

**ANALYSIS OF LAND-USE CHANGE IMPACT ON SOIL EROSION
VULNERABILITY IN THE TRANSBOUNDARY SIO-MALABA-
MALAKISI CATCHMENT OF KENYA AND UGANDA**

ATONYA STANLEY CHASIA

MSc. (UoN)

EECY/06447P/2017

**A Thesis Submitted in Partial Fulfilment of the Requirements for the Award of the
Degree of Doctor of Philosophy in Civil Engineering (Water Resources)**

in

The School of Civil and Resource Engineering

of

Technical University of Kenya

2024

DECLARATION

This thesis is my original work and has not been presented in any other institution for the award of a degree or any other qualification.

Atonya Stanley Chasia, MSc. UoN

Reg. no. EECY/06447P/2017

Signature: 

Date: 27th August, 2024

This thesis has been submitted with our approval as supervisors:

Luke O. OLANG, PhD

Associate Professor of Hydrology and Water Resources,
Department of Biosystems and Environmental Engineering &
Director, Centre for Integrated Water Resources Management
Technical University of Kenya (TU-K)

Signature: 

Date: 27th August, 2024

Dr. Jacinta Kimuyu

Senior Lecturer,
Department of Geoinformation and Earth Observation
Technical University of Kenya (TU-K)

Signature: 

Date: 27th August, 2024

Dr. Lewis Sitoki

Senior Lecturer,
Department of Geosciences and The Environment
Technical University of Kenya (TU-K)

Signature: 

Date: 27th August, 2024

DEDICATION

This research is dedicated to my loving family, whose unwavering support, encouragement, and sacrifices have been my constant source of motivation throughout this journey. I am deeply grateful for your belief in me and for always being there, cheering me on, even when the challenges seemed insurmountable. This accomplishment is as much yours as it is mine!

ACKNOWLEDGEMENT

I owe a debt of gratitude to so many people who have contributed in one way or another during this long, and sometimes arduous academic journey, culminating into this thesis. In particular, I sincerely thank my advisor and principal supervisor Prof. Luke Olang for patiently walking with me from the conceptualization of the research objectives, publication of this work, and writing of this thesis. Indeed, his constant emails, phone calls, and virtual meetings kept me on track, particularly during the challenging times during the pandemic when things were very difficult. His encouragement kept me motivated, especially while going through moments of writer's block. Secondly, I would like to thank my other co-supervisors, Dr. Lewis Sitoki and Dr. Jacinta Kimuyu for their valuable insights and critique that positively impacted the quality of this work. Much appreciation goes to the Austrian Development Cooperation, through the Austrian Partnership Programme in Higher Education and Research for Development (APPEAR), through which this study was funded under the "*Capacity Building on the Water-Energy-Food Security Nexus through Research and Training in Kenya and Uganda (CapNex)*" project. I would also like to appreciate the support from the local government institutions and CBOs operating in the study region for providing administrative support and coordinating field visits that made it possible for us to engage with local communities in their jurisdictions. My sincere thanks also go to the School of Graduate and Advanced Studies of the Technical University of Kenya for facilitating my studies and providing me valuable counsel that enabled me navigate through this journey. I'm also grateful to Dr. Ayugi, my thesis correction officer, for his valuable insights that have helped improve this document. My appreciation also goes to the Technical University of Kenya, through the office of the Vice Chancellor for allowing me to pursue my Ph.D. studies, as well as providing the financial support needed to complete my studies. Last, but not least, I would like to thank my family for their unwavering support and inspiration that motivated me to complete this journey!

ABSTRACT

Changes in land surface conditions affect hydrological processes which have important feedback on regional climate and local ecosystems. It is therefore essential to assess space-time alterations in land-surface conditions to support hydrological impact assessment and integrated environmental management. This study evaluated the impact, and extent of present and future land-use/cover (LULC) changes on soil erosion and sediment deposition, to develop a framework for managing soil erosion in the transboundary catchment of Sio-Malaba-Malakisi (SMM). This was achieved through four objectives: First, historical LULC conditions for SMM were analyzed, to understand historical trends in LULC state for the area. This was accomplished by analyzing archived Landsat satellite data for the period 1986 – 2017, using a hybrid image classification technique that clustered individual satellite images using the Iterative Self-Organizing Data Analysis Technique algorithm; the Maximum Likelihood Function was then used to assign image pixels into land-cover classes with the highest probability. Thereafter, transition matrices were applied to the classified maps to identify space-time alterations. An overall classification accuracy of between 84 % – 88 % was obtained for all the years, and kappa statistic values ranging between 0.80 – 0.86 were realized, indicating a strong correlation between classified results and the actual LULC map. It was also noted that approximately 12 % of mixed forest cover declined, while cropland area increased by 30% over the period 1995 – 2008. The second objective, modelled future LULC conditions using two conceptual scenarios plausible in the study area. This was important to understand how future land-use (LU) scenarios could affect soil erosion dynamics in the study region. The scenarios studied represented options for agricultural expansion (Scenario I), and land reclamation (Scenario II). To achieve this, the potential LULC driving factors, which were estimated from physical datasets in a Geographical Information System (GIS), were identified and analyzed. The datasets and concerned factors were thereafter applied within the Conversion of Land Use and its Effects at small regional extent (CLUE-s) modelling framework to simulate potential LULC change trajectories between the period 2017 and 2047, representing thirty years prioritized for catchment conservation by the local managers. The results of this objective indicated that Scenario I could lead to an increase in the cropland area by 24 %, covering approximately 62 % of the whole basin area by 2047. Scenario II indicated a 30 % increase in forest cover, indicating an improvement in forest recovery, and restoration of ecosystem area. The third objective of the study, analyze soil erosion and deposition patterns consequent to current and projected LU change scenarios in the basin. The Unit Stream Power-based Erosion

Deposition (USPED) model, capable of accounting for potential impacts of present and future change-effects on erosion and deposition patterns across the basin was adopted and applied. Considering limitations about consistently harmonized land-cover datasets, a classified LU map for the year 2017 was used to simulate the baseline reference situation from where the effects of the two LU scenarios for the period 2027 to 2047 were compared. The results of this objective indicated that the study area recorded high erosion rates in the upper sub-catchments of Lwakhakha and Malakisi, while sediment deposition was mainly concentrated along stream banks and floodplain zones where Mpologoma and Malaba sub-catchments are located. When compared to the reference year (2017), the erosion rate for Scenario I increased by 16.3 %, while that of Scenario II decreased by 61.2 %. Further, a coefficient determination (R^2) value of 0.74 was recorded in the study, depicting a strong relationship between USPED-modelled results and total suspended sediments recorded for the basin. The fourth and final objective of the study evaluated soil erosion vulnerable areas by estimating the annual rate of soil erosion, and their zonal spatial distribution to propose targeted conservation strategies recommended for appropriate soil conservation practices in the affected areas. The annual soil loss for the SMM basin was thus estimated by analysing physical parameters driving soil erosion using the Revised Universal Soil Loss Equation (RUSLE). The study recorded a maximum soil loss rate of approximately 5,703 t ha⁻¹ yr⁻¹ for SMM. High erosion rates (>50 t ha⁻¹ yr⁻¹) were recorded in the sub-catchments of Lwakhakha and Malakisi, representing a high severity class for soil conservation prioritization. Overall, the findings of this study present important empirical baseline information which could support the development of appropriate land and water management programs in the region, as well as establishing a policy framework for governing the transboundary water resource.

PREFACE

The main content of this doctoral thesis constitutes four papers. Chapters 3, 4, 5, and 6 are written in manuscript format, with a standard structure representing the abstract, introduction (literature review), methodology, results, discussion and conclusion. Chapters 3,4 and 5 have been published and the respective abstracts are presented in appendix H. In all the manuscripts, I am listed as the first author. The research concept, formulation of the research questions, problem statement and objectives, the development of the modelling frameworks, analysis and interpretation of results, and the compilation of the thesis were my original contributions. This was carried out under the continuous guidance and support of my supervisors. Any other assistance provided to support my studies is acknowledged under the authors contribution section in the journal articles, as well as the acknowledgement section of this thesis.

Table of Contents

DECLARATION.....	i
DEDICATION.....	ii
ACKNOWLEDGEMENT.....	iii
ABSTRACT.....	iv
PREFACE.....	vi
Table of Contents	vii
List of Equations	xiii
List of Abbreviations & Acronyms	xiv
CHAPTER 1 General Introduction	1
1.1 Location and Geography	1
1.1.1 Climate and Hydrology	2
1.1.2 Vegetation Characteristics	5
1.1.3 Soils and Geomorphology	8
1.1.4 Population and Demography	9
1.1.5 Land Degradation in SMM Catchment	11
1.2 Statement of the Problem	12
1.3 Justification of the Study.....	12
1.4 Research Gap.....	14
1.5 Research Questions	15
1.6 Objectives of Study	16
1.7 Scope of the Study.....	16
1.8 Scientific Contribution	17
1.9 Organization of the Thesis	18
CHAPTER 2 Literature Review.....	19
2.1 Background Information	19
2.1.1 Global Land-use/cover Changes.....	20
2.1.2 Land-use/cover Monitoring and Assessment	20
2.1.3 Land-use/Cover State in the Study Region.....	21
2.1.4 Land-use Legislative Framework	22
2.1.5 Land-use Land Cover Change Modelling	24
2.1.6 The Soil Erosion Process.....	26
2.1.7 Global Assessment of Soil Erosion	28
2.1.8 Soil Erosion Management Strategies.....	29
2.1.9 Transboundary Water Resource Management	30
2.2 Conceptual Framework	31

CHAPTER 3 Analysis of Historical Land-Use Cover Conditions.....	35
3.1 Introduction	35
3.2 Methodology	38
3.2.1 Materials and Methods	38
3.3 Results	45
3.3.1 Classification Accuracy Results	45
3.3.2 Land Cover State – 2017	46
3.3.3 Land Cover State 1986 - 2008.....	47
3.3.4 Land Cover Change Trends and Trajectories	48
3.4 Discussion	51
3.4.1 Bitemporal Change Detection	51
3.4.2 Analysis of the Classification Approaches.....	54
3.5 Conclusion.....	55
CHAPTER 4 Assessment of Future Land-Use/Cover Changes	56
4.1 Introduction	56
4.2 Methodology	59
4.2.1 Materials and Methods	59
4.2.2 Identification of Key LULC Change Driving Factors.....	64
4.3 Results	67
4.3.1 Importance of Driving Factors for Land-use/cover Change.....	67
4.3.2 Multicollinearity Analysis	67
4.3.3 Calibration and Validation Results.....	69
4.3.4 Historical Land-use/cover state in SMM catchment	71
4.3.5 Simulation results of Land-use Cover state for SMM Catchment.....	72
4.4 Discussion	75
4.4.1 Importance of Potential Driving Factors	75
4.4.2 Assessment of Calibration and Validation	76
4.4.3 Scenario Analysis for SMM Catchment.....	77
4.5 Conclusion.....	78
CHAPTER 5 Impact of Land Use Change on Soil Erosion	79
5.1 Introduction	79
5.2 Methodology	83
5.2.1 Materials and Methods	83
5.2.2 Modelling Framework	85
5.2.3 Validation of Model Results.....	90
5.3 Results	91

5.3.1 Estimated Model Parameters	91
5.3.2 Validation Results of the Model	95
5.4 Discussion	96
5.4.1 Soil Erosion and deposition in SMM catchment	96
5.4.2 Assessment of Erosion/Deposition Patterns and Sediment Concentration	99
5.5 Conclusion.....	100
CHAPTER 6 Soil Erosion Vulnerability Assessment.....	102
6.1 Introduction	102
6.2 Methodology	105
6.2.1 Datasets.....	105
6.2.2 Methodological Framework	105
6.2.3 Model Description	106
6.2.4 Analytical Hierarchy Process (AHP).....	109
6.3 Results	114
6.3.1 Estimate RUSLE parameters	114
6.3.2 Soil Erosion Susceptibility Parameters.....	116
6.3.3 Soil Loss and Soil Erosion Vulnerability Assessment	117
6.4 Discussion	119
6.4.1 Soil Erosion Hazard Assessment.....	119
6.4.2 Erosion Vulnerability Mitigation and Prioritization for SMM catchment	120
6.5 Conclusion.....	121
CHAPTER 7 General Discussion, Conclusions and Recommendations.....	123
7.1 Discussion	123
7.2 Conclusion.....	125
7.3 Recommendations	127
REFERENCES.....	129
APPENDICES.....	149
Appendix A. Similarity Index Report	149
Appendix B. Theory of Land-use/Cover Change Scenarios	150
Appendix C. Potential LULC Driving Factors used in the Regression Equation.....	151
Appendix D. Logistic Regression Model Performance	152
Appendix E. Hydrometeorological Timeseries from available data in SMM.....	153
Appendix F. Data Collection Questionnaire sample	156
Appendix G. Statistical Data Analysis and Visualization.....	163
Appendix H. Abstracts of Published Manuscripts	170

List of Tables

Table 1-1. General characteristics of study area and sub-catchment extent	1
Table 3-1. Land-use/land cover classification scheme adopted from USGS.....	38
Table 3-2. Sensor characteristic of satellite data used to generate land-use/cover maps	39
Table 3-3. Sites visited to generate training data from a participatory mapping exercise.....	40
Table 3-4. Training and accuracy assessment data collected for each sub-catchment area. ...	41
Table 3-5. Overall and kappa accuracy assessment report obtained for classified images	45
Table 3-6. Error matrix from classifying training set pixels.....	46
Table 3-7. Cumulative percentages of land cover types	46
Table 3-8. Cumulative land-use/ land cover conversion matrix from 1986 to 2017	54
Table 4-1. Land use/cover conversion elasticities	63
Table 4-2. Land use change simulation factors	65
Table 4-3. Z score and p-values from a regression model	67
Table 4-4. Multicollinearity analysis	68
Table 4-5. Overall accuracy scores from <i>Ksimulation</i> and Kappa statistic	70
Table 4-6. Land use/cover change statistics	72
Table 4-7. Simulation results for land-use change scenarios.....	72
Table 5-1. Datasets for generating input layers for USPED model	83
Table 5-2. Sediment load data recorded from sub-catchments stations.....	85
Table 5-3. C factor value for different land cover types.....	90
Table 5-4. Erosion and deposition categorization and rates	91
Table 5-5. Slope vs. length, mean NDVI and erosion/deposition rates	92
Table 5-6. Paired sample t-test between ED estimates and observed values.....	95
Table 5-7. Soil loss statistics for the study area.....	97
Table 5-8. Annual soil loss for all land cover classes.....	98
Table-6-1. Datasets and sources for soil erosion susceptibility	105
Table-6-2. P-factor for contour support practice for different slope gradients.....	109
Table 6-3. Weight allocation for criterion factors	112
Table 6-4. Erosion susceptibility criteria and sub-criteria	113
Table 6-5. Sub-catchment soil loss	118
Table 6-6. Range of soil erosion values and severity class.....	121

List of Figures

<i>Figure 1-1. Location of the Sio-Malaba-Malakisi water catchment area</i>	<i>2</i>
<i>Figure 1-2. Long-term mean precipitation and temperature maps</i>	<i>3</i>
<i>Figure 1-3. Trends in precipitation variability.....</i>	<i>4</i>
<i>Figure 1-4. Major hydrological features in Sio-Malaba-Malakisi catchment.</i>	<i>5</i>
<i>Figure 1-5. Common vegetation types in the study area (a) blue gum/eucalyptus trees, (b)marshland, (c) grevillea robusta, (d) open shrubland near a quarry site.</i>	<i>6</i>
<i>Figure 1-6. Vegetation characteristic map adopted from the Potential Natural Vegetation Map of Eastern Africa.....</i>	<i>7</i>
<i>Figure 1-7. Soil classification and characteristic for the SMM catchment.....</i>	<i>9</i>
<i>Figure 1-8. Population density for 2019 aggregated for the study area comprising both Kenya and Uganda from the respective national bureau of statistics.....</i>	<i>10</i>
<i>Figure 1-9. Major land-use practices and associated impacts: (a) strip farming on steep slopes, (b) tilled land with no soil protection measures, (c) effect of gulley erosion, and (d) sedimentation of rivers.....</i>	<i>11</i>
<i>Figure 2-1. Major land-use/cover classes prepared from Sentinel-2A prototype land cover 20-meter map of Africa 2016.</i>	<i>22</i>
<i>Figure 2-2. Gradual development of the erosion process: a) unprotected cropland soil, b) development of sheet erosion, c) initial stage of gulley, d) advanced stage of gulley development</i>	<i>27</i>
<i>Figure 2-3. An illustration of erosion and deposition process on a uniform slope</i>	<i>28</i>
<i>Figure 2-4. Conceptual framework illustrating land use analysis, future land use modelling and erosion and deposition patterns modelling.....</i>	<i>32</i>
<i>Figure 3-1. Digital image processing workflow integrating qualitative data with remote sensing data.</i>	<i>42</i>
<i>Figure 3-2. Classified land-use/cover maps from the selected classes from 1986 to 2017 for Sio-Malaba-Malakisi catchment.</i>	<i>48</i>
<i>Figure 3-3. Time series trends in land-use/land cover change</i>	<i>49</i>
<i>Figure 3-4. Trends in land-use/cover changes representing percentage cover per land-use/cover class for a ten-year period.....</i>	<i>50</i>
<i>Figure 3-5. Key sampled sites highlighted in green boxes indicating areas that recorded significant cumulative land-use/cover changes from 1986 to 2017.....</i>	<i>52</i>

<i>Figure 3-6. Post-classification land use/cover change detection illustrating changes for open shrubland, mixed forest and built-up land-use/cover classes.</i>	53
<i>Figure 4-1. CLUE-s methodological framework and flowchart.</i>	62
<i>Figure 4-2. Correlation coefficient matrix for independent variables</i>	69
<i>Figure 4-3. Actual, observed and simulated land-use/cover changes</i>	70
<i>Figure 4-4. Validation of simulated land-cover map- a) Simulated land-use condition, b) actual land-use map for 2018</i>	71
<i>Figure 4-5. Scenario results from the simulation of land-use/cover classes</i>	73
<i>Figure 4-6. Trends in scenario demand for land-use/cover classes</i>	75
<i>Figure 4-7. Beta values from regression analysis for land-use/cover classes</i>	76
<i>Figure 5-1. a) Land-use/cover changes for baseline condition (2017), b) agriculture expansion scenario, b) land reclamation scenario.</i>	84
<i>Figure 5-2. A methodological framework for modelling ED using USPED model</i>	87
<i>Figure 5-3. USPED model component factors: a) rainfall erosivity, b) soil erodibility, c) slope-length, d) cover management.</i>	93
<i>Figure 5-4. Range of C factor values derived from land-use change scenarios: a) agriculture expansion scenario, b) land reclamation scenario</i>	94
<i>Figure 5-5. Relationship between modelled ED estimates and observed values</i>	96
<i>Figure 5-6. Spatial distribution of erosion/deposition zones for entire catchment (left) and sub-catchment (right).</i>	97
<i>Figure 5-7. Erosion/deposition patterns for prevailing rill erosion: a) agricultural expansion, b) land reclamation.</i>	99
<i>Figure 5-8. USPED simulated net ED rates Vs. stream flow total suspended sediments</i>	100
<i>Figure 6-1. Methodological framework for estimating soil erosion and vulnerability</i>	106
<i>Figure 6-2. Obtained RUSLE parameters for soil erosion estimation</i>	115
<i>Figure-6-3. Soil erosion susceptibility variables</i>	117
<i>Figure 6-4. a) predicted soil loss, b) erosion risk characterization for SMM basin.</i>	118
<i>Figure 6-5. a) soil erosion critical areas, b) elevation levels for administrative units</i>	119
<i>Figure 6-6. Mean annual soil loss for administrative units</i>	120

List of Equations

<i>Equation 3-1 – Multinomial probability distribution.....</i>	<i>43</i>
<i>Equation 3-2 – Overall accuracy</i>	<i>44</i>
<i>Equation 3-3 – User’s accuracy</i>	<i>44</i>
<i>Equation 3-4 – Producer’s accuracy</i>	<i>44</i>
<i>Equation 3-5 – Kappa coefficient.....</i>	<i>44</i>
<i>Equation 4-1 – Land-use location preference.....</i>	<i>63</i>
<i>Equation 4-2 – Logit probability model</i>	<i>63</i>
<i>Equation 4-3 – Logistic regression model.....</i>	<i>64</i>
<i>Equation 4-4 – Regression equation.....</i>	<i>64</i>
<i>Equation 4-5 – Variance inflation factor</i>	<i>64</i>
<i>Equation 5-1 – Transport capacity</i>	<i>86</i>
<i>Equation 5-2 – Sediment transport capacity</i>	<i>86</i>
<i>Equation 5-3 – Slope length.....</i>	<i>86</i>
<i>Equation 5-4 – steam power for sediment transport.....</i>	<i>86</i>
<i>Equation 5-5 – Erosion & deposition pattern</i>	<i>87</i>
<i>Equation 5-6 – Soil erodibility factor.....</i>	<i>88</i>
<i>Equation 5-7 – Regression equation.....</i>	<i>89</i>
<i>Equation 5-8 – Topographic parameter.....</i>	<i>89</i>
<i>Equation 6-1 – RUSLE equation</i>	<i>107</i>
<i>Equation 6-2 – Rainfall erosivity factor.....</i>	<i>107</i>
<i>Equation 6-3 – Soil erodibility factor.....</i>	<i>108</i>
<i>Equation 6-4 - Slope length and steepness</i>	<i>108</i>
<i>Equation 6-5 – Crop management factor</i>	<i>108</i>
<i>Equation 6-6 – Consistency index.....</i>	<i>110</i>
<i>Equation 6-7 – Consistency Ratio</i>	<i>110</i>
<i>Equation 6-8 – Erosion potential.....</i>	<i>110</i>
<i>Equation 6-9 – Drainage density.....</i>	<i>112</i>

List of Abbreviations & Acronyms

AHP	Analytical Hierarchy Process
ARS	Agriculture Research Service
AVHRR	Advanced Very High-Resolution Radiometer
CEC	Cation Exchange Capacity
CBO	Community Based Organizations
CLUE-s	Conversion of Land Use and its Effects at small regional extent
CORINE	Coordination of Information on the Environment
CT	Column Total
DEM	Digital Elevation Model
EUROSEM	European Soil Erosion Model
FAO	Food and Agricultural Organization
FGD	Focus Group Discussions
GIS	Geographical Information Systems
GLASOD	Global Assessment of Soil Degradation
GPS	Global Positioning Systems
ISODATA	Iterative Self-Organizing Data Analysis Technique
ISRIC	International Soil Reference and Information Centre
ITCZ	Intertropical Convergence Zone
KNBS	Kenya National Bureau of Statistics
LU	Land Use
LULC	Land Use Land Cover
m.a.s.l	metres above sea level
MAM	March April May
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Multispectral Instrument
OA	Overall Accuracy
OND	October November December
OLI	Operational Land Imager
PA	Producer's Accuracy

QGIS	Quantum Geographical Information Systems
RT	Row Total
RUSLE	Revised Universal Soil Loss Equation
SOC	Soil Organic Carbon
SI	Scenario I
SII	Scenario II
SMM	Sio Malaba Malakisi
SRTM	Shuttle Radar Topographic Mission
TM	Thematic Mapper
UA	User's Accuracy
UBOS	Uganda Bureau of Statistics
UNEP	United Nations Environmental Programme
USDA	United States Department of Agriculture
USGS	United States Geological Survey
USLE	Universal Soil Loss Equation
USPED	Unit Stream Power-based Erosion Deposition
UTM	Universal Transverse Mercator
VIF	Variance Inflection Factor
WaTEM/SEDEM	Water and Tillage Erosion Model/Sediment Delivery Model
WEPP	Water Erosion Prediction Project
WGS	World Geodetic Survey

CHAPTER 1

General Introduction

This chapter describes the general study region, including the location of the catchment and the sub-catchments forming the larger Sio-Malaba-Malakisi transboundary catchment. The chapter explores the biophysical characteristics of the study region, including the prevailing hydro-climate, vegetation, soil and geomorphological characteristics, and the demographic patterns of the area. The chapter concludes by highlighting the state of land degradation in SMM catchment, including natural and human-induced factors driving the degradation.

1.1 Location and Geography

The Sio-Malaba-Malakisi (SMM) basin is a cross-boundary water catchment area located on the border region between Kenya and Uganda. It's bounded by Latitudes 1°13'30" N to 0°19'30" S near the Equator, and Longitudes 33°67'30" E to 34°57'10" E (Fig.1-1). The elevation ranges between approximately 1,000 to 4,200 m.a.s.l. The basin consists of five sub-catchments covering a total area of approximately 5,230 km², out of which, 1,448 km² is covered by the Sio River catchment, representing 28 % of the total basin (Chasia et al., 2021; Roussel, 2012). The remaining 3,782 km², is covered by the Malaba Malakisi catchment. The sub-catchments include: Malaba and Mpologoma in Uganda, Lwakhaka on the shared boundary, Malakisi and Sio within Kenya (Table 1-1). The Malaba-Malakisi catchment originates from the southern slopes of Mt. Elgon while the Sio catchment originates from the hills south of Mt.Elgon (Chasia et al., 2021; Roussel, 2012). The Malaba-Malakisi catchment drains its waters towards Lake Kyogo whereas rivers originating from the Sio catchment drain their water in Lake Victoria.

Table 1-1. General characteristics of study area and sub-catchment extent

No.	Sub-catchment	Area (Km ²)	Country
1.	Malakisi	624	Kenya
2.	Sio	1,407	Kenya
3.	Lwakhakha/Upper Malaba	592	Kenya/Uganda
4.	Malaba	1,037	Kenya/Uganda
5.	Mpologoma	1,528	Uganda
TOTAL		5,188	

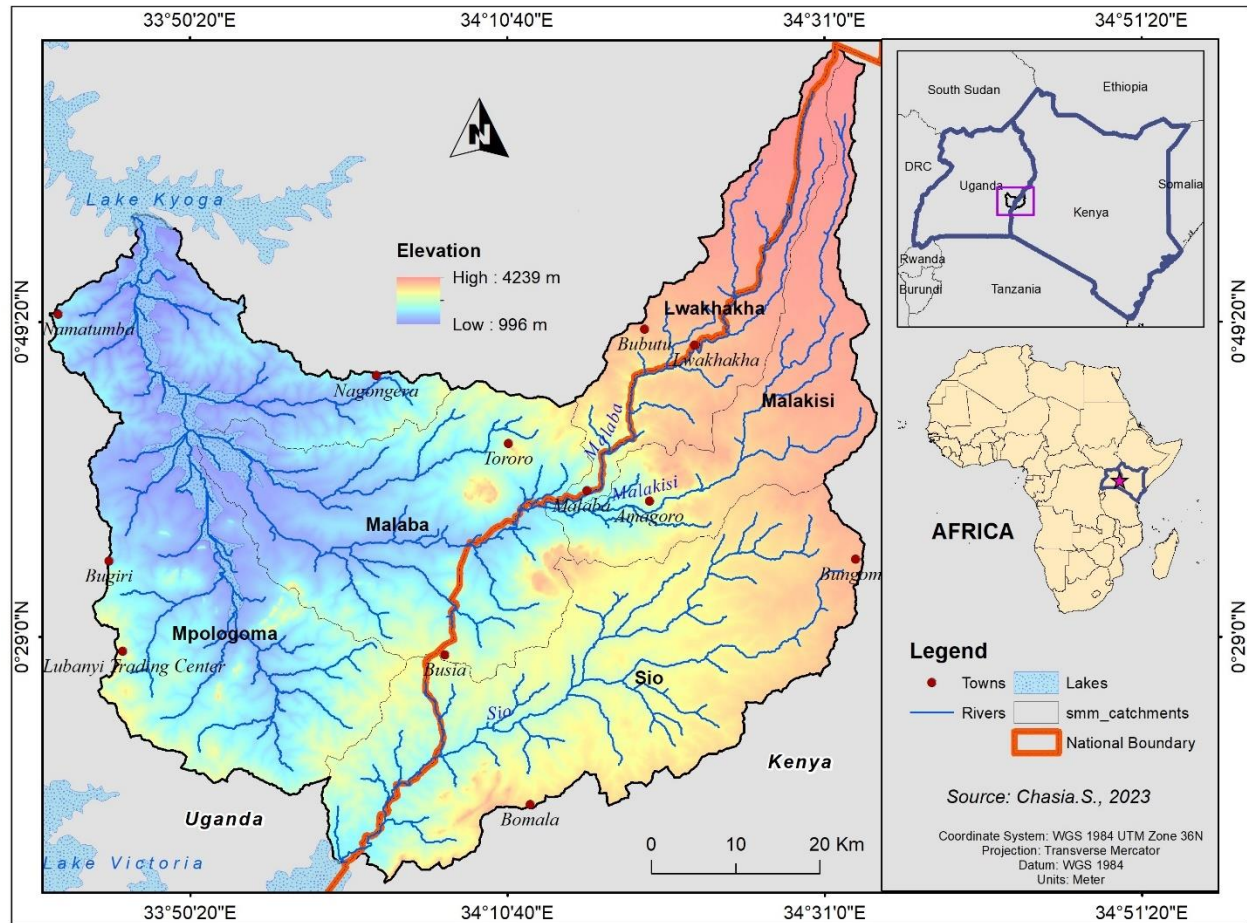


Figure 1-1. Location of the Sio-Malaba-Malakisi water catchment area

1.1.1 Climate and Hydrology

The study area experiences a bimodal rainfall pattern (Alemayehu et al., 2017) with a minimum annual rainfall of approximately 1,500 and a maximum of 2,000 mm (Reed & Clokie, 2000; Wanyama et al., 2020). Precipitation is lowest in the month of January, averaging 62 mm, while the month of April records the most precipitation around 260 mm. Due to the orographic effects, rainfall away from the shoreline increases from 1,250 mm on the plains to slightly above 2,000 mm on the medium slopes (Figure 1-2). The Sio sub-catchment rainfall range is 1,800 mm on the upper zones of the catchment to 1,590 mm on the outfall reaches (Roussel, 2012). Seasonal weather patterns are characterized by a period of “long-rains” (March to May), and “short rains” (October to December) (Ongoma et al., 2018). This coincides with the passage of north-south/south-north intertropical convergence zone (ITCZ) (Camberlin & Okoola, 2003; Yang et al., 2015). The mean maximum temperature is 27.5° C on the low-lying areas and 5° C on the lower slopes of Mt. Elgon.

Evaporation is greatest in the months of January and February, where on average, 175 mm of water is evaporated monthly over the open water bodies.

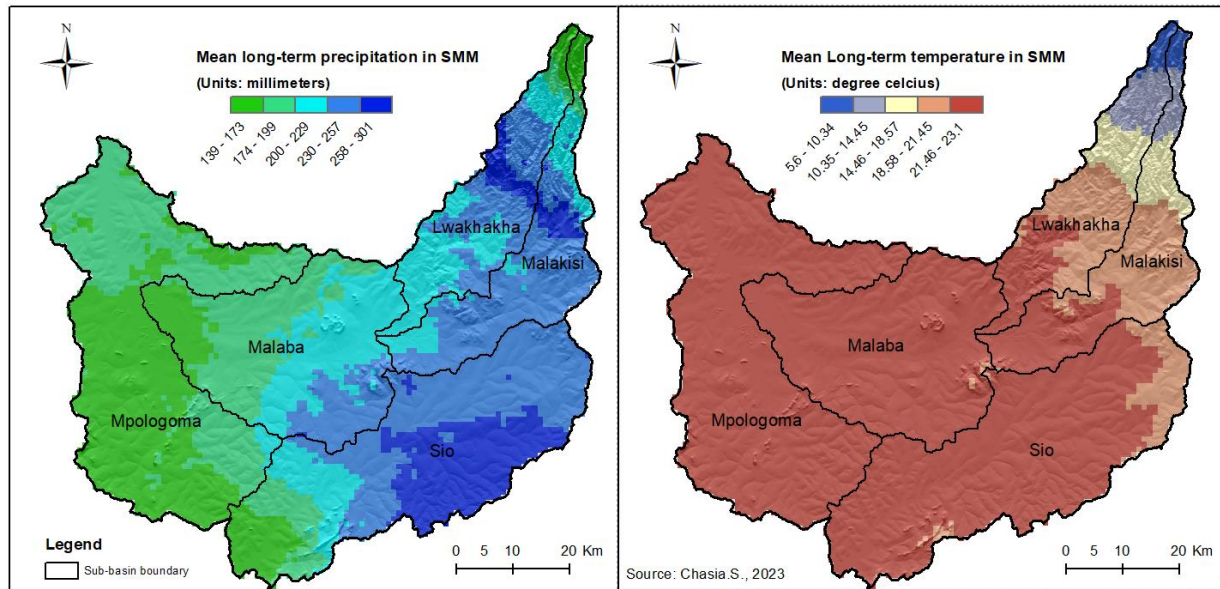


Figure 1-2. Long-term mean precipitation and temperature maps

Historical trends in precipitation variability across the SMM catchment, for the period of 01-Jan-2007 to 31-Dec-2017 with four precipitation indices are illustrated in figure 1-3 (de Sousa et al., 2020). The red lines indicate the historical mean of each index in the time series, while blue line indicates the smoothed trends in each index using the 'loess' method. MLDS denotes the maximum length consecutive dry days; MLWS is the maximum length of consecutive wet days; Rtotal represents the total precipitation (mm), and Rx5day is the maximum consecutive 5-day precipitation (mm) (de Sousa et al., 2020). Overall, there is a marked increase in consecutive dry days (MLDS), with a corresponding decrease in the number of rainy days (MLWS) across the time series, which stays above the historical average for MLDS, while MLWS stays below the historical average (Figure 1-3). However, it is noted that the total rainfall (Rtotal) in the 30-day interval, stays above average for the entire period, but begins to drop in the year 2015. Similarly, the maximum consecutive 5-day precipitation for SMM stays above historical average and begins to dip around the year 2015.

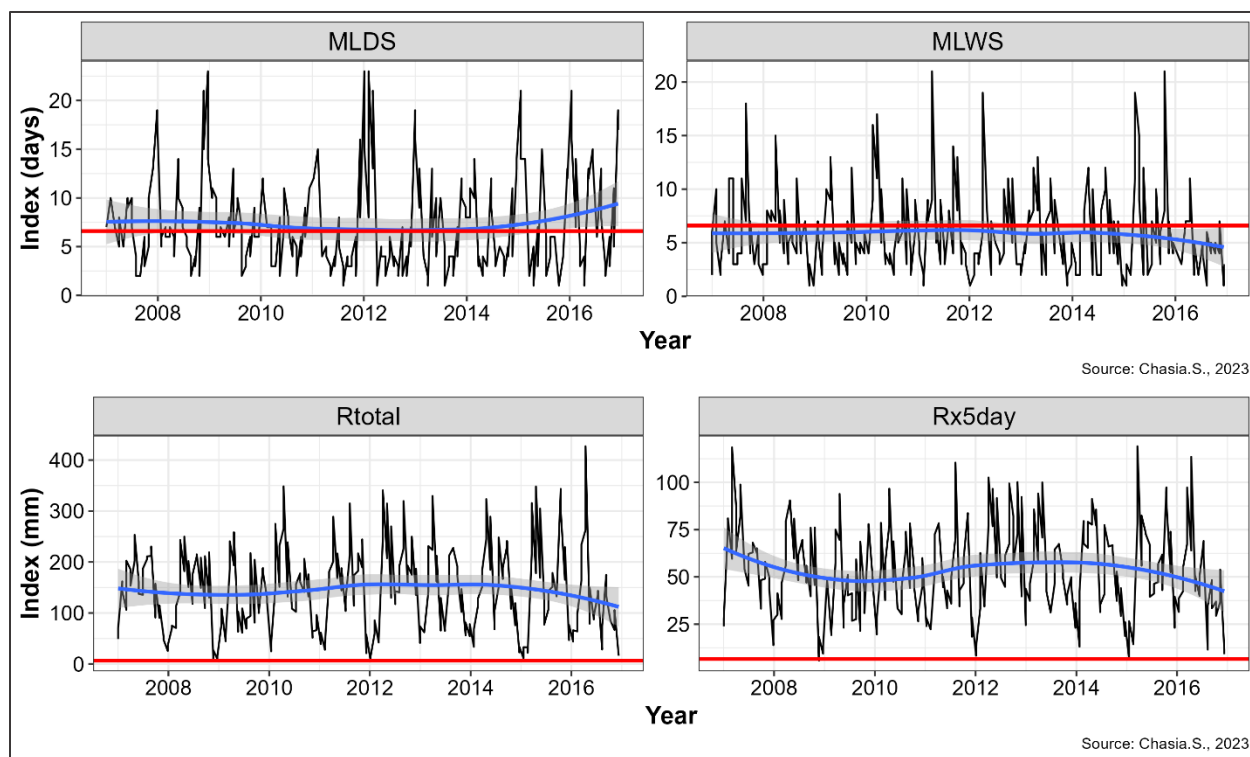


Figure 1-3. Trends in precipitation variability

The local hydrology is characterized by three major rivers originating from the upper catchment zones (Sio, Malaba and Lwakhakha), and one located at the flood plains (Mpolongoma). The Lwakhakha River also acts as a physical boundary, forming the border between Kenya and Uganda, before changing to Malaba and then joining the Malakisi River. The Malaba River in Kenya, changes to Mpolongoma River as it approaches the floodplain, and flows into swamps towards Lake Kyoga. The Sio River originates west of Bungoma town and south of Mt.Elgon and flows into Lake Victoria basin (Figure 1-4).

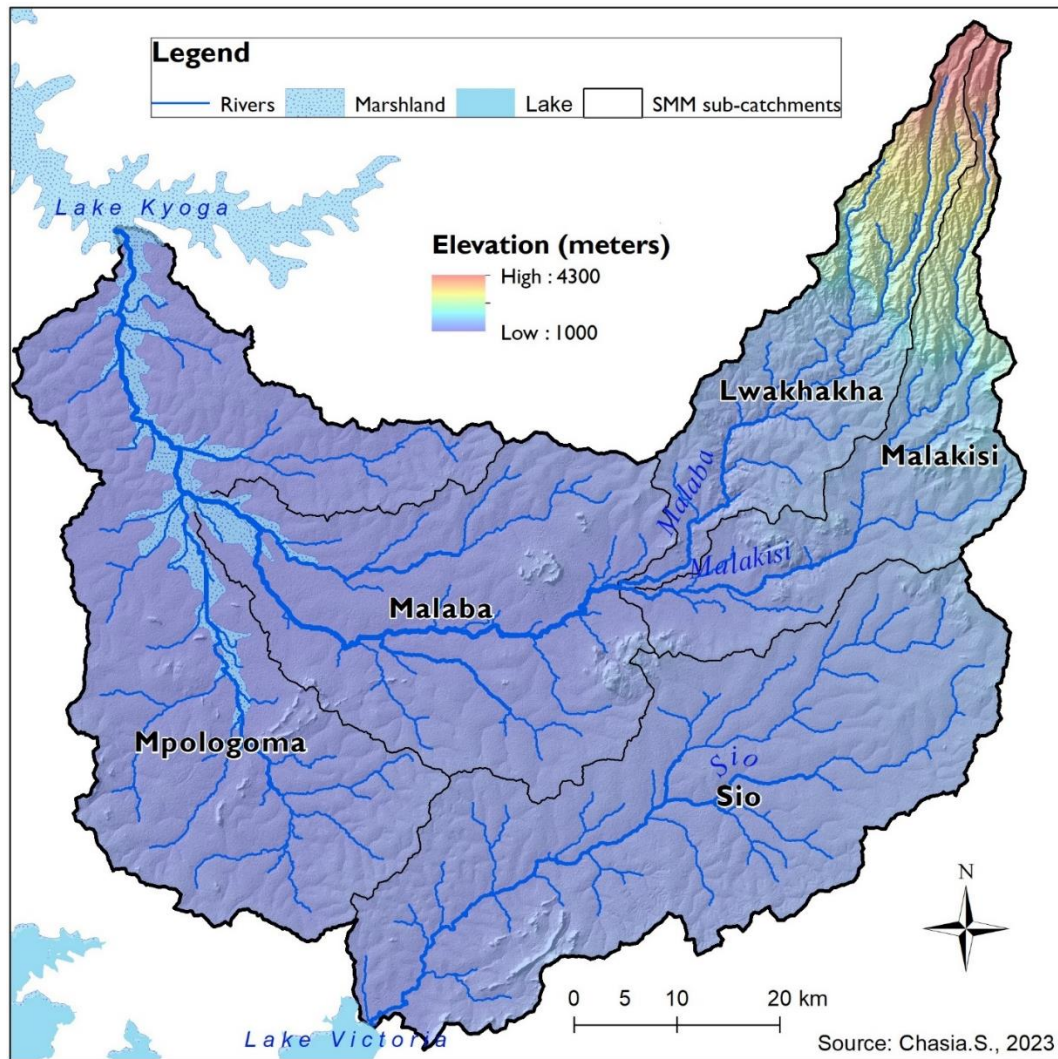


Figure 1-4. Major hydrological features in Sio-Malaba-Malakisi catchment.

