstem sediment

4.4.2 Proportional sediment contribution from land-use and riverine sources

The MixSIAR outputs for the Simiyu Main RS revealed that the Simiyu sub-tributary accounted for 63.2% ± 10.4% and the Duma sub-tributary for 36.8% ± 10.4% of the total sediment (Fig. 21a). The higher proportion of sediment from the Simiyu tributary to the main river was expected since its sub-catchment is slightly bigger (5540.67 km^2 compared to 5435.11 km^2 in the Duma) and has higher average slopes and rainfall compared to the flatter and drier areas in the west of the Duma sub-catchment. Moreover, some of the headwaters of the Duma sub-catchment are protected as Serengeti National Park (Fig. 21b), where there is a more permanent vegetation cover, and only moderate sediment yield was modelled in previous studies (Kimwaga *et al.,* 2012b; Van Griensven *et al.,* 2013a). Although the Simiyu sub-tributary has a higher sediment contribution to the main river than Duma, the difference is relatively small, indicating that high sediment yield is not limited to the Simiyu alone. Both sub-catchments have been modelled to have high soil erosion risk, which is attributed mainly to the expansion of agricultural land and overgrazing on sloped areas with high-intensity rainfall (Mati *et al.,* 2008; Zhang *et al.,* 2020a). Besides, surface erosion risk, unsustainable farming practices in both sub-catchments may also promote sediment connectivity from the hillslope to the channel networks (Guzha *et al.,* 2018). Overall, only 57% of the total catchment experiences low to very low soil erosion risk, while the high and very high patches of soil loss risk of 16.14% and 2.16%, respectively, are distributed mainly in the cultivated part of the catchment, characterized by gentle slopes (Zhang *et al.,* 2020a). The high contribution of eroded soils from agricultural land to riverine sediment is also found in the neighbouring Mara catchment (Dutton *et al.,* 2019; Stenfert *et al.,* 2020).

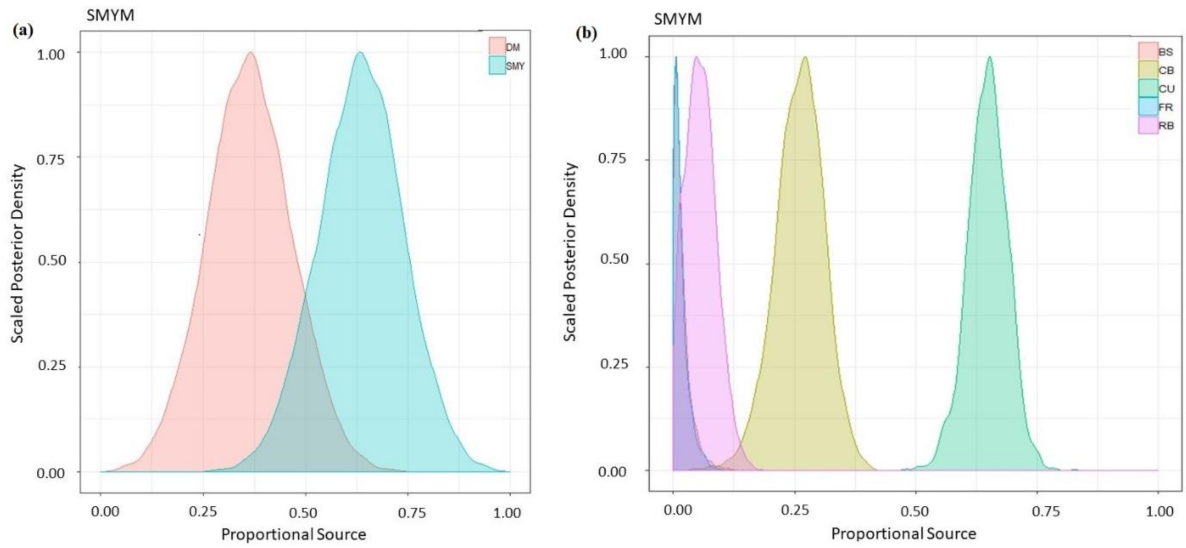


Figure 21: Sediment source apportionment of the main Simiyu River against the riverine and land-use sources