1.1.2 Vegetation Characteristics

Vegetation pattern and distribution in the study region is mainly controlled by altitude, ranging from Afroalpine, Montane Ericaceous belt, Afromontane bamboo and undifferentiated forest on the upper reaches of the catchment, to wooded grassland and semi-evergreen Guineo-Congolian rainforest in the middle region (Van Breugel et al., 2015). The lower catchment on the other hand is characterized by freshwater swamp, palm wooded grassland and evergreen and semi-evergreen bushland and thicket (Figure 1-6). The northern tip of the Sio-Malaba-Malakisi catchment area which begins from the peak of Mt. Elgon Forest, and stretching south-west towards Uganda is where Lwakhakha and Malakisi sub-catchments. This region exhibits a mixture of vegetation

zonation typical of mountainous ecosystem comprising of different biomes, ranging from barren rocks, tundra, mixed montane forest, bamboo, dwarf bushes, and deciduous trees (Wasonga & Opiyo, 2018). However, as you descend further south, vegetation characteristics changes from the permanent to season crops interspersed with open shrubs and herbaceous plants (Figure 1-5). Wetland zones, mainly located downstream in Mpologoma and Malaba sub-catchments, consist of tall papyrus reeds and marshes spread along the entire stretch of the western flanks of the catchment near Lake Kyoga. The study region is also composed of agroforestry areas composed mainly of woodland vegetation consisting of eucalyptus trees (Figure 1-5 (a)) and semi-deciduous *grevillea robusta* (Figure 1-5 (c)). The latter is mainly used to provide shade on cultivated crops and also as a source of fuel, timber and firewood. Eucalyptus is mainly used for firewood, charcoal, timber, as well as acting as a windbreaker (www.worldagroforestrycentre.org).

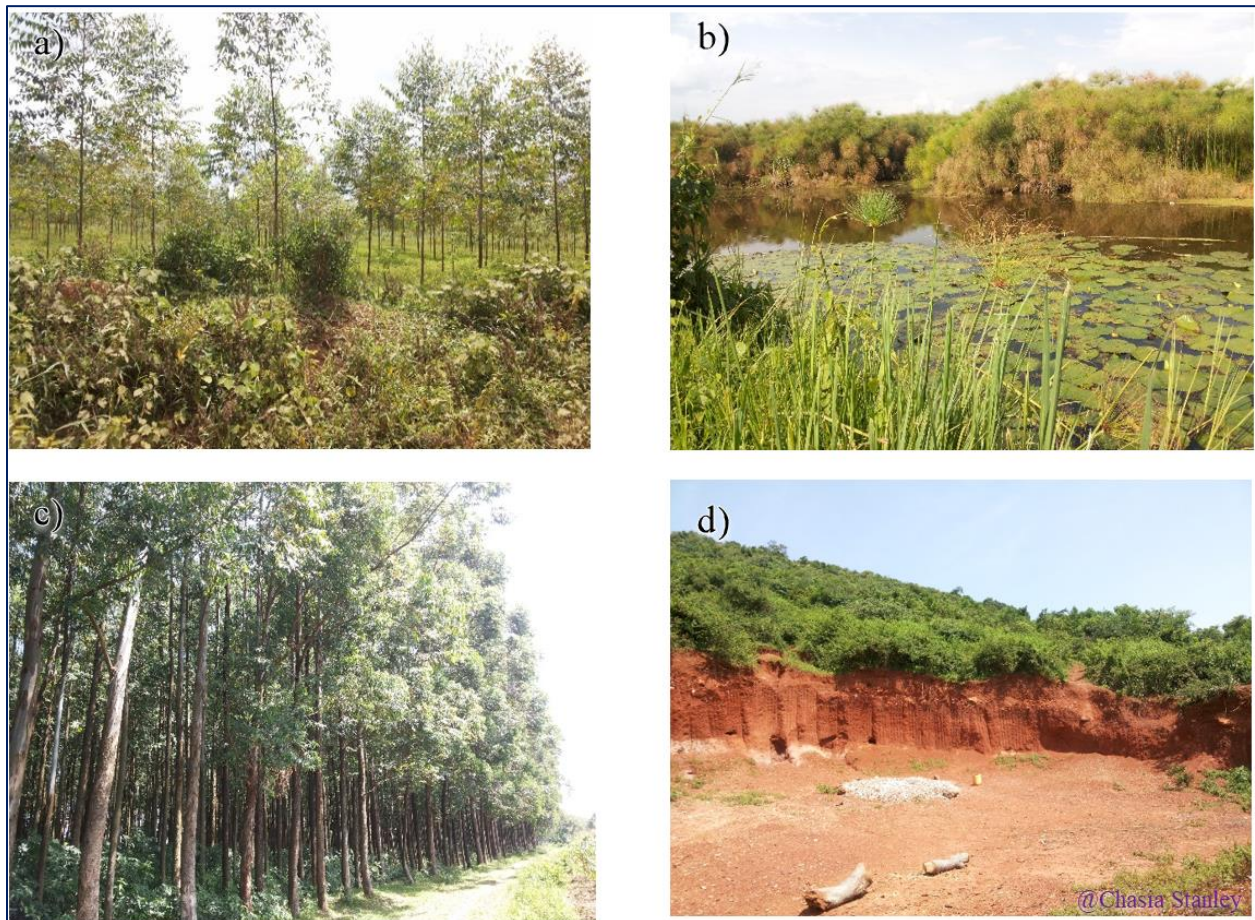


Figure 1-5. Common vegetation types in the study area (a) blue gum/eucalyptus trees, (b)marshland, (c) *grevillea robusta*, (d) open shrubland near a quarry site.

Seasonal variation in vegetation cover is mainly observed among seasonal crops corresponding to the long rain season (MAM) and the short rain season (OND) when vegetation condition is at its peak. However, permanent crops exhibit physical changes due to seasonal variations in climatic conditions, especially during dry seasons when most vegetation undergoes stress due to limited moisture.

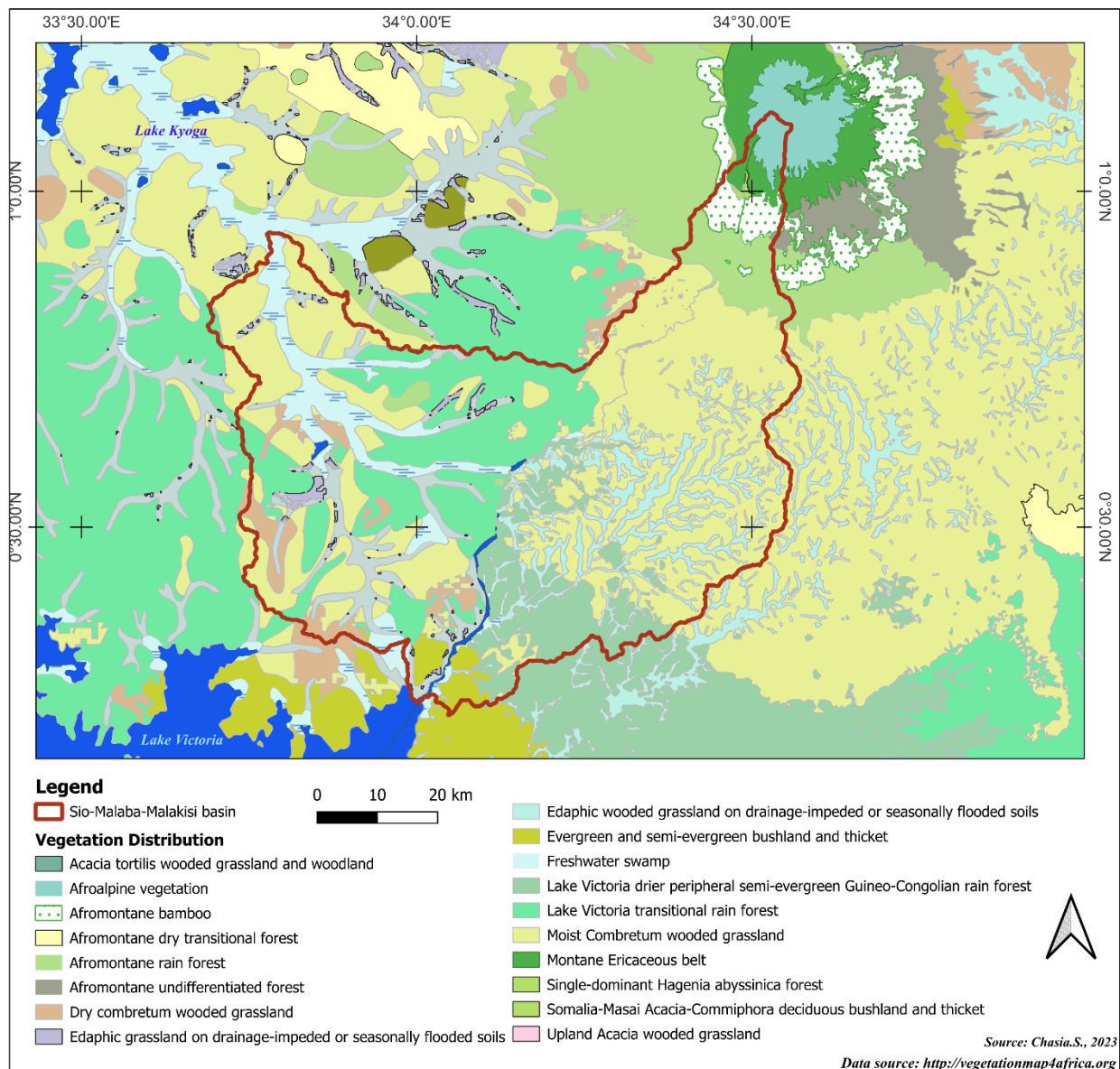


Figure 1-6. Vegetation characteristic map adopted from the Potential Natural Vegetation Map of Eastern Africa.

1.1.3 Soils and Geomorphology

This area is mainly composed of soils of volcanic origin. On the upper slopes of Mt. Elgon, *andosols*, *nithosols* and *histosols* soils are also found (Chasia et al., 2021; Roussel, 2012). The mountainous parts of the basin have young rich mineral volcanic soils with moderate to high fertility rates (Figure 1-7). The upper part of Mt. Elgon is made up of clay loam, well-drained, shallow to moderate, deep, dark reddish-brown, rock and stony soils. On the undulating slopes, there are pockets of granitic soils which are well-drained and extremely deep. The middle and lower catchment consists of well drained, moderately deep to very deep, friable clay over basement/country rock. On the riverbanks and valleys, the soils that dominate there are characterized by a complex structure, imperfectly drained to poorly drained, very deep, dark soils of sandy clay to clay origin. The topography of SMM is characterized by steep volcano slopes, escarpments, rolling and undulating hills, gentle and undulating plains and wetlands. The top parts of the basin have steep slopes, averaging 20-30 % and 40-45 % on the steeply incised valleys (Juma et al., 2021). At the peak of the basin, there is the Chepkitale National Reserve and the Mt. Elgon National Park which consists of heather vegetation. Below this at an altitude of 2,000 – 3,000 m.a.s.l., is the Mt. Elgon Forest.

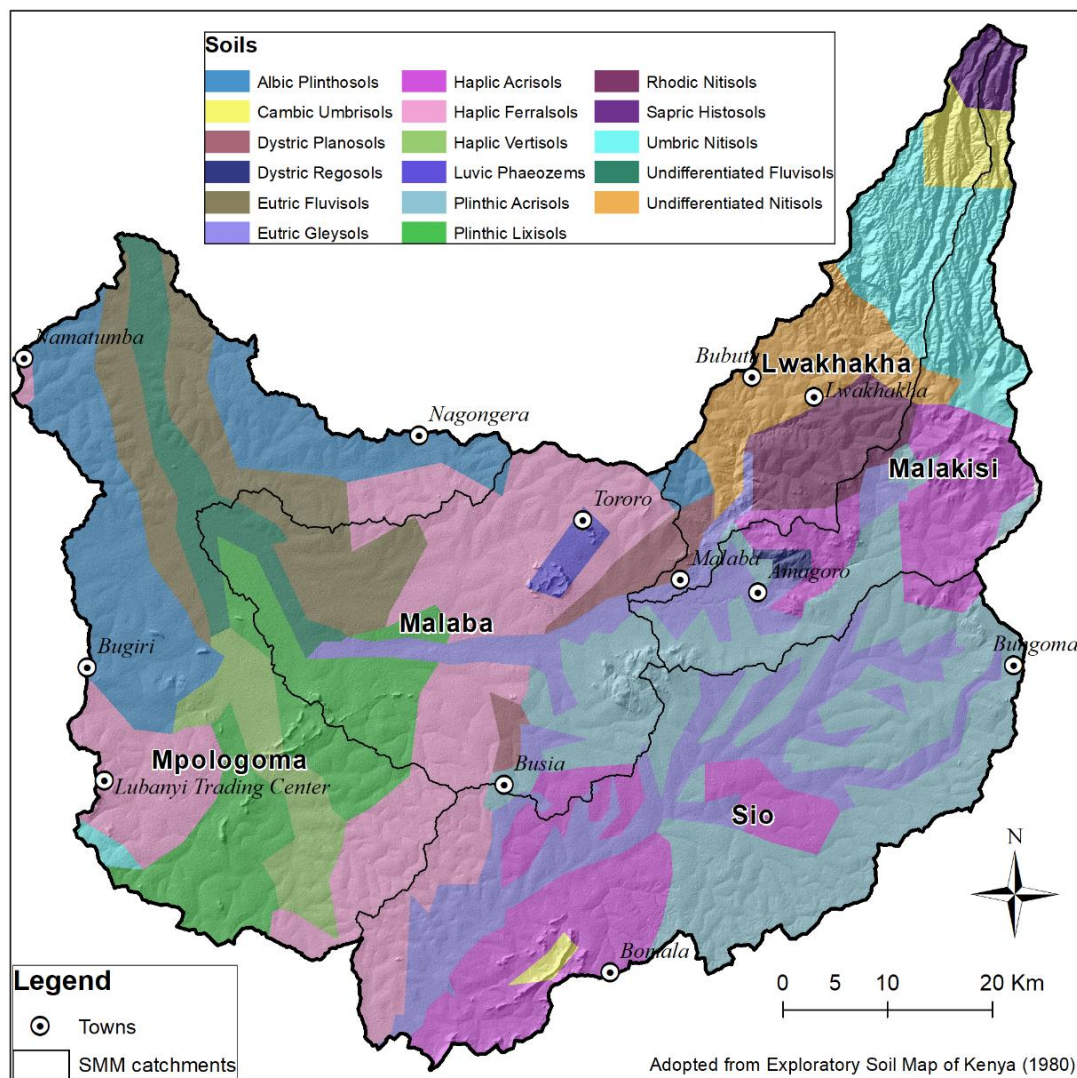


Figure 1-7. Soil classification and characteristic for the SMM catchment

1.1.4 Population and Demography

According to census data from the KNBS (2019) and UNBS (2019), the SMM basin recorded a total population of 4,302,758 aggregated from the twenty-two constituencies and districts of Kenya and Uganda respectively. This translates to a population density of approximately 450 people per square kilometre against a national average population density of 94 people per Km² in Kenya and 196 people per km² in Uganda. Most of the population is concentrated in the north-western parts of SMM catchment in areas such as Namisindwa and Bududa districts in Uganda, and mid-zones of the catchment in Amagoro and Bungoma constituencies in Kenya (Figure 1-8).

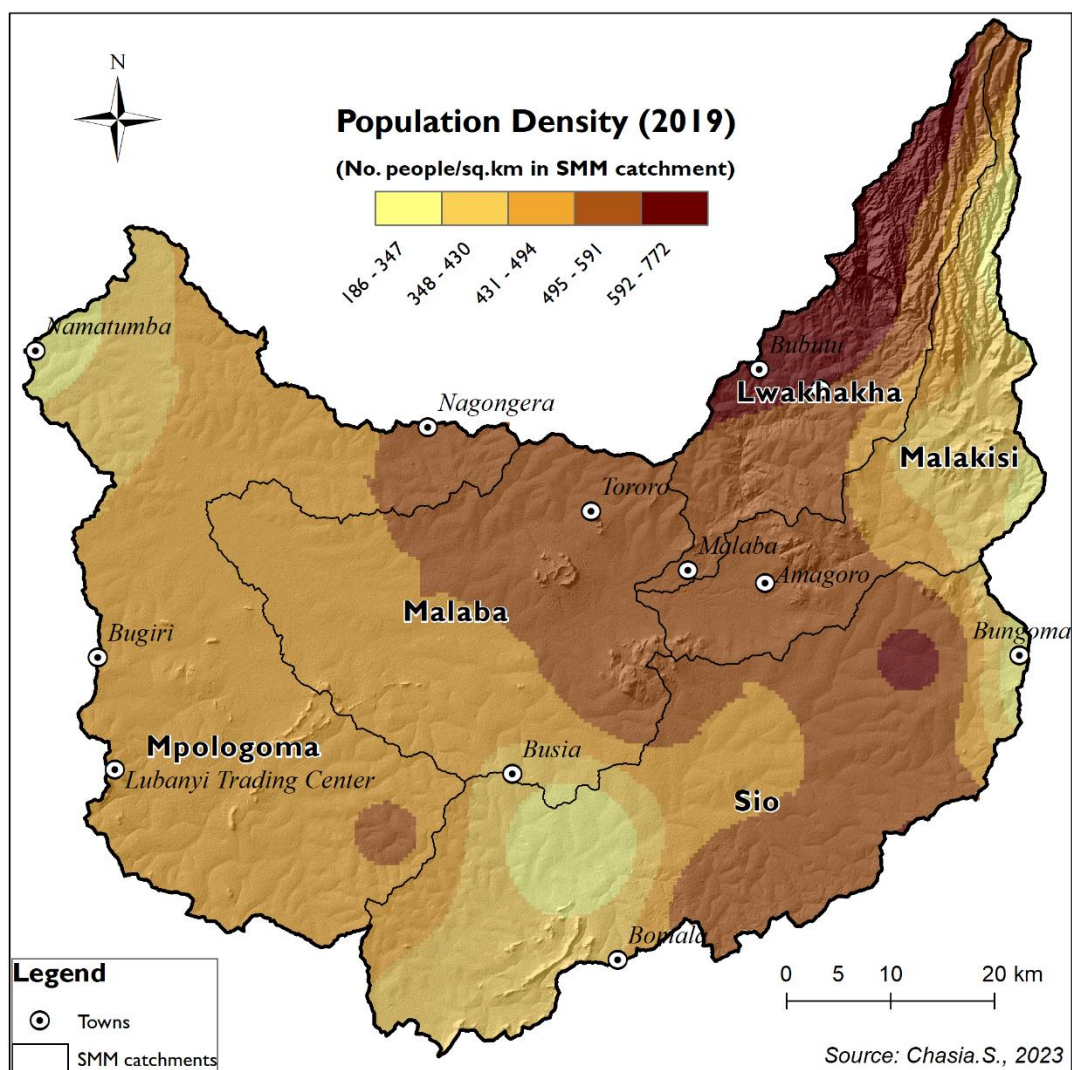


Figure 1-8. Population density for 2019 aggregated for the study area comprising both Kenya and Uganda from the respective national bureau of statistics

According to population projections in the study area, it is estimated that by 2025, the total population in SMM catchment will have reached approximately 5,226,251 people, translating to a 20% increase from the 2019 census records. This represents an average population density of approximately 641 people per km².

In terms of socioeconomic activities, the communities living in the SMM catchment mainly practice subsistence agriculture, including small-scale livestock keeping. A few households cultivate cash crops, such as coffee on the foot slopes of Mt. Elgon, while others grow rice adjacent to wetlands.

1.1.5 Land Degradation in SMM Catchment

The SMM is an agricultural water catchment area dominated by communities mainly practising rainfed agriculture and cash crop farming. However, over the recent past, due to an increase in human population in the region, many farms have been fragmented into smaller units to accommodate the competing land-use activities. Consequently, as demand for more cultivation land increases, cropland area has extended to marginal lands, and other fragile zones where unsustainable cultivation practices, such as strip farming are common thus negatively affecting the local environment (Figure 1-9 (a)). In particular, the presence of rich volcanic soils, especially on the upper catchment zones, and a bimodal rainfall pattern which enables crop cultivation twice a year has led to the depletion of soil fertility due to limited fallowing period. As a mitigation measure, many farmers resort to using agricultural chemicals and fertilizers to boost productivity. Therefore, during periods of heavy storms, unprotected soils laden with agrochemicals and other disease pathogens are washed downstream to nearby rivers thus affecting the quality of water and the integrity of the local freshwater ecosystem.



Figure 1-9. Major land-use practices and associated impacts: (a) strip farming on steep slopes, (b) tilled land with no soil protection measures, (c) effect of gulley erosion, and (d) sedimentation of rivers.

1.2 Statement of the Problem

Land degradation, particularly soil erosion, is a common environmental problem in many regions, negatively affecting the environment and agricultural productivity (Borrelli et al., 2021; Rosas & Gutierrez, 2020). In the Sio-Malaba-Malakisi (SMM) catchment area, rapid population growth and urbanization have led to dynamic land-use changes, exacerbating soil erosion and sedimentation (Chasia et al., 2021; Maitima et al., 2009), hence negatively affecting water quality, ecosystem health, and soil fertility in the area (Chasia et al., 2021, 2024; Mwanake et al., 2023). Globally, approximately 75 billion tons of soil are washed away annually from arable lands, costing over US \$400 billion annually (Borrelli et al., 2017). In the highland zones of East Africa, around $5 \text{ mg}^{-1} \text{ ha}^{-1} \text{ yr}^{-1}$ of fertile soil is lost, leading to a decline in food production (Borrelli et al., 2021; Fenta et al., 2020). These degradation affects ecosystem services, contributes to climate change and threatens food security. Therefore, addressing it is crucial for environmental sustainability and community livelihoods. Despite past attempts to model soil erosion in the SMM region (Karamage et al., 2017; Schürz et al., 2020), the lack of complete and quality hydrological data in the area has persistently limited the accurate prediction of erosion models. Moreover, none of the previous studies has attempted to explore potential changes and trajectories of future land-use/cover state and their impacts on soil erosion (Chasia et al., 2024; Karamage et al., 2017; Schürz et al., 2020). This study aims to analyse current and future LULC changes, as a basis for evaluating their impacts on soil erosion and deposition patterns across the transboundary SMM catchment. Additionally, the study estimated erosion occurrence, and associated sub-catchment erosion metrics in order to identify vulnerable areas to erosion, and guide the development of effective soil conservation interventions and sustainable land management practices in the region.

1.3 Justification of the Study

The Sio-Malaba-Malakisi watershed has experienced significant land degradation as a result of land-use changes over the past decades. These transformations have raised concerns about the potential consequences of soil erosion, a phenomenon with far-reaching implications for water quality, agricultural productivity, and ecosystem health. This research aims to investigate the impact of land-use change on soil erosion and deposition patterns, to identify vulnerable areas to soil erosion which is required to guide conservation prioritization initiatives. The increasing rate of LULC changes in the SMM watershed poses pressing environmental concerns with potential

negative consequences if the present situation persists. Human activities, such as deforestation, urban sprawl, and intensive agriculture could lead to land and soil degradation, thus affecting soil fertility, water quality, and overall ecosystem resilience. The management of soil and water in the region as captured in the Water Resource Management Strategy of Kenya (Ministry of Water and Irrigation, 2008), is based on administrative boundaries as opposed to ecological units, a phenomenon that has resulted in fragmented and uncoordinated land and water use planning. This study, therefore, posits that understanding the extent of soil erosion, consequent of land-use changes is crucial for developing effective mitigation strategies and promoting sustainable land management practices. However, despite the evident importance of land-use change and soil erosion problem in the region, there is a notable lack of comprehensive studies and quality data for addressing these issues as highlighted in the Kenya National Water Resource Management Strategy (Ministry of Water and Irrigation, 2008) and National Land-use Policy (*Sessional Paper No. 01 of 2017 on National Land Use Policy, 2017*). Moreover, the establishment of a transboundary management framework has been recognized by both Kenya's and Uganda's national land-use policies as an important undertaking for developing nature-based solutions that could support sustainable development outcomes while safeguarding critical ecosystems (Ministry of Lands Housing and Urban Development, 2006). Nonetheless, due to limitations in existing research studies, these management ambitions have remained unrealized leading to further degradation within the study region. Therefore, this study aims to conduct a comprehensive analysis of historical long-term LULC changes and assess potential future land-use patterns to understand their impacts on soil erosion and deposition occurrence and vulnerability. The findings of this study will provide valuable data to support evidence-based land-use planning and transboundary catchment management strategies. Land managers, policymakers, and other stakeholders in the region can use this information to develop sustainable land-use policies and implement effective land-use practices. By identifying areas most vulnerable to erosion and deposition, decision-makers can prioritize conservation efforts and allocate resources efficiently. Therefore, the outcomes of this research will contribute to the development of a soil and water conservation plan relevant to the SMM watershed's unique conditions. Moreover, the understanding of factors driving soil erosion under different LULC types in the area, would not only support the design of targeted interventions capable of preventing further soil and land

degradation but also promote soil health, enhance the basin's climate resilience, as well as safeguard the long-term productivity of the region's agricultural land.

1.4 Research Gap

Soil erosion is a significant environmental issue that affects both agricultural productivity and ecosystem stability (Borrelli et al., 2021; Chasia et al., 2024). In transboundary water catchments such as the Sio-Malaba-Malakisi in Kenya and Uganda, the problem of soil erosion is compounded by varying land use practices and policies across borders (Chasia et al., 2023; Jing et al., 2022). Land use and land cover (LULC) changes, driven by factors such as agricultural expansion, deforestation, and urbanization, can exacerbate soil erosion risks, leading to adverse effects on water quality, sediment transport, and overall catchment health (Cohen et al., 2019; Karamage et al., 2017).

Numerous studies have examined the relationship between LULC changes and soil erosion in different parts of the world. For instance, research by Riquetti et al., (2023) demonstrated the significant impact of deforestation on soil erosion rates in the Amazon Basin. Similarly, Zhou et al., (2013) explored how urbanization has increased soil erosion risks in the Yangtze River Basin. In the context of East Africa, several studies have highlighted the challenges of soil erosion, particularly in the highland regions of Kenya (Chasia et al., 2024; Mati et al., 2000) and Uganda (Karamage et al., 2017; Kulimushi et al., 2021). However, while these studies provide valuable insights into the general trends and impacts of LULC changes on soil erosion, there remains a notable gap in the literature regarding transboundary water catchments. Specifically, there is limited understanding of how differing land use policies and practices across national borders within the same catchment area influence soil erosion dynamics. Moreover, existing studies often focus on either biophysical assessments or policy analyses in isolation, rather than integrating these aspects to provide a comprehensive understanding of the problem.

Despite the growing body of literature on soil erosion and LULC changes, there is a critical gap in understanding how transboundary dynamics between Kenya and Uganda influence soil erosion risks in shared catchments. Current research has not adequately addressed the following key questions:

- 1. How do differing land use practices and policies between Kenya and Uganda affect soil erosion rates in the shared catchment area?*
- 2. What are the spatial and temporal patterns of LULC changes in the SMM transboundary catchment, and how do these patterns correlate with observed soil erosion risks?*
- 3. How can integrated land management strategies be developed to mitigate soil erosion in such transboundary contexts, considering the socio-political and environmental complexities?*

Addressing these research gaps is crucial for developing effective land management and soil conservation strategies in transboundary water catchments. By providing a detailed analysis of LULC changes and their impacts on soil erosion risk across the Kenya-Uganda border, this study aims to contribute to the existing body of knowledge in several ways:

- 1. Enhancing understanding of the transboundary effects of LULC changes on soil erosion.*
- 2. Informing policymakers on the need for harmonized land use practices and conservation policies across borders.*
- 3. Providing a framework for integrated catchment management that can be applied to other transboundary water catchments facing similar challenges.*

This study seeks to fill the identified research gaps by conducting a comprehensive analysis of LULC changes and their impacts on soil erosion risk in the SMM transboundary water catchment of Kenya and Uganda. Through this research, we aim to provide actionable insights that can guide sustainable land management practices and policies, ultimately contributing to the resilience and health of transboundary water catchments.

1.5 Research Questions

The following research questions guided this research work:

1. Has land-use/cover condition varied in space and time over the past 30 years from the 2017 base year across the transboundary SMM catchment?
2. What future LULC patterns will emerge when LULC change scenarios on (i) agriculture expansion, and (ii) land reclamation, are applied in a conceptual land use change model for a period of 30 years in the study catchment?
3. How does land-use/cover changes affect erosion and deposition occurrence and patterns in the SMM water catchment?
4. Which regions in the SMM catchment are most vulnerable to soil erosion?

1.6 Objectives of Study

The main objective of this study was to analyze land use/cover changes in the area and assess their impact on soil erosion vulnerability in the basin. This was achieved through the specific objectives provided below:

1.5.1 Specific objectives

1. To analyze and quantify historical land-use changes prevalent in the basin over thirty years (1987-2017) as the basis for identifying the change patterns using satellite Remote Sensing and GIS techniques.
2. To quantify potential land-use change scenarios from historical trends using the CLUE-s model as a basis for supporting land-use management plans for the region.
3. To simulate the effects of land-use changes using the USPED model to understand their associated effects on soil erosion and deposition patterns across the basin.
4. To assess soil erosion vulnerability across the region with the support of the RUSLE model and AHP framework for recommendation of options for soil conservation guidelines for the basin.

1.7 Scope of the Study

Globally, historical land cover changes can be identified using several methods (Falcucci et al., 2007; Wanyama et al., 2020). In data-scarce regions, advances in remote sensing have made it possible to quantify space-time alterations in land cover conditions using satellite-archived data (Coulter et al., 2016; Phiri et al., 2020). This study used physically-based datasets from remote sensing to understand historical changes in land cover conditions. Within these constraints, satellite sensors with the ability to discern the changes at a finer resolution (i.e., 30m), were preferred. Considering subtle land-use patterns, fine-resolution datasets were not possible within the constraints of the study. Further, understanding future trends in land-use changes can be done by integrating land-use models with potential land-use change factors in a GIS (Batista et al., 2019; Chasia et al., 2023; Schneider & Gil Pontius, 2001). In this study, therefore, an empirical land-use change model was adapted to simulate future changes in land cover conditions using plausible scenarios for the study region. Considering the dynamic trends in the basin generally, this study did not delve too much into associated uncertainties from the model as well as within the temporal periods selected for the study. Finally, monitoring and management of catchments requires an

understanding of the soil erosion process which leads to the identification of the affected areas for implementing soil control measures. This research therefore employed hydrological models (i.e., USPED and RUSLE) and a decision support framework (i.e., AHP) to simulate soil erosion and deposition pathways. Also, the models were employed to support the identification of critical zones representing vulnerabilities that can be targeted for interventions.

1.8 Scientific Contribution

This study was conducted in a transboundary water catchment area characterized by inconsistent and disparate cross-border catchment management framework between Kenya and Uganda, which is manifested by the existing poor and unsustainable soil and water management practices which threatens the well-being of the vulnerable watershed, as well as livelihoods of people living in the region. This research therefore contributes knowledge towards the understanding of the intricate cross-border resource governance issues by highlighting critical human activities and processes contributing to land degradation through soil erosion and sedimentation. Three key objectives have already been published as outlined in the corresponding citations:

Chapter 3:

Chasia, S., Herrnegger, M., Juma, B., Kimuyu, J., Sitoki, L., & Olang, L. (2021). Analysis of land-cover changes in the Transboundary Sio-Malaba-Malakisi River Basin of East Africa: Towards identifying potential land-use transition regimes. *African Geographical Review*, 1-17. <https://doi.org/10.1080/19376812.2021.2007143>. **(Published)**

Chapter 4:

Chasia, S., Olang, L.O., Sitoki, L., 2023. Modelling of land-use/cover change trajectories in a transboundary catchment of the Sio-Malaba-Malakisi Region in East Africa using the CLUE-s model. *Ecol. Modell.* <https://doi.org/10.1016/j.ecolmodel.2022.110256>. **(Published)**

Chapter 5:

Chasia, S., Olang, L. O., Juma, B., & Sitoki, L. (2024). Understanding the linkages between land-use transitions and soil erosion/sediment deposition: A case study of the transboundary Sio-Malaba-Malakisi watershed in Kenya and Uganda. *Physics and Chemistry of the Earth, Parts A/B/C*, 133, 103529. <https://doi.org/10.1016/j.pce.2023.103529>. **(Published)**

Chapter 6:

Chasia, S., Olang, L. O., Bess, C., Kimuyu, J., & Sitoki, L. (2024). Assessment of soil erosion risk and vulnerability in the transboundary Sio-Malaba-Malakisi watershed in Kenya and Uganda. *Journal of Environmental Management* (**Under review**).

1.9 Organization of the Thesis

This thesis is organized into seven chapters. The first chapter begins with a general introduction and background of the study, including the problem statement, rationale and the research gap being investigated by the study. Chapter two provides a comprehensive literature review on the global, regional and local land use/cover change research, land-use legislative framework, modelling land use, soil erosion studies and modelling, and transboundary water catchment management issues. Chapter three to chapter six presents the study objectives, which are all organized systematically using the standard journal paper format and structure. The seventh chapter summarizes the entire research study by presenting the overall discussion, conclusion, and recommendation of the study based on the research findings. A comprehensive bibliography and reference list used in the study is also presented towards the end of this thesis, together with auxiliary material in the Appendices section.

CHAPTER 2

Literature Review

This chapter presents literature review on land-use land-cover changes at local and global scales. It also discusses the present land cover state of the study region by examining the dominant land-use classes across the basin. The strengths as well as opportunities for improvement related to the existing legal frameworks governing land-use activities in both Kenya and Uganda are also examined. The chapter also describes modelling approaches used in land-use change analysis as well as soil erosion processes and transboundary water management issues.

2.1 Background Information

Land is a limited and non-renewable natural resource of global importance (Newbold et al., 2015; UNCCD, 2019). It's the foundation of human existence and life support for all the biotic components of our ecosystem and sustains the life of the terrestrial ecosystem through the provision of ecosystem goods and services such as food and habitat for flora and fauna (Borrelli et al., 2017; Guerra et al., 2020b; Ma et al., 2022). However, over the recent past, land has been facing a lot of transformation and disturbance mainly driven by anthropogenic activities in many parts of the world (Cohen et al., 2019; Liu et al., 2020). For instance, due to the growing human population and unsustainable resource consumption habits, undue pressure has been exerted on land resources causing unprecedented human-induced and irreversible land degradation (Alkama, Cescatti, 2016; Chasia et al., 2021; Newbold et al., 2015).

While studying land transformation processes, it is important to distinguish between two concepts used to describe land i.e., land use (LU) and land cover (LC). Land-use and land cover are related concepts, normally used interchangeably but refer to different aspects of the Earth's surface (Judex & Menz, 2006). Generally, LU refers to the different ways humans utilize land resources such as forestry, crop production, and conservation (Kucsicsa et al., 2019). Conversely, LC encompasses all land uses and refers to all biophysical features of the land surface, such as wetlands, bushlands, rangelands, and forests (Marcos-Martinez et al., 2017; Verburg et al., 2006). Globally, land transformation is usually driven mainly by human activities such as clearing forests for agriculture, settlement, and infrastructural development (Muhati et al., 2018; Newbold et al., 2015). Land cover changes are also driven by natural processes such as natural fires, volcanic eruptions, and soil erosion (Guerra et al., 2020b; Poesen, 2018). To properly manage natural resources, conserve

biodiversity, and prevent environmental destruction, it is important to understand these processes. The use of Earth observation satellites and geospatial mapping technologies have supported many programs aimed at monitoring and analysing LULC changes over space and time (Chasia et al., 2021; DeFries et al., 2007; Friedl et al., 2002). The outputs from such studies have supported conservation programs and land-use policies in many parts of the world (Cegielska et al., 2018; Noszczyk, 2019).

2.1.1 Global Land-use/cover Changes

The transformation of land in many parts of the world has resulted in many negative consequences such as loss of critical biodiversity, habitat fragmentation, soil erosion, and eutrophication in many freshwater ecosystems (Chasia et al., 2021; Eric F. Lambin, 2006; Newbold et al., 2015). Over the recent past, land-use changes have been associated with global warming and climate change due to the emission of greenhouse gases associated with land-use changes. For instance, studies have shown that LULC changes resulting in soil erosion can influence the spatial distribution, magnitude, and temporal change of terrestrial carbon sources and sinks (Liu et al., 2003; Zhao et al., 2013). Others include deforestation, which reduces carbon intake, and urbanization which creates heat islands, hence affecting local and regional climate patterns (Aksoy et al., 2019; Duveiller et al., 2020; Zhang et al., 2017). Due to the scale of LULC changes and the associated impacts, several global initiatives have been developed to enhance our understanding of land transformation processes to stem the trend in ecological destruction in our planet and promote sustainable development practices (Friedl & Brodley, 2002; Tadesse et al., 2017). The global land cover mapping initiatives, such as International Geosphere-Biosphere Programme Data and Information System (IGBP-DIS), and the Global Land Cover (GLC2000) by the Joint Research Centre, have developed several global land-cover datasets using remote sensing data such as MODIS, AVHRR and Landsat data for mapping hotspot areas experiencing the highest environmental changes (Friedl & Brodley, 2002; Song et al., 2018). Studies have also indicated a steady reduction of tree cover and expansion of cropland and settlement (Potapov et al., 2022).

2.1.2 Land-use/cover Monitoring and Assessment

To streamline and standardize land-use data collection, different land-cover mapping projects have been initiated both at continental, regional, and national scales (Maxwell et al., 2018; Walsh J. Stephen, 2002). The Africover project, for instance, was initiated by FAO, involving twelve

African countries, including Kenya, to create reliable, timely, and location-specific land cover information (Di Gregorio & Latham, 2009; Eric F. Lambin, 2006; FAO, 1997). The final product, among others, included a digital land cover map developed from Landsat 4 satellite at 30 m spatial resolution. In Europe, the CORINE is one of the oldest land cover mapping projects which was started in 1985 to develop a digital inventory of Europe's land cover condition using multispectral image data from Landsat and SPOT (Cegielska et al., 2018; Walsh & Crews-Meyer, 2002). Recently, a higher resolution LULC cover map for the whole world has been developed from Sentinel-2 data at 10 m spatial resolution for 2016 (Phiri et al., 2020). A more detailed global LULC map was developed for 2020 by Esri using a deep learning model to generate a composite of land-use/cover prediction for ten classes (Maxwell et al., 2018).

2.1.3 Land-use/Cover State in the Study Region

Land cover in SMM is mainly characterized by vegetation cover (cropland, mixed forest, shrubs and aquatic vegetation), built-up, open land, water, swamps and barren land (Figure 2-1) (Wasonga & Opiyo, 2018). The major land use types include urbanization, agropastoralism, and conservation. Agriculture is the major land-use activity in SMM, covering more than 60% of the total basin area (Chasia et al., 2021). Focal points for urban developments are mainly concentrated around the border towns of Busia and Malaba. Other pockets of urban development are located along major roads, as well as where key social amenities, such as schools, hospitals and administration offices are found. LULC changes in the study area is mainly characterized by the conversion of forestland and grasslands to cropland, especially on the foot-slopes of Mt. Elgon Forest ecosystem where rich soils present in the area sustains multiple crops (Chasia et al., 2021; Opedes et al., 2022). The expansion of agricultural land has precipitated the problem of soil erosion, especially in the upper reaches which are susceptible to runoff associated with poor land cultivation practices (Karamage et al., 2017). Urbanization has also accelerated the rate of conversion from arable land to built-up land cover. This is mainly attribute to the sustained increase in family size and subsequent subdivision of family land into smaller parcels sizes only suitable for establishing living spaces (Opedes et al., 2022).

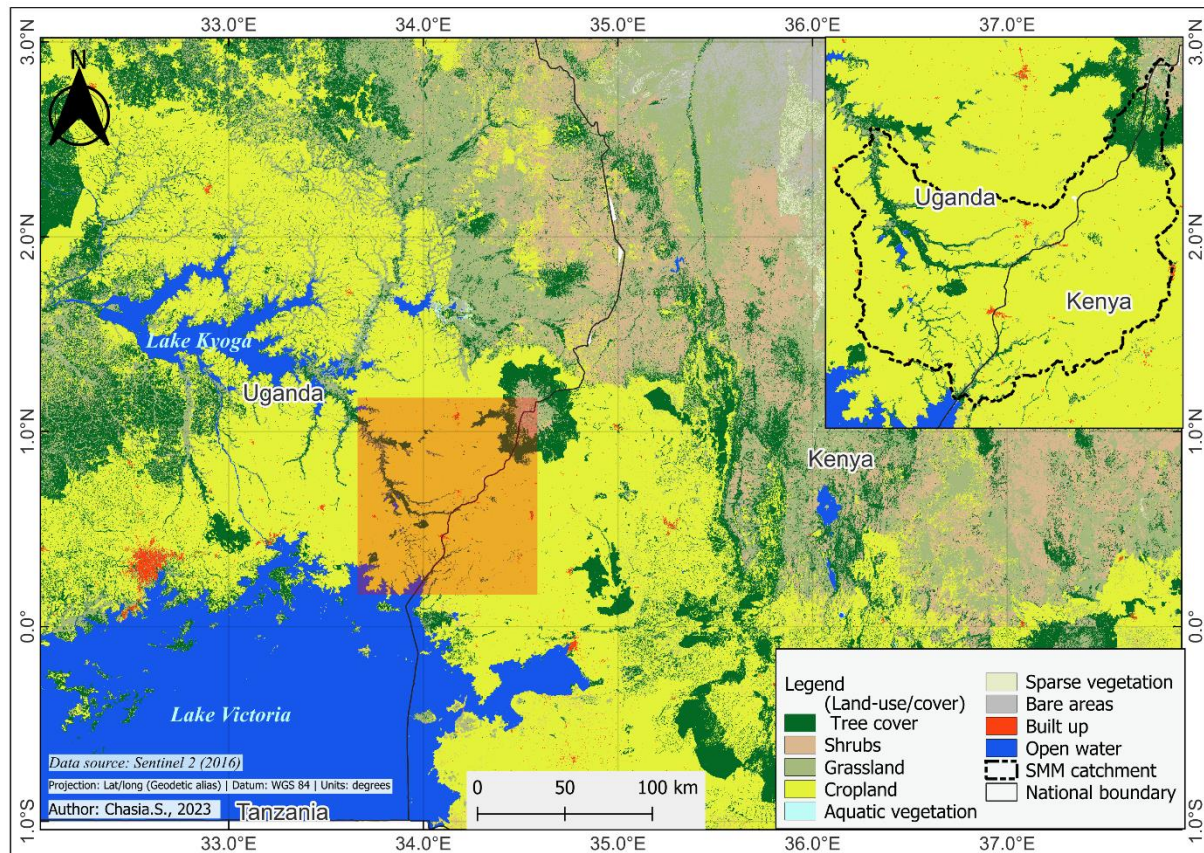


Figure 2-1. Major land-use/cover classes prepared from Sentinel-2A prototype land cover 20-meter map of Africa 2016.

2.1.4 Land-use Legislative Framework

(a) National Land-use Policy – Kenyan Case

The National Land-use policy of Kenya is anchored on *Sessional Paper, No. 1 of 2017*, which outlines the land use in Kenya and the legislative framework (*Sessional Paper No. 01 of 2017 on National Land Use Policy, 2017*). The policy recognizes the interconnection between land use and land cover, and the role of human activities in the alteration of the physical environment leading to land cover changes. Generally, land uses in Kenya include agriculture, industrial, commercial, human settlement, recreational areas, forests, national reserves, and cultural sites among others. The policy acknowledges, however, that the area under forest cover falls below the minimum 10% forest cover required to effectively sustain ecological goods and services and contribute to a reduction in global warming. The loss in forest cover has been occasioned by conversions to other competing land uses such as real estate development, agriculture, and infrastructural development.

Land management in Kenya has been affected by several issues over the past decades which have impacted the implementation of the National Land-use Policy. For instance, the lack of coordination among various state corporations has led to duplication of efforts and entrenched bureaucracy in many government ministries. Furthermore, the existing land use data in Kenya was developed during colonial times and is therefore outdated. Besides, access to this data is limited to only a few institutions that generate this data thus limiting its use (Sessional Paper No. 01 of 2017 on National Land Use Policy, 2017). Other problems identified in the Draft Land Use Policy of Kenya 2016, include the lack of a common definition and standardization scheme for the different land use types in Kenya, the lack of a systematic data collection scheme, challenges in data interpretation, and the lack of a mechanism for the continuous data capturing that reflects changes in land use classes. The policy acknowledges the challenges of managing transboundary natural resources due to conflicting policies and approaches by the stakeholders (Sessional Paper No. 01 of 2017 on National Land Use Policy, 2017). It therefore makes a few recommendations including the enactment of a Land Conservation and Improvement Act to guide land use development, especially in conservation areas, identify and map transboundary resources, harmonize policies and legal framework for environment and natural resource management, and promote bi-lateral agreements that facilitate the sustainable use of trans-boundary resources.

(b) National Land-use Policy - Ugandan Case

Land use policy for Uganda is based on the Uganda *National Land Policy of 2013*, whose contents reflect on the historical background and colonial legacy of Uganda's national land-use policy, land tenure, constitutional and legal framework, including land-use and land management framework, and regional and international framework. Unlike in Kenya, land in Uganda is categorized into private land, public land, and government land. Land fragmentation is one of the challenges facing land-use management, especially in densely populated highland areas (Ministry of Lands, 2013). This is due to the associated negative consequences, such as land degradation and reduced land productivity. However, the government of Uganda has developed strategies to contain this trend such as setting minimum acreage and regulating land subdivision in rural and urban areas. The national land use policy further recognizes the role and responsibilities of Uganda in the conservation of transboundary resources. It sets commitments in implementing international and regional obligations on land-use policy. In particular, the Land use policy acknowledges the

importance of effective management of transboundary resources (Ministry of Lands, 2013). In its policy statement, the country has committed to setting up a participation framework in developing policies and protocols for the management of transboundary resources. However, it is noted that much emphasis is made on the Lake Victoria and Nile Basin catchments at the expense of other smaller catchment areas shared with neighboring countries. Nonetheless, some strategies have been put forward towards the realization of a transboundary resource management framework such as negotiating an integrated management framework, reducing the impact of anthropogenic activities on the environment, and the design of a monitoring mechanism for all the transboundary resources. Others include stakeholder involvement to ensure cooperation and coordination in management.

2.1.5 Land-use Land Cover Change Modelling

Land-use models are mathematical or conceptual frameworks, normally used to understand and predict how land is used in a particular area (Koomen et al., 2007; Van Soesbergen, 2016). They act as tools that support the analysis of the causes and effects of land-use change (Veldkamp & Verburg, 2004) by disentangling the complex suite of socio-economic and biophysical forces that influence the rate and spatial pattern of land-use change (Veldkamp & Verburg, 2004). Land-use models have therefore been used by both researchers in exploring the dynamics and drivers of land-use/land cover change (Agarwal et al., 2002), and policymakers, including decision-making agents, to help in understanding how land is being used in a particular area, and how it might be used in the future (Lambin et al., 2001).

Generally, land-use models can be classified based on the methodology used, the assumptions of the model, spatial or geographic extent, and the model's data requirements (Michetti, 2012; Van Soesbergen, 2016). (Agarwal et al., 2002), developed a framework to categorize and review land-use models based on the level of human-environmental dynamics, model scale, and spatial resolution/extent of a model. The human-environmental models highlight the interplay between the spatiotemporal dynamics in biophysical and human processes and their influence on decision-making (Wang et al., 2021). The model scale, on the other hand, looks at the duration of a model, which is the length of time the model is applied or the time step, representing the smallest unit of analysis for change. The resolution could be represented by a cell in a raster grid system while the extent describes the total geographic area to which a model is applied (Agarwal et al., 2002).

Models, however, are faced with various constraints among which is the availability of data for validation (van Vliet, 2013). Models with significant amounts of primary data are constrained in extent and duration (Agarwal et al., 2002; Schneider & Gil Pontius, 2001). There is also duplication of efforts where models addressing similar systems are developed independently which requires considerable documentation (Van Soesbergen, 2016).

The process of calibrating land-use models involves several iterative steps by adjusting the model's parameters to match observed or mapped data on land-use/cover patterns in a given region (Noszczyk, 2019; Tekwa et al., 2021). Generally, before using a particular model, the model's objectives and scope have to be defined (Agarwal et al., 2002). This involves defining the spatial and temporal parameters of the region, selecting model parameters relevant to the geographical region, and preparation of land cover maps (Van Soesbergen, 2016). Further, before running the model, the initial model parameters have to be set based on expert knowledge and previous research (Koomen et al., 2007; van Vliet, 2013). The model is then run using the initial parameter values defined, and thereafter the model's output and the observed or mapped data (Van Soesbergen, 2016). To evaluate the model performance, the model's outputs are compared to observed data to assess the precision and sensitivity of changes in parameter values (Congalton et al., 2014; Gil Pontius Jr. & Schneider, 2001). Thereafter, parameter values are adjusted to improve the model's performance and ensure they match observed data within an acceptable degree of accuracy. This process is iterative until the model's outputs match the observed data. This therefore ensures that the model is well-suited for prediction and scenario analysis.

In the study region, due to a lack of research infrastructure and limited funding, there have been very limited studies on land-use modelling. Other challenges include poor data quality, such as hydrometeorological datasets, and the complexity of many modelling frameworks which are designed mainly for countries in the global north (Omonge et al., 2022). However, some studies in the region have attempted to model land-use conditions using different approaches. Serneels & Lambin, (2001) for instance, used a spatial statistical model that applies a multiple logistic regression model to identify the driving forces of land-use changes in the Mara Ecosystem of Kenya. Their study demonstrated that the spatial distribution of the different LULC types could be modelled based on the cultural and physiographic properties of the area. However, such a model could not account for potential future land-use changes based on dynamic socio-economic driving factors. On the other hand, using a spatially explicit CLUEs land-use model, and scenarios of land-

use change, Schulp et al., (2019) demonstrated the potential of land-use models to produce future land-use/cover configurations under different scenarios. However, due to the complexity of the data preparation procedure and the problem of data scarcity, the application of land-use models remains a challenge (Chasia et al., 2023).

2.1.6 The Soil Erosion Process

Soil erosion is defined as the process by which soil is displaced by both natural and human-induced factors. It occurs when the protective layer of the topsoil is washed away, leaving the subsoil exposed (Borrelli et al., 2021). Soil erosion is a significant environmental issue worldwide, and is known to be the driver of land degradation and associated negative impacts, such as loss of soil fertility and the consequent overall reduction in agricultural productivity and net yield, sedimentation, and slope instability (Abdulkareem et al., 2019). Additionally, soil erosion is known to cause major degradation of key ecosystems, while high concentrations of nutrients and sediment load from agricultural fields usually alter water quality endangering the fragile aquatic life (Waturu et al., 2023). Further, tillage-induced erosion contributes to the emission of carbon dioxide (approximately 1Gt C/year) (Lal, 2005) thus contributing to the warming of the planet.

Water erosion is the most common form of soil erosion, mainly caused by rainfall, runoff, and the overland flow of rivers and streams (Van Oost et al., 2000). It is usually triggered by heavy raindrops that dislodge soil particles which are subsequently carried by flowing water resulting in gullies. It is particularly common in areas characterized by intense and prolonged rainfall, steep slopes, and inadequate vegetation cover (Poesen, 2018; Raza et al., 2021). Water erosion is categorized into three main groups: sheet erosion, rill, and gully erosion. Sheet erosion occurs when a thin layer of soil is gradually removed from the surface by the impact of rainfall and runoff (Ebabu et al., 2022). Rill erosion, on the other hand, occurs when small channels (rills) are formed due to the concentration of water flow (Poesen, 2018). It mainly occurs on sloping terrain and is usually more noticeable than sheet erosion. Gully erosion happens when water flow concentrates into well-defined, deep channels (gullies) (Poesen, 2018; Vanmaercke et al., 2021). These gullies can be several meters deep and can pose a significant threat to soil and land stability. Figure 2-2 illustrates prevailing erosion in the study area, including sheet erosion (Figure 2-2: b) and severe gulley erosion (Figure 2-2: d).

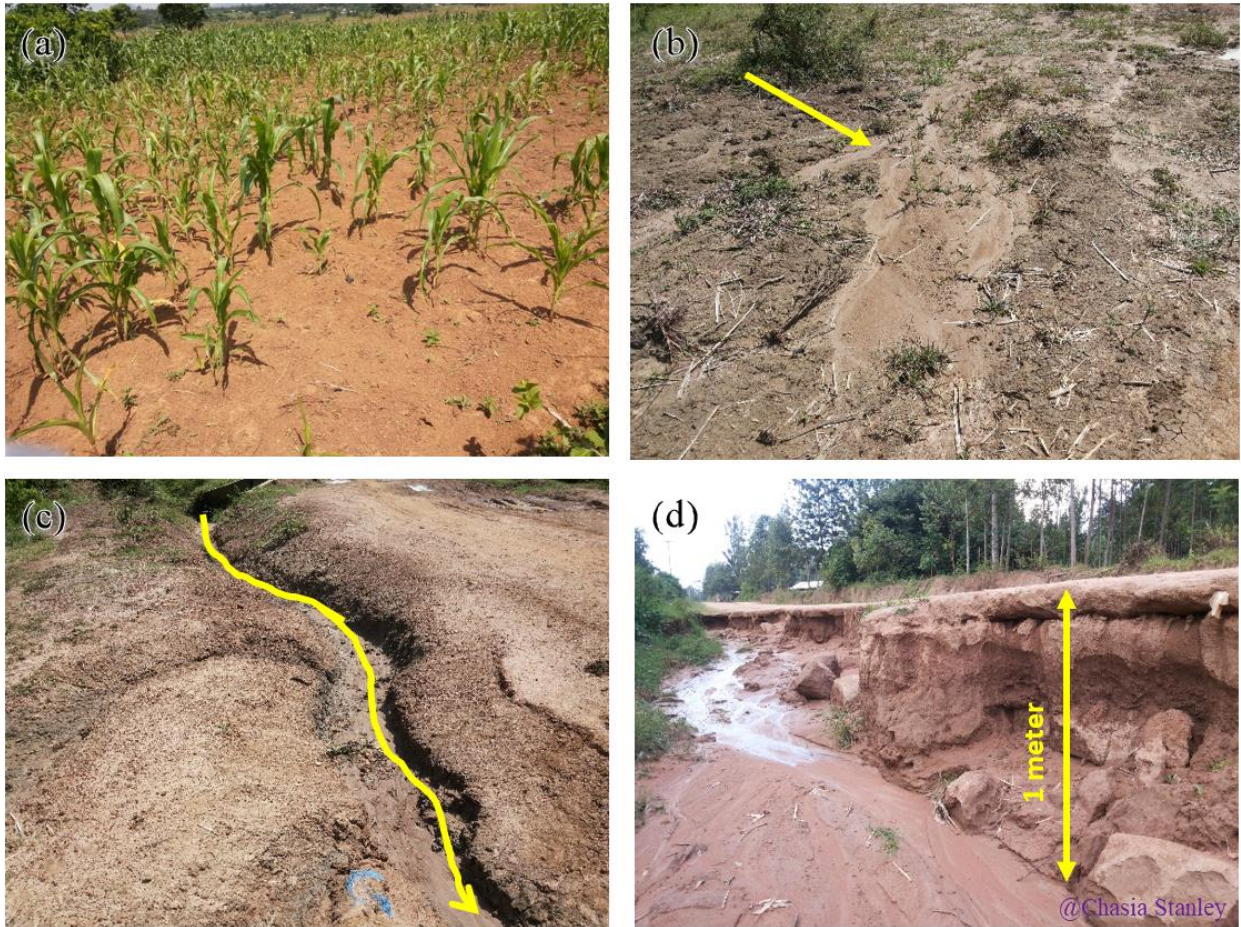


Figure 2-2. Gradual development of the erosion process: a) unprotected cropland soil, b) development of sheet erosion, c) initial stage of gulley, d) advanced stage of gulley development

Soil deposition occurs in lower-velocity areas when the water loses the energy to carry the eroded soil particles (Doetterl et al., 2016; Pelacani et al., 2008). Larger and heavier particles usually settle more quickly, while smaller particles can be carried over longer distances before being deposited (Figure 2-3). The deposition of particles is normally influenced by factors such as the velocity and energy of the transporting agent, the size and density of the sediment particles, and the nature of the landscape (Wu & Chen, 2012; Yao et al., 2023).

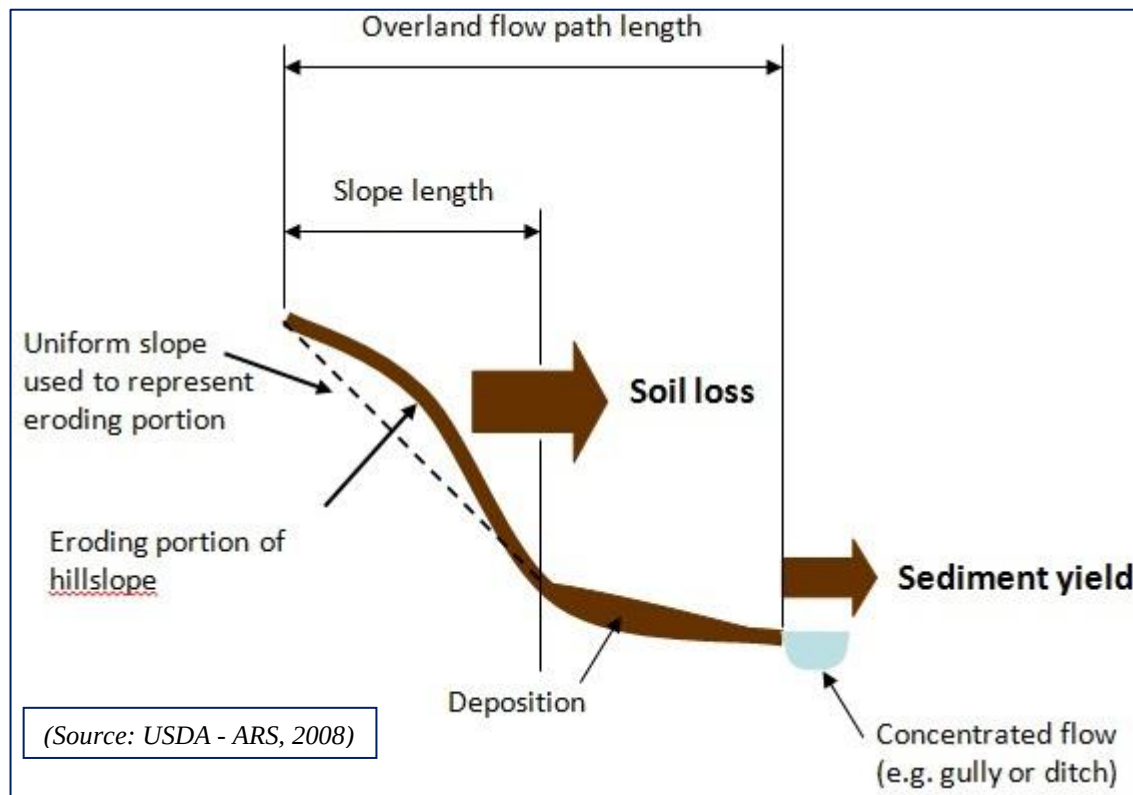


Figure 2-3. An illustration of erosion and deposition process on a uniform slope

2.1.7 Global Assessment of Soil Erosion

Soil erosion assessment is usually conducted to understand the magnitude, patterns, and drivers of soil erosion across different regions and landscapes (Allafta & Opp, 2022). It therefore provides valuable information needed for developing strategies for soil conservation and sustainable land-use practices, by identifying regions at high risk of erosion to guide efforts to conserve soil resources (Gelagay & Minale, 2016). Globally, several studies and assessments have been conducted before to improve our understanding of soil erosion on a global scale and help mitigate the impacts on ecosystems and food security (Guerra et al., 2020b). The GLASOD for instance, is one of the earliest global soil erosion assessments conducted by UNEP and ISRIC, which provided a comprehensive overview of soil degradation processes across different regions of the world (Vagen Tor-Gunnar, Winowiecki, 2019). The Global Soil Biodiversity Atlas, on the other hand, provides a detailed assessment of soil erosion worldwide, including estimates of soil erosion rates and erosion hotspots across the globe using soil erosion models and high-resolution satellite imagery (Orgiazzi et al., 2016).

Generally, soil erosion monitoring involves the use of modelling tools capable of combining different physical parameters of soil erosion to derive information on soil erosion rates and patterns. These models are usually mathematical representations of processes that occur during erosion (Pandey et al., 2016). They thus help in the investigation of the physical and mechanical processes governing erosion and identifying high-risk areas (Tamene & Vlek, 2008). Soil erosion models are based on defining key driving factors, and relating them to soil using observation, field measurements, experiments, and statistical techniques (Evans, 2006), for estimating soil loss caused by destructive land-use activities and poor land and soil management practices (Karamage et al., 2017).

The growth and development of erosion models have been driven by several needs, such as conservation management, project evaluation, and the realization that it's not practically possible to measure the occurrence of soil erosion at every point in the landscape (Evans, 2006). Several soil erosion models have been developed so far, including empirical, conceptual, and physical models (Borrelli et al., 2021). Empirical models are based on the statistical relationship between soil loss and known potential driving factors such as precipitation, soil physical and chemical properties, and prevailing land-use activities (Batista et al., 2019; Merritt et al., 2003). Conceptual models are premised on the representation of physical processes that occur during erosion (de Vente & Poesen, 2005; Santos et al., 1998). Physical models, on the other hand, operate under the laws of physics when simulating processes that occur during erosion (Kumar et al., 2016; Merritt et al., 2003). Some commonly used soil erosion models include the Revised Universal Soil Loss Equation (RUSLE) and its derivatives, the Water Erosion Prediction Project (WEPP), and the WaTEM/SEDEM model (Pandey et al., 2016).

2.1.8 Soil Erosion Management Strategies

Successful soil erosion management strategies require an integrated approach that considers soil characteristics and landscape conditions within a given area, water management options, and land use planning, to effectively preserve soil resources and achieve long-term sustainability (Evans, 2006). Effective soil erosion management aims to maintain and preserve soil fertility and promote sustainable land-use systems that reduce sedimentation and protect critical ecosystems. Different soil erosion management options exist today including conservation tillage, contour farming, terracing, erosion control structures such as retaining walls and grassed waterways, cover cropping

and sustainable land management practices such as crop rotation, agroforestry, and agroecology, and integrated watershed management (Ebabu et al., 2022; Karamage et al., 2017). However, the implementation of these soil management strategies suffers from several challenges based on the geographical region, socioeconomic conditions, and existing land-use practices. Generally, the limited understanding of the importance of soil conservation and sustainable land management practices, limited investment infrastructure, lack of institutional support and capacity, and land tenure system are some of the challenges common in many areas. Others include lack of technical expertise and training, social and cultural factors, such as traditional practices, social norms and attitudes, and climate change and environmental variability can exacerbate soil erosion risks and hinder the adoption and effective implementation of soil management practices.

2.1.9 Transboundary Water Resource Management

(i) Global Perspective

Water scarcity is a global challenge. Its quality and quantity are increasingly being affected by the steady increase in global population (Uitto & Duda, 2002). The projected population growth, coupled with changes in living standards is projected to significantly increase per capita water use (Uitto & Duda, 2002). Further, the demand for food has resulted in an intensification of irrigated agricultural practices for cultivating high-yielding crop varieties that demand more water. The impacts of global warming and climate are becoming more evident in many parts of the world. Climate change projections in sub-Saharan Africa, for instance, point to a warming trend, particularly in the inland subtropics (IPPC, 2007; Serdeczny et al., 2017). Precipitation deficits are likely to affect water flows in some of the major rivers leading to water diversion for agricultural use. This potentially could cause upstream conflicts, especially in areas with a shared water resource.

(ii) Regional Perspective

With over 80% of land area in sub-Saharan Africa located in transboundary watersheds, allocation and management of these water resources remains one of the major challenges due to weak governance, inadequate capacity, and lack of commitment (Robert Rangeley, Bocar M. Thiam, Randolph A. Andersen, 1994). In addition, there is a lack of an integrated water resources management plan (Igad, 2007). Unilateralism in the management of shared water resources often produces conflicts with negative impacts on the biodiversity and livelihoods of the basin dwellers.

These effects are often felt differently by upstream and downstream users. Where water is used to compete across a shared water resource, the establishment of agreed laws governing water resource allocation and management across national borders would help avert conflict while ensuring the sustainability of the shared resource (Brels et al., 2008b). Cooperation among the countries and stakeholders ought to be based on scientific evidence and the analysis of the potential problems and opportunities that would lead to solutions and shared benefits (Uitto & Duda, 2002). Other proposed solutions include the setting up of a joint fact-finding mission, establishing strategic actions the nations involved should undertake, and the establishment of an institution for periodic review and evaluation of progress (Uitto & Duda, 2002). Towards achieving these goals, there is an existing draft memorandum of understanding, midwifed by IGAD for the joint management of the Sio-Malaba-Malakisi basin between Kenya and Uganda (IGAD, 2019). The African Union also in its Convention on the Conservation of Nature and Natural Resources, expects member states to adopt measures for the conservation and management of land resources including soil and any transboundary resource in a way that averts conflicts and guarantees maximum benefits to all the stakeholders (African Union, 2017).

2.2 Conceptual Framework

The conceptual framework adopted for the study is illustrated in Figure 2-4. First, historical land cover changes were analyzed using satellite remote sensing to identify land-use changes in the basin over the past thirty years. Future land-use changes were also evaluated in a land-use model by integrating biophysical and socioeconomic factors that influence land cover changes in a GIS. A process-based model was then used to simulate erosion and deposition patterns using land-use maps derived from simulating future land-use change scenarios. The output was used to highlight soil erosion vulnerable areas. This information is important for developing sustainable land and soil management policies for the transboundary catchment area.

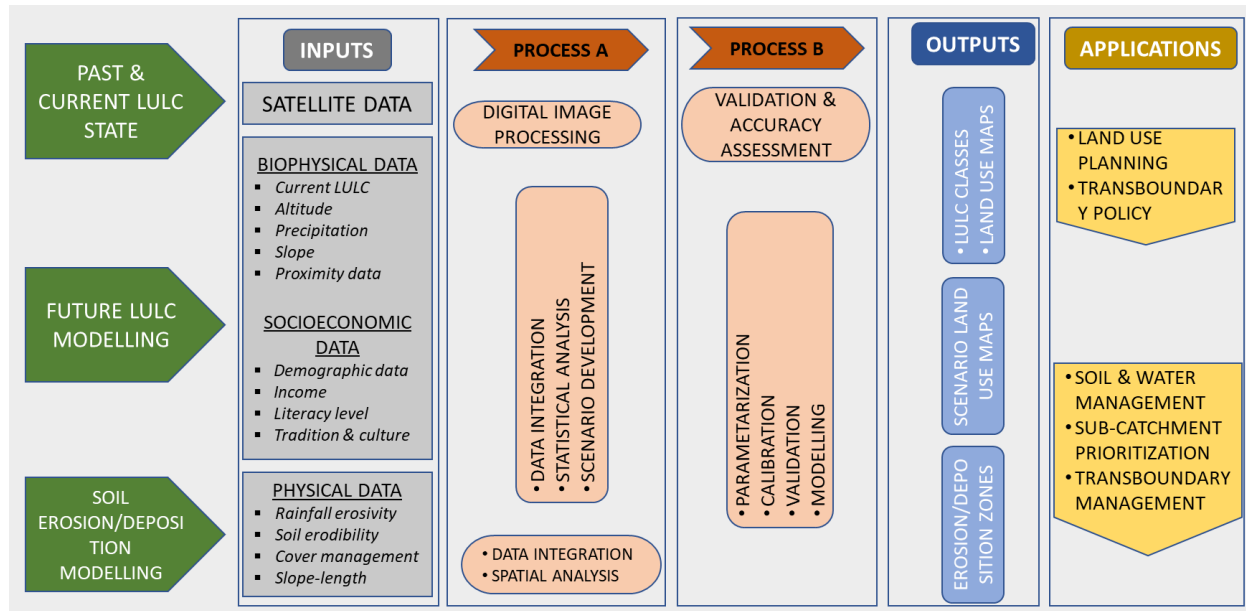


Figure 2-4. Conceptual framework illustrating land use analysis, future land use modelling and erosion and deposition patterns modelling

The following sections highlight the theoretical foundation of different key elements in the methodology underpinning land-use change. This includes the theories on land use change, land use modelling, and the erosion and deposition process, integrating land-use change and soil erosion, and concludes by discussing the policy implications of the study.

Conceptualizing Land Use Change

Several theories exist explaining land-use change patterns such as the Land Rent Theory (Irwin & Geoghegan, 2001) which suggests that land-use changes occur as a result of varying land rent values across different land uses. It thus emphasizes the economic factors driving land-use decisions, such as the profitability of different land uses and the competition for different land uses. Land Suitability Theory (Qiu et al., 2014) on the other hand postulates that land-use changes are influenced by the inherent suitability of land for different purposes. It thus considers biophysical factors, such as soil fertility, slope, water availability, and ecological conditions as key factors that determine the appropriateness of land for specific land uses. The other theory of Institutional Change highlights the role of institutional factors, including property rights, land tenure systems, and governance structures in shaping land-use change (Coral et al., 2021). It, therefore, emphasizes the social, political, and cultural dimensions that influence land use decisions and land management practices.

Land-use change (LUC) can be conceptualized based on patterns, drivers, land-use trajectories, impacts on the ecosystem, and the spatial and temporal scale (Claessens et al., 2009). Spatial patterns of LU involve analyzing the spatial distribution of different land-use types and how the changes have occurred over time (Wang et al., 2021). Temporal patterns examine the temporal dynamics of land use change, including the rates, frequencies, and durations of changes (Chasia et al., 2021; Olang et al., 2011). LU change can be driven by natural factors or human activities. Land-use trajectories explore conversions such as natural land to agriculture and reforestation. It also involves analyzing the drivers and feedback loops that contribute to specific land-use trajectories (Chasia et al., 2023). LUC can also be conceptualized in terms of the impacts on ecosystem services, such as biodiversity, carbon sequestration, water regulation, and soil fertility (Falcucci et al., 2007; Newbold et al., 2015). Here, the effect of different LU transitions on the provision of ecosystem services is investigated, including trade-offs and synergies between different land uses and ecosystem services (Reyers et al., 2009). LU can also be studied by considering the spatial and temporal scale at which land-use change occurs. Patterns in LU change are usually analyzed at local, regional, and global scales (Malek et al., 2018).

(a) Land Use Modelling

The theoretical foundations of land use modeling include the categorization of LU models, such as Cellular Automata, agent-bases, integrated, land suitability, and econometric land use models. Cellular Automata (CA) models are based on the principles of local interactions and spatial dynamics (Jazouli et al., 2019). They simulate land use change by dividing the study area into cells and applying transition rules that govern the conversion of land use types based on neighboring conditions and specified parameters. Agent-based models, on the other hand, represent individual actors with defined attributes, behaviours, and decision-making processes (Matthews et al., 2007). They therefore capture the interactions and decision-making processes of multiple agents with a spatial context, thus enabling the simulation of emergent land use patterns and changes. Integrated land-use models aim to capture the complexity of land-use change by integrating multiple factors and processes, including socioeconomic, environmental, and policy variables (Noszczyk, 2019). They often combine elements from different modelling approaches to provide a holistic understanding of land use dynamics and their interactions with other systems. Land suitability models assess the appropriateness of land for specific land uses based on a range of biophysical

and socio-economic factors (Raza et al., 2021). Econometric models on the other hand analyse land use change from an economic perspective by utilizing economic theories and statistical techniques to quantify the relationship between land use decisions and various economic variables (Van Soesbergen, 2016).

(b) Soil Erosion and Deposition

Several soil erosion models have been devised and used in previous studies to estimate the annual rate of erosion in a given area. One of the earliest and widely used theoretical frameworks for estimating soil erosion rates is the USLE and its other derivatives, such as RUSLE and MUSLE (Renard et al., 2011). These models incorporate factors such as rainfall erosivity, soil erodibility, slope length, slope steepness, cover management, and conservation practice to predict soil loss in a given area. The revised RUSLE provides a more comprehensive estimation of soil erosion rates by accounting for a broader range of variables and their interactions, such as climate change, soil organic matter content, and topographic complexity (Allafta & Opp, 2022; Panagos, Borrelli, Poesen, et al., 2015). Sediment transport models, on the other hand, focus on the process of sediment movement and deposition in water bodies. These models incorporate hydrological factors, sediment characteristics, and hydraulic conditions to simulate sediment transport and predict the spatial distribution of sediment deposition (Aksoy et al., 2019).

(c) Integrating Land-Use Change and Soil Erosion Models

Integrating land-use change and soil erosion models involves incorporating the dynamics of land-use change into soil erosion models (Jazouli et al., 2019; Sharma et al., 2011). This is aimed at allowing a more comprehensive understanding of the interactions and feedback between land-use change and soil erosion processes (Mitasova & Mitas, 2011). The current study first selected suitable models for both land-use change modelling and soil erosion modelling based on the objectives. Input data was obtained and analyzed including land cover maps, land-use change scenarios, soil and topographical data, etc. Two models were spatially aligned to ensure that the spatial frameworks of both models were compatible. This was achieved through resampling and reprojecting data to match the desired resolution, extent, and coordinate system (Chasia et al., 2021). The results were then analyzed and interpreted after they were validated using observed data and field measurements.

CHAPTER 3

Analysis of Historical Land-Use Cover Conditions

This chapter provides the analysis steps and findings of the first objective of study. The outline of this chapter is based on published work provided in *Appendix H (Manuscript 1 - <https://doi.org/10.1080/19376812.2021.2007143>)*. First, some background information related to studies of land-use/cover changes are introduced. Thereafter, the methodology used for assessing the past land-use/cover conditions for the catchment is described, including a selection of satellite data used, the choice of important LULC classes for study and classification and validation techniques. Finally, results of the classification process that discerned the historical states of the land-use conditions are presented.

3.1 Introduction

Human-induced processes often leading to changes in land-cover conditions continue to render many landscapes susceptible to accelerated land degradation across the globe (Abdulkareem et al., 2019; Briassoulis, 2019). While such changes are predominantly at localized scales, their cumulative effects have important feedbacks on regional climate and desertification (Briassoulis, 2019). Adverse land-cover changes are often pervasive, exacerbating not only changes in climate through global warming but also degradation of detracted lands through decrease in soil organic carbon (Yigini & Panagos, 2016), loss of biodiversity and terrestrial habitats (Liping et al., 2018), and negative effects on hydrology and water resource systems (Guzha et al., 2018; Olang et al., 2011, 2014). Consequently, several global studies, coordinated through global environmental accords have attempted to quantify and assess the effects of land-cover changes with a view to providing information to support environmental conservation and management at various scales (Ban et al., 2015; Falcucci et al., 2007). The Africover¹ and the Global Land Cover mapping projects exemplify such global initiatives (Ban et al., 2015). However, their lumped spatial coverage, coupled with inconsistent updates with time (Vancutsem et al., 2013), still limits their applications for hydrological impact assessment at localized scales.

In sub-Saharan Africa, land-cover changes are mainly driven by human activities, and often observed in areas characterized by rich fertile soils and high population density (Guzha et al.,

¹ A United Nations project which collects and collates geographical information on Africa using satellites

2018). Such areas attract agricultural practices from the rural population seeking a living through subsistence farming. This ultimately exerts pressure on the land resources as the demand increases exponentially with increasing population (Roussel, 2012). In East African regions, studies have shown that land degradation is eminent in the highland regions with predominantly steep elevation (Roussel, 2012). For most regions however, there is limited information about the land-cover changes at finer time-scales to enable associated environmental impact assessments. Also, considering that the changes in land-cover are largely subtle and highly dynamic in space and time, an updated inventory at sub-decadal timescales could help detail the change trajectories thereby supporting timely adoption of appropriate soil and water management strategies. Many times, the impact of such land-use changes in the region is often manifested through soil erosion and sedimentation on streams and water bodies (Olang et al., 2011; Schürz et al., 2020).

In regions of data scarcity generally (Mengistu & Waktola, 2016), quantifying and understanding potential changes in land-use require the application of spatial models built using physically-based datasets obtained through rigorous fieldwork procedures. In this regard, satellite-based datasets have found wide applicability across the globe for various studies on historical land-cover states. For instance, (Midekisa et al., 2017), mapped land-cover changes for the African continent using Landsat data to quantify and monitor spatiotemporal land-cover dynamics critically required to support policy towards better resource management. Similarly, (Sano et al., 2010) used Landsat data to map the tropical savanna in Brazil in order to support conservation efforts and sustainable resource use. In the East African region, (Brink et al., 2014) used Landsat to monitor land-cover changes for a 20-year period, while (Muhati et al., 2018) in a similar study characterized land-use changes in the sub-humid montane forest of Kenya. (Olang et al., 2011; Omondi & Musula, 2011), also analysed spatiotemporal land-cover changes in Kenya with a view to assessing its spatiotemporal dynamics for potential impacts on overall hydrology of the regions.

To date, several methods used to classify satellite data have been documented in different studies. (Kiage et al., 2007), for example, used the Interactive Self-Organizing Data Analysis (ISODATA) algorithm to map land degradation in a semi-arid area characterized by complex vegetation and topography, obtaining overall classification accuracy of 87.3%. Similar accuracy levels were obtained by (Were et al., 2013) using a similar method. (Muhati et al., 2018) on the other hand, applied a hybrid approach, combining unsupervised (K-means) classification algorithm and the maximum likelihood function where they obtained overall classification accuracy of 87%. In all

the methods outlined, the hybrid classification approach produced the desired accuracy levels when applied on optical remote sensing data. This approach was therefore adopted in our study due to its ability to accurately discriminate heterogeneous land-cover classes, a characteristic prevalent in Sio-Malaba-Malakisi (SMM) catchment.

In order to obtain realistic and acceptable accuracy levels, an assessment of classified results against ground-based data is necessary (Lu & Weng, 2007). For near real-time analysis, the requisite number of ground reference test samples can be obtained using different methods i.e. binomial probability theory (Coulter et al., 2016). However, in some regions in developing countries where no consistent inventory of land-cover database exist (Wasige et al., 2012), indigenous knowledge can be used for plausibility checks and augment the validation of such classification involving historical data (Hoover et al., 2017; Zaehring et al., 2018). It should be noted however, that such indigenous knowledge may not provide sufficient information comparable to empirical datasets but may be used to reconstruct the past land-cover state. (Eddy et al., 2017) for instance, integrated local ecological knowledge and remote sensing in monitoring rangelands and watershed studies respectively, and obtained results that showed a strong agreement between local knowledge and classified results. (Hoover et al., 2017) and (Zaehring et al., 2018) also recorded a marked improvement in the overall accuracy when participatory remote sensing augmented the classical remote sensing methods.

In land-cover studies, change detection is an important procedure for revealing qualitative and quantitative transformations of the landscape by comparing changes between two or more time series data (Asokan & Anitha, 2019). Different change detection methods are available and employed based on (1) their suitability to detect spatiotemporal changes in Land-use/Land Cover (LULC) and (2) the overall objective(s) of the study (Thenkabail, 2015). For this study, the post-classification comparison change detection method was adopted because it provides detailed “from-to” change information and is less affected by atmospheric interference (Asokan & Anitha, 2019).

3.2 Methodology

3.2.1 Materials and Methods

3.2.1.1 The Selected Land Cover Classes

A total of nine predominant land-cover classes of the study area were chosen *a-posteriori* based on the United States Geological Survey (USGS) Land-Use/Land-Cover Classification System. The USGS system is driven by the interpretation of remotely sensed data obtained at various resolutions and scales (Lillesand T.M., Kiefer R.W., 2015). The system contains classification levels ranging from I-IV based on the spatial resolution of satellite data. For this study, level I was chosen for its suitability in classifying medium spatial resolution satellite data i.e., Landsat TM and Landsat 8 (30x30 m), used in the study. The selection of the land cover classes was based on their potential impact on hydrology and soil erosion in the area (Guzha et al., 2018; Olang et al., 2011; Schürz et al., 2020). Table 3-1 provides the general description of the selected land cover classes of study.

Table 3-1. Land-use/land cover classification scheme adopted from USGS.