Unmixing of the land-use types against the Simiyu Main RS revealed that cultivated land had the greatest contribution of sediments, accounting for 64.7% ± 4.1%, channel banks with 26.5 % ± 5.0%, riverbanks with 5.8 % ± 3.1%, bushland with 1.6 % ± 1.7% and forest 1.4 % ± 1.5% (Fig. 21b). The MixSIAR outputs for the land-use types against the individual RS also revealed that cultivated land had the greatest contribution of sediments in both sub-tributaries with 86.4% ± 7.6% and 80% ± 8.2% to the Duma and Simiyu respectively. In the Duma sub-tributary, channel banks contributed 9 % ± 7.2%, riverbanks contributed 2.7% ± 2.1%, bushland contributed 1.1% ± 0.9%, and forest contributed 0.7% ± 0.6% (Fig. 22a). In the Simiyu sub-tributary, channel banks contributed 9%± 6.8%, riverbank contributed 6.3% ± 5.2%, bushland contributed 2.9% ± 2.1%, and forest contributed 1.7% ± 1.4% (Fig. 22b).

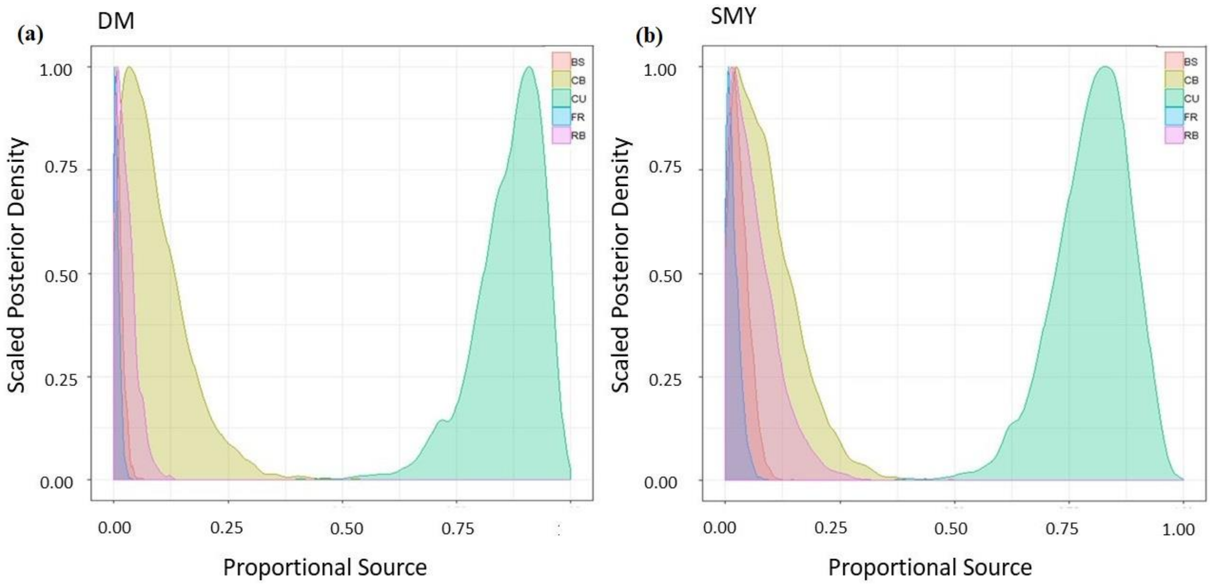


Figure 22: The MixSIAR of the land-use from the Duma (DM) and Simiyu (SMY) tributaries