Land-cover class	Description
Mixed forest	An area >1 acre dominated by trees with a canopy cover >40% and height >2m.
Cropland	Communities with a mixture of secondary plantations, woodland and deciduous bushland Land covered with temporary/seasonal crops followed by harvest and fallow land. Perennial woody crops are classified as forest or shrub land-cover type.
Pasture	Natural grassland consisting mainly of grasses and glades used normally for grazing
Built-up	Comprises building and other man-made structures i.e., residential, commercial and services, industrial, transportation and communication utilities, mixed urban and built-up land and other semi-permanent structures; impervious surfaces i.e., roads (paved and unpaved)
Permanent wetlands	Composed of non-forested wetlands with permanent mixture of water and woody vegetation, reeds and other aquatic vegetation in freshwater.
Open shrublands	Woody vegetation <2m tall with shrub canopy cover between 10% - 60%. The shrub foliage is mostly evergreen throughout the year.
Open land	Open soil with <10% vegetation cover throughout the year.
Water	Areas of open water both permanent and seasonal water bodies including lakes, marsh, ponds and river channels with <25% cover of vegetation or soil
Barren	Areas covered by in situ exposed rock outcrops and barren land <10% vegetated during the year.

3.2.1.2 Datasets

(a) Satellite Imageries

Satellite imageries acquired from USGS data archive were used to characterize the land cover changes for the study area. In particular, the Thematic Mapper (TM) Landsat 4 and 5 images for the years 2008, 1995, 1986, and the Operational Land Imager (OLI) Landsat 8 image for 2017 were acquired and used (Table 3-2). Imageries obtained during the cropping season, often between March – May (during the long-rains), and/or October – December (before the onset of short rains), were preferred in order to distinguish between natural vegetation and cultivated land cover classes (Vancutsem et al., 2013). Satellite images with cloud cover of less than 10% were selected to minimize shadow effects that often block land surface condition (Wang et al., 2019) thereby affecting the classification results by enhancing differences in radiometry among similar objects. In cases where imageries with less cloud cover were not available, other Landsat images captured on a date closer to the original image were selected. In overall, to minimize errors during classification and change detection analysis, imageries with less phenological differences were chosen.

Table 3-2. Sensor characteristic of satellite data used to generate land-use/cover maps

Satellite	Sensor	Date	Swath width(km)	Resolution	Cloud cover
Landsat 8	Operational Land Imager (OLI)	14-April-2017	170x185	30m multispectral 15m panchromatic	< 5%
Landsat 5	Thematic mapper (TM)	10-March-2008	170x185	30m	< 10%
Landsat 5	Thematic mapper (TM)	02-April-1995	170x185	30m	< 5%
Landsat 4	Thematic mapper (TM)	09-March-986	170x185	30m	< 5%
Sentinel2	Multispectral Instrument (MSI)	24-June & 01-July- 2017	100x100	10, 20m	< 10%

(b) Reference Datasets

(i) Reference Data - 1986 and 1995 imageries

A participatory mapping technique was used to reconstruct past land-cover state of the catchment using data obtained through targeted focus-group discussions (FGDs) (Zaehringer et al., 2018). Previous studies have shown that qualitative chronological land-cover information can be obtained

by integrating such participatory mapping approaches with empirical methods to generate land-cover data that can be used to support classification in areas of data scarcity (Zaehringer et al., 2018). To generate reference data for 1995 and 1986 classified images, a total of 200 participants drawn from 22 sites (Table 3-3) were randomly selected to participate in the FGD and interview sessions as proposed by (Ramirez Gómez, 2019). To ensure consistency within the periods of study, the discussions largely targeted participants with a long history and experience in the catchments (i.e., more than 50 years of age). Table 3-3 provides details of the sites for the mapping procedure.

Table 3-3. Sites visited to generate training data from a participatory mapping exercise.

Sub-catchment	Country	Site name	Number of participants	Number of polygons
Sio	Kenya	Bumula, Busibwabo, Nangina, Koyonzo	37	20
Malaba	Kenya/Uganda	Chakol North, Iyolwa, Busia, Nabuyoga	36	25
Malakisi	Kenya	Saboti, Amukura East, Ang'urai South, Malakisi, Chesikaki	46	30
Lwakhakha	Kenya/Uganda	Cheptais, Bumbo, Lwandanyi, Ang'urai North, Mella	45	15
Mpologoma	Uganda	Buliisa, Budumba, Iwamba, Nabuyoga	36	33

To orientate participants and help them identify key landmark features during the mapping process, topographical maps at a scale of 1:50,000 for the year 1970 were acquired from the line departments of Survey of Kenya and Uganda. Also, a natural colour Google Earth image depicting physical features in colour was obtained and overlaid on a hill-shade layer derived from a 30m DEM acquired from the Shuttle Radar Topography Mission (<http://srtm.csi.cgiar.org/srtmdata/>) of the area (Thenkabail, 2015). Polygons representing different LULC classes were delineated from the transparent paper overlaid on the printed topographical map and systematically coded using a unique identifier. Attributes of each LULC were noted and later transferred to a spreadsheet file. The reconstructed maps were subsequently scanned, georeferenced and digitized in a GIS (Zaehringer et al., 2018) and their attributes later joined with the land cover layers to form a complete dataset.

(ii) *Reference Data - 2008 and 2017 imageries*

Reference data for accuracy assessment and data for training the classifier were collected and recorded independently, but simultaneously corresponding with the reference imagery dates (June, and July). A stratified random sampling technique was used to acquire reference data for training (Congalton & Green, 2008). For each cluster category from a classified Sentinel 2 image (10 m) using the ISODATA algorithm (Alphan et al., 2009; Memarsadeghi et al., 2007), a minimum number of samples were selected from each stratum (Table 3-4). Conversely, sampling points for accuracy assessment were produced using a random number generator in Erdas Imagine 2015 software. In overall, a total of 6,267 points were marked and visited. During the field survey, more emphasis was placed on points where LULC classes exhibited similar spectral characteristics in order to gain invaluable information that could support the classification.

Table 3-4. Training and accuracy assessment data collected for each sub-catchment area.

Sub-catchment	Area (km ²)	Training assessment	Accuracy assessment
Sio	1,407	1,233	664
Malaba	1,037	932	502
Malakisi	624	368	198
Lwakhakha	592	406	219
Mpologoma	1,528	1,134	611
TOTAL	5,188	4,074	2,193

3.2.1.3 *Satellite Data Processing*

(a) Satellite Data Pre-processing

Figure 3-1 illustrates the workflow used in the study to classify and map land cover changes. Images were processed using Erdas Imagine software® (Erdas 2015), where each scene was independently analysed to minimize errors associated with classifying multi-date images of varied radiometry. Line drops due to detector malfunction present in Landsat 4 and 5 data, were eliminated by averaging values above and below the defective lines (Giri, 2012). The radiometric differences caused by changes in environmental conditions during the acquisition of multitemporal images (Hansen & Loveland, 2012), were normalized using a linear regression model by applying a sun-elevation correction to the images (Lu & Weng, 2007).

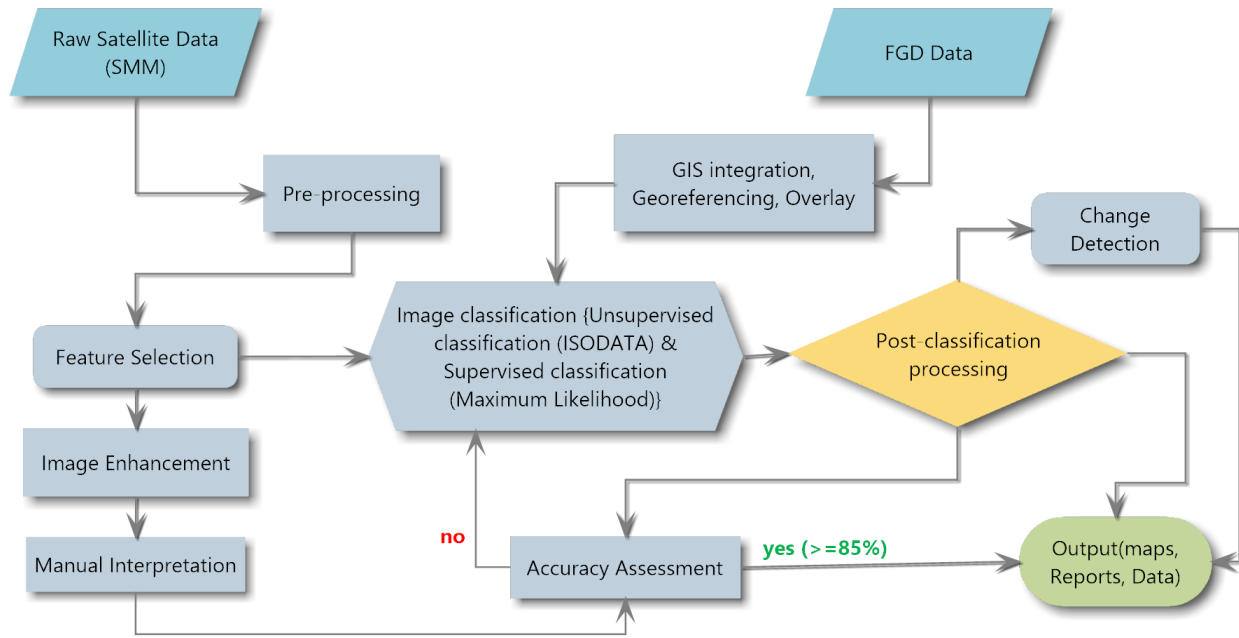


Figure 3-1. Digital image processing workflow integrating qualitative data with remote sensing data.

Topographic normalization was later applied on mountainous regions of the study area to reduce the slope-aspect effects, using a 30 m digital elevation model (Allen, 2000). The final corrected bands were subsequently stacked together into a single composite image for each year of study. Afterwards, the two image composites, each representing a separate scene, were mosaicked together resulting in a single seamless image. The final product was an image of the SMM catchment, obtained by subsetting the mosaicked image. This was the image used for performing classification. The whole process was repeated for all images for the different years of study.

(i) Feature Selection

Training sites for classifying satellite images were prepared using on-screen polygonal selection of training data (Lillesand T.M., Kiefer R.W., 2015), supplemented by *in situ* information from the field. To generate training sites for each land cover class, polygons were digitized around areas of pure pixels within the image belonging to a single class. During the digitization, much care was taken to avoid pixels located along the edges of neighbouring land cover classes which would potentially decrease the accuracy of a given cover class. In addition, areas with a visually “rough” appearance on the image – possibly indicating presence of mixed pixels (Lillesand T.M., Kiefer R.W., 2015; Phiri et al., 2020) were also avoided. To establish the accuracy of class signatures in

identifying land cover classes, a spectral separability analysis was conducted using a scatter diagram, and continuously refined to improve class separability. Training sites with more than one class were either deleted or split apart yielding only pure class signatures. Likewise, edge pixels along the boundaries of some training sets were deleted.

(ii) Image Classification

Considering spatial variability of land-cover types in the SMM catchment, a hybrid of supervised and unsupervised classification technique was used to classify the images. Such a technique is known to improve classification accuracy in regions with heterogeneous landscapes (Badjana et al., 2017). First, the 2017 image was partitioned into 20 clusters using the ISODATA unsupervised algorithm (Lillesand T.M., Kiefer R.W., 2015). Considering the spatial variability, the minimum cluster size was set to 0.01%, with a convergence threshold of 95% that stops the iteration process once 5% or less pixels change clusters between iteration. Similar clusters were merged interactively to form eight classes which were used to define the signature file for the Maximum Likelihood classification function (Mather & Tso, 2010). The final signature file was used to generate a land cover map. This procedure was repeated in all the images. A post-classification smoothing process (Qian et al., 2005) was subsequently applied on the classified images to remove misclassified and isolated pixels belonging to other classes. A pixel majority filter operation was applied on the classified images using a 5x5 moving window to weed-out isolated pixels (Huang et al., 2014). The identity of centre pixels within the window that did not belong to the majority class were changed to correspond to the majority class. This process was repeated for all the classified images until classes with pure pixels were produced.

(iii) Classification Accuracy Assessment

A multinomial probability distribution (Alba-Fernández et al., 2020; Russell G. Congalton, 2009) method was used to determine the sample size needed to generate an error matrix for the classification, with a 95% confidence level. The high confidence level was selected considering the heterogeneity among land cover classes. The sample size N was based on the equation (Congalton & Green, 2008):

$$N = \frac{B\Pi_i(1 - \Pi_i)}{b_i^2}$$

Equation 3-1 – Multinomial probability distribution

where, Π_i is the proportion of a population in the i^{th} class out of k classes that has the proportion closest to 50%, b_i is the desired precision (5%) for the class, B is the upper $(\alpha/k) * 100$ th percentile of the chi-square (χ^2) distribution with 1 degree of freedom, while $k = 9$ is the number of classes. From the equation, a total of 848 samples were randomly selected for the error matrix, translating to a minimum of approximately 106 samples per class. More samples were taken for categories with more variability like cropland and pasture, open land and non-forested wetland (permanent wetland). A stratified random sampling scheme was chosen since it reduces the bias in sampling (Congalton & Green, 2008). The samples were compared with the classified map using error matrices and evaluated using simple descriptive statistics for computing the overall accuracy (see equation 3.2), user's accuracy (see equation 3.3), and producer's accuracy (see equation 3.4), using the formula proposed by (Olofsson et al., 2014).

$$O = \sum_{j=1}^q P_{jj} \quad \text{Equation 3-2 - Overall accuracy}$$

$$U_i = P_{ii}/P_i \quad \text{Equation 3-3 - User's accuracy}$$

$$P_{j=} = P_{ji}/P_{.j} \quad \text{Equation 3-4 - Producer's accuracy}$$

Where, P_{ij} represents the proportion of area of the classified map with class i and reference class j . Afterwards, a discrete multivariate statistical technique was applied to generate the error matrix to estimate the Kappa (Khat) using (Lillesand T.M., Kiefer R.W., 2015):

$$Khat = (Obs - Exp)/(1 - Exp) \quad \text{Equation 3-5 - Kappa coefficient}$$

where, Obs represents overall accuracy results from the error matrix. Exp on the other hand, represents correct classification.

(iv) Change Detection

Two independently produced classified maps representing different temporal periods i.e., 2008 and 2017, were used to detect land-cover changes. In this approach, pixels from classified maps were individually compared to highlight and identify areas that recorded change and those that remained unchanged. Classification results between two time periods i.e. $T1$ -1986/ $T2$ -1995, $T1$ -1995/ $T2$ -2008, $T1$ -2008/ $T2$ -2017, were separately coded in a GIS to produce change maps showing the matrix of change between the years.

3.3 Results

3.3.1 Classification Accuracy Results

The accuracy assessment results obtained from the analysis of the satellite images varied from year to year (Table 3-5). Generally, overall accuracy (OA) and kappa coefficient values improved markedly from 1986 map to 2017 map. The study attributed the relatively low OA values in 1986 and 1995 classified maps to several factors, including the low resolution of the resampled Landsat 4 and 5 data, limited training data, and the effect of mixed pixels among the vegetation classes.

Table 3-5. Overall and kappa accuracy assessment report obtained for classified images

Sn.	Year	Overall accuracy (%)	Kappa coefficient
1.	2017	88.0	0.86
2.	2008	86.7	0.83
3.	1995	84.4	0.81
4.	1986	84.3	0.80

Open land-cover class for the 2017 map recorded the highest producer's accuracy (PA) and user's accuracy (UA) values of 95% and 93% respectively (Table 3-6). Built-up and barren cover classes displayed similarity in spectroscopy, therefore, resulting in misclassification of pixels under the open land category. Areas dominated by vegetation class, i.e., cropland (Cp), pasture (Ps), mixed forest (Mf), and permanent wetland (Pw), recorded UA values ranging between 70% - 90%. The low PA for the barren land cover (78%), was attributed to misclassification of barren land into the built-up and open land cover classes.

Table 3-6. Error matrix from classifying training set pixels

		Reference (Training data set) - 2017										
Classified image (map)		Mf	Pw	Ol	Bu	Wt	Br	Cl	Ps	Os	RT	UA
	Mf	280	15	0	0	1	0	28	2	18	402	81%
	Pw	4	218	3	0	6	0	8	3	7	262	88%
	Ol	0	0	554	23	9	6	0	1	0	602	93%
	Bu	0	0	14	201	2	11	0	0	0	228	88%
	Wt	1	4	7	3	165	0	6	2	2	190	87%
	Br	0	0	5	12	1	61	0	0	0	84	77%
	Cl	13	11	0	0	9	0	445	8	8	470	90%
	Ps	2	6	2	0	3	0	9	42	0	64	66%
	Os	15	6	0	0	6	0	13	2	287	327	87%
CT	315	260	585	239	202	78	509	60	322	2570		
PA	89%	84%	95%	84%	82%	78%	87%	70%	89%	OA	88%	

3.3.2 Land Cover State – 2017

Table 3-7 highlights the proportion of different LULC types in each sub-basin recorded for the 2017 image. In all the sub-basin, cropland was the dominant land-use type, occupying on average 45% of the total sub-basin area. This is followed by open land and built-up occupying approximately 16.34 % and 16.33 % respectively. Pasture land occupied the least area at approximately 0.09 %.

Table 3-7. Cumulative percentages of land cover types

Basin	Country	Mf	Pw	Ol	Bu	Wt	Br	Cl	Ps	Os
Lwakhakha	Kenya/Uganda	26.18%	0.91%	11.13%	17.31%	0.00%	7.63%	33.21%	0.00%	3.62%
Malaba	Kenya/Uganda	3.41%	9.57%	15.48%	16.68%	0.12%	1.36%	48.49%	0.04%	4.84%
Malakisi	Kenya	12.08%	1.61%	14.99%	15.77%	0.00%	6.07%	44.44%	0.43%	4.60%
Mpologoma	Uganda	3.95%	8.14%	14.44%	16.34%	0.83%	0.39%	54.04%	0.00%	1.88%
Sio	Kenya	2.54%	4.31%	25.66%	15.53%	0.00%	0.79%	46.71%	0.00%	4.46%
Total perc. proportion		6.98%	5.78%	17.38%	16.23%	0.27%	2.20%	47.41%	0.06%	3.70%

Areas covered by primary vegetation were mainly found on the north-eastern tip of the catchment, while the upper part of the forest was covered by rock outcrops. Open bush and shrubs were found scattered evenly on the study area, but largely concentrated in the middle part of the catchment where Busitema forest is located (Figure 3-2).

3.3.3 Land Cover State 1986 - 2008

In 1986, open land cover class occupied an area of 172,758ha (34 % of total catchment area), compared to other subsequent years. The study attributed this to the prolonged drought-spell during the 1980s (Awange et al., 2007) affecting large parts of Kenya. However, improvements in weather conditions in the 1990s promoted the regeneration of plant growth and refilling of wetland areas. Consequently, cropland areas expanded gradually during the same period, with the peak growth recorded in the year 2008. Urban areas concentrated on the Kenyan side of the basin did not record visible changes until the early 2000s (Figure 3-2). From 2008, areas located on the north-eastern tip of the basin were mainly under primary forest. However, approximately 1,900 ha of mixed forest land was converted to cropland during that period.

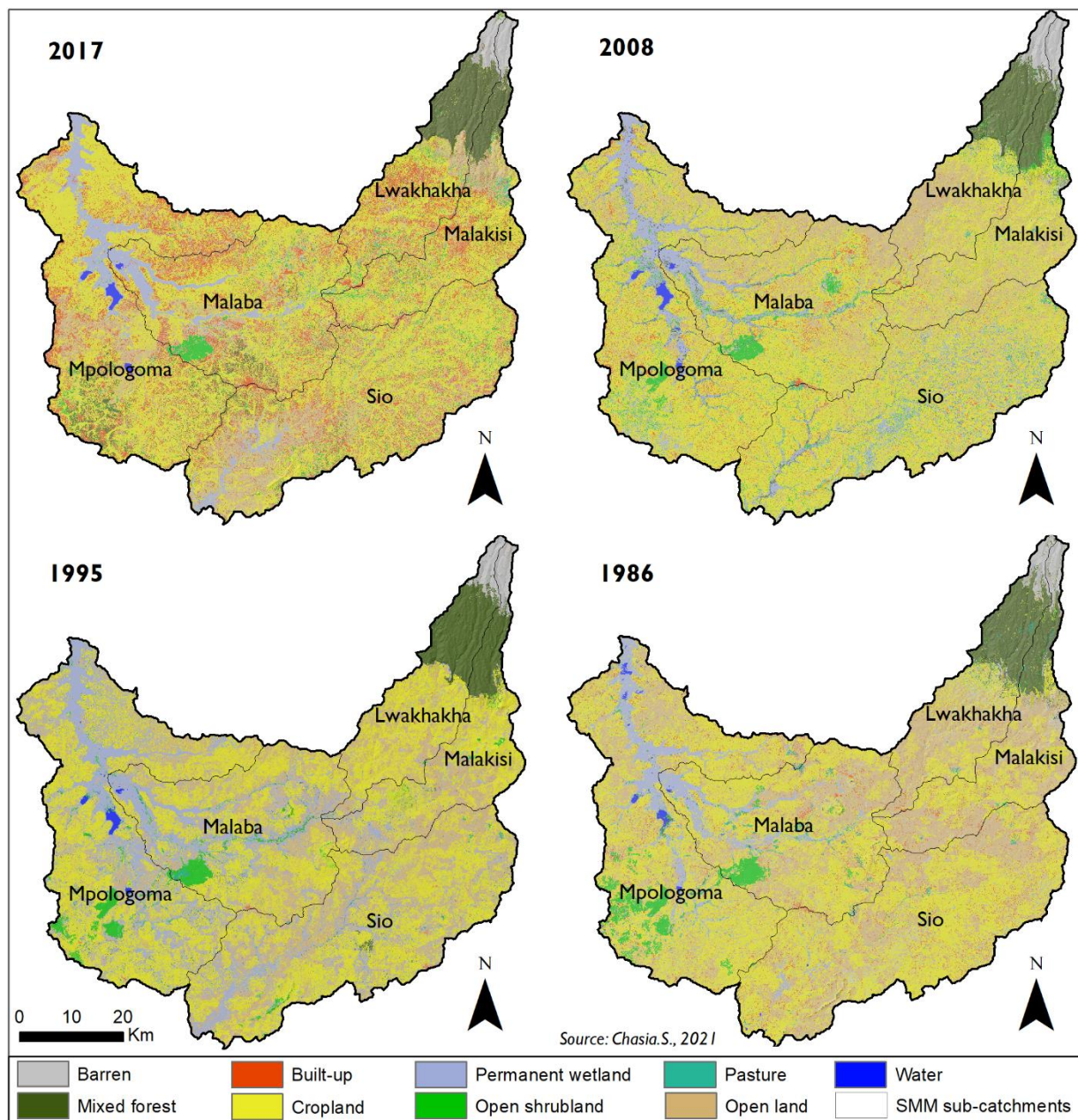


Figure 3-2. Classified land-use/cover maps from the selected classes from 1986 to 2017 for Sio-Malaba-Malakisi catchment.

3.3.4 Land Cover Change Trends and Trajectories

Figure 3-3 illustrates two phases characterizing trends in LULC change in the study area. Phase-I (1995 – 2008), represents a period of expansion and transformation of land cover types, while Phase-II (2008 - 2017) depicts a period of intensification and conversion of land cover types. Overall, mixed forest, open land and open shrubland covers recorded a net reduction in total area

from 1986 to 1995 (Figure 3-3). Generally, increasing and decreasing trends in land-cover classes remained the same over the analysis period.

In 1986, the area under cropland was approximately 164,036 ha, increasing further to 180,101 ha in 1995, representing a 9.8 % increase during that period (Figure 3-3). Most growth in cropland was recorded in the period beginning 1995 – 2008 where it grew by 20.5 %. In the 2008 – 2017 period, it grew further by 24.9 %. These results correspond with Brink et al., (2014), who reported an average growth rate of between 1-1.5 % per annum in the cropland cover type in the East African region.

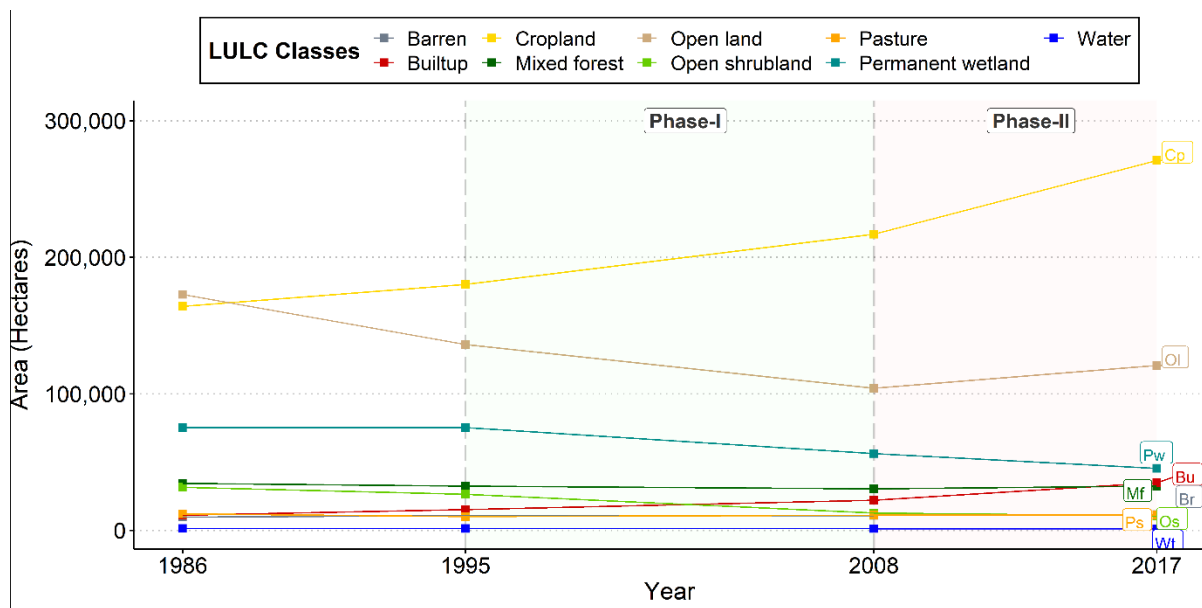


Figure 3-3. Time series trends in land-use/land cover change

Mixed forest LC class stood at 34,422 ha in 1986. In 1995, the area reduced slightly to 32,411 ha and then 30,382 ha in 2008, representing a 5.8 % and 6.3 % reduction respectively. In 2017, however, the area increased by approximately 2,068 ha representing a 6.8 % from 2008. Visible changes under mixed forest class, were mainly observed on the edges of Mt. Elgon Forest Reserve. Areas under the open shrubland category reduced steadily at a rate of 1.6 % p.a. (Figure 3-4). The reduction is depicted in the 2017 map (Figure 3-6), especially in the area around Bugiri in the Mpologoma sub-basin. Here, beginning 2008, a complete patch of vegetation cover appears to have been cleared for other land-use types, mainly cropland.

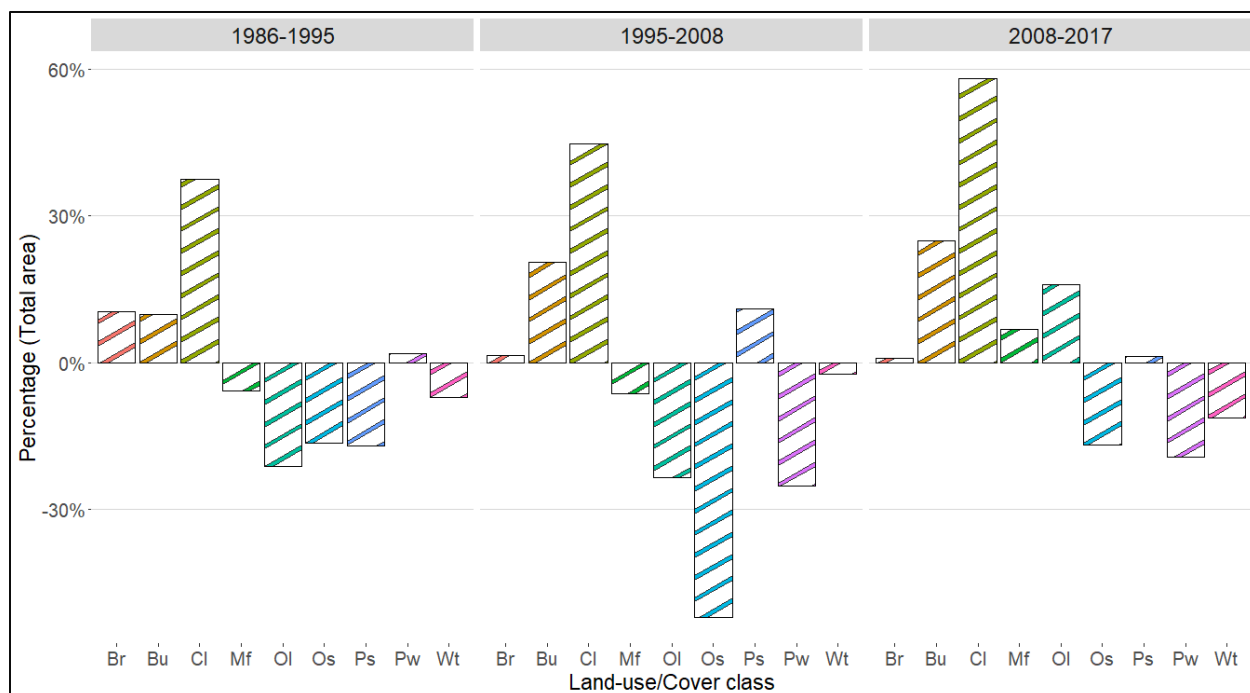


Figure 3-4. Trends in land-use/cover changes representing percentage cover per land-use/cover class for a ten-year period.

In 1986, permanent wetland zones occupied approximately 14.5 % of the total catchment area. By 2017 however, this area had shrunk further down to 8.4 %, representing a 38.5 % loss to other LULC classes. The open land cover category continued to reduce further from the initial area of 172,758 ha in 1986 to 120,783 ha in 2017. In 1986, open land accounted for approx. 33.8 % of the total catchment area. However, by the year 2017, this area reduced to 22.4 % of the total catchment area. Some were converted to built-up due to the gradual urban expansion and growth. In 1986, the total area under built-up land-use type was 11,093 ha. By 2017, this area grew to approx. 34,897 ha, representing cumulatively a 215 % growth for a period of thirty years. The water class remained largely unchanged, with fluctuations in water levels attributed to climatic variability (Figure 3-6).

The upper catchment areas of Lwakhakha and Malakisi were characterized by seasonal crops on small parcels of land (approx. 0.25 ha). As a result, there was an intensification of farming activities, and thereafter, expansion of farmlands into areas on steep slopes, originally covered by forest.

3.4 Discussion

3.4.1 Bitemporal Change Detection

The results from 1986 classification were cross-tabulated against the 2017 map to identify changed areas within the basin. High conversion rates in areas dominated by farming activities were common due to the expansion of agriculture in the catchment. Areas with tree cover (approx. 39.8 ha), mainly on the fringes of Mt. Elgon Forest (Figure 3-5), were converted to farmlands (coffee and maize). However, in 2017, mixed forest class recorded a net increase of 2,068 ha/ ~6.8 % per annum over a nine-year period, a trend attributable to on-farm tree plantations. Cumulatively, approximately 110,002 ha of land previously under open land cover category, from 1986 to 2017, and with potential for agriculture, was converted to cropland, which corresponds with the steady growth in human population increasing the demand for food. The expansion of urban areas was gradual and mainly concentrated on the border towns of Busia and Malaba (Fig.3-6). Small towns and market centres serving regions located on the edges of the basin also grew over the same period.

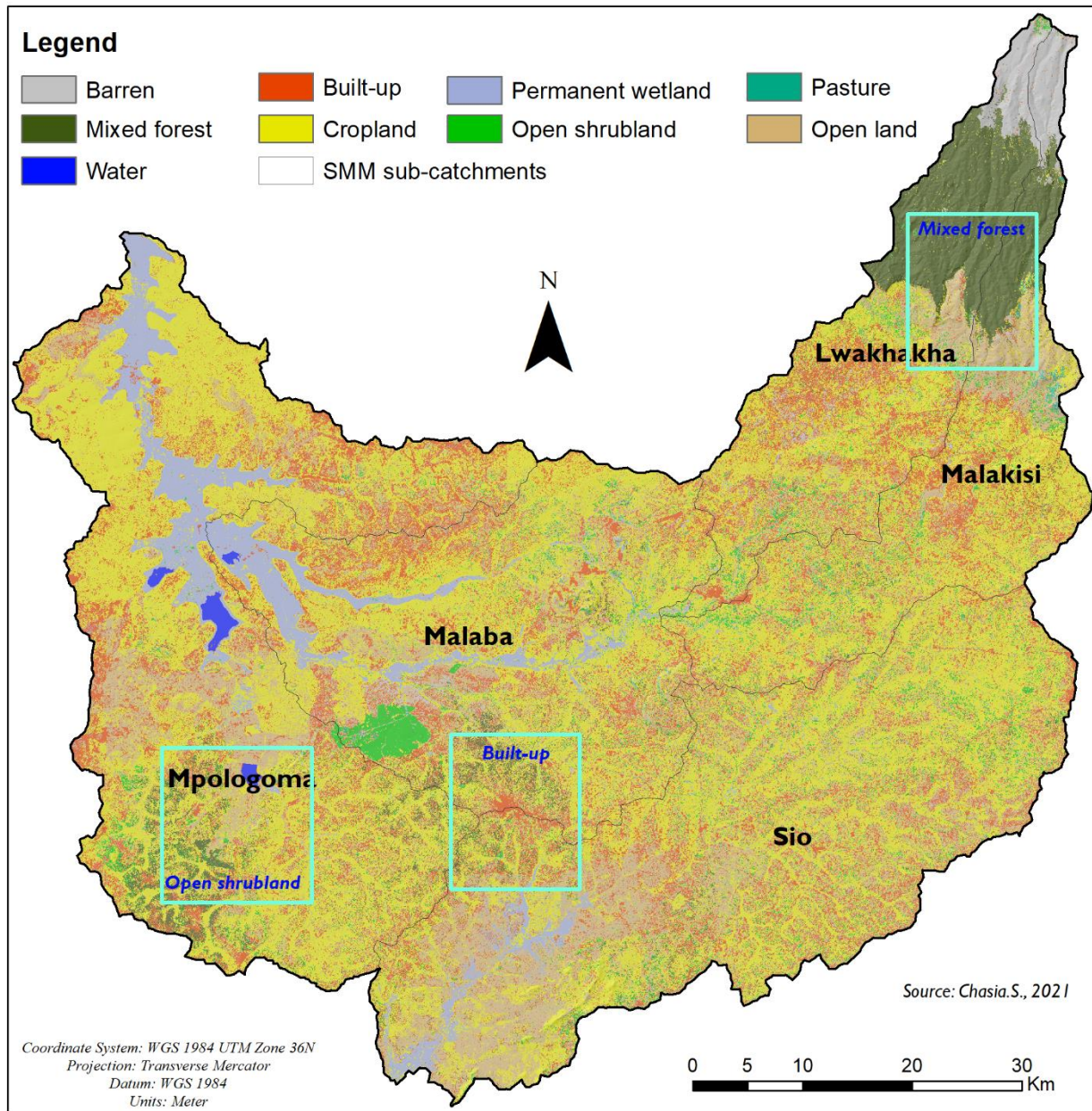


Figure 3-5. Key sampled sites highlighted in green boxes indicating areas that recorded significant cumulative land-use/cover changes from 1986 to 2017.

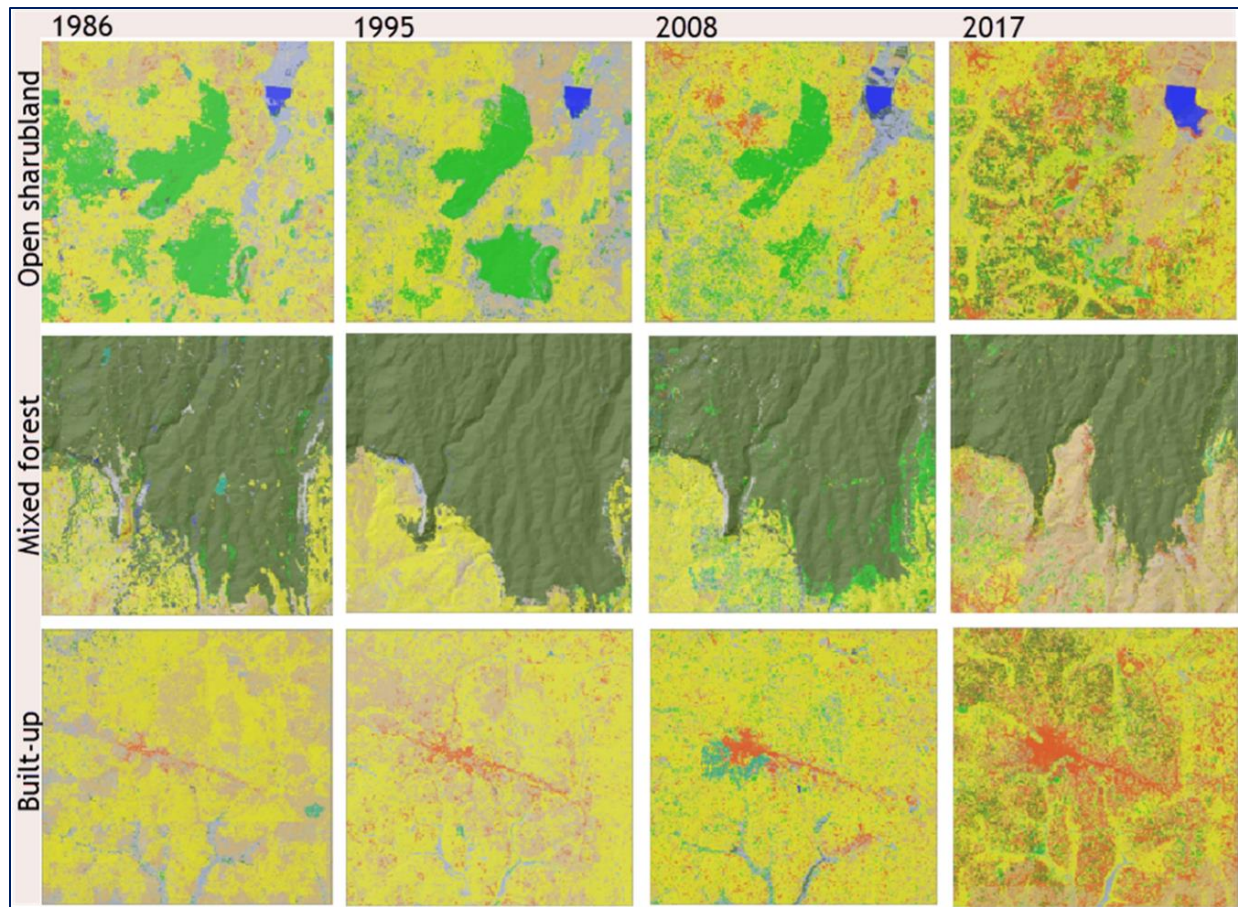


Figure 3-6. Post-classification land use/cover change detection illustrating changes for open shrubland, mixed forest and built-up land-use/cover classes.

The study also observed gradual conversion of some agricultural fields to built-up cover class which was attributed to the rapid growth in human population in the catchment (Roussel, 2012). Consequently, approx. 34,768 ha (6.8 %) of the catchment area was cumulatively converted to built-up (Table 3-8). On the other hand, approx. 15,116 ha (2.9 %) of permanent wetland was converted to cropland. Some conversions however, were not realistic i.e., the conversion of built-up areas to either mixed forest, cropland and pasture or wetland. Such changes however, could be attributed to seasonal changes captured on the acquisition date of satellite images, difference in sun illumination angle and noise from other sources, thereby enhancing differences in image radiometry (Table 3-8).

Table 3-8. Cumulative land-use/ land cover conversion matrix from 1986 to 2017

		2017 (ha)									1986
		<i>Mf</i>	<i>Pw</i>	<i>Ol</i>	<i>Bu</i>	<i>Wt</i>	<i>Br</i>	<i>Cl</i>	<i>Ps</i>	<i>Os</i>	
1986	<i>Mf</i> (ha)	156	1,063	1,935	166	2,451	552	21,175	2.4	344	27,842
	<i>Pw</i>	861	4,373	2,783	702	1,025	33	15,116	3.4	118	25,011
	<i>Ol</i>	2,951	18,688	63,853	10,866	22,433	5,581	110,002	11.9	29	234,403
	<i>Bu</i>	515	601	12,599	15,801	3,483	3,182	2,886	0	3	39,070
	<i>Wt</i>	38	829	99	13	15	0	31	0.1	0	1,025
	<i>Br</i>	7	72	462	59	706	6,482	445	0	0	8,233
	<i>Cl</i>	1,850	16,707	52,198	7,148	18,023	2,360	77,369	8.2	109	175,764
	<i>Ps</i>	0.05	0.14	0.27	0.18	0.02	0.00	0.30	0.6	0.16	2.29
	<i>Os</i>	10	220	384	13	658	57	655	1.2	1,767	3,764
2017		6,388	42,553	134,313	34,768	48,794	18,247	227,679	27.8	2,370	515,112
Mf mixed forest, Pw permanent wetland, Ol open land, Bu built-up, Wt water, Br Barren, Cl Cropland, Ps Pasture, Os open shrubland											

3.4.2 Analysis of the Classification Approaches

The study applied a combination of a hybrid classification technique for classifying 2008 – 2017 images, and the participatory mapping (PM) approach for the 1986 – 1995 images. Overall, on average, the hybrid classification method yielded a higher *Kappa* value of 85 % compared to the PM technique with a *Kappa* of 81 %. For the hybrid approach, the higher overall accuracy (OA) results (88 %) also, were attributed to several factors i.e., availability of current training data, improved satellite data resolution i.e., Landsat 8 (OLI) and the use of high-resolution Sentinel 2 data for accurately training the classification algorithm. Conversely, the PM approach relied on qualitative historical narrative and other secondary data which could not be accurately georeferenced, especially among spatially smaller and dynamic LULC classes i.e., cropland. However, it was possible to visually identify LULC classes i.e., mixed forest, permanent wetland, barren and areas under water using image enhancement techniques and band combinations.

3.5 Conclusion

In conclusion, the study established that by 2017, cropland was the dominant land-use type covering approximately 50.3 % of the total land area. The conversion of open shrublands, open land, mixed forest and permanent wetland to cropland, followed historical trends within the basin. Most changes were recorded on the upper reaches of the basin (Lwakhakha and Malakisi), which was attributed to the expansion of small-scale agricultural lands. On average, lower OA values of less than 85 % were recorded among classified images covering the period 1995 and 1986 due to limited training and accuracy assessment data available for the study. However, the findings of the study present important empirical baseline data for supporting existing land and water management programs in the Great Lakes region, geared towards developing a comprehensive transboundary catchment plan and policy. In addition, the space-time information generated by the study could be used to enhance the understanding of future land-use change dynamics in the catchment by incorporating an empirical land-use change model.

CHAPTER 4

Assessment of Future Land-Use/Cover Changes

This chapter presents the analysis steps and findings of objective two of study. The presentation is based on the published work presented in *Appendix H (Manuscript 2 - <https://doi.org/10.1016/j.ecolmodel.2022.110256>)*. First, background information on the current literature on land-use modelling techniques are discussed, including the theoretical basis and required datasets. The methodology used to select and evaluate the likely biophysical and socio-economic LULC driving factors for the study area are discussed, and the procedure used to parameterize and validate the results of the model outlined. The chapter concludes by providing the study results illustrating the future land-use patterns under the scenarios evaluated.

4.1 Introduction

Land-use changes are universal earth processes of global importance and environmental change research (Cegielska et al., 2018; Chen et al., 2019; Duveiller et al., 2020; Thenkabail, 2016). They manifest locally, but cumulatively affect the sustainability and proper functioning of Earth's land surface processes (Midekisa et al., 2017; Song et al., 2018) and system functioning (Lambin et al., 2001). The net effects of Land-Use-Land-Cover (LULC) changes on socio-economic activities and the well-being of environments are manifested differently in different geographical settings. However, the outcome is generally similar, exhibiting both short-term and long-term impacts (Foley et al., 2005; Marcos-Martinez et al., 2017). Generally, the effects of land-use change may lead to loss of critical biodiversity (Newbold et al., 2015), land degradation (Olang et al., 2014), global climate change (Duveiller et al., 2020) and habitat destruction (Ban et al., 2015; Du & Huang, 2017). At local scales, these may lead to loss of soil productivity, alterations of local hydrological regimes (Olang et al., 2014), increasing risk of hazards like landslides (Lambin et al., 2001), soil erosion and water pollution (Duveiller et al., 2020; Newbold et al., 2015; Schürz et al., 2020). Socio-economic impacts of land-use change may also arise from loss of livelihoods, increased vulnerability to food insecurity and land related conflicts (Lone & Mayer, 2019).

In sub-Saharan Africa, where rain-fed agriculture is the dominant socio-economic activity (Maitima et al., 2009), the negative feedback from land-use changes and impacts on people's livelihoods are usually more pronounced and immediately felt by small-holder farmers and local communities (Hartemink & van Keulen, 2005; Karamage et al., 2017; Lambin & Ehrlich, 1997).

The overall increase in human population exerts more pressure on the limited productive land resource, leading to the intensification of farming activities on small parcels of land, and accelerating the rate of degradation (Fetzel et al., 2016; Vanwalleggem et al., 2017). In some cases, farming activities have shifted or expanded to ecologically fragile areas and other protected habitats, thus threatening ecosystem functions and stability (Karamage et al., 2017). In smaller and transboundary catchment areas, the negative effects of LULC changes are manifested in the form of severe soil erosion and land degradation (Schürz et al., 2020) resulting in loss of soil productivity. In addition, upstream-downstream and transboundary conflicts may arise due to water pollution and sedimentation of rivers (Fayos, 2002; Petursson et al., 2011).

Land use-change studies attempt to qualitatively and quantitatively measure LULC changes at different spatiotemporal scales using available satellite data (Ban et al., 2015) and field measurement techniques (Bartholome et al., 2002; Congalton et al., 2014). Understanding the impacts of LULC involves unpacking and evaluating the complex interrelationships between the biophysical and socio-economic factors using empirical models and scientific tools (Behera & Behera, 2020; Veldkamp & Verburg, 2004). However, developing sustainable land-use management plans and policy in the long-term, requires an assessment of future land-use trajectories using techniques that extrapolate trends and perform scenario analysis (Briassoulis, 2019). Land-use change models provide a means to explore and simplify the complex spatiotemporal relationships between LULC and potential driving factors (Briassoulis, 2019; Verburg et al., 2004).

Models help create abstractions and approximation of reality through simplification of complex processes happening in the world (Briassoulis, 2019). The choice of a given model would normally depend on the purpose of the model, study requirements and application domain. Specifically, land use models have gained a pivotal role in helping explore future land-use scenarios and design spatial policies (van Vliet, 2013). To date, several models have been developed across the globe to help in understanding and explaining drivers and consequences of land-use change dynamics (Veldkamp & Verburg, 2004) knowledge and tools from biophysical and socio-economic disciplines to enhance our understanding of the complex linkages and feedbacks between these changes and potential driving factors (Chaudhuri & Clarke, 2013; van Soesbergen & MacArthur Foundation, 2016; Veldkamp & Verburg, 2004). Generally, land-use models can be classified as either spatially explicit or agent-based models (van Soesbergen & MacArthur Foundation, 2016;

Veldkamp & Verburg, 2004). Other categorization of models are based on the spatial resolution, extent and scale of data, and the core modules of a model (Agarwal et al., 2002). Spatially explicit models operate at both local and regional scales, allocating land-use types on the basis of biophysical and socio-economic properties (Agarwal et al., 2002; Chaudhuri & Clarke, 2013). Agent-based models on the other hand, focus on the underlying decision process behind LULC changes driven by demand and supply factors and their net effect on land-use allocation decisions (Veldkamp & Verburg, 2004). Ultimately, the predictive ability and precision of a land-use model would normally be assessed by comparing simulation results against the actual land-use map (van Vliet, 2013).

The Conversion of Land-use/cover and its Effects at Small regional extent (CLUE-s) model, is one of the most widely used modeling tools for predicting LULC change given a set of potential driving factors (Verburg & Overmars, 2009). It is a cross-disciplinary model (Briassoulis, 2019) covering a wide range of biophysical and human drivers of LULC at different spatiotemporal scales for predicting land-cover in the future (Agarwal et al., 2002). CLUE-s is also a flexible, integrated, spatially explicit, multi-scale and dynamic modeling framework with a biophysical, land-use objective and allocation module (Agarwal et al., 2002; Briassoulis, 2019). The model has been utilized in various studies i.e., hydrology (Peng et al., 2020; Waiyasusri et al., 2016; Wang et al., 2021; Zhou et al., 2013), environmental and land-cover change dynamics (Behera & Behera, 2020; Griscom et al., 2010; Kucsicsa et al., 2019; Mohammady et al., 2018; Verburg & Overmars, 2007), urban studies (Huang et al., 2019; Jiang et al., 2015), predictive tool (Judex & Menz, 2006), and land-cover change simulation (Tizora et al., 2018). In this study, the CLUE-s model was adopted to help answer the following research questions pertinent to land-cover change dynamics in SMM catchment:

1. What are the expected future change trajectories in LULC patterns in the study?
2. What are the existing and potential future driving factors for land cover change?
3. How would simulated changes in LULC affect the local environment, and inform land management practices and policy in a transboundary setting?

This is as a result of the immense socio-economic and environmental transformation experienced in the study area in the past due to a steady increase in human population which exerted undue

pressure on the limited land resource in the area. Consequently, agricultural and other land-use activities have been intensified in the area, expanding even to marginal lands and ecologically fragile zones resulting in habitat fragmentation, land degradation, water pollution, severe soil erosion and consequently loss in soil productivity. The pervasiveness, range and dynamic nature of these land-use changes over space and time was the driving force behind this study. Ultimately, this research aims to contribute scientific knowledge and information to the ongoing land management efforts in the catchment and provide critical baseline data for supporting impact studies towards the development of a transboundary integrated land-use planning framework that promotes sustainable development.

4.2 Methodology

4.2.1 Materials and Methods

4.2.1.1 *Preparation of Datasets*

(a) Historical Land Cover Map

Historical land use/cover maps (1986, 1995, 2008, and 2017) were prepared from raw Landsat satellite datasets in order to assess past LULC state as well as predict future land cover change trajectories for SMM catchment. Given the spatial variability of land-cover types in the study area, a hybrid classification methodology that combines the ISODATA clustering and maximum likelihood classifier (Sharma et al., 2011) was used to prepare thematic land use maps into nine dominant land-use/cover classes namely: mixed forest, cropland, open land, water, permanent wetland, pasture, open shrubland, built-up and barren land using the United States Geological Survey classification scheme (Lillesand T.M., Kiefer R.W., 2015). The LULC maps of the years 1986, 1995, and 2008 were generated using Landsat 4 and 5, while the 2017 map was developed from Landsat 8 data. Pre-processing, classification and post-processing of satellite images were carried out in the Semi-Automatic Classification Plugin (*version 7.9.9*) found in QGIS® *version 3.18.3* software at the time of this analysis. The 1986, 1995 and 2008 datasets were used to assess past changes for the period 1986-1995, 1995-2008 and 2008-2017. Spatial validation of the model was conducted using the 2018 dataset to evaluate CLUE-s ability to replicate reality. The 2017 dataset which coincided with the period when ground-truthing data was collected, was considered appropriate for preparing the initial land-use map for time step at year zero and for allocating future scenarios (2017-2047) and prepare LULC classes for simulation (Kucsicsa et al., 2019).

(b) Other Spatial Data sets

In order to calibrate the model and analyse future potential land cover patterns, other datasets that comprise key driving factors for LULC change in the catchment were acquired and analysed. Table 4-2 provides a summary of biophysical and socioeconomic data and their sources that were considered for this study. Overall, the study acquired topographical data i.e., Digital Elevation Model (DEM) data and used it to derive slope and aspect parameters at 90 m resolution; soil data represented parameters on pH in water, cation exchange capacity and organic carbon; climate data comprised of historical monthly weather data i.e., average minimum and maximum temperature and precipitation (1985-2017); demographic data represented population density for the administrative regions of both Kenya and Uganda combined to form a single raster layer. Proximity to roads, rivers and major towns layer was prepared by calculating the Euclidean distance (1 km) buffer. All the layers were resampled to the same resolution i.e., 250 m which is optimized to work in the model. Thereafter, the layers were converted to ASCII format with the similar extent, number of rows and columns and projection (WGS 1984-UTM zone 36N).

4.2.1.2 Selection of the Base Year

The study selected 2017 as the base year for modelling land-use-cover change for the catchment which was available for the study area at moderate resolution, while also representing present land cover conditions for SMM catchment (Chasia et al., 2021). In the CLUE-s model therefore, the 2017 land cover map represented the initial LULC state for time-step zero as required by the model as a basis for simulating potential future changes.

4.2.1.3 Modelling Future Land-use/cover Dynamics

In order to model future LULC change patterns in this study, the CLUE-s model was adopted. CLUE-s is relatively simple and functional to use (Briassoulis, 2019), with the ability to integrate both aspects of environmental modelling and a geographic information systems (Briassoulis, 2019), which has enhanced its applications in a wide range of land-use change investigations in several regions of the world (Behera & Behera, 2020; Huang et al., 2019; Peng et al., 2020). However, it has several limitations worth noting: (1) limited explanatory capability, (2) statistical associations do not imply causal relationships, (3) statistical analysis cannot capture qualitative aspects and determinants of LULC change (Agarwal et al., 2002; Briassoulis, 2019). Figure 4-1

illustrates the methodology used to project future LULC patterns using the CLUE-s model. Land cover changes in SMM catchment were modelled for the period 2017 – 2047. This represented a 30-year period corresponding with the land cover classification in the study from 1986 – 2017 (Chasia et al., 2021), providing consistent statistical data for trend extrapolation. The chosen duration also corresponds with both medium to long-term projections for socioeconomic development blueprints used in both Kenya and Uganda, which have direct impacts on land-use decisions (Government of Kenya (GOK), 2007; *Uganda Vision 2040* | *Uganda National Web Portal*, n.d.). Nine dominant LULC classes namely: cropland, mixed forest, open land, built-up, barren, pasture, water, open shrubs and permanent wetlands, were selected for simulation. The conversion elasticities and land-use transition sequences were the two parameters used to determine the temporal dynamics of each LULC type during the simulations (Verburg et al., 2005). To achieve this, CLUE-s model (Verburg *et al.*, 2002; Verburg & Overmars, 2007) was applied, which is an integrated, spatially explicit, dynamic and multi-scale modelling framework developed at Wageningen University to model land-use change trajectories and processes that determine land-cover patterns at local to regional scales (Briassoulis, 2019; Verburg & Overmars, 2007; Verburg et al., 2002; Verburg & Overmars, 2009). The model is composed of two modules namely: (i) a non-spatial demand module used to compute the cumulative area change in LULC and, (ii) a spatially explicit allocation module used to allocate projected demands in LULC to cell grids based on location characteristics, land-use transition sequences and demand (Verburg & Veldkamp, 2002). The contribution of potential drivers (herein known as Explanatory Variables) of land-use change are normally estimated using empirical analytical methods (outside the model), where potential driving factors are determined using either local knowledge of the area, or theories of factors of land-use change (Lambin et al., 2001). Simulations using the model require definitions of land requirements, spatial policies and restrictions, conversion elasticity and land use conversion sequences.

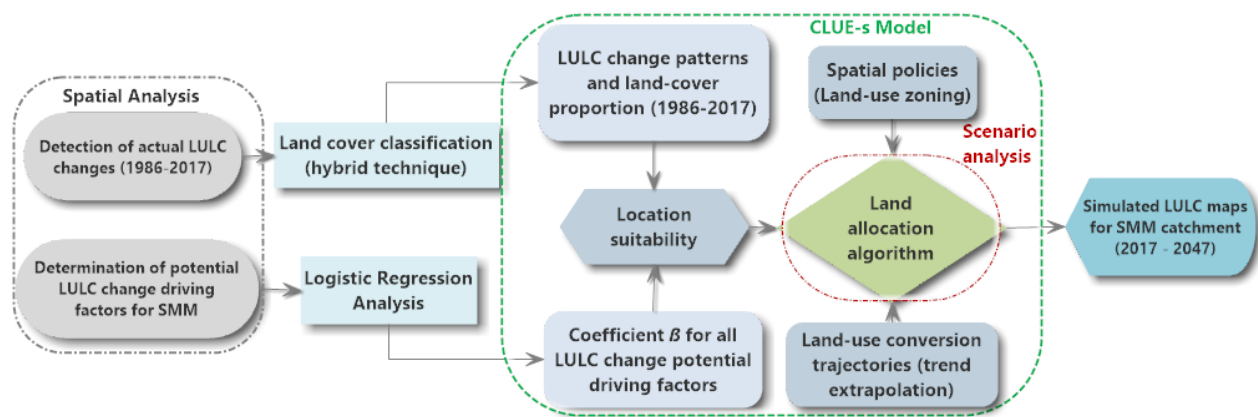


Figure 4-1. CLUE-s methodological framework and flowchart

The land requirement files were prepared through simple trend extrapolation in land-use change over the recent past into the near future (Verburg et al., 2002; Verburg & Schulp, 2005). The trends were corrected for changes in population growth using population projection data from the Kenya National Bureau of Statistics (<https://www.knbs.or.ke/>) and the Uganda National Bureau of Statistics (<https://www.ubos.org/>). Spatial policies restrictions defined areas where land use changes are allowed and areas under government protection through government policies (Verburg & Veldkamp, 2002). The present study experimented with two scenarios; the first scenario represented status-quo whereby existing policies restricted the conversion of protected areas i.e., forest reserve, wetlands and catchment area to other land-use types. In the second scenario, a section of protected land was converted to other land use types if they met certain set conditions i.e., forest land with fertile soil and favourable climate was converted to agricultural land. Within the CLUE-s model, this requirement was enforced using spatial layers created that define cells not allowed to change during the simulation.

Land-use types were allowed to change from one state to another based on their elasticity, which is defined as the ease with which a given LULC type can be converted to another type (Verburg & Overmars, 2007). Land-use types with high capital investment or irreversible impact on the environment are normally allocated higher elasticity values and not allowed to easily change (Verburg et al., 2002). A dimensionless factor representing relative elasticity to conversation was used, ranging from 0-easy conversion to 1- irreversible change (Kucsicsa et al., 2019; Verburg & Overmars, 2007). Table 4-1 illustrates the elasticity values assigned to LULC classes based on local knowledge and conversion trends in the study area. Generally, areas with permanent

structures i.e., urban centres, tree cover and wetlands under protected area were assigned high elasticity values (0.7 – 0.9) constraining their conversion to other land use types. Cropland and open soils on the other hand were assigned low elasticity values in the model i.e., 0 – 0.4.

Table 4-1. Land use/cover conversion elasticities

Land-use/cover class	Elasticity (E)
Mixed forest	0.9
Permanent wetland	0.8
Open land/field	0.1
Built-up	1.0
Water	1.0
Open shrubland	0.7
Barren	1.0
Cropland	0.2
Pasture	0.3

Land-use conversions normally occur at locations characterized by suitable conditions suitable for a given land-use (Luo et al., 2010). The preference of a location is normally an empirical estimation of factors that determine land-use change (Verburg et al., 2005), calculated as:

$$R_{ki} = a_k X_{1i} + b_k X_{2i} + \dots \quad \text{Equation 4-1 - Land-use location preference}$$

Where, R is the preference to devote location i to land use type k . $X_{1,2,\dots}$ are biophysical and socio-economic characteristics of the location i and a_k and b_k represent the relative impact of these characteristics on the preference of land use type k . However, since the R_{ki} can neither be observed nor measured directly (Judex & Menz, 2006; Verburg et al., 2002), it is calculated as a probability, which relates biophysical and socio-economic location characteristics using the following logit model:

$$\text{Log} \left\{ \frac{P_i}{1 - P_i} \right\} = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \dots \beta_n X_{n,i} \quad \text{Equation 4-2 - Logit probability model}$$

Where, P_i is the probability of a grid cell for the occurrence of the considered land-use type on location i , and X are the location factors. The coefficients (β) were estimated using logistic regression using the actual land use pattern as dependent variable (Schneider & Gil Pontius, 2001; Verburg & Schulp, 2005).

4.2.2 Identification of Key LULC Change Driving Factors

Independent variables with the greatest influence on the distribution of the dependent variable (LULC class), were determined using a logistic regression model (see equation 4.3) at 0.05 significance level (Greenland et al., 2016; Serneels & Lambin, 2001).

$$\hat{y} = \mathbf{b}_1 \cdot \mathbf{x}_1 + \mathbf{b}_2 \cdot \mathbf{x}_2 + \cdots + \mathbf{b}_k \cdot \mathbf{x}_k + \mathbf{a} \quad \text{Equation 4-3 - Logistic regression model}$$

Where $\hat{y}$ is the dependent variable (occurrence of LULC class), b_1, b_2, b_k are the coefficients, x_1, x_2 and x_k are the independent variables i.e., potential driving factors, while a is the y-intercept of the regression equation. Driving factors with p-values ($p \leq 0.05$) were considered to be statistically significant in explaining the dependent variable. In order to meaningfully interpret regression coefficients and ensure stability of the regression model, a multicollinear analysis was conducted for all the selected driving factors to identify and eliminate independent variables with collinearity which may could reduce observed differences of individual variables in the model (Michetti, 2012). Here, a new regression model was created for each independent variable leaving out the original dependent variable and replacing it with one of the independent variables. In Eq.4.4 therefore, multicollinearity for variable x_1 against variables b_1 and b_k was determined by regression equation following:

$$\hat{x}_1 = \mathbf{b}_2 \cdot \mathbf{x}_2 + \cdots + \mathbf{b}_k \cdot \mathbf{x}_k + \mathbf{a} \quad \text{Equation 4-4 - Regression equation}$$

Where, $\hat{x}_1$ is an independent variable from Eq. 4.3 correlated with other independent variables x_2 and x_k . The Variance Inflation Factor (VIF), which detects the presence of multicollinearity in the dataset, was used to calculate the tolerance value which measures the degree in which variance is inflated (Daoud, 2018):

$$VIF = \frac{1}{1 - R_i^2} \quad \text{Equation 4-5 - Variance inflation factor}$$

Where, R_1^2 is the coefficient of determination. Therefore, a VIF greater than 10 ($VIF > 10$) is considered critical, indicating presence of severe multicollinearity among variables in the data (Daoud, 2018).

Table 4-2. Land use change simulation factors

Variable	Driving factor	Data source	Model application
Demographic & socioeconomic	Population density	National Bureau of Statistics	Simulation for all scenarios
Topographic/physiographic data	(i) Altitude (Alt)	Digital elevation model (DEM – 90 m)	Effect of relief on land-use/cover
	(ii) Slope (degree)	Digital elevation model (DEM – 90 m)	Effect of slope on land-use/cover
	(iii) Aspect (Asp)	Digital elevation model (DEM – 90 m)	Effect of aspect on land-use/cover
Geographic	(i) Proximity to roads (trunk, primary and secondary class) (RdDst)	Open street map roads. Distance calculated using Euclidean distance function (https://download.geofabrik.de/)	Effect of distance to roads on land use type (1 Km)
	(ii) Proximity to rivers (StrDst)	DEM. Distance calculated using Euclidean distance function	Effect of distance to rivers on land use type (buffer dist. 1 Km)
	(iii) Proximity to major towns (TwnDst)	Open street map towns. Distance calculated using Euclidean distance function	Effect of distance to major towns on land use type (buffer dist. 5 km)
Climatic conditions	(i) Annual average temperature (Temp)	Global climate and weather data -WorldClim (30 seconds/~1Km)	Simulation of temperature effect of on LULC pattern
	(ii) Annual average precipitation (mm) (Ppt)	Global climate and weather data -WorldClim (30 seconds/~1Km)	Simulation of precipitation effect of on LULC pattern
Soil characteristics	(i) Soil cation exchange capacity in mmol(c)/kg (CEC)	Soil Grids (250x250m)	Simulation of CEC on vegetation cover and pattern
	(ii) Soil organic carbon in dg/kg (SOC)	Soil Grids (250x250m)	Simulation of SOC on vegetation cover and pattern
	(iii) pH water in soil (pH)	Soil Grids (250x250m)	Simulation of pH on vegetation cover and pattern

4.2.2.4 Model Calibration and Validation

The CLUE-s model was calibrated to simulate known historical land-use changes in SMM catchment (van Vliet, 2013). In this study, the 1986 land-use map was used to initialize the start of the simulation period (T1), while 2017 represented the end of the simulation period (T2). The actual 2017 land-use map (Chasia et al., 2021) was compared to the simulated map to assess model performance. Twelve independent variables for the regression equation with most variables, were used to parameterize the CLUE-s model. The initial model run allowed changes in all land-use classes without a constraining restriction file layer in place. Conversion elasticities were initially set to 0.1, which made changes in all the classes possible. The final simulated land-use map for 2018 (T3) was validated using the Kappa simulation ($k_{simulation}$) method (van Vliet, 2013) – an

extension of Kappa (Gil Pontius Jr & Schneider, 2001) - which evaluates the agreement between simulated land-use transitions and the actual land-use transitions by randomly allocating class transitions relative to the initial map. $k_{simulation}$ values normally range from -1 to 1 (van Vliet, 2013), where 1 denotes a perfect agreement, while scores below 0 indicate less accurate class transitions as compared to scores from a random allocation of class transitions (van Vliet, 2013). This was done by cross-tabulating each class in the simulated map against the actual classified 2018 land-use map of the study area in order to measure the degree of agreement to determine the accuracy of the results.

4.2.2.5 Formulation of Land-use/cover Scenarios

Overall, the research study explored changes in land-cover for a period of 30-years (2017-2047), beginning with 2017 as the base year using ten-year interval assessment period in order to capture cumulative and significant changes in LULC comparable to the historical land cover maps for the study area (Chasia et al., 2021). Given the dominance and potential impacts of unsustainable agricultural activities in SMM catchment, the study explored possible scenarios likely to influence the trajectories in land-use/cover patterns and land transformation. The formulation of the scenarios was based on the analysis of historical trends in LULC changes in the study area between 1986-2017 (Chasia et al., 2021), and their potential impacts on local hydrology, including potential impacts on soil erosion and sediment deposition. In the first scenario (S_1), the study postulated that cropland area would expand and occupy neighbouring areas under permanent wetland areas, capable of supporting agriculture. This scenario assumes an environment with overlapping mandates and consequently weaker enforcement of existing land-use regulations hence allowing encroachment into wetlands and other protected areas. The second scenario (S_2) on the other hand, explored possible land-use configuration patterns and trajectories when soil conservation and land reclamation measures are implemented in the basin. Consequently, areas covered by mixed forest class are expected to increase significantly as a result of public education and the implementation of afforestation programs by public and conservation organizations which are aimed at reducing the rate of land degradation and massive soil erosion. In this scenario, therefore, areas previously under open land category would be converted to mixed forest. It is assumed that human population growth rate would follow historical trends, and the conservation programs towards soil and environmental conservation would be embraced and implemented by the communities living in SMM catchment.

4.3 Results

4.3.1 Importance of Driving Factors for Land-use/cover Change

A logistic regression analysis was carried out to determine the independent variables, which represent the potential LULC driving factors used in the regression model. Table 4-3 illustrates results obtained from a regression model for five land-use/cover classes, likely influenced by the selected driving factors in the equation. The p-values associated with mixed forest, cropland and open shrubland classes for the potential drivers analysed were less than the 0.05 threshold, indicating statistical significance. The variable aspect produced p-values greater than the cut-off value for all the land-cover classes. Soil properties i.e., CEC and SOC recorded lower p-values ($p < 0.01$) in all the classes except permanent wetland. An adjusted R^2 value of 0.85 (85 %) when the dependent variable was regressed against the independent variable in the regression model.

Table 4-3. Z score and p-values from a regression model

	Statistic	altitude	slope	temp	ppt	ph	aspect	cec	soc
Mixed forest	z value	33.246	10.311	11.057	15.093	13.111	-0.425	-31.451	26.967
	p-value	<2e-16	<2e-16	<2e-16	<2e-16	<2e-16	0.671	<2e-16	<2e-16
Permanent wetland	z value	-18.915	0.137	1.927	-11.039	-0.194	-0.424	-5.369	1.139
	p-value	2.00E-16	0.8914	0.0539	2.00E-16	0.8458	0.6719	7.91E-08	0.2546
Cropland	z value	-12.954	-1.105	5.898	9.068	-1.219	0.013	-4.344	0.221
	p-value	2.00E-16	0.269	3.68E-09	2.00E-16	0.223	0.99	1.40E-05	0.825
Built-up	z value	-5.301	5.825	3.254	2.042	-	-0.795	-	-
	p-value	1.15E-07	5.69E-09	0.00114	0.04111	-	0.42647	-	-
Open shrubland	z value	-11.892	-1.998	1.71	11.382	-1.241	0.328	0.74325	5.081
	p-value	< 2e-16	0.04569	0.08727	< 2e-16	0.2145	0.74325	0.00176	3.75E-07

4.3.2 Multicollinearity Analysis

The study investigated collinearity within the dataset by fitting a model using all the variables (11) against altitude as the predicted value. An adjusted R^2 of 0.68 and a p-value ($p < 2.2e-16$) were obtained. Table 4-4 illustrates results from a multicollinearity analysis indicating the variance inflation factors (VIF) when the variable altitude (Alt) is correlated with all other driving factors in the regression equation. The CEC and SOC factors recorded a moderate degree of collinearity against altitude. However, the score was still below VIF threshold value considered significant

i.e., >5. None of the driving factors recorded a VIF collinearity score above the severe threshold of >10 against the independent variable altitude.

Table 4-4. Multicollinearity analysis

<i>Model</i>	<i>Slope</i>	<i>PopDen</i>	<i>Temp</i>	<i>Ppt</i>	<i>pH</i>	<i>CEC</i>	<i>SOC</i>	<i>StrDst</i>	<i>RdDst</i>	<i>TwnDst</i>	<i>Asp</i>
Alt	1.005	1.089	1.957	1.080	1.500	2.510	2.756	1.270	1.453	1.733	1.002

Figure 4-2 is a graphical representation of a correlation matrix measuring the correlation between different independent factors used in the regression equation. Altitude (Alt) had a strong positive correlation with soil properties including CEC, SOC and proximity to major towns. On the contrary, the variable temperature produced a strong negative correlation with the same classes. Other classes when cross-tabulated produced lower values for both negative and positive correlation.

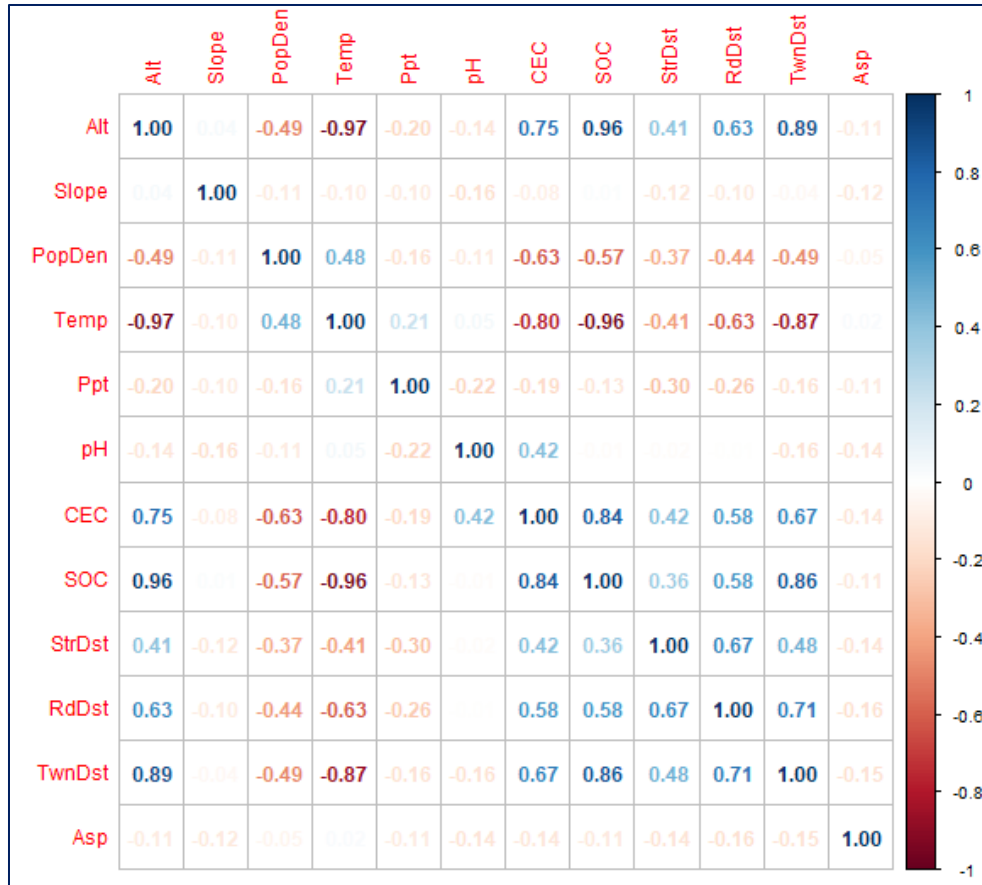


Figure 4-2. Correlation coefficient matrix for independent variables

4.3.3 Calibration and Validation Results

Figure 4-3 illustrates results obtained from the actual classified LULC map for T1 i.e., 1986 and the simulated map obtained from the CLUE-s model at T2 during the calibration procedure. Nine land- use/cover types dominant in SMM catchment from the initial classified 1986 map were simulated. After performing ten model runs, elasticity values that provided the most reliable results were 1.0, 0.9, 0.7, 0.8, 0.2, 0.3, 1.0, 1.0, and 0.1 for barren, mixed forest, open bushland, permanent wetland, cropland, pasture, built-up, water and open land dependent variables respectively. During the simulation, pixels representing barren and water land-cover types remained static and therefore unchanged over the modelling period since they were not significantly affected by human activities.

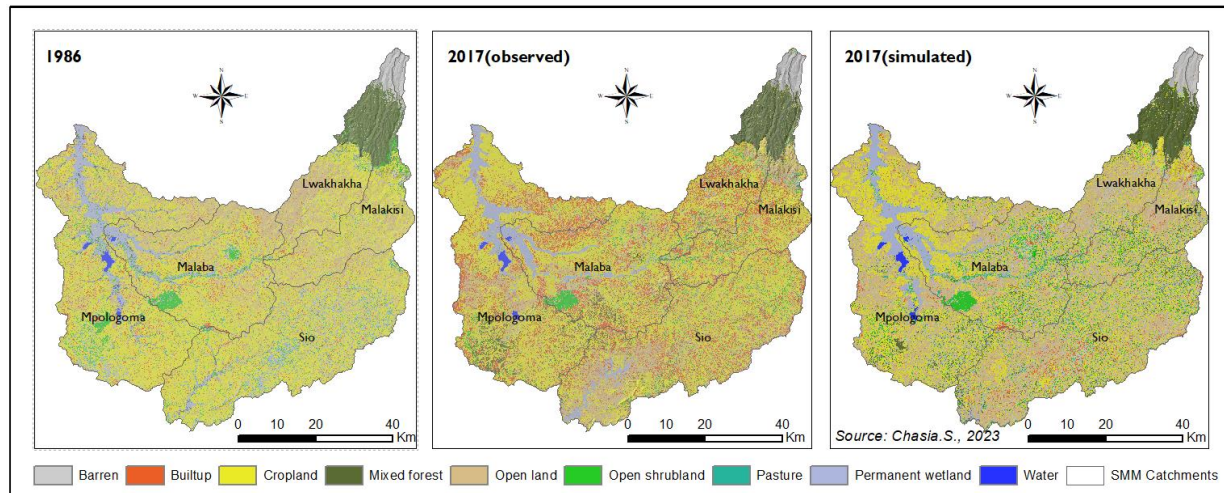


Figure 4-3. Actual, observed and simulated land-use/cover changes

Table 4-5 illustrates scores obtained from using $K_{simulation}$ and the Kappa statistic methods used during validation process, to determine degree of agreement between simulated maps (S1-S10) and actual map at T2 for 2018. Overall, simulation Map S6 produced comparatively higher values for both $K_{simulation}$ and Kappa statistic. On average, the model simulation produced $K_{simulation}$ of 0.4 and a Kappa statistic of 0.78.

Table 4-5. Overall accuracy scores from $K_{simulation}$ and Kappa statistic

Statistic	Map – S1	Map – S2	Map – S3	Map – S4	Map – S5	Map – S6	Map – S7	Map – S8	Map – S9	Map – S10
$K_{simulation}$	0.00	0.18	0.43	0.32	0.57	0.72	0.26	0.51	0.80	0.17
Kappa	0.78	0.72	0.84	0.68	0.75	0.89	0.73	0.82	0.72	0.86

Figure 4-4, compares simulated map for 2018 and the actual classified map for the same period. It highlights areas with persistence i.e., land-use/cover classes correctly simulated with no-change i.e., water and barren land; it also shows simulation misses i.e., pixels indicated as change in the model in the wrong class (purple box) i.e., change in cropland simulated as change in open shrubland. In addition, land-use/cover classes correctly simulated by the model i.e., built-up areas are also shown in the map.

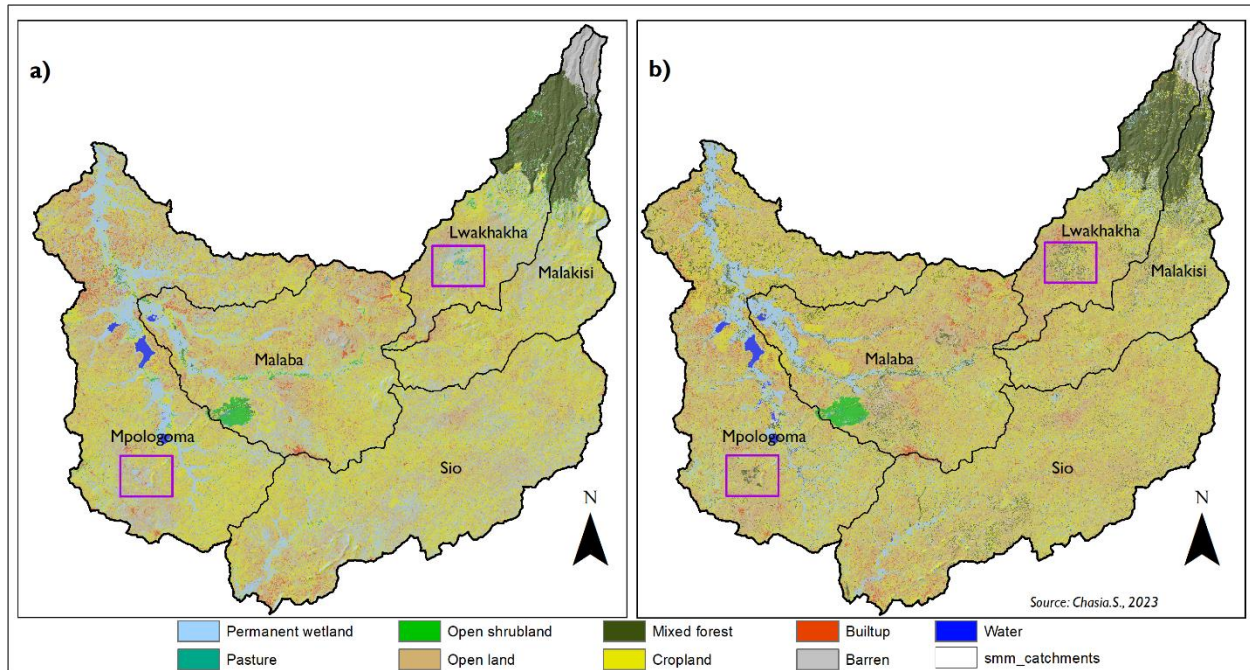


Figure 4-4. Validation of simulated land-cover map- a) Simulated land-use condition, b) actual land-use map for 2018

4.3.4 Historical Land-use/cover state in SMM catchment

The results of the spatial analysis of LULC change during the period 1986 – 2017 are presented in Table 4-6. Overall, approximately 40 % of the catchment experienced change over the analysis period. Changes within individual LULC varied across the years, where some classes recorded net gain while other classes a loss in total cover area. Between the period 1986 to 1995, areas covered by vegetation, except cropland, recorded a loss in the total area. Areas under permanent wetland recorded the highest loss at approximately 35 %. Built-up areas maintained a consistent growth-rate trajectory at an average rate of 43 %, with most visible changes recorded on the border towns of Malaba and Busia. Mixed forest class remained steady, losing approximately 6 %, before recording a gain in total area in 2008 to 2017 period (Chasia et al., 2021). The most common conversion in LULC was mainly recorded among the open land and permanent wetland categories which were converted to cropland. Conversion of mixed forest class occurred mainly on the southern fringes of Mt. Elgon Forest.