The dominant contribution from cultivated land to the sediment in both sub-tributaries confirms agriculture's high impact on soil erosion and sediment transport in the catchment, probably due to its large proportion of the catchment, combined with bad soil and water management. Previous research in Northern Tanzania has shown that poor agricultural practices decrease soil organic matter content and structure, increasing the susceptibility to water erosion (Amasi *et al.,* 2021a). This assertion is further supported from the study by Kimwaga *et al.* (2012b) which revealed that agricultural land expanded significantly from 19.33% in 1975 to 73.44% in 2006. A parallel study found similar temporal trends in land cover between 1986 and 2016, wherein agricultural land increased from 8.71 % to 68.43 %, bushland decreased from 30.14% to 23.74 %, and grassland decreased from 59.33 % to 7.56 % (Zhang *et al.,* 2020a). The land use and land cover changes have likely altered the hydrology in the Simiyu River, leading to increased peak flows (Guzha *et al.,* 2018), erosion rates, and suspended sediments and nutrients in the river (Dutton *et al.,* 2018; Mango *et al.,* 2011).

Interestingly, direct unmixing of the Simiyu Main RS against the land-use sources revealed a higher proportional contribution of channel banks (26.5% ± 5.0%) compared to the separate unmixing of the two sub-tributaries (9%± 6.8%, and 9%± 7.2%, in Simiyu and Duma, respectively). Interestingly, the proportional contribution of channel banks was higher to the Simiyu Mainstem (26.5%) compared to the two sub-tributaries (9% in both). A potential explanation for the higher importance of channel banks further downstream could be the complex hydrology of the catchment, which is characterized by distinct topographic changes and high seasonality in rainfall and river flow. During extreme rainfall events, there may be a higher contribution of gully erosion, but the high river flow transports the sediment further downstream (Wynants *et al.,* 2021a). Another explanation could be that there is significant channel bank erosion closer to the outlet that enters the mainstream through small sub-tributaries below the sampling points. However, field observations and a study by Zhang *et al.* (2020a) locate most gullies upstream of the sub-tributary sampling points. Finally, the complex soil geochemistry in the catchment could also influence the model performance, leading to better representations on smaller scales (Blake *et al.,* 2018).

Nonetheless, the dominance of CU with significant contribution of CB indicates that the model finds similar outcomes on both spatial levels and is thus a robust tool for catchment soil- and water management in the Lake Victoria basin. It is also important to note that the low proportional contribution of other land-use types does not necessarily reflect low absolute rates of soil erosion on these land-use types but can be masked by high absolute values of sediment originating from cultivated land and/or the lower proportions of these land cover types in the catchment. In this study, CB contributed 9-26% of the total sediment, which is significant considering the more spatially constrained location of gully erosion in the catchment. The impacts of gully erosion also go beyond the direct contribution of sediment since they increase the connectivity between hillslopes and the river channel, as demonstrated by Wynants *et al.* (2021b) in northern Tanzania. Gully erosion and hillslope surface erosion are likely connected, leading to a rapid downstream movement of eroded soils from agricultural hillslopes through highly connected ephemeral gully networks. Further research is needed on integrating geochemical fingerprinting with sediment dating techniques on deposited sediments in floodplains or reservoirs (Pulley *et al.,* 2015a) to evaluate how sedimentation rates and sources have changed historically through a period marked by significant changes in human and livestock population densities, and land-use.

4.4.3 Limitation of the Bayesian mixing model

Despite the distinct results obtained from this study, a critical reflection on the assumptions of the Bayesian Mixing Modelling is warranted. The first major challenge of this study was the difficulty of capturing the entire variability of the sediment flux by time-specific sampling events, creating a sampling error. The present results represent a snapshot of time, which might be potentially impacted by seasonal or interannual variations in source contribution (Lizaga *et al.,* 2019; Lizaga *et al.,* 2020). This uncertainty is; however, partly accounted for in the model structure as a residual error. Secondly, some areas in the catchment are potentially not captured during sampling due to their large size and logistical constraints (lack of roads, necessary permits and safety). Wynants *et al.* (2021a), gullies that develop in deeply weathered hillslope soils have similar geo-chemical fingerprints as surface erosion from those hillslopes. If there are gullies like this in the Simiyu Catchment that were not captured by sampling, this could have led to underestimating the contribution of hillslope gully erosion in the mixing model. In addition, the observed overlap between forest and bushland, and the large variance in cultivated land, might have influenced the model performance. However, since the contribution of both forest and bushland is marginal, the impact of this overlap is unlikely to be significant.

Moreover, while the PCA highlights overlap from individual sampling points, the model accounts for the entire group's mean and variance, which is distinctively different between forest and bushland. The representation of this study could be improved by integrating other types of tracers, such as compound-specific stable isotopes of fatty acids (Upadhayay *et al.,* 2017), or fallout radionuclides (Evrard *et al.,* 2020), which are driven by vegetation and erosion processes respectively. However, given the strong difference in signature between the Simiyu and Duma River sediment, applying geo-chemical fingerprints has proved a robust tool for source attribution of tributary sources. Moreover, the distinct differences in source contribution of land-use types and the similar outcomes for both model runs are promising results and demonstrate the potential of geo-chemical tracers for attributing the contribution of major soil source groups in the data-poor Lake Victoria Basin.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this study, dominant sources of riverine sediment in the Simiyu River flowing towards LV were determined. The current impacts of land-use and climate changes for the period of 1990-2019 and the near future (2030 – 2060) impacts of climate changes on the river discharge at this critical agroecological region of the Simiyu catchment were also assessed. The study used the geo-chemical tracers and a Bayesian Mixing Model (MixSIAR) to trace the dominant sources flowing towards Lake Victoria and the semi-distributed hydrological SWAT model to assess the impacts of land use and climate changes on Simiyu river discharge.

The MixSIAR model output ascribed the Simiyu sub-tributary (63.2%) as the dominant contributing sub-tributary to the main Simiyu riverbed sediment over the Duma sub-tributary (36.8%). In addition, the fingerprinting analysis pointed to the cultivated land (CU) and channel banks (CB), with 64.7% and 26.5 %, respectively, as the main sources of the main Simiyu riverine sediment. A similar observation was observed in individual Simiyu and Duma tributary sediments, the main sources of which are agricultural land and channel banks. Although the CU from the Duma sub-catchment accounted for 86.4% while the Simiyu sub-catchment accounted for 80%, overall, the contribution seems to be well balanced between both sub-catchments. Combined with observations of high sediment yield from other research, this study revealed agricultural practices in the area are causing high rates of soil erosion, which cascades down the river, leading to high sediment supply in the Simiyu River and eventually to Lake Victoria.

The SWAT model results indicated a significant increase in temperature of about 0.4°C over the past 30 years (21.8°C in 1990 to about 22.2°C at the end of 2019). The climate model predicted that under RCP6.0, the average annual temperature will increase by 1.4°C in 2030 and by 2°C in 2060, while the precipitation in the catchment is predicted to reduce by 7.8% in 2060 compared to the 1990-2019 baseline. These results imply that these changes will be accountable for altering the hydrological cycle by decreasing the Simiyu River discharge. The climate elasticities of the discharge revealed that the predicted changes in climate would result in a 29.0% decrease in discharge in the catchment, which would negatively affect the catchment's water resource availability. This implies that, the alteration of the hydrological cycle by decreasing precipitation and the Simiyu river discharge will also cause a reduction in sediment flowing towards LV.

Moreover, the mutual effect of land-use and climate change is predicted to have increased the chances of extreme discharges more so than the singular effects of climate change or land-use change. Since sediment connectivity is inseparably linked to water fluxes in the hydrological cycle, changes in hydrological connectivity will influence Sedimentological connectivity. While the sediment tracing identified the in-stream sediment provenance, the SWAT model simulated erosion rates/patterns and catchment runoff responses. Their outputs are both influenced by land use and climate change. Understanding the impact of climatic and land-use changes on sediment and river discharge dynamics underpins constructive and sustainable land-use and water management practices, particularly in vulnerable, arid and semi-arid environments of the Simiyu catchment.

5.2 Recommendations

The research findings highlights the high relative sediment contribution to Lake Victoria comes from agricultural land use type which recommends the Water Managers and Policy Makers to take note on the following actions to be taken onboard:

(i) The need for catchment mitigation plans that emphasizes the decreasing soil erosion rates in agricultural areas and disconnecting sediment delivery to the Simiyu river networks.