Table 4-6. Land use/cover change statistics

<i>LULC class</i>	Area (ha)				Gain/loss (%)		
	<i>1986</i>	<i>1995</i>	<i>2008</i>	<i>2017</i>	<i>1986-1995</i>	<i>1995-2008</i>	<i>2008-2017</i>
Barren	9,735	10,752	10,909	11,516	10.4	1.5	5.6
Mixed forest	34,422	32,411	30,382	32,250	-5.8	-6.3	6.8
Open shrubland	31,561	26,388	12,679	10,261	-16.4	-52.0	-19.1
Permanent wetland	75,298	75,298	56,300	45,154	-34.7	-25.2	-19.8
Cropland	164,036	180,101	216,945	260,149	9.8	20.5	19.9
Built-up	11,093	15,247	22,072	32,697	37.4	44.8	48.1
Water	1,409	1,308	1,277	1,134	-7.2	-2.4	-11.2
Open land	172,758	136,168	104,114	115,583	-21.2	-23.5	11.0
Pasture	12,125	10,058	11,168	11,321	-17.0	11.0	1.4

4.3.5 Simulation results of Land-use Cover state for SMM Catchment

The simulation results for land-use/cover change under scenarios one and two, which presents options for agricultural expansion, and land reclamation respectively are illustrated in Table 4-7. Open water, and barren LULC classes remained unchanged in modelling both scenarios due to their respective high elasticity values that restricted their conversation to other land cover classes. However, significant changes were observed in the cropland category for scenario one, and mixed forest in scenario two, where both recorded a general increase.

Table 4-7. Simulation results for land-use change scenarios

	Year	Wt	Pw	Ol	Bu	Os	Mf	Br	Cl	Ps	Total
Scenario											
S ₀	2017	1,134	45,154	115,583	32,697	10,261	32,250	11,516	260,149	11,321	520,065
S ₁	2027	1,134	44,251	78923	33,796	9,919	30,380	11,516	299,338	10,808	520,065
	2037	1,134	43,348	42268	34,890	9,577	28,509	11,516	338,528	10,295	520,065
	2047	1,134	42,445	5611	35,986	9,235	26,639	11,516	377,717	9,782	520,065
	Mean change	1,134	43,348	42,267	34,891	9,577	28,509	11,516	338,528	10,295	
S ₂	2027	1,134	43,771	96218	33,397	9,816	31,025	11,516	280,961	12,227	520,065
	2037	1,134	42,388	76855	34,096	9,372	29,799	11,516	301,773	13,132	520,065
	2047	1,134	41,005	57490	34,796	8,927	28,574	11,516	322,585	14,038	520,065
	Mean change	1,134	42,388	76,854	34,096	9,372	29,799	11,516	301,773	13,132	

Figure 4-5 illustrates modelling results obtained for scenarios one and two from 2017 to 2047. The 2017 map represented the baseline state of land-use/cover condition in the study used to initialize the model at *T1* i.e., 2017 (Chasia et al., 2021). In total, nine dominant land-cover classes were used in the model simulation to explore potential changes in LULC. Overall, LULC changes in scenario one was dominated by the conversion of open land, shrublands, and mixed forest classes

to cropland cover. These conversions were mainly controlled by availability of land or pixels to allocate cropland cover, including prevailing biophysical conditions that promote the cultivation of crops. In scenario two however, restrictions were enforced in the model which prevented land-use conversions on protected land, especially permanent wetland and mixed forest classes. The main objective for this scenario was to rehabilitate and reclaim areas previously occupied by natural vegetation in order to restore them to their original state.

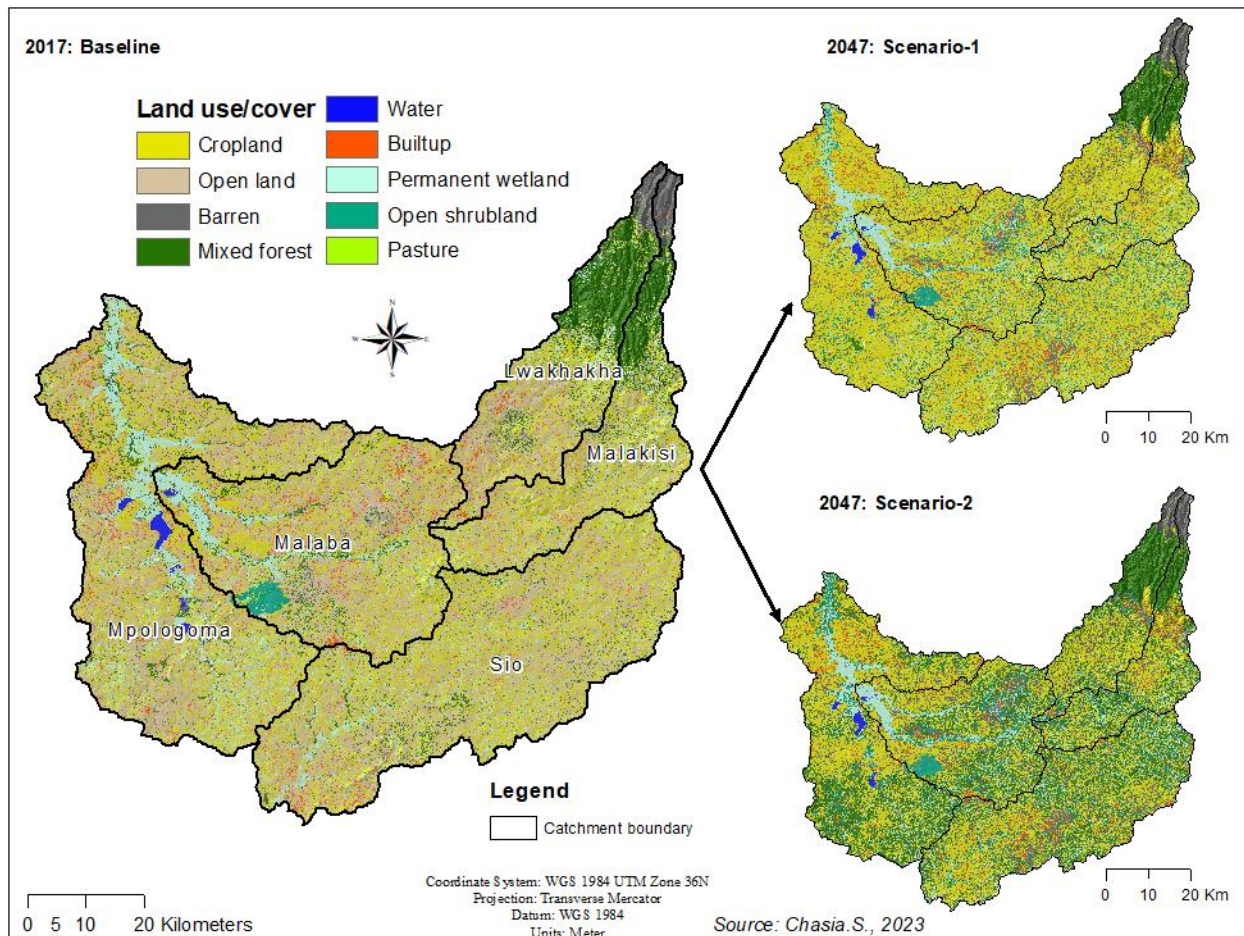


Figure 4-5. Scenario results from the simulation of land-use/cover classes

4.3.5.1 Agricultural Expansion – Scenario 1

This scenario projected a period of rapid expansion in cropland category following historical trends observed from analysis of past satellite data in the study area (Chasia et al., 2021). Here, cropland area was projected to increase cumulatively by 39.7 % by 2047, representing 72.6 % of the total catchment area. This growth in cropland category coincided with a corresponding cumulative growth of 9.7 % growth in built-up area, which could be attributed to expansion in human

settlement pushing up demand for arable land. The kind of LULC conversion in this scenario involved conversion of open shrubland, pasture, open land, and dry areas previously under permanent wetland cover. Improvement in weather conditions, access to farm inputs like fertilizer and improvements in commodity prices for cash crops in the area like rice, were assumed to be the key driving forces of change under this scenario. These conversions represent a worst-case scenario where an environment of weak legislation and lack of protection for fragile ecological zones and ecosystem is prevailing.

4.3.5.2 Land Reclamation – Scenario 2

The land reclamation scenario explored possible land-cover patterns when afforestation programs are implemented across the catchment in order to mitigate against the negative impacts of soil erosion and land degradation. Here, the study postulated that the growth of both exotic and indigenous tree species in the study would be promoted by (1) the availability of suitable land that supports tree growth, and (2) presence of subsidies and other incentives to local communities living in the basin. In this scenario therefore, mixed forest class and open shrubland land-cover areas were projected to increase. From the simulation therefore, mixed forest and open shrubland classes grew cumulatively by 27.4 % and 14.3 % respectively by 2047 (Figure 4-6). This growth involved conversion of areas previously under open land, and with biophysical conditions suitable for forest regrowth. On the edges of Mt. Elgon Forest, this involved conversion of cropland areas in the Chepyuk settlement scheme which was originally under natural forest in 1986. Other regions that experienced significant change include Busitema forest in Uganda and its surrounding which was encroached by neighbouring farming communities.

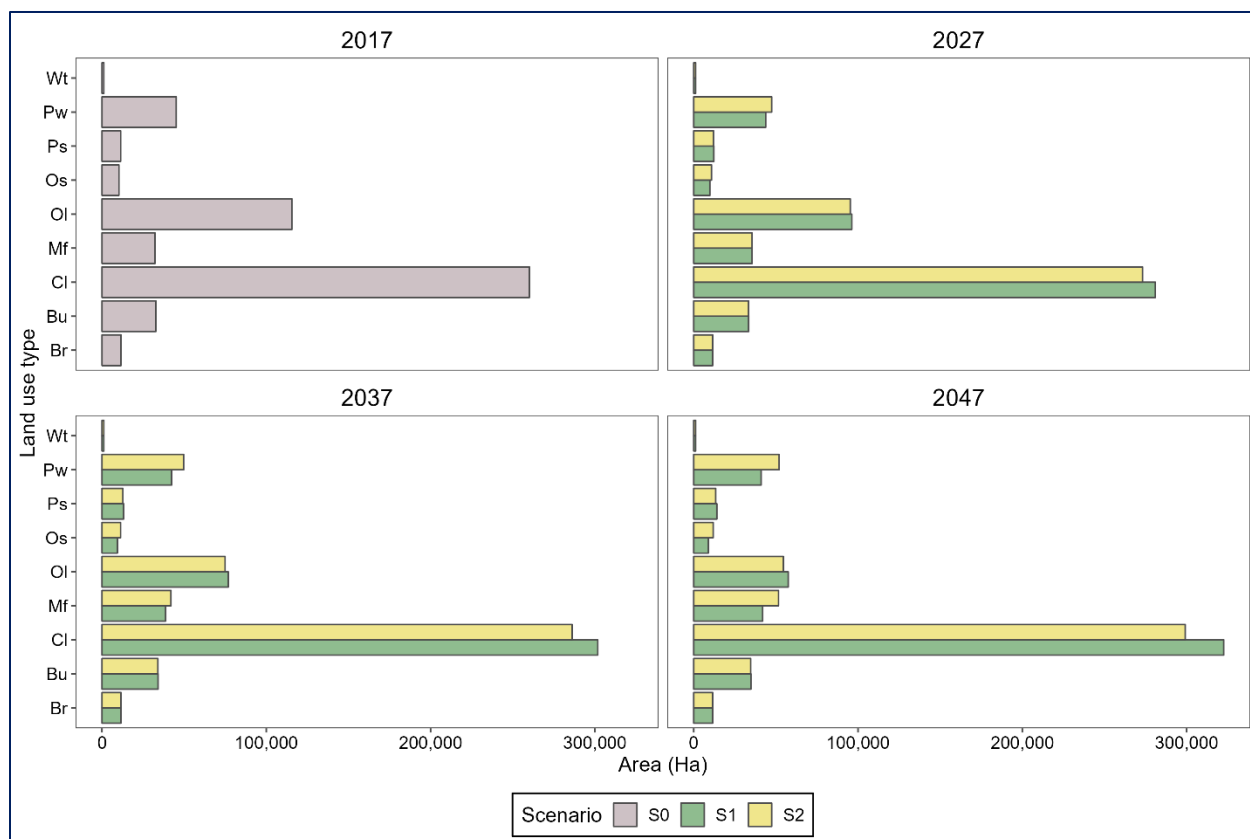


Figure 4-6. Trends in scenario demand for land-use/cover classes

4.4 Discussion

4.4.1 Importance of Potential Driving Factors

In order to ensure model stability and eliminate highly correlated independent variables from the regression model, the present study used the Variance Inflation Factor statistic in all the variables. The variable altitude was used as the dependent variable in the equation to quantify degree of collinearity with all the other independent variables. All the variables recorded a VIF score of less than five, indicating they were not highly correlated. The study also measured the influence of the driving factors on different LULC classes using a generalized linear model in *R* software (Figure 4-7). Overall, the influence of different potential drivers on the distribution of land-cover classes varied across the study. However, the influence of a combination of the drivers was observed at varying degrees. In the cropland class, for instance, the variables altitude, temperature, precipitation and soil organic carbon were significant in explaining the spatial distribution of cropland with p -values ($p < 0.01$) at 0.05 significance level. The effect of precipitation and

temperature variables corresponds with a study done in East Africa by (Hawinkel et al., 2016), highlighting the impact of weather conditions on vegetation distribution and characteristics. The distribution of permanent wetland in the study could be explained by altitude, precipitation and the CEC factors p-values of $<2e-16$. Temperature recorded a significant result with a p-value of ($p=0.054$). The mixed forest class was influenced by all the variables recording p-values of $<2e-16$. Distribution of open shrubland on the other hand could be explained by altitude, precipitation and SOC which were highly significant, while slope and CEC recorded p-values of 0.046 and 0.002 respectively. Built-up was mainly influenced by altitude, temperature and precipitation, proximity to major roads and towns. Overall, vegetation classes were mainly influenced by soil conditions (CEC, SOC, pH), altitude, and prevailing climatic conditions (precipitation and temperature). However, the degree of influence among the variables varied among different crop types. Further, exogenous factors not included in the model i.e., use of organic and inorganic fertilizers, soil conservation practices and *agro*-cultural traditions etc., could also affect crop distribution.

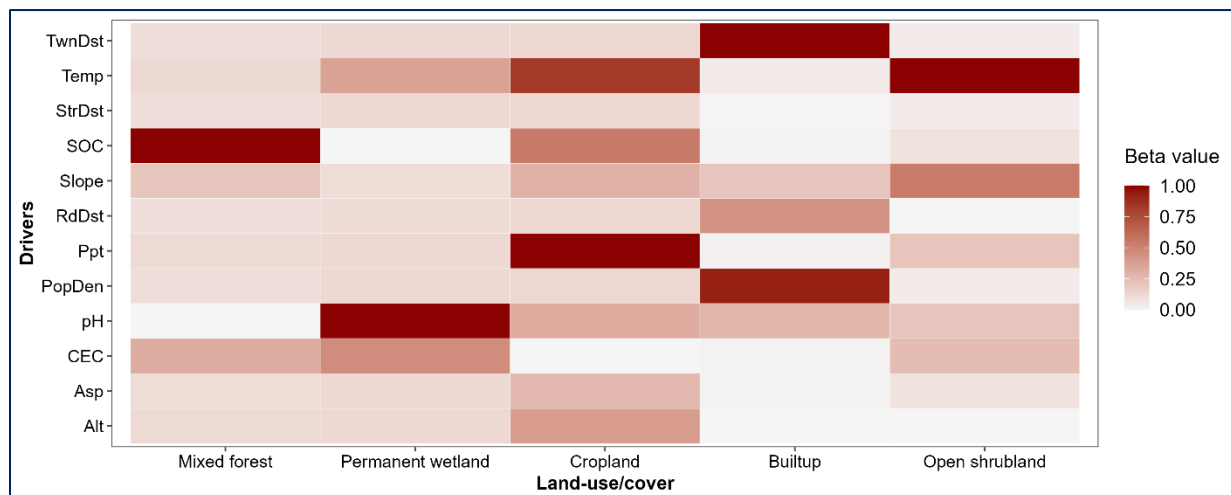


Figure 4-7. Beta values from regression analysis for land-use/cover classes

4.4.2 Assessment of Calibration and Validation

The CLUE-s model was calibrated by adjusting parameters of potential driving factors of landcover change in the study area against the existing 2008 land-cover map at *T1*. After ten-model runs, the model output at *T2* (2017) was compared to the existing land-cover map for the same year. Elasticity values for the different LULC classes were thereafter assigned based on the

model's ability to replicate reality. Visual assessment of the model's output was also conducted to compare the two maps and evaluate the model's performance. The quality of the calibration was assessed using the $K_{simulation}$ method which accounts for change in LULC, and avoids inflating simulation results where little change has occurred (van Vliet, 2013). On average, the model produced a $K_{simulation}$ score of 0.4 which means the model was able to replicate change in LULC 40% of the time. Conversely, the Kappa statistic score of 0.78 indicates an overall 78% agreement in classification of land cover classes between the final model's output and the actual classified map.

4.4.3 Scenario Analysis for SMM Catchment

The afforestation scenario in the study presented an optimistic view of land management in the basin following years of intensive human activities leading to land degradation. In this scenario, areas that were originally under natural forests were reclaimed while any available open land area capable of supporting tree plantations would be used to increase the percentage forest cover. The scenario envisioned a situation where incentives for land conservation outweighed short-term benefits from logging that normally lead to soil erosion and land degradation. Scenario two under intense agriculture, presented a situation where farmlands extend into protected areas including wetlands and open fields capable of supporting agriculture. A steady increase in human population and an improvement in market prices, promoted the growth of crop varieties favoured by the biophysical environment i.e., rice in sections of wetlands capable of supporting rice cultivation. Other factors that promote crop cultivation include access to farm inputs like fertilizers and farming technology. The third scenario projected a future characterized by expansion in agriculture but only in areas not restricted by government policy like protected areas. In this scenario therefore, less than 0.4% of the permanent wetland area would be converted to cropland and pasture.

4.5 Conclusion

In this study, a spatially explicit model, integrating statistical analysis approaches and geographic information system (GIS) was applied to model land cover patterns in a transboundary catchment area dominated by agricultural activities. Initially, historical land-use/cover patterns were quantified to establish trends and conversion patterns. Potential biophysical and socio-economic factors were analysed and their effect on land-use patterns recorded for calibrating the model. Plausible scenarios based on local knowledge and trend extrapolation from the analysis of historical land-cover data, were explored to establish future land cover change trajectories and patterns. Overall, from the regression analysis, spatial distribution of vegetation classes was influenced mainly by the prevailing temperature and precipitation, soil properties i.e., pH, cation exchange capacity and soil organic carbon content and altitude. Generally, future patterns in LULC in the study were mainly influenced by biophysical variables which are known to control certain conditions like suitable areas for plant growth i.e., temperature regime, precipitation and soil fertility. However, access to modern technology, farmers training and use of fertilizers has enabled farmers to overcome some of the biophysical limiting factors that control land use activities. Consequently, this study considers socio-economic drivers as playing a pivotal role in land-use decisions, mainly at household levels, and therefore recommends their inclusion in future studies to improve model's performance and predictive capability. Additionally, since no method from available literature has been found to satisfactorily calibrate and validate land-use models, other subjective methods like visual assessment of simulated results, have been suggested to complement model's results. These findings are expected to provide insights into how future land-use trajectories under different scenarios could affect soil erosion in a transboundary water catchment area and ecological stability. The data could also support studies on Earth system modeling, and provide policy makers in the region with baseline data and information needed for developing practical soil conservation strategies.

CHAPTER 5

Impact of Land Use Change on Soil Erosion

This chapter presents the methodology and results obtained from objective three of the study. The presentation is based on the published work presented in *Appendix H (Manuscript 3-<https://doi.org/10.1016/j.pce.2023.103529>)*. First, the scenarios for land-use change used in the study to evaluate the impacts of LULC change on soil erosion and deposition patterns are described. The methodology used to evaluate and standardize physical factors known to influence the displacement and lateral movement of soil across landscapes is also discussed, and the procedure used to assign cover factors for LULC classes for each scenario explained. Finally, results from modelling erosion and deposition patterns are presented for each scenario.

5.1 Introduction

The sustainable management of land and soil resources has more recently become a critical issue of global importance considering their contributions to earth system functions (Borrelli et al., 2017; Chhabra et al., 2006; Cimusa Kulimushi et al., 2023; Yao et al., 2023) and delivery of ecosystem goods and services (Guerra et al., 2020a). However, due to increasing pressure from human-induced perturbations and environmental stressors related to changes in climatic and land-use activities (Yirgu, 2022), the ability of these resources to deliver critical natural services, and which are important today for sustaining the existence of life and human well-being has been negatively impacted (Poesen, 2018; Reyers et al., 2009). Globally, approximately 75 billion tons of fertile soil are estimated to be removed annually from arable land (Zhang et al., 2023), and about 1.1 billion hectares of global land (21 % in Africa) degraded by soil erosion (Bai et al., 2008; Ebabu et al., 2022), translating to about US \$400 billion financial losses annually (Borrelli et al., 2021). In Sub-Saharan Africa (SSA), where agriculture is the main source of livelihood for many rural population (Adenle et al., 2022), an estimated 5 Mg/ha/year of fertile soil is lost to large water reservoirs on annual basis (Angima et al., 2003). In the tropical regions of SSA, erosion rates are estimated to be in the region of 90 to 680 t ha⁻¹ yr⁻¹ (Cimusa Kulimushi et al., 2023; Karamage et al., 2017). Consequently, the mean productivity loss from past erosion in this region, estimated at 9 %, is projected to decline further by 14.5 % if accelerated erosion persists (Lal, 2001). Further, the per capita food production has declined (Fleitmann et al., 2007), where over 65 % of soil has

been degraded over the last five decades, leading to a decline in per capita arable land of approximately 0.2 ha, from 1950 to 1990 (FAO,1993).

Within the highland zones of East Africa, where more than 50 % of the population depend on agriculture as their main-stay (Djoumessi, 2022), more than 12 million ha of land is estimated to have been lost through erosion by water (Borrelli et al., 2017; Endalew & Biru, 2022; Karamage et al., 2017). In severely affected agro-ecoregions, this decline could precipitate the problem of food insecurity if erosion continues unabated (Wynants et al., 2019).

In the Sio-Malaba-Malakisi basin of Kenya and Uganda, the abundance of tropical orographic rainfall, together with its unique landscape, characterized by gentle rolling topography, steep slopes and fertile soils (Karamage et al., 2017), supports two cropping seasons in a year. This exerts undue pressure on the fragile soils thus accelerating soil erosion and sedimentation rates in the basin. This is especially evident in the headwaters, where intensive agricultural activities, and poor soil conservation practices are common (Chasia et al., 2021). These eroded sediments, laden with agrochemicals and toxic contaminants are usually transported by runoff to nearby streams, and deposited downstream, or along stream banks. This has worsened the pollution of freshwater ecosystems (Lal, 2001), and eutrophication of waterways. Other problems include damming and siltation of connected reservoirs and water systems (Olang et al., 2014; Poesen, 2018), fertility loss and land degradation (Borrelli et al., 2017; J. Liu et al., 2007).

Globally, several studies have been conducted aimed addressing the erosion problem using various modelling frameworks, in order to estimate soil erosion rates and guide conservation initiatives (Aiello et al., 2015; Endalew & Biru, 2022; García-Ruiz et al., 2015; Panagos, Borrelli, Meusburger, Alewell, et al., 2015; Vagen Tor-Gunnar, Winowiecki, 2019), and soil biodiversity risk analysis (Guerra et al., 2020a). Within the study region, a few studies aimed at understanding the erosion problem at localized scales, have been conducted targeting areas affected by erosion (Cimusa Kulimushi et al., 2023; Endalew & Biru, 2022; Karamage et al., 2017; Schürz et al., 2020). Such studies, have employed widely used empirical erosion models, such as Universal Soil Loss Erosion (USLE), and its derivatives such as RUSLE (revised) and MUSLE (modified), to estimate the annual rate of soil erosion (Endalew & Biru, 2022; Karamage et al., 2017; S. Kumar & Kushwaha, 2013; Renard et al., 2011; Yirgu, 2022). These tools are not only relatively easy to use, given the parameter values (Merritt et al., 2003; Swarnkar et al., 2018), but also generate

important baseline information, and scientific knowledge on the overall erosion problem such as Europe (Panagos, Borrelli, Meusburger, Alewell, et al., 2015), East Africa (Fenta et al., 2020) and Asia (Wu & Chen, 2012). However, these tools only predict soil erosion and sediment transport rates at the outlets of a catchment (Batista et al., 2019), even when deposition may occur (Capolongo et al., 2008). Therefore, information on erosion dynamics within the landscape is lacking (Warren et al., 2005). In addition, when applied to areas with complex topography, they may not yield accurate results (Capolongo et al., 2008; Mitasova et al., 1996). Furthermore, their application in the study region may not yield the information required to understand the complexities of erosion due to the transboundary nature of the catchment, and lack of regular hydrometeorological monitoring data (Olang et al., 2014).

Therefore, for proper diagnosis, control and efficient management of the erosion problem, especially within a transboundary area such as SMM catchment, knowledge on sediment sources, and deposition pathways, is becoming increasingly important in many scientific studies aimed at developing site-specific interventions for reducing erosion rates. To this end, a few models have recently been developed for such purposes (Desmet & Govers, 1995; S. Kumar & Kushwaha, 2013; Lizaga Villuendas et al., 2022; Mitasova et al., 1996). One of the models that has gained prominence in the recent past is the Unit Stream Power-based Erosion Deposition (USPED) model (Mitasova et al., 1996; Mitasova and Mitas, 2011). The spatially-explicit model is based on the unit stream power theory (Moore & Wilson, 1992), and used to analyze both spatial and temporal patterns of erosion and sediment deposition on landscapes with complex topographical landscapes, (Aiello et al., 2015), such as SMM catchment. The model parameters include local precipitation data, soil physical properties, topographical characteristics and the cover management practices (Aiello et al., 2014). The soil conservation practice (P) factor however, is not used in the USPED model because it is accounted for by the cover and topographical factors (Warren & Ruzyski, 2022). In this study therefore, the value $P=1$ was assigned (Wischmeier & Smith, 1978). In addition, the slope and slope length factor (LS), which is operated on planar surfaces, was replaced with the upslope contributing area, representing the flow accumulation or drainage area. Such a representation of the terrain factor is applicable to regions with complex geometries (Pistocchi et al., 2002; Van Oost et al., 2004), such as most highlands in the East African region. This allows the model to predict erosion as a result of an increase in flow concentration without the need to define the topographic factor (LS) in advance (Warren & Ruzyski, 2022).

To date, several studies have implemented the USPED model for modelling erosion/deposition zones (Aiello et al., 2014; Liu et al., 2007; Pricope, 2009); simulating the impact of land-use on erosion and deposition (Gioia et al., 2021; Leh et al., 2011; Mitasova et al., 2001; Pelacani et al., 2008); modelling the effect of soil erosion and land cover change on watershed carbon dynamics (Liu et al., 2021); soil conservation programs (Pricope, 2009); land conservation practices (Pistocchi et al., 2002) and analysis of deposition patterns as a function of land-use patterns (Capolongo et al., 2008). However, Mitasova et al., (2001) cautions that care should be taken when interpreting USPED results because RUSLE parameters were originally developed for simple plots, and therefore, re-calibration of input parameters is required. However, despite this limitation, USPED model has successfully been used to predict sediment flux in areas of complex terrain, and remains to be a useful tool for guiding land management strategies (Mitasova et al., 2001). It also provides a rationale for ranking intervention priorities, as well as a framework for evaluating different management scenarios (Pistocchi et al., 2002). Further, with increasing availability of freely available global datasets, such as remotely-sensed satellite data and biophysical datasets (Ebabu et al., 2022), the wider application of the USPED model is expected to increase and improve the understanding of erosion and deposition patterns among the scientific community. The aim of this study therefore, was to assess the impact of different land-use scenarios on erosion/deposition patterns in the Sio-Malaba-Malakisi catchment, by applying a spatially-explicit erosion and deposition USPED model, together with physical datasets. By analyzing hillslope erosion, and ultimately estimating patterns of sediment distribution across the landscape, the model can predict erosion risk areas which could provide a framework for ranking and prioritizing intervention measures, and therefore act as a basis for comparing different soil and land management scenarios in the catchment. This would ultimately be important in guiding policy makers in designing data-driven sustainable soil and water conservation programs and strategies, and provide a basis for efficient allocation of scarce resources by decision makers in the region.

5.2 Methodology

5.2.1 Materials and Methods

5.2.1.1 Datasets

(a) Physical Datasets

Physical datasets required to derive the model parameters were acquired from various sources (Table 5-1). The digital elevation model (DEM) was used to generate the topographic component factor, which accounts for the influence of terrain shape, especially in areas with complex topographic conditions. Annual precipitation layer was used to estimate the rainfall run-off erosivity factor; land-use map provided the cover management factor, while the soil layer was used to generate soil erodibility factor.

Table 5-1. Datasets for generating input layers for USPED model

Datasets	Source	Application	References
Topography	Digital Elevation Model - ASTER Global Digital Elevation Model (GDEM) Version 3 (ASTGTM)	Calculation of slope and slope length (<i>LS</i> factor)	US Geological Survey (https://earthexplorer.usgs.gov) (Mitasova et al., 1996)
Precipitation	CHIRPS ² (0.05° resolution)	Calculation of <i>R</i> factor (Rainfall erosivity)	(T. R. Moore, 1979)
Land-use/cover	Classified Landsat-8 imagery	Calculation of <i>C</i> factor (soil cover)	(Chasia et al., 2021)
Soil	SoilGrids (soilgrids.org)	Calculation of soil erodibility (<i>K</i> factor) from soil texture (sand, silt, clay, organic matter)	(Karamage et al., 2017; Williams, 1995)

² Climate Hazards Center InfraRed Precipitation with Station data

(b) Land use Data

(i) *The Reference Land-use Map*

A baseline land use/cover (LULC) layer used for the study was acquired for the year 2017 (Chasia et al., 2021), coinciding with the period when a comprehensive field data collection was carried out in the basin (Figure 5-1a). The dataset was prepared from Landsat 8 satellite image, and consisted of nine LULC classes considered to have significant impact on the local hydrology. The land-use classes were subsequently used to generate the cover factor parameter used in the model.

(ii) *Land-use Map for the Scenarios*

Two land-use change scenarios with potential impact on soil erosion rates in the study area were explored using the Conversion of Land-use and its Effects at Small regional extent (CLUEs) modelling framework (Chasia et al., 2023). They included: (a) agricultural expansion - exploring change patterns under an environment characterized by rapid expansion in agriculture, and (b) reclamation scenario - which assessed potential LULC patterns when afforestation programs aimed at increasing overall soil cover, and consequently reduce the impact of raindrop on soils are implemented in the catchment. The scenario development involved analysing the relationship between prevailing biophysical and socioeconomic factors, and land-use allocation decision using a stepwise logistic regression model (Chasia et al., 2023). The final layer (Figure 5-1: b and c) was used to generate the cover factor values used in the USPED model for the scenarios.

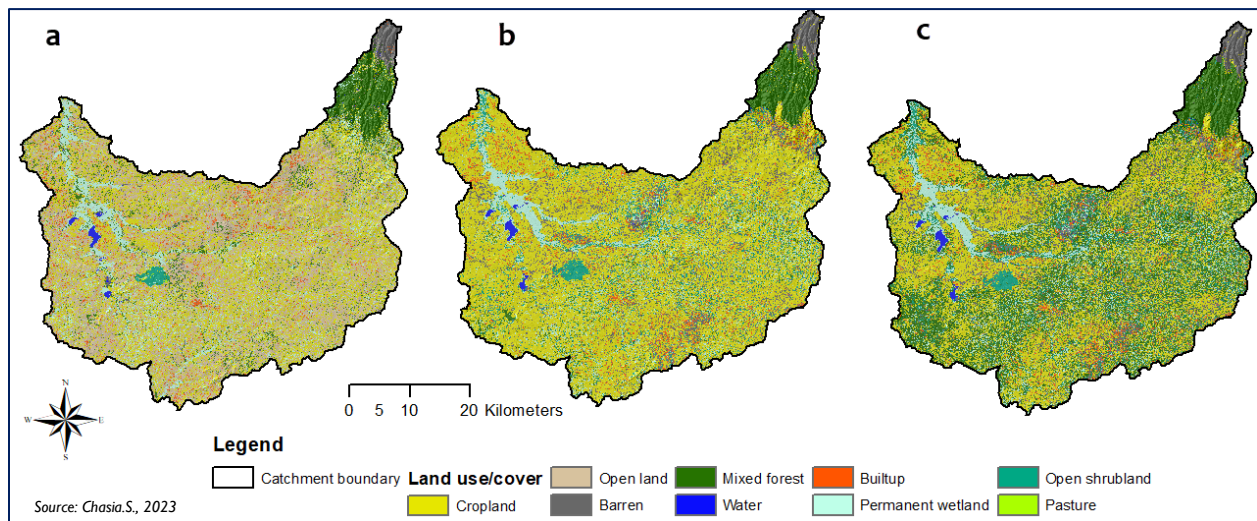


Figure 5-1. a) Land-use/cover changes for baseline condition (2017), b) agriculture expansion scenario, b) land reclamation scenario.

(c) Sediment Data

Sediment load data for the study area was obtained from the local water resource authority, representing data for the period 2007 to 2016 (Table 5-2). Historical sediment data was available for Sio, Malaba and Malakisi sub-catchment. Due to data gaps, additional data on sediment data and erosion occurrence zones was collected during the fieldwork conducted between 2017 and 2018 during the months of April to June, coinciding with the “long-rainy” season in the study area.

Table 5-2. Sediment load data recorded from sub-catchments stations

Malaba		Malakisi		Sio	
date	[t/day]	date	[t/day]	date	[t/day]
27.10.2007	42.76	27.10.2007	74.96	21.02.2011	280.42
31.01.2008	2.51	31.01.2008	0.82	02.05.2012	123
04.03.2008	128.12	04.03.2008	122.34	25.05.2012	607.73
07.05.2008	267.32	07.04.2008	224.84	03.06.2012	193.9
20.05.2010	1281.21	09.09.2009	6.28	01.11.2012	454.2
03.06.2011	91.34	20.05.2010	613.88	06.02.2013	48
07.11.2011	226.96	18.02.2011	12.44	13.05.2013	232
14.12.2011	469.13	03.06.2011	204.66	12.11.2013	17.87
31.01.2012	9.87	14.12.2011	330.94	16.06.2014	439.89
28.02.2012	2.55	31.01.2012	4.31	11.03.2015	6.87
10.04.2012	13.74	28.02.2012	0.32		
02.05.2012	725.39	02.05.2012	445.97		
08.06.2012	247.48	06.08.2012	150.16		
06.02.2013	41	06.02.2013	26		
20.05.2013	979	20.05.2013	218		
12.11.2013	4.76				
Mean	283.32	162.39		240.39	

5.2.2 Modelling Framework

5.2.2.1 USPED Model Formulation

The Unit Stream Power based Erosion/Deposition model (USPED) is a 2-dimensional soil erosion model used to predict the spatial distribution of erosion and deposition rates (Mitasova et al., 2001; Mitasova & Mitas, 2011) in a terrain with a continuous sediment transport and steady overland flow (Liu et al., 2007; Pistocchi et al., 2002). It assumes soil erosion and deposition is a function of sediment transport capacity of the surface runoff (Liu et al., 2007).

The sediment transport capacity T is thus estimated by:

$$\mathbf{T} = K_t |q|^m \sin b^n \quad \text{Equation 5-1 - Transport capacity}$$

Where, K_t is transportability coefficient as a function of soil type and vegetation cover, q represents water flow rate, b is the slope while $m = 1.6$ and $n = 1.3$ are constants.

Due to lack of experimental data during the development of the USPED model, (R)USLE parameters were incorporated to approximate the impacts of soil and vegetation cover to obtain relative estimates of net erosion and deposition (Blanco and Nadaoka, 2006). It was therefore assumed that sediment flow can be estimated as sediment transport capacity (Mitasova and Mitas, 2011):

$$\mathbf{T} = R.K.C.P.A_s^m (\sin \beta)^n \quad \text{Equation 5-2 - Sediment transport capacity}$$

Where, R is rainfall-runoff erosivity factor, K is a soil erodibility factor, C is a cover management factor, P is a support practice factor, and A_s is the upslope contributing area per unit contour width. Flow accumulation A_s is used instead of slope-length factor (LS) in order to account for landscape effects (Pistocchi et al., 2002). The LS factor is replaced by drained area or upslope contributing area A_s and slope angle β . m and n are empirical coefficients whose values depend on the prevailing erosion i.e., $n = 1.3$ for rill erosion and $m = 1$ for prevailing sheet erosion (Blanco and Nadaoka, 2006). Therefore, “ LS ” can be derived from as:

$$\mathbf{LS} = A_s^m . (\sin \beta)^n \quad \text{Equation 5-3 - Slope length}$$

Equation 5.2 is a pattern model of erosion which doesn't estimate absolute quantities but refers to relative availability of steam power for sediment transport (areas with high mass transport capacity) (Pistocchi et al., 2002).

$$\mathbf{TP} = K_c . A^m . (\sin b)^n \quad \text{Equation 5-4 - steam power for sediment transport}$$

Where, K_c is the combined soil erodibility (K) and cover factor (C). Equation 5.4 operates under the following assumptions: (1) Erosion and deposition factors are not determined by the R -factor, (2) no conservation practice considered, (3) “ K ” and “ C ” factors are combined representing ordinal scale of erosion susceptibility.

The net erosion/deposition can thus be estimated as the divergence of the pattern T with planar coordinates x, y (Mitasova et al., 2001):

$$USPED = \text{div}(T.s) = \frac{\partial(T.\cos \alpha)}{\partial x} + \frac{\partial(T.\sin \alpha)}{\partial y} \quad \text{Equation 5-5 - Erosion \& deposition pattern}$$

Where, s is the unit vector in the flow direction, α represents the aspect of the terrain surface (degrees). $\partial x = \partial y$ is the grid resolution, while T represents the sediment transport capacity.

5.2.2.2 USPED Model Application

Figure 5-2 illustrates the methodological framework used in the study to model lateral movement of soil and deposition in the study area. Relevant physical datasets acquired from different sources were initially pre-processed to a uniform standard projection system i.e., (WGS84 UTM Zone 36N), and pixel resolution (250 m) for proper overlay. The pre-processed factor layers were applied into the model in order to estimate erosion and deposition rates in the study area.