(ii) The necessity for reducing both hillslope erosion and the sediment connectivity from the hillslope to Lake Victoria to maintain food, livelihood and water security in the Lake Victoria Basin.

(iii) The new advanced technological structural design of improved water resource management and adaptation strategies to climate change eg. half-moon holes.

However, this research recommends future studies as follows:

5.2.1 Compound Specific Stable Isotope (CSSI) for specific crop cover

The observed overlap between land-use types, e.g. forest and bushland and intercropping agricultural landuse might have influenced the mixing model performance. In addition, the off-site and on-site sediment source tracing in agro-ecosystems is a scientific challenge that requires a specific set of tracers since the current geo-chemical approaches do not provide such information. The CSSI technique distinguishes itself from the traditional geochemical methods because it is currently the only sediment source tracking approach that can positively identify and apportion the sources of soil by land use, contributing to the suspended load or the sediment in a deposition zone. Analysis of soil material from a range of crop covers in a mixed land-use agricultural catchment shows that the carbon CSSI signatures of particle-reactive fatty acids label surface agricultural soil with distinct crop-specific signatures, thus permitting sediment eroded from each land cover to be tracked downstream. The representation of this study could be improved by integrating other types of tracers, such as compound specific stable isotopes of fatty acids or fallout radionuclides, which are driven by vegetation and erosion processes, respectively.

5.2.2 Integration of MixSIAR within spatial GIS models

Integration of MixSIAR within Arc GIS could offer a better scope for inclusion of the gullies and river nodes would be an advantage in interpreting the high erosion risk areas in hierarchical complex catchment. The GCM models have shown discrepancies over regional climate change (Wilby & Wigley, 1997; Zhang *et al.,* 2020b) due to differences in the spatial domains and predictor variables, downscaling with dynamic and statistical downscaling methods (Wilby & Wigley, 1997; Zhang *et al.,* 2020b) or even within different statistical downscaling methods. This study used an ensemble of 3 GCM models and 3 representative concentration pathways (RCPs 4.5, 6.0 and 8.5) to understand the effect of future climate on the Simiyu River discharge. In view of this, the GCM outputs results in this study are inferred as best available simulations and not as empirical observations because of the temporally and spatially simplified representations of the catchment environment and hydrological processes. Given the range of RCPs and GCM models, these results represent a range of potential outcomes, and resource management should be adopted in response to the trajectory that is most representative of actual development. Due to the large size of the catchments and logistical constraints that include lack of roads, necessary permits and safety, some areas in the catchment were not captured during sampling. For instance, the gullies that were not captured in this study could have led to an underestimation of the contribution of hillslope gully erosion in the mixing model since the gullies in deeply weathered hillslope soils have shown to have similar geo-chemical fingerprints as surface erosion from those hillslopes (Wynants *et al.,* 2021a).

5.2.3 Integrating geochemical fingerprinting with sediment dating techniques

Gully erosion and hillslope surface erosion are likely connected, leading to a rapid downstream movement of eroded soils from agricultural hillslopes through highly connected ephemeral gully networks. Further research is needed on integrating geochemical fingerprinting with sediment dating techniques on deposited sediments in floodplains or lakes to evaluate how sedimentation rates and sources have changed historically through a period marked by major changes in human and livestock population densities and land use.

5.2.4 Combination of the future landuse and climate change on Simiyu river discharge

The rapid growth of population leads to growth of towns as well as expansion of agricultural land use. The projected landuse could give the estimated future impacts on river discharge towards Lake Victoria.

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REASEARCH OUTPUTS

(i) Publications

James, R., Amasi, A. I., Wynants, M., Nobert, J., Mtei, K. M., & Njau, K. (2023). Tracing the dominant sources of sediment flowing towards Lake Victoria using geochemical tracers and a Bayesian mixing model. *Journal of Soils and Sediments*, 23(3), 1568-1580.

Shinhu, R. J., Amasi, A. I., Wynants, M., Nobert, J., Mtei, K. M., & Njau, K. N. (2023). Assessing the impacts of land use and climate changes on river discharge towards Lake Victoria. *Earth,* 4(2), 365-383.

(ii) Poster Presentation