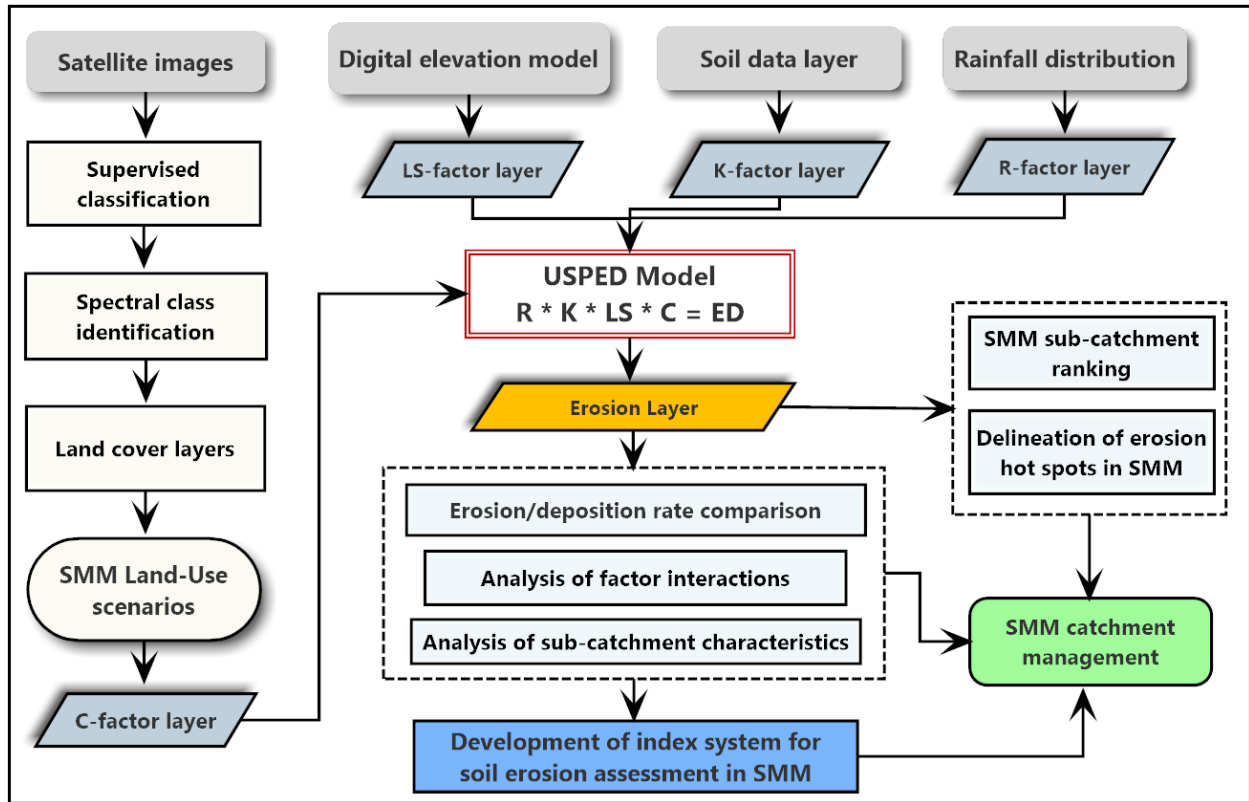


Figure 5-2. A methodological framework for modelling ED using USPED model

5.2.2.3 Derivation of the Model Parameters

Soil, rainfall, topographic parameters and land cover data for Sio-Malaba-Malakisi basin were acquired from a number of sources as illustrated on Table 5-1. These datasets were used to derive parameters required for modelling soil loss (see equation 5.4) and generate erosion patterns (see equation 5.5) for the study area. These parameters for running the model were derived as follows:

(a) Soil Erodibility (K) Factor Estimation - (Mg h MJ-1 mm-1)

The soil erodibility factor represents the soil response to a set of complex and dynamic erosion and hydrologic processes which are a function of the soils physical and chemical properties i.e., texture, structure, organic matter content, permeability and surface roughness (Torri et al., 1997). Generally, soils with high silt content are most erodible and easily detached, producing high rates of runoff. As a result, their K values tend to be higher (> 0.4) (Allafta & Opp, 2022). Conversely, clay-rich soils and soils rich in organic matter are resistant to detachment due to increased infiltration. Therefore, they tend to have low K values ranging between 0.05 to 0.15 (Institute of Water Research, 2002). The soil erodibility K of the basin was derived by combining physical soil parameters of Sand, Silt, Clay and Organic carbon (or matter) obtained from the *SoilGrids250m 2.0* portal. To calculate K , the study used a method proposed by Karamage et al., (2017) and (Williams, 1995), by considering the percentages of Clay, Organic carbon, Silt and Sand content from the *SoilGrids* data using the following expression:

$$K = [A * B * C * D] * 0.1317 \quad \text{Equation 5-6 – Soil erodibility factor}$$

Where, A, B, C, D represent the percentages of silt, clay, sand and organic carbon respectively. The final product of K was converted to SI units by multiplying it by 0.1317 (Fenta et al., 2020).

(b) Rainfall-runoff Erosivity (R) Factor Estimation - (Mj mm ha-1 h-1 yr-1)

The R factor quantifies the raindrop impact giving information on the amount and rate of runoff that is likely to be associated with the storm (Swarnkar et al., 2018). In this study, data obtained from CHIRPS was used to prepare the R factor layer using the method proposed by Moore following a study on rainfall erosivity in East Africa (Moore, 1979). According to this study, R can be inferred from long-term mean annual precipitation which can be correlated with strong rainfall events.

The regression equation 5.7 assumes a correlation between R and the kinetic energy ($KE_{15>25}$) for the stations under study.

$$y = 11.46x - 2226 \quad \text{Equation 5-7 – Regression equation}$$

Where, y is the kinetic energy (KE). The correlation coefficient x was derived by multiplying the erosivity parameter ($R = 0.029 \text{ ft.tons acr}^{-1}\text{year}^{-1}$) by the kinetic energy ($KE = 26.0$) and converting the final result from imperial units to SI units by multiplying by 17.02.

(c) Topographic Parameter (LS) Factor Estimation

Topographic parameters of slope length (L) and slope steepness (S) factors have significant contributions to the rate and velocity of erosive power in any given landscape (Mitasova et al., 2001). For estimation of soil erosion on watersheds with complex topography, LS is usually calculated from the upslope contributing areas which describes the amount of runoff water accumulated from the upslope area sent through down-stream land pixel (Warren & Ruzyski, 2022; Wu et al., 2021). The LS factor used by the USPED model was calculated in ArcGIS software program and a 30 m DEM following:

$$LS = A^m(\sin \beta)^n \quad \text{Equation 5-8 – Topographic parameter}$$

Where, A is the upslope contributing area and β is slope angle. It was determined from field visits that sheet erosion was predominant, therefore, both m and n constants were set to 1.0 (Pelacani et al., 2008).

(d) Cover and Management (C) Factor Estimation

The C factor is dimensionless, and represents the ratio of soil loss from an area with specified cover management to soil loss from an identical area in tilled fallow (USDA, 1996). C values normally range between 0 for (well-protected lands) to 1 (bare lands). It is normally either inferred from vegetation indices, satellite-based remote sensing data (van der Knijff et al., 2000), or from classified land cover products and agronomic statistics (Borrelli et al., 2017; Panagos, Borrelli, Meusburger, Alewell, et al., 2015). The study derived the C parameter values separately for the baseline land cover state from the classified land cover map for SMM catchment for the year 2017 (Chasia et al., 2021), and for both scenarios I and II from simulated land cover maps of the area (Chasia et al., 2023). This was achieved by converting the raster maps to vector format and using equivalent C factor values for each LULC obtained from literature (Table 5-3).

Table 5-3. C factor value for different land cover types

LULC	C Factor Range	Mean	Reference
Built-up	0.05-0.1	0.075	(Borrelli et al., 2017)
Barren	0.4-0.6	0.5	(Panagos, Borrelli, Meusburger, Alewell, et al., 2015)
Mixed forest	0.001 - 0.003	0.002	(Borrelli et al., 2017; Panagos, Borrelli, Meusburger, Alewell, et al., 2015)
Open shrubland	0.01 - 0.02	0.015	(Borrelli et al., 2017)
Open land	0.10 - 0.265	0.183	(Borrelli et al., 2017; Evans, 2006)
Permanent wetland	0.0001-0.0005	0.0003	(Borrelli et al., 2017)
Open water	0	0	(Borrelli et al., 2017)
Pasture	0.01–0.025	0.0175	(Evans, 2006)
Cropland	0.15 - 0.3	0.225	(Panagos, Borrelli, Meusburger, Alewell, et al., 2015)

5.2.3 Validation of Model Results

Due to the limited long-term total suspended sediment data in the study, the modelled erosion/deposition (ED) results were compared to previously observed and recorded ED values during field data collection in order to assess USPED model performance (Capolongo et al., 2008). This was accomplished by first assigning 100 random points spread across all the ED categories (Table 5-4) to each of the five sub-catchments (500 total) (Warren & Ruzyski, 2022). Together with field observation data on ED sites, the random points were overlaid on Google Earth application, and visually inspected in order to assign the actual ED values based on observed conditions.

Table 5-4. Erosion and deposition categorization and rates

Category	Range (tons ha ⁻¹ yr ⁻¹)	Description
High Erosion	>50	Removing of fine soil particles; runoff patterns such as rills and huge gullies present; subsoils exposed with limited plant density
Medium Erosion	20.1 – 50	Lower plant density; smaller gullies evident of surface runoff patterns; soil scouring; surface may appear rockier compared to non-eroded areas
Low Erosion	5 – 20	Very limited signs of fluvial movement and soil detachment
Stable	0-5	No significant occurrence of erosion/deposition; terrain is flat with limited soil disturbing land-use activities
Low Deposition	5 – 20	Mainly occurs in low-lying areas; minor sediment deposits
Medium Deposition	20.1 – 50	Clear signs of deposition especially foot slopes and river banks; silty soil surface texture with dense vegetation compared to the surrounding areas.
High Deposition	>50	Generally located in low-lying terrain showing significant signs of deposition forming mounds of soils mixed with debris; luxuriant vegetation distribution

5.3 Results

5.3.1 Estimated Model Parameters

In the following section, the study presents results for the model parameters prepared for modelling erosion and deposition patterns using the USPED model.

5.3.1.1 Soil Erodibility Factor

K values for clay-rich soils are generally low due to their persistence to separation (Allafta & Opp, 2022). Coarse-grained soils i.e., sandy soils with low *K* values have low run-off potential; medium-grained soils such as loamy soils have high *K* values and therefore susceptible to run-off impact. Soil erodibility factor values (*K*) for SMM catchment ranged between 0.3-0.5. Higher *K* values were associated with erosion zones, mainly observed on the upper catchment areas (Fig.5-3b),

characterized by steep slopes ($>60^{\circ}$) and coarse textured soils such as haplic and plinthic Acrisols, and eutric Gleysols rich in silt content. Deposition zones were associated with lower K values (0.2-0.3), and slope angle of less than 5° . Such areas were dominated by marine deposit soils with high clay content including haplic Vertisols, plinthic Lixisols and eutric Fluvisols.

5.3.1.2 Rainfall Runoff Factor

Rainfall-runoff erosivity values for the study ranged between 600-10000 $\text{Mj mm ha}^{-1}\text{year}^{-1}$ (Fig.5-3a). Higher R values were recorded on highland areas near Lwakhakha and Malakisi sub-catchments, with slopes of approximately 65° . Other zones with high R values were observed on the south-eastern parts of the catchment, especially in the Sio sub-catchment. Mpologoma sub-catchment on the upper-eastern side, recorded the lower R values between 700-800 $\text{Mj mm ha}^{-1}\text{year}^{-1}$.

5.3.1.3 Slope Length and Slope Steepness Factor

The topographical factor LS is used to model the impact of slope length (L) and slope steepness (S) on soil erosion (Wu et al., 2021). LS was used to calculate the sediment transport capacity, describing the erosive force of surface runoff. Higher LS values (0.124-0.158) were associated with high altitude areas with maximum slope angles of between 43° - 54° in sub-catchments such as Lwakhakha and Malakisi (Table 5-5), corresponding with high erosion rates (Figure 5-3c).

Table 5-5. Slope vs. length, mean NDVI and erosion/deposition rates

Sub-catchment	Area (Ha)	Max. slope (degrees)	Mean LS factor	Mean NDVI
Lwakhakha	59,200	54	0.158	0.618
Malakisi	62,400	43	0.124	0.653
Malaba	103,700	41	0.022	0.635
Sio	140,700	30	0.025	0.640
Mpologoma	152,800	26	0.018	0.602

5.3.1.4 Cover and Management Factor

The range of *C* factor values obtained for all the LULC classes for the baseline land cover condition is illustrated in figure 5-3d. Lower *C* values (0-0.024) were found in LULC such as open water, mixed forest, barren land, permanent wetland and open shrublands, where mainly low erosion and deposition occurs. Conversely, comparatively high *C* values (>0.23) were found in land-use classes such as cropland and open land categories, which provide inadequate seasonal soil cover.

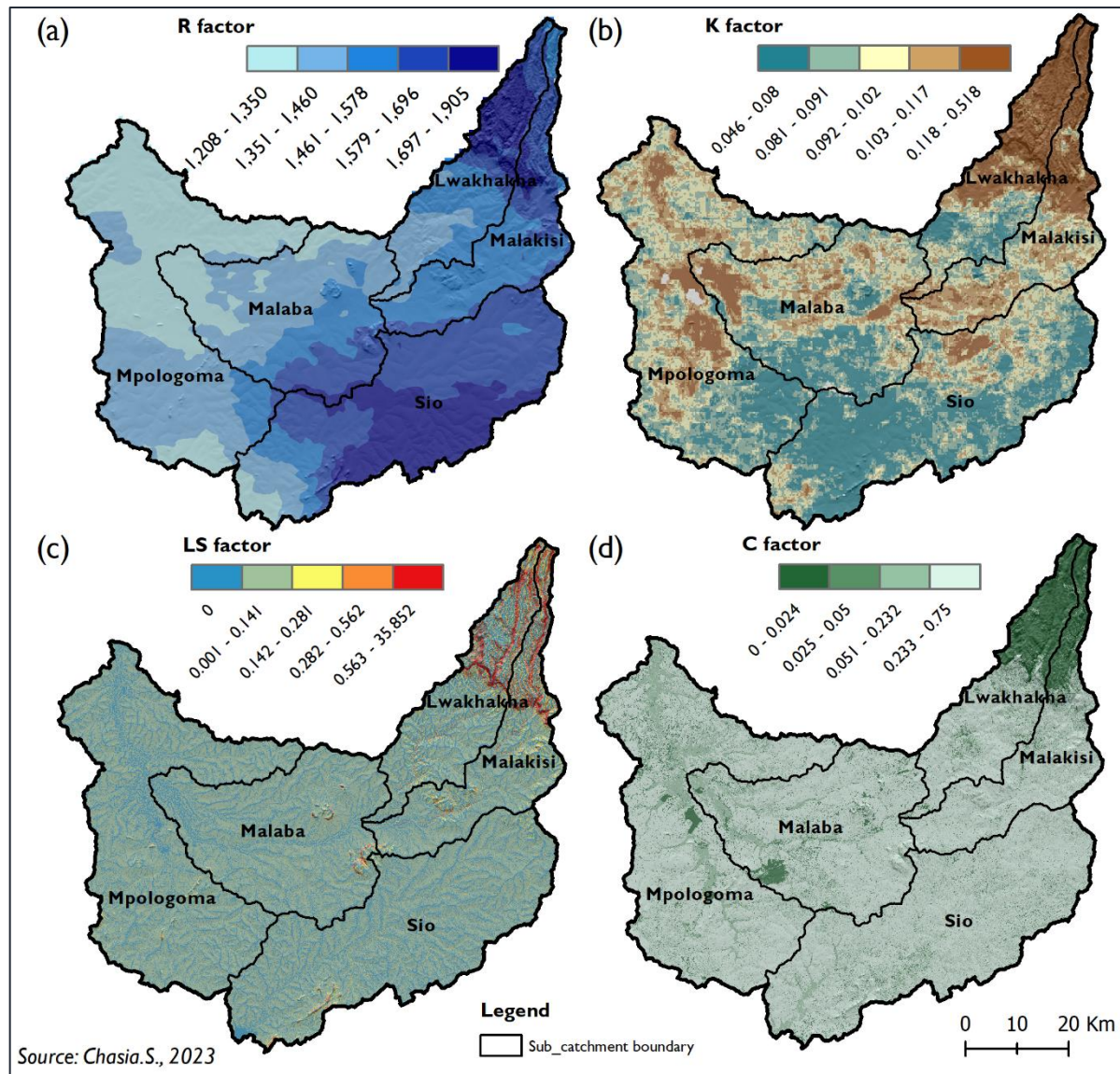


Figure 5-3. USPED model component factors: a) rainfall erosivity, b) soil erodibility, c) slope-length, d) cover management.

The *C* factor values for the two LULC scenarios were prepared separately as illustrated in figure 5-4. Overall, values ranged from 0-0.1 under both scenarios as a result of the dominance of cropland (SI) and mixed forest (SII). For the agricultural scenario (SI), *C* factor values ranged between 0.075-0.1 (Figure 5-4a). This follows the conversion of open arable land to cropland, and mixed forest outside protected areas. Seasonal crops provide limited soil cover, especially when cultivation is conducted on steep slopes. Conversely, in scenario II, the reclamation of forest land and subsequent increase in canopy cover increased soil protection across the basin. As a result, *C* value increased significantly, and thus values ranged between 0 - 0.05 (Figure 5-4b). This has the overall impact of reducing the rate of surface runoff that usually accelerate erosion rate and sedimentation.

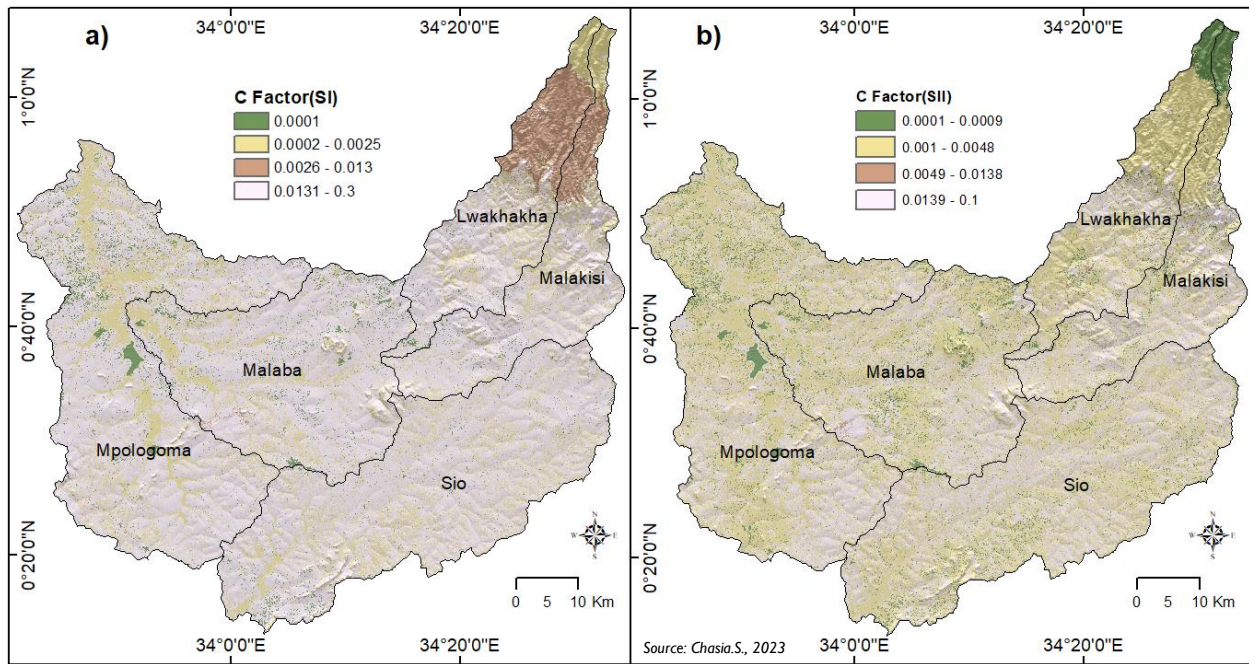


Figure 5-4. Range of *C* factor values derived from land-use change scenarios: a) agriculture expansion scenario, b) land reclamation scenario

5.3.2 Validation Results of the Model

A two-sample t-test was conducted to determine if there is a significant difference between the means of model ED estimates and observed values as illustrated in Table 5-6. Overall, there were no significant difference between model estimates and observed values as illustrated by the lower p-values obtained. However, the mean difference between ED values for Lwakhakha, Malakisi and Malaba sub-catchments was statistically significant because of the difference between the extreme modelled values for erosion/deposition and the underestimated observed values for the same region.

Table 5-6. Paired sample t-test between ED estimates and observed values

Sub-catchment	t-test	p-value	Mean difference
Lwakhakha (LWK)	3.4008	0.00138	13.1760
Malakisi (MKS)	2.1296	0.03826	8.7796
Malaba (MLB)	-4.7493	1.817e-05	-7.3254
Sio (SIO)	-0.6144	0.5418	-0.9808
Mpologoma (MLG)	0.8651	0.391	0.5242

Results from model estimates were compared against observed data in order to assess the accuracy against a predetermined threshold for acceptability of 80 %. Generally, results from the model and field observation agreed 83 % of the time (Figure 5-5). The upper catchment zones of Lwakhakha and Malakisi were correctly predicted under the high erosion category, generating $>20 \text{ t. ha}^{-1}\text{yr}^{-1}$ of sediments annually. Lower catchment areas comprising mainly Mpologoma, and the lower zones of Malaba and Sio were mainly categorized as deposition zones. Streams in these zones are in the mature stage, carrying high volumes of suspended sediments but with limited stream power due to the gentle topography. Consequently, some of the sediments are deposited on the adjacent stream banks, while the rest are transported to nearby reservoirs of Lake Victoria and Lake Kyoga.

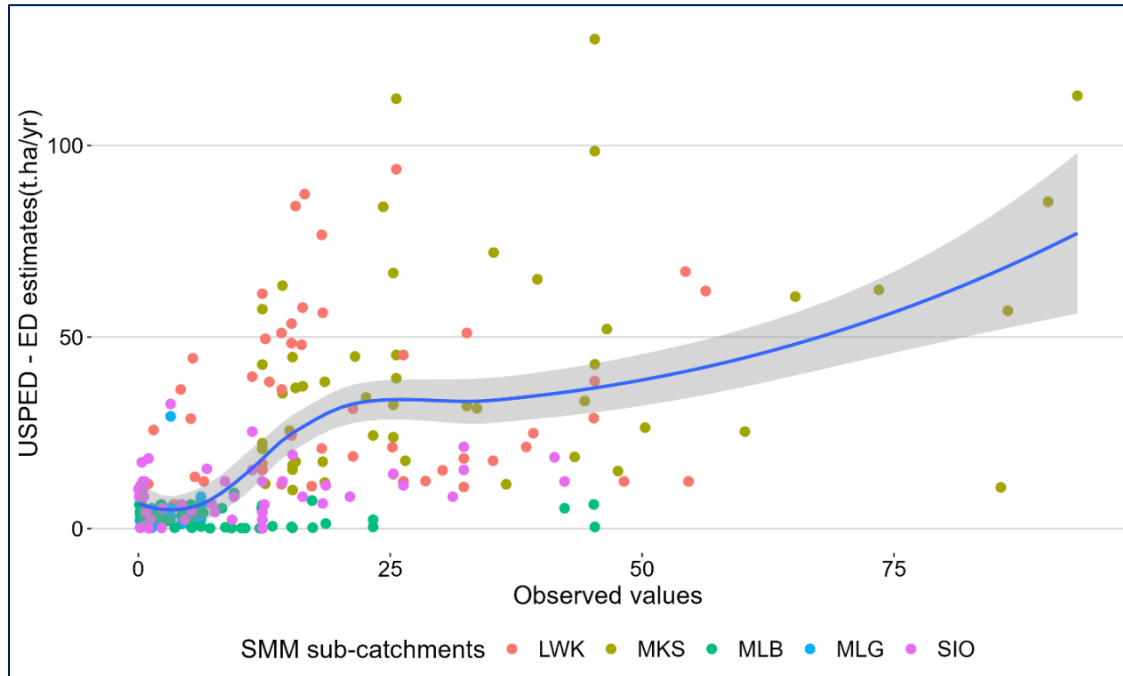


Figure 5-5. Relationship between modelled ED estimates and observed values

5.4 Discussion

5.4.1 Soil Erosion and deposition in SMM catchment

5.4.1.1 The Present Situation

Figure 5-6 illustrates the spatial distribution of the calculated erosion/deposition values at the SMM catchment. The annual soil loss rate of the basin ranges between 0 and 460 t ha⁻¹ year⁻¹, with a mean erosion rate of 160 t ha⁻¹ year⁻¹ and a standard deviation of 6.6. zones with very high to severe erosion were recorded in Lwakhakha and Malakisi sub-catchments located on the upper catchment area (Figure 5-6). These zones occupy the headwaters of the SMM catchment where stream power is higher due to steep topography. Deposition zones were located in Sio, Malaba, and Mpologoma sub-catchments. The mean elevation in these areas is approximately 900-1,200m above sea level. Here, deposition begins forming on stream banks when sediment load exceeds the streams transport capacity. Stream diversion to farmlands also reduces the stream's velocity leading to the deposition of sediments.

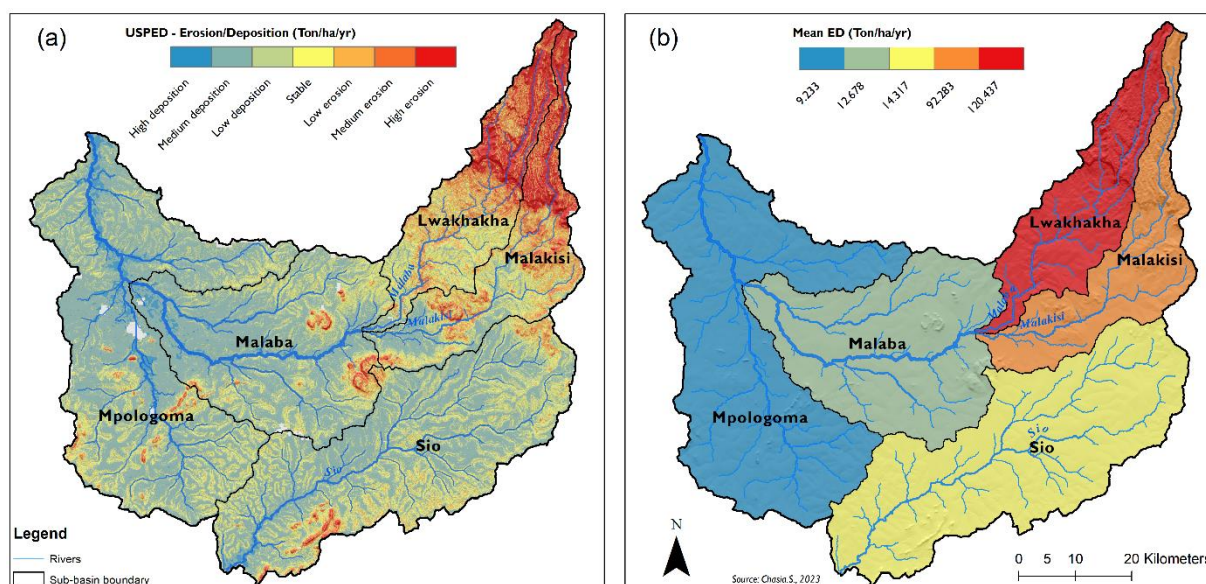


Figure 5-6. Spatial distribution of erosion/deposition zones for entire catchment (left) and sub-catchment (right).

Overall, between 7 % to 10 % of the catchment was categorized under prevailing medium to high erosion rates (Table 5-7). These zones were mainly concentrated in regions characterized by steep topography ($>20^\circ$ slopes) and altitudes of more than 1,400 m above sea level. Additionally, soils in these zones were originally rich in organic matter content, however, due to intense cultivation, coupled with poor soil management practices, they now have low infiltration capacity and therefore susceptible to detachment thus generating significant runoff.

Table 5-7. Soil loss statistics for the study area

Erosion/deposition state	Soil erosion rate (t. ha ⁻¹ yr ⁻¹)	Area (ha)	Area (%)
High erosion	>-50	384	7.4
Medium erosion	-20.1/-50	562	10.8
Low erosion	-5.1/-20	873	16.7
Stable	0-5	807	15.5
Low deposition	5.1-20	661	12.7
Medium deposition	20.1-50	899	17.2
High deposition	>50	1035	19.8

Negative notation (-) indicates erosion while positive values represent deposition occurrence

5.4.1.2 Sub-catchment Erosion and Deposition Rates

Generally, high erosion rates were recorded in the high-gradient headwater watersheds of Lwakhakha ($460 \text{ t ha}^{-1} \text{ yr}^{-1}$) and Malakisi ($270 \text{ t ha}^{-1} \text{ yr}^{-1}$), representing zones with high erosion severity class. Here, as a result of the high intensity orographic rainfall, the subsequently generated runoff eroded loose surface coarse to medium textured soils, regularly disturbed by agricultural activities. Consequently, large streamflows with high velocity and carrying large volumes of sediments downstream are generated. The low-gradient zones of lower Mpologoma, Sio, and Malaba experienced low erosion to moderate rates of 9, 10, and $51 \text{ t ha}^{-1} \text{ yr}^{-1}$ respectively, notwithstanding higher net deposition mainly along the banks of major rivers and floodplains. Whereas Lwakhakha and Malakisi sub-catchments occupy less than 30 % of the total catchment area, they contributed over 75 % of total annual soil loss (Table 5-8). This was mainly attributed to the steep topography prevailing on the upper reaches of the catchment that lends stream power to surface runoff.

Table 5-8. Annual soil loss for all land cover classes

Sub-catchment	Total area (km ²)	Area (%)	Total soil erosion (t h ⁻¹ yr ⁻¹)	Total soil loss (%)	Category/zone
Lwakhakha	592	11	460	57.5	Erosion
Malakisi	624	12	270	33.7	Erosion
Malaba	1,037	20	51	6.3	Transition
Sio	1,407	27	10	1.3	Erosion/Deposition
Mpologoma	1,528	29	9	1.2	Deposition
	5,188	100	801	100	

5.4.1.3 The Scenarios

Results of soil erosion and deposition patterns under the agricultural scenario (SI) and reclamation scenario (SII) are illustrated in Figure 5-7. In SI, the cropland area, with a *C* factor value of 0.15, was projected to increase annually by 0.8 %, representing 62 % of the total basin area (Chasia et al., 2023). In SII, emphasis was placed on reclaiming land through afforestation programs, and therefore, the total area under mixed forest was projected to increase by 1 % annually to occupy 8 % of the catchment. Scenario I resulted in approximately 16.3 % ($1.1 \text{ t ha}^{-1} \text{ yr}^{-1}$) erosion reduction rates, compared to 61.2 % ($3.8 \text{ t ha}^{-1} \text{ yr}^{-1}$) erosion reduction rate in SII, as a result of afforestation

programs implemented across the catchment, mainly targeting the upper reaches characterized by steep slopes, poor soil management practices and loose silty-rich soils (Figure 5-7b). In both scenarios, relatively large sub-catchments of Malaba, Sio, and Mpologoma that are located in mid to lower zones, recorded cumulative erosion rates of less than 30 %. However, considering the limited total available arable land, prevailing steep topography, silty soils, and poor soil management practices in Lwakhakha and Malakisi sub-catchments, the impact of erosion was higher due to the velocity of the surface run-off.

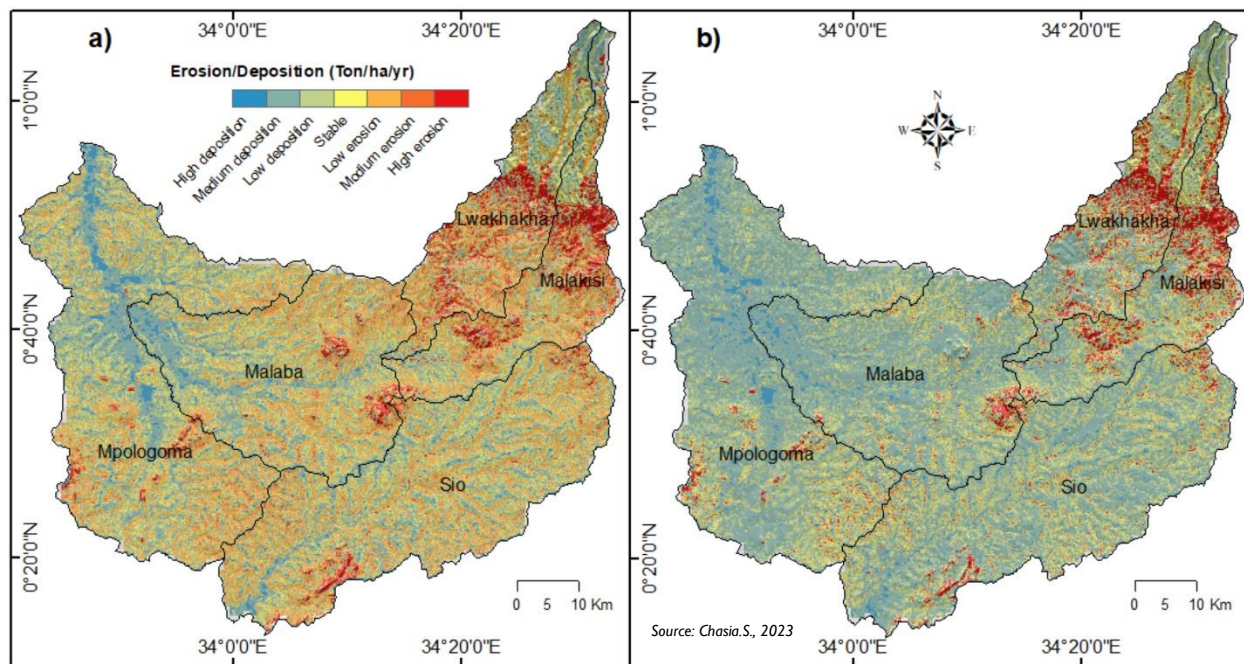


Figure 5-7. Erosion/deposition patterns for prevailing rill erosion: a) agricultural expansion, b) land reclamation.

5.4.2 Assessment of Erosion/Deposition Patterns and Sediment Concentration

The estimated erosion (rill) from the USPED model showed a close relationship with the total suspended sediments ($R^2 = 0.74$), using data recorded for SMM catchment (Fig.5-8). The highest sediment concentrations were observed within the Malakisi sub-catchment which is characterized by intense agricultural activities and steep topography that sustains flow velocity. The higher correlation between USPED-generated erosion and deposition estimates and the measured total suspended sediments in stream water within the SMM catchment validates the

usefulness of the model. Overall, these results indicate that the USPED model is effective in estimating watershed erosion using land cover maps together with physical datasets.

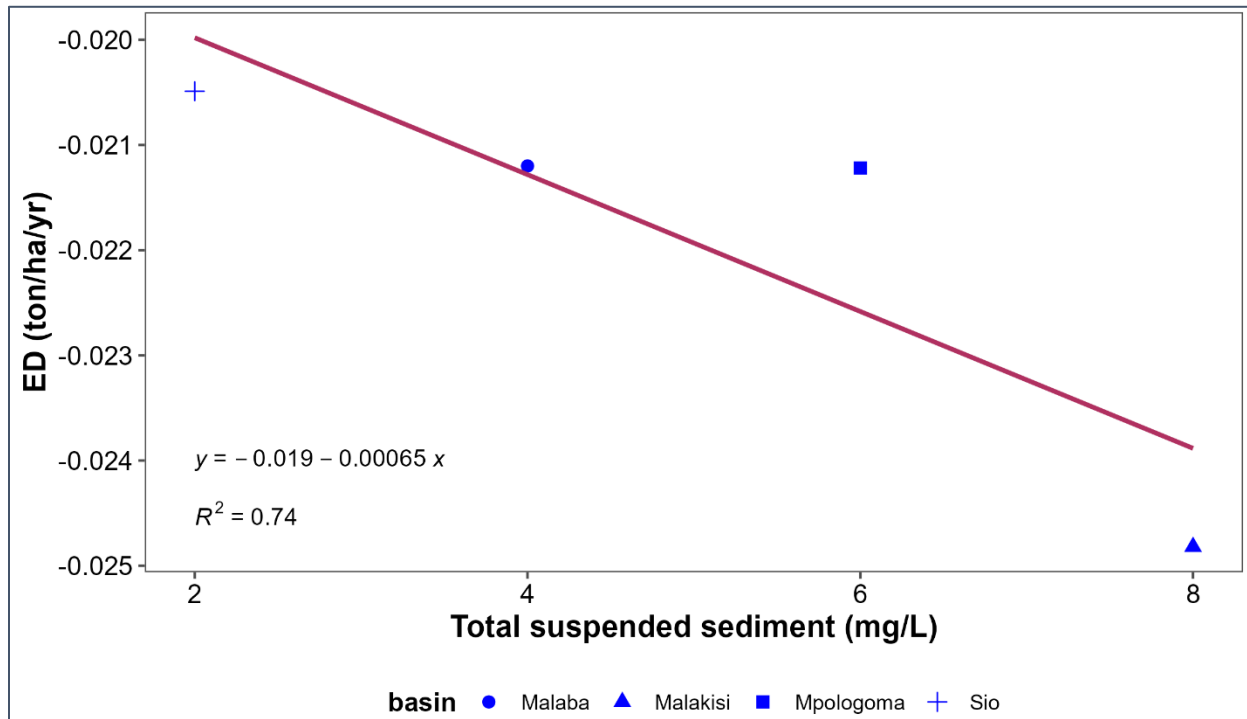


Figure 5-8. USPED simulated net ED rates Vs. stream flow total suspended sediments

5.5 Conclusion

The present study estimated erosion and deposition patterns in Sio-Malaba-Malakisi catchment using the Unit Stream Power-based Erosion and Deposition model on two land use change scenarios i.e., agricultural expansion and reclamation scenarios. The physical datasets required to run the model were first standardized in a Geographic Information Systems in order to conform to the same resolution and projection system. The USPED model was then used to generate a layer depicting erosion and deposition zones in the catchment by combining soil erodibility, rainfall run-off, slope length and cover management factor layers. C factor values were derived from the two land cover change scenarios were used to generate two separate erosion/deposition maps, each depicting the effect of cover management under a scenario characterized by agricultural expansion providing limited seasonal cover (scenario I), and scenario II comprising of an increase in mixed forest cover providing canopy cover against rainfall run-off impact. It was determined that under SI, erosion rates increased significantly, especially in the upper catchment areas with steep slopes

and intensive agricultural activities. This had negative impacts on downstream water quality due to an increase in sedimentation. On the other hand, SII which focused on reclaiming forested lands, and promoting afforestation and agroforestry programs on farmland, had the positive impact of reducing erosion rates across the catchment. The strong relationship between catchment net erosion and sediment concentration indicates the ability of the USPED model to simulate relative magnitudes and spatial patterns of soil erosion and deposition. Therefore, the simulated spatial variability of soil erosion and deposition can be useful in identifying areas where actions to implement soil management programs can lead to best outcomes that minimize the impact of soil erosion. Land use change scenarios can be used to assess spatiotemporal dynamics of erosion and deposition on landscape from different land use activities. This will enable decision makers to identify areas where soil conservation efforts need to be intensified for maximum impact and adopt management systems which recognize peak erosion periods that facilitate erosion reduction in the basin.

CHAPTER 6

Soil Erosion Vulnerability Assessment

This chapter discusses the process of assessing soil erosion vulnerability in the study region, and presents results highlighting affected zones for targeted intervention. The presentation is based on the manuscript submitted for review as outlined in *Appendix H (Manuscript 4)*. The chapter begins with background information on soil erosion vulnerability assessment, followed by a description of the methodology used in soil loss estimation and vulnerability assessment. The results from the analysis are thereafter presented, together with a discussion on vulnerability mitigation measures, before concluding by identifying soil conservation priority areas based on the defined severity levels for soil erosion for the study.

6.1 Introduction

Soil erosion is a global phenomenon which may have severe impacts to the environment through land degradation, fertility loss, and other off-site effects, such as sedimentation, siltation and enhanced flooding (Borrelli et al., 2017; Fenta et al., 2020; Raza et al., 2021; Wuepper et al., 2019). In the global south, specifically in sub-Saharan Africa where agriculture is the main source of livelihood for many communities, accelerated soil erosion process may precipitate a food security crisis, disrupting food systems, and negatively impacting the vulnerable incomes of many households (Fenta et al., 2017, 2020; Karamage et al., 2017). Within the East African highlands and surrounding regions, the demand for agricultural products has significantly increased over the recent past due to the rising human population and the improvement in household income (Chasia et al., 2021; Wuepper et al., 2019). Consequently, farming activities have expanded to marginal lands and vulnerable ecosystems in order to meet the growing demand (Chasia et al., 2021; Karamage et al., 2017). In such areas, the combined effects of intensive cultivation, and poor soil management practices may lead to the loss of the thin nutrient-rich top soil due to erosion, especially in unprotected lands. Further, the exposed and friable soils may be dislodged by the raindrop impact and washed away by surface runoff leading to loss of soil fertility and land degradation (Kucuker & Cedano Giraldo, 2022; Raza et al., 2021). In addition, suspended sediments and debris may accumulate along river banks and drainage channels causing damage to civil infrastructure, or blockages to existing drainage systems and potentially resulting in floods (Juma et al., 2021). Further, runoff water from nearby farmlands, usually rich in nutrients and

agrochemicals, may pollute freshwater ecosystems making them unsuitable for domestic use and uninhabitable for aquatic organisms as a result of eutrophication (Chasia et al., 2023; Karamage et al., 2017; Zacharia, 2013).

In many regions affected by severe erosion, the management of soil erosion and associated risks is an important undertaking aimed at mitigating the negative consequences associated with soil erosion (Kidane et al., 2019; Kucuker & Cedano Giraldo, 2022). Effective soil erosion prevention strategies require investments in regular monitoring of soil loss rates, and the adoption of suitable soil conservation practices. However, in many vulnerable watersheds affected by erosion, limited studies on the complex processes driving soil erosion has hampered the adoption of appropriate strategies adaptable to the prevailing unique biophysical and socio-economic conditions (Chasia et al., 2023). In transboundary watersheds, such as SMM catchment, the situation may further be compounded by disparate management frameworks, and national environmental conservation priorities (Brels et al., 2008a; Chasia et al., 2023). The need to develop a harmonized catchment management framework, is thus supported by a previous study which indicate that soil erosion rates may vary across the border by magnitudes of up to $\sim 1.4 \text{ t ha}^{-1}\text{yr}^{-1}$, which cumulatively could have significant impact on the total amount of soil lost in a catchment (Wuepper et al., 2019). Nonetheless, soil erosion estimation, especially in regions with limited regular sediment monitoring data have greatly improved in the recent past due to the availability of freely available global datasets, such as satellite remote sensing data and modelling tools (Raza et al., 2021). However, in order to establish soil erosion vulnerability zones required for targeted conservation measures, knowledge on sediment sources and deposition is paramount (Pricope, 2009).

Empirical modelling tools, such as the Universal Soil Loss Equation (USLE) and its derivatives have been used in previous studies to quantify annual soil loss in many regions affected by soil erosion (Ganasri & Ramesh, 2016; Ghosal & Das Bhattacharya, 2020; Karamage et al., 2017). In a GIS, these tools help integrate various factors that contribute to erosion, allowing for a more comprehensive understanding of erosion dynamics (Rajbanshi & Bhattacharya, 2020). However, understanding the contribution of these individual factors to soil erosion is important for carrying out soil erosion risk assessment in order to develop site-specific soil conservation strategies in the affected regions (Das et al., 2020). Previous studies have attempted to achieve this objective by integrating the Revised USLE (RUSLE), and the Analytical Hierarchy Process (AHP) to map soil hazard areas (Tavana et al., 2023; Vaidya & Kumar, 2006). The implementation of RUSLE and

AHP incorporates both qualitative and quantitative soil erosion risk factors in order improve the accuracy of the final product (Das et al., 2020). Using AHP framework, this is usually done using pairwise comparisons matrices, and weights for each criterion and sub-criterion for soil erosion assessment (Tavana et al., 2023). AHP and RUSLE have been successfully implemented in previous studies, for instance, in the identification of soil erosion risk areas and hazard mapping (Das et al., 2020; Pradeep et al., 2015; Tairi et al., 2019), and vulnerability assessment (Kulimushi et al., 2021; Makaya et al., 2019). Kucuker & Cedano Giraldo, (2022) in a different study also integrated GIS, RUSLE and AHP for carrying out erosion assessment, where they observed that the topographic parameter of slope had the highest influence for erosion occurrence. This was similar to another study by Das et al., (2020) which modelled erosion hazard zones at watershed scale. Haidara et al., (2019) on the other hand, generated erosion severity classes in a soil erosion vulnerability study using the same technique. In another study by Ambarwulan et al., (2021), GIS and AHP were used to delineate erosion-induced land degradation in a sub-watershed. Overall, the integration of AHP, RUSLE and GIS have demonstrated the ability to assess soil erosion vulnerable areas, especially in watersheds with limited data.

The present study therefore implemented AHP and RUSLE in a GIS with the aim of identifying soil erosion vulnerability zones in the SMM catchment. The RUSLE model was used to estimate annual soil erosion rate, while the AHP framework was used to evaluate soil erosion factors using a pairwise matrix that determined the weight of each factor. The soil erosion factors were selected from both field observation and literature. They include factors such as slope, precipitation, soil, vegetation cover, land-use/cover and drainage density. The final product was a map showing the spatial distribution and extent of soil erosion risk areas within the study catchment (Das et al., 2020). The results of this study may provide important information needed by decision-makers in the transboundary region for identifying priority areas for implementing conservation programs for tackling the soil erosion problem.

6.2 Methodology

6.2.1 Datasets

Table 6-1 illustrates datasets used in the study to generate input layers for estimating the amount of annual soil erosion in the SMM watershed. Some datasets have multiple applications in the analysis, such as DEM which was used to generate topographic parameters (slope, slope length and slope steepness). The precipitation data was used to calculate the annual rainfall amount, and for generating the rainfall runoff erodibility factor (*R*-factor) for soil erosion estimation.

Table-6-1. Datasets and sources for soil erosion susceptibility

Data	Source	Description	Application	Reference
Digital Elevation Model (DEM)	³ GDEM - https://earthdata.nasa.gov	30 m - ASTER Global Digital Elevation Model V003	Calculation of slope length and steepness factor (<i>LS</i>)	(Gelagay & Minale, 2016)
Precipitation	⁴ CHIRPS - (https://data.chc.ucsb.edu/products/CHIRPS-2.0/)	0.05° – monthly precipitation	Calculation of <i>R</i> - factor	(Funk et al., 2015)
Soil	SoilGrids - (https://soilgrids.org/)	SoilGrids 250 m v2	Calculation of <i>K</i> -factor	(Rosas & Gutierrez, 2020)
NDVI	MODIS	8-day NDVI series	Calculation of <i>C</i> - factor	

6.2.2 Methodological Framework

Figure 6-1 illustrates the adopted methodological framework for estimating the annual soil loss and mapping soil erosion vulnerable zones for the SMM catchment. Various physical input layers were used to generate input factor layers for estimating the annual rate of soil erosion in SMM catchment. The annual soil erosion was calculated by multiplying all in put factors together, generating a raster layer indicating the total amount of annual soil loss in each pixel. Soil erosion vulnerability zones were calculated using weighting factors such as precipitation, soil properties, slope, drainage density, vegetation cover and land-use. The generation of each factor is discussed in great detail in section 6.2.4.1.

³ Global Digital Elevation Model

⁴ Climate Hazards Group Infrared Precipitation with station data

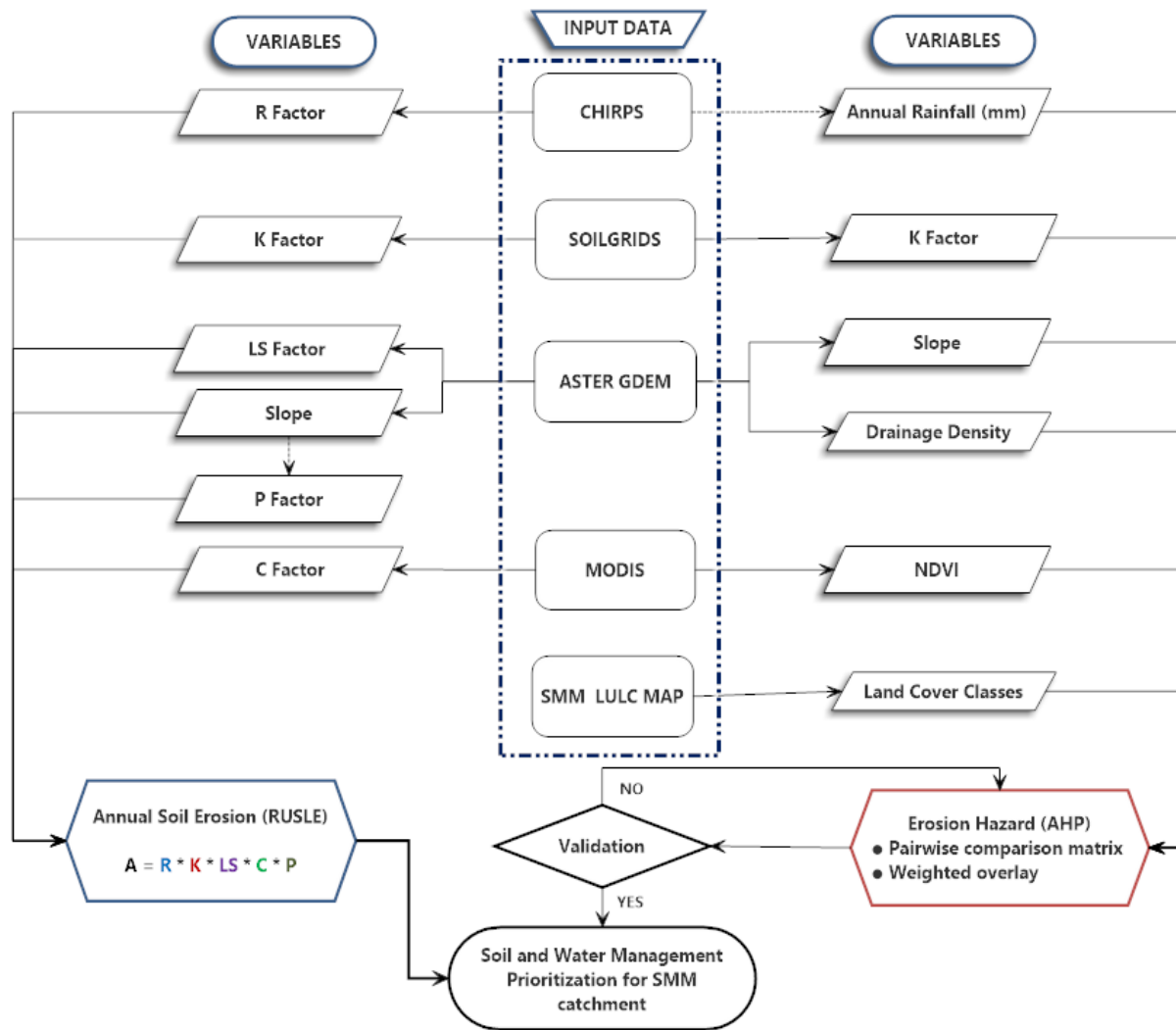


Figure 6-1. Methodological framework for estimating soil erosion and vulnerability

6.2.3 Model Description

6.2.3.1 RUSLE

The annual soil erosion rate for the study area was calculated using the Revised Universal Soil Loss Equation (RUSLE). RUSLE is a widely used mathematical model developed by the U.S Department of Agriculture (USDA) to estimate and predict soil erosion rates (Merritt et al., 2003; Renard et al., 2011). The RUSLE equation is an empirical model designed to provide a quantitative assessment of the average annual soil loss in a given area, by incorporating several factors that contribute to soil erosion (Pradeep et al., 2015). The annual soil loss for SMM catchment was estimated using the RUSLE equation (Eq.6.1). The total annual soil loss is a product of all input

factors expressed in units of tonnes per hectare within a given period of time ($t \text{ ha}^{-1} \text{ yr}^{-1}$), and is expressed as follows:

$$A = R * K * LS * C * P \quad \text{Equation 6-1 – RUSLE equation}$$

Where, A represents the long-term average annual soil loss ($\text{th}^{-1} \text{ yr}^{-1}$); R is rainfall erosivity in Mj mm ha^{-1} ; K is soil erodibility factor in $\text{th MJ}^{-1} \text{ mm}^{-1}$; LS represents a unitless slope length and slope steepness factor; C is the unitless crop management factor, while P is the unitless support practice factor (Schürz et al., 2020). By multiplying these factors together, the RUSLE equation estimates the average annual soil loss in tons per unit area, which is a useful tool for assessing soil erosion potential, identifying risk areas, and developing appropriate erosion control strategies (Rosas & Gutierrez, 2020).

6.2.3.2 Generation of RUSLE Parameters

The annual soil erosion rate for the study was estimated using factors such as rainfall erosivity, soil erodibility, slope length and steepness factor, crop management, and support practice factor. The following section describes the procedure used to prepare RUSLE input factor layers.

(i) ***R Factor (Rainfall Erosivity)***

The R -factor represents the erosive power of rainfall, and considers the amount, intensity, and frequency of rainfall events (Renard et al., 2011). Due to lack of consistent hydrometeorological data for the study basin, the R -factor was calculated using long-term CHIRP rainfall data following:

$$R = \sum_{i=1}^{12} 1.735 * 10^{[1.5 \log_{10}(\frac{P_i}{P}) - 0.08188]} \quad \text{Equation 6-2 – Rainfall erosivity factor}$$

Where, R is rainfall erosivity factor (Mj mm/ha/yr); P_i is the monthly rainfall (mm); P is the annual rainfall (mm) (Wischmeier & Smith, 1978).

(ii) ***K Factor (Soil Erodibility)***

The K -factor reflects the inherent characteristics of the soil that determine its susceptibility to erosion by considering factors such as texture, structure and organic matter (Das et al., 2020). K -factor was calculated in this study using a method proposed by Karamage et al., (2017), which

combines the soil's physical parameters of sand, silt, clay and organic matter. The equation is expressed as follows:

$$K = [A * B * C * D] * 0.1317 \quad \text{Equation 6-3 - Soil erodibility factor}$$

Where, K is the estimated soil erodibility factor; A, B, C , and D represents the percentages of silt, clay, sand and organic matter content in the soil respectively. The product is converted to SI units by multiplying it by 0.1317 (Fenta et al., 2020).

(iii) LS Factor (Slope Length and Steepness)

The LS -factor usually accounts for the combined effect of both slope length and steepness on soil erosion. Generally, longer slopes and steeper have a high LS factor which indicates increased potential for soil erosion (Zhang et al., 2017). In this study, the LS factor was calculated using the recent Digital Elevation Model (DEM) at 30 m and applying the equations proposed by Moore & Wilson, (1992) following:

$$LS = (A_s/22.13)^m (\sin\beta/0.0896)^n \quad \text{Equation 6-4 - Slope length and steepness}$$

Where the constants $m = 0.4$, $n = 1.3$, and A_s is the specific catchment area.

(iv) C Factor (Crop Management)

The C -factor usually represents the impact of land management practices, such as crop cover on soil erosion rates. Therefore, different crops and land management practices have varying effects on soil erosion (Panagos, Borrelli, Poesen, et al., 2015). For the present study, C factor was estimated from NDVI values using the formular applied by van der Knijff et al., (2000) following:

$$C = \exp \left[-\alpha \cdot \frac{NDVI}{\beta - NDVI} \right] \quad \text{Equation 6-5 - Crop management factor}$$

Where, α, β are unitless parameters that determine the shape of the NDVI- C curve (Pradeep et al., 2015; van der Knijff et al., 2000). The values 2 and 1 were used for α and β respectively, because they gave reasonable results for estimating the C factor (Pradeep et al., 2015).

(v) P Factor (Support Practice Factor)

The P -factor considers the effectiveness of various soil and land conservation measures, such as terracing, contouring, strip cropping and conservation tillage on soil erosion rates. Typical P factor values ranges from about 0.2 where there are effective erosion control measures, to 1.0 where there

is no erosion control practice. Therefore, the lower the *P*-factor value, the more effective the soil erosion conservation practice (Panagos, Borrelli, Meusburger, van der Zanden, et al., 2015). In this study, due to lack of accurate data on soil conservation measures, the study estimated *P* factor values for contouring conservation practice using percentage slope values for different slope gradient (Panagos, Borrelli, Meusburger, van der Zanden, et al., 2015; Wischmeier & Smith, 1978). Table 6-2 illustrates the support practice factor values assigned for different slope ranges (degrees).

Table-6-2. P-factor for contour support practice for different slope gradients

Slope (degree)	Support practice factor for contouring
0-2	0.6
3-6	0.7
7-12	0.8
13-21	0.9
22-54	0.95

6.2.4 Analytical Hierarchy Process (AHP)

The Analytical Hierarchy Process (AHP) is a multiple criteria decision-making framework developed by Thomas L. Saaty in the 1970s (Tavana et al., 2023). It provides a structured approach to solving complex problems by breaking them down into a hierarchy of criteria and alternatives and then evaluating their relative importance on the basis of the selected criteria (Das et al., 2020; Tavana et al., 2023). AHP is based on the idea that decision-making involves comparing and prioritizing multiple criteria and alternatives in order to solve complex decision-making problems such as identifying the main soil erosion drivers in a catchment (Kabo-bah et al., 2021). In this study, we used AHP technique to identify and map critical areas of soil erosion in SMM by analyzing the contribution of several input layers that often cause soil erosion (Das et al., 2020; Pradeep et al., 2015; Vaidya & Kumar, 2006). The criteria selection for the present study was based on expert knowledge which guided the derivation of key factors such as slope, precipitation, soil, vegetation, land-use/cover, and drainage density. These factors were integrated as illustrated in figure 2. The first step in AHP is to create a hierarchical structure with the main criteria defining the decision problem. Thereafter, pairwise comparison matrix is formed that compares elements of each level in pairs. The consistency/inconsistency rate and index are then calculated to evaluate the validity of the expert's judgement (Tavana et al., 2023). This was achieved following:

$$CI = (\beta_{max} - n) / (n - 1) \quad \text{Equation 6-6 – Consistency index}$$

Where, β_{max} represents the maximum eigenvalue of the comparison matrix of rank n . The second step calculates the consistency ratio CR , which measures the consistency of the pairwise matrix within acceptable limit of $< 10\%$ (Kabo-bah et al., 2021) following:

$$CR = CI / RI \quad \text{Equation 6-7 – Consistency Ratio}$$

The erosion vulnerability map was then obtained by integrating soil erosion criteria using the linear combination which helps in eliminating bias. The erosion potential E_s is thus obtained by summing up the normalized value of factor weight W_i and the criterion score Y_i of factor i following:

$$E_s = \sum W_i Y_i \quad \text{Equation 6-8 – Erosion potential}$$

The final erosion potential map is then classified into high, moderate, low and very low classes, and validated using previous maps of erosion rates in the study.

6.2.4.1 Generation of erosion vulnerability parameters

(i) **Slope**

The length of a slope influences soil erosion through increased water flow, especially on longer slopes, thus enhancing surface runoff and flow concentration (Kulimushi et al., 2021). Further, longer slopes reduce water infiltration and promotes erosion concentration resulting in increased sediment deposition (Kumar & Kushwaha, 2013). In the present study, the slope, in degree unit, was calculated using the 30 m- DEM data in the Slope Tool found in Esri® ArcMap™ 10.8 software, Surface toolset in Spatial Analyst Toolbox. The output layer was then classified into five classes marching the severity class range chosen for the study i.e., very low to very high.

(ii) **Precipitation**

The amount, intensity, duration and frequency of rainfall events are important factors that determine the erosive power of water on the soil surface (Vanmaercke et al., 2021). Soil erosion is usually driven by rainfall through the raindrop impact that acts on the loose surface soil by dislodging and transporting the eroded material downstream through surface runoff. In the current study, we used the CHIRPS data, to prepare the mean annual rainfall layer used to assess the impact of precipitation on soil erosion (Funk et al., 2015; Omonge et al., 2022). The output layer was

classified into five classes based on the ranking used to classify the susceptibility class range i.e., 1(low) and 5(high) (Makaya et al., 2019).

(iii) Soil

Different soil types have distinct physical and chemical properties, such as, texture, organic matter content, structure and permeability, that influence their susceptibility to erosion (Abdulkareem et al., 2019). In this study, we calculated the soil susceptibility using the physical parameters of sand, silt and clay fraction, and the organic matter fraction (see equation 6.3). The output soil erodibility layer was classified into five classes based on erodibility levels.

(iv) Vegetation cover

Vegetation cover acts as a natural barrier, intercepting rainfall thus reducing the impact of raindrop on the loose surface soil. Therefore, soils with adequate vegetation cover experience reduced erosion rates compared to bare areas. The vegetation cover layer was prepared from the time series of NDVI data (Tadesse et al., 2017), derived for the rainy season (March-June, October-December) for the years 2012-2017 from the MODIS dataset. The output NDVI layer was generated by calculating the mean of all the NDVI time series data.

(v) Land use/cover (LULC)

Land-use practices such as deforestation, intensive farming practices, urbanization and poor soil conservation practices are known factors that accelerate the rate of soil erosion. In the study area, agriculture is the dominant land-use activity occupying more than 50% of the total land area (Chasia et al., 2021). This has the potential to accelerate soil erosion rate in the area leading to and degradation. The land-use for the study was adopted from a recent study in the catchment where by Chasia et al., (2021) who developed a land-use map representing nine dominant LULC classes with the greatest impact on the local hydrological regime. The land-use/cover classes include: mixed forest, permanent wetland, open land, water, barren, cropland, pasture, built-up and open shrubland.

(vi) Drainage density

Drainage density (D_d) is defined as the total length of channels per unit area (Tucker et al., 2001), and outlines the concentration and interconnectedness of the drainage network within a watershed. Zones with higher drainage density often experience increased soil erosion rates and sediment

transportation downstream, thus causing siltation which often negatively affects freshwater ecosystems and civil structures. Drainage channels were prepared from the ASTER GDEM data in ArcGIS software Hydrology tool. The flow direction was calculated from the DEM using the D8 flow method, which assigns flow direction to the steepest downslope (Liao et al., 2023). The output was used to generate the flow accumulation in each pixel, and later assigning numeric order to segments of a linear network using the Strahler method (Gleyzer et al., 2004). Drainage density was then calculated by dividing the total length of all the streams by the total area of the SMM watershed following:

$$D_d = L_T/A \quad \text{Equation 6-9 - Drainage density}$$

Where, L_T is the total length of river channels within an area A .

6.2.4.2 Determining Variable Weights

Weight determination involves calculating the relative importance of criteria and alternatives based on the pairwise comparison judgement (Vaidya & Kumar, 2006). Weights for AHP are usually determined using mathematical approaches such as eigenvector and geometric mean method (Das et al., 2020; Kabo-bah et al., 2021). In this study, we applied the eigenvector method which provides a consistent way to derive weights from the pairwise comparison data. The steps include, first constructing a square matrix (pairwise comparison matrix) where each element represents the relative importance of the soil erosion susceptibility criteria. The pairwise comparison matrix would then be normalized to ensure values in each column represents relative weights. The average weight for each criterion was then calculated and normalized to obtain the final weights as illustrated in table 6-3 and 6-4.

Table 6-3. Weight allocation for criterion factors

Criterion	Weight (%)
Soil erodibility	21.60
Precipitation	21.33
Vegetation cover	24.37
Land-use/cover	15.37
Slope	9.15
Drainage density	8.18
Total	100.0

Table 6-4. Erosion susceptibility criteria and sub-criteria

Erosion causative criterion	Unit	Class	Susceptibility class ranges and ratings	Susceptibility class ratings	Weight (%)
<i>Slope</i>	Degree	0	Very low	1	9.15
		0.001-0.141	Low	2	
		0.142-0.281	Moderate	3	
		0.282-0.562	High	4	
		0.563-35.852	Very high	5	
<i>Rainfall</i>	mm	5,823-6,802	Very low	1	21.33
		6,803-7,381	Low	2	
		7,382-8,405	Moderate	3	
		8,406-9,562	High	4	
		9,563-11,499	Very high	5	
<i>Soil erodibility</i>	Mg h MJ ⁻¹ mm ⁻¹	0.046-0.08	Very low	1	21.60
		0.081-0.091	Low	2	
		0.092-0.102	Moderate	3	
		0.0103-0.117	High	4	
		0.118-0.518	Very high	5	
<i>Vegetation cover (NDVI)</i>	Level	-1.991-2.194	Very high	5	24.37
		2.195-5.041	High	4	
		5.042-5.99	Moderate	3	
		5.991-6.896	Low	2	
		6.897-9.01	Very Low	1	
<i>Land-use/cover</i>	Level	Open water, barren, permanent wetland	Very low	1	15.37
		Vegetation (mixed forest, open shrublands, pasture)	Low	2	
		Built up	Moderate	3	
		Cropland	High	4	
		Open land	Very high	5	
<i>Drainage density</i>	Level	0-0.37	Very low	1	8.18
		0.37-0.74	Low	2	
		0.74-1.11	Moderate	3	
		1.11-1.47	High	4	
		1.47-1.84	Very high	5	
					100.00

6.3 Results

6.3.1 Estimate RUSLE parameters

The annual rate of soil erosion for SMM catchment was calculated using a combination of factors such as the rainfall erosivity, soil erodibility, slope length and steepness, cover management and the support practice factors (Figure 6-2). The mean *R*-factor value obtained was 6,944 MJ mm ha⁻¹ h⁻¹ yr⁻¹; Higher *R*-factors values were associated with high altitude zones, and areas East of the study area in Sio sub-catchment located near Lake Victoria indicating the effects of orographic and convectional rainfall respectively. The mean *K*-values obtained in the study was 0.097 t h MJ⁻¹ mm⁻¹. Higher values were recorded on the upper zones characterized by steep slopes and soils rich in silt content. The upper reaches of the SMM catchment recorded maximum *LS*-factor values of between 10 - 15. However, the mean *LS*-value was <1 for more than 60 % of the total catchment area. Higher *C*-factor values recorded in the study, were associated with barren, open water and built-up land-use/cover classes (Figure 6-2d). Lower values normally indicate landscapes with sufficient vegetation cover offering protection against raindrop impact and surface runoff (van der Knijff et al., 2000). The support practice factor (*P*-factor) was calculated from the slope layer assuming the application of contour farming in areas characterized by steep slopes. Higher values recorded indicate areas where there is limited to no application of erosion control measures such as strip and contour farming. Consequently, in the event of a big storm, these areas usually contribute a lot of sediments to nearby streams due to high velocity of runoff water passing through unprotected soils.

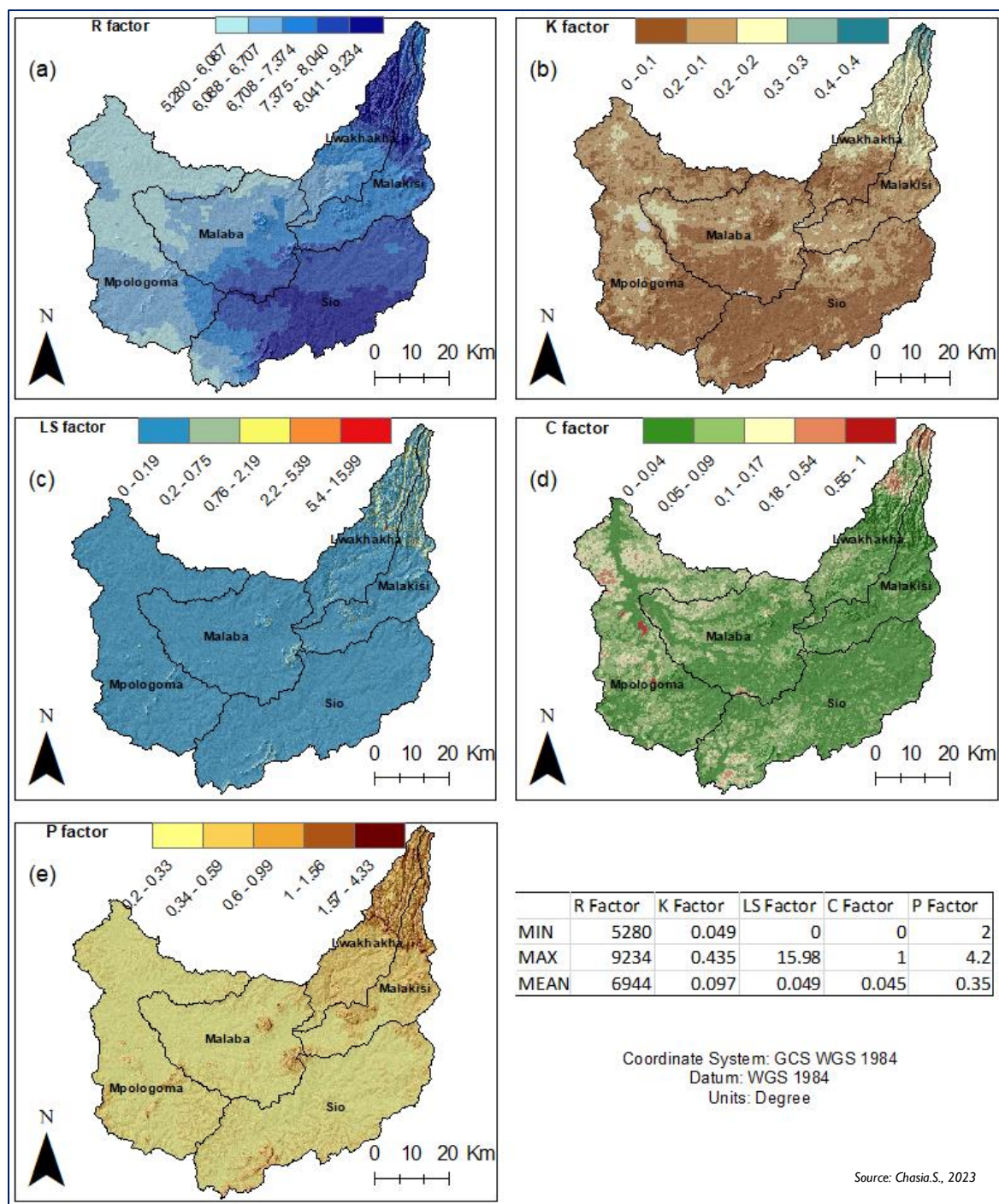


Figure 6-2. Obtained RUSLE parameters for soil erosion estimation

6.3.2 Soil Erosion Susceptibility Parameters

Soil erosion risk/hazard regions in the study area were prepared using variables outlined in figure 6-3. These variables were selected on the basis of their influence on erosion occurrence across the catchment. Areas recording precipitation amounts of more than the annual average rate of 1,500 mm yr⁻¹ in the study region, were assigned high susceptibility ratings compared to areas below the annual average. Generally, Lwakhakha and Malakisi sub-catchments are located near Mt. Elgon Forest and receive >1,500 mm yr⁻¹ of orographic rainfall, while Sio – located near Lake Victoria normally experiences convectional rainfall of > 1,600 (Figure 6-3a). The study also analysed the soils susceptibility to erosion represented by the soil erosivity factor. This factor is a product of the physical properties represented as percentages of sand, silt, clay, and the organic matter content. High erodibility values (>0.4 t h MJ⁻¹ mm⁻¹) indicate soils that are easily dislodged due to the concentration of high silt content. In the study region, these areas were observed mainly at the edge of Mt. Elgon Forest where there is intensive farming on steep slopes with no conservation practice. Consequently, the top soil rich in organic matter have gradually been eroded leaving the silt and sand rich soil. Slopes were analyzed considering their effect on surface runoff velocity. Steep slopes (> 20°) were recorded in areas characterized by high elevations indicating high susceptibility to erosion. High drainage density values indicate areas susceptible to erosion due to their proximity to streams. Areas with a high concentration of streams tend to experience channel erosion. The study also evaluated the impact of land-use on erosion risk. Generally, barren land with no vegetation, together with arable lands with seasonal crops are more susceptible to erosion compared to regions under permanent vegetation such as forest and shrublands. Additionally, built-up are more prone to erosion to disturbance from civil works and other construction activities. Vegetation cover distribution for SMM catchment was prepared using the time series NDVI data. NDVI indices are usually sensitive to vegetation change at different growing periods and thus represent the general health of vegetation. In the study region, NDVI values of 0.7-0.9 were recorded in areas covered by permanent vegetation such as shrubs and mixed forest class. Conversely, built-up and bare areas recorded negative NDVI value indicating absence of both seasonal and permanent vegetation cover. Soils in such areas are thus more susceptible to raindrop impact and ultimately soil erosion.

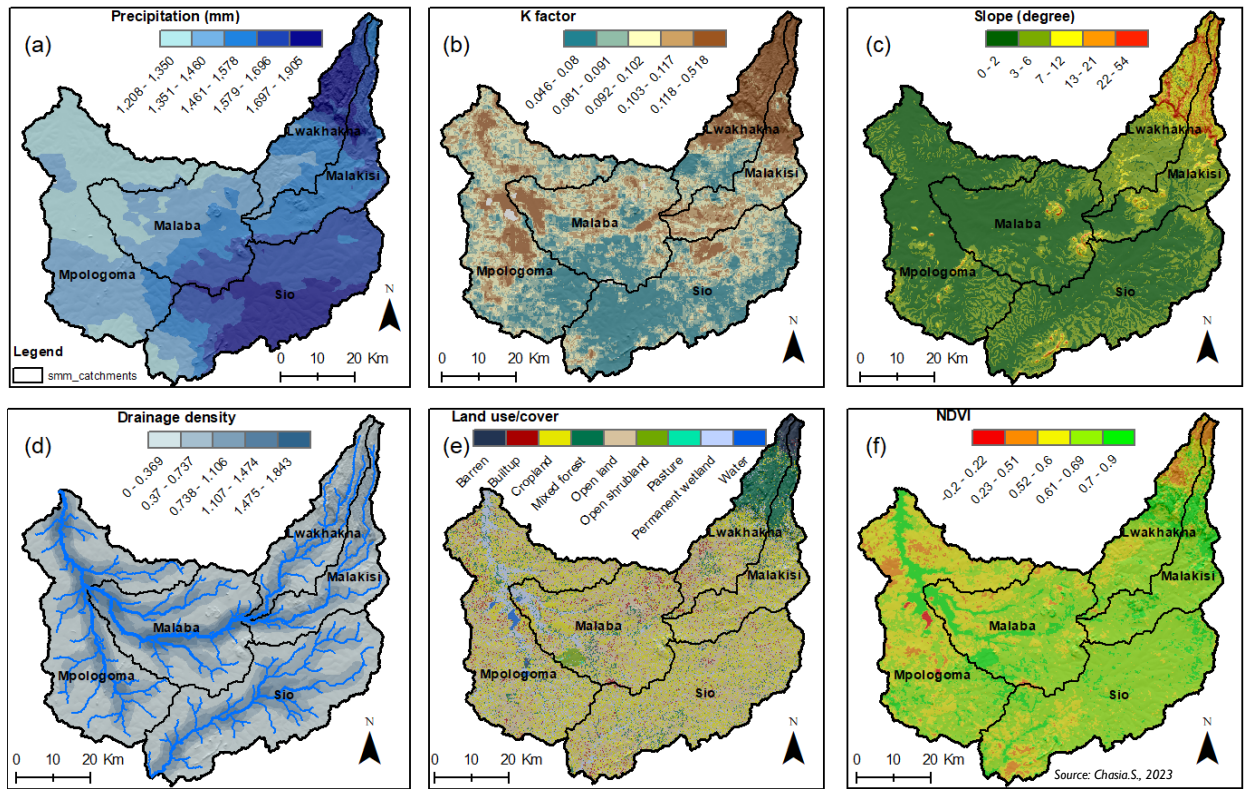


Figure-6-3. Soil erosion susceptibility variables

6.3.3 Soil Loss and Soil Erosion Vulnerability Assessment

Figure 6-4 illustrates the estimated annual soil loss and associated soil erosion vulnerable areas obtained for Sio-Malaba-Malakisi catchment. The mean erosion values for SMM approximately $4.3 \text{ t ha}^{-1}\text{yr}^{-1}$, while the maximum recorded soil value for the basin was $5,703 \text{ t ha}^{-1}\text{yr}^{-1}$. Soil erosion values exceeding $100 \text{ t ha}^{-1}\text{yr}^{-1}$ were measured in zones characterized by slopes of $>30^\circ$ mainly at the foothills of Mt. Elgon Forest. It was however noted that areas within the same region covered by permanent vegetation and protected from human activities especially farming, the rate of soil erosion was less than $5 \text{ t ha}^{-1}\text{yr}^{-1}$. Overall, high erosion rates ($> 1,400 \text{ t ha}^{-1}\text{yr}^{-1}$) were recorded in Lwakhakha and Malakisi sub-catchments together with other regions with high elevation. While there was a concentration of farming activities on the lower sections of the basin comprising Sio and Mpologoma sub-catchments, the amount of soil erosion recorded was less than $10 \text{ t ha}^{-1}\text{yr}^{-1}$. Regions recording soil erosion rates of more than $20 \text{ t ha}^{-1}\text{yr}^{-1}$ were categorized as moderate to high-risk areas (Figure 6-4b). Despite covering the least total area of the basin i.e., 592 km^2 and 624 km^2 respectively (Table 6-5), the Lwakhakha and Malakisi sub-catchments contributed $> 90\%$ of soil erosion. These sub-catchments are also located in zones characterized as high-risk areas for

erosion due to the presence of steep slopes and limited vegetation cover. Conversely, erosion risk in the low-lying Malaba and Mpologoma sub-catchments, ranged from very low (areas experiencing deposition) to low. Generally, from the analysis, the majority of the SMM catchment can be characterized as low to moderate erosion risk areas.

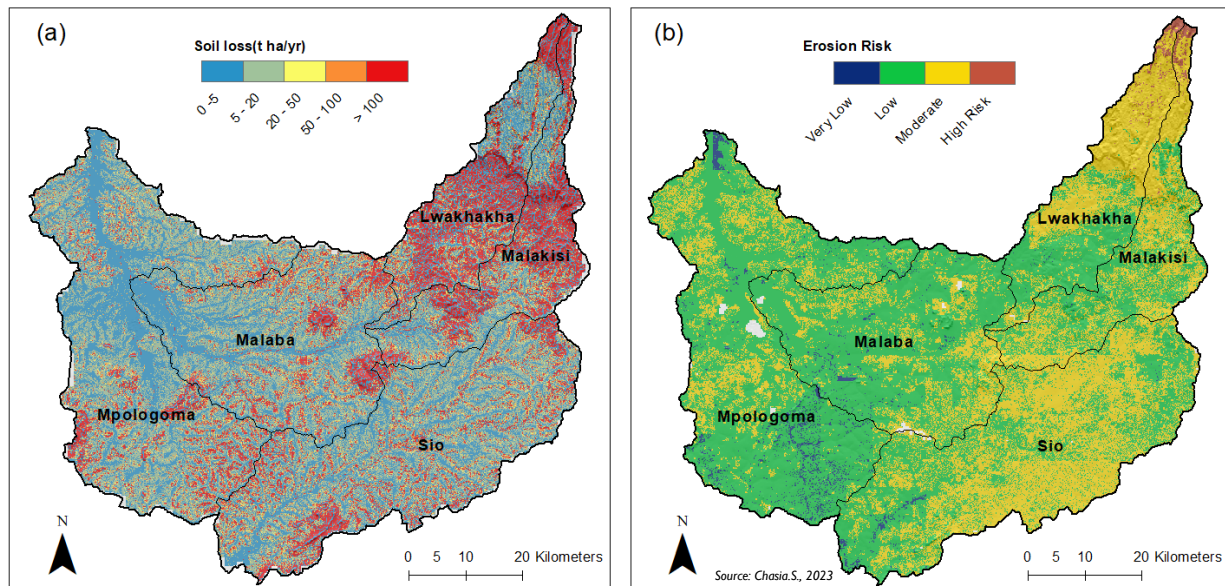


Figure 6-4. a) predicted soil loss, b) erosion risk characterization for SMM basin.

Table 6-5. Sub-catchment soil loss

Rank	Sub-catchment	Area (km ²)	Area (%)	Mean soil loss (t ha ⁻¹ yr ⁻¹)	Range soil loss (t ha ⁻¹ yr ⁻¹)	Standard deviation
1	Lwakhakha	592	11	11.12	0-1,777	39.23
2	Malakisi	624	12	7.05	0-1,482	37.37
3	Mpologoma	1,528	29	0.58	0-1,297	4.28
4	Sio	1,407	27	0.47	0-55	0.95
5	Malaba	1,037	20	0.47	0-36	1.03
	Total	5,188	100	20	4,647	

6.4 Discussion

6.4.1 Soil Erosion Hazard Assessment

Soil hazard assessment was conducted in all administrative units located in the SMM catchment based on soil loss tolerance levels (T value) adopted from literature (Li et al., 2009; McCormack et al., 2015). The administrative units include wards (Kenya) and sub-county (Uganda) (Figure 6-6). The determination of T values is usually important for the identification of areas for prioritization of soil and water conservation interventions and programs in order to mitigate the negative impacts of soil erosion on the local environment and food production. In this study therefore, areas recording mean annual soil erosion rates above $12 \text{ t ha}^{-1} \text{ yr}^{-1}$, were classified as critical areas for monitoring and enhancing soil and water conservation programs. Such areas include Bukalasi and Bumayoka in Uganda, which recorded a mean annual soil loss of $89.4 \text{ t ha}^{-1} \text{ yr}^{-1}$ and $83.2 \text{ t ha}^{-1} \text{ yr}^{-1}$ respectively. Others include Bubiita ($42.1 \text{ t ha}^{-1} \text{ yr}^{-1}$), Nalwanza ($21 \text{ t ha}^{-1} \text{ yr}^{-1}$) and Mukoto ($13 \text{ t ha}^{-1} \text{ yr}^{-1}$) at slightly above the threshold value. In Kenya, areas recording soil loss rates above the critical level were Chepyuk ($22.8 \text{ t ha}^{-1} \text{ yr}^{-1}$), Chesikaki ($18.9 \text{ t ha}^{-1} \text{ yr}^{-1}$), Cheptais ($17.4 \text{ t ha}^{-1} \text{ yr}^{-1}$) and Kapkateny ($13.4 \text{ t ha}^{-1} \text{ yr}^{-1}$). Overall, areas listed as critical in both Kenya and Uganda were located at elevations of $> 2,000 \text{ m.a.s.l}$, on the upper reaches of the SMM catchment (Figure 6-5). These zones are characterized by intensive farming activities on the steep slopes thus promoting soil erosion and sedimentation of streams.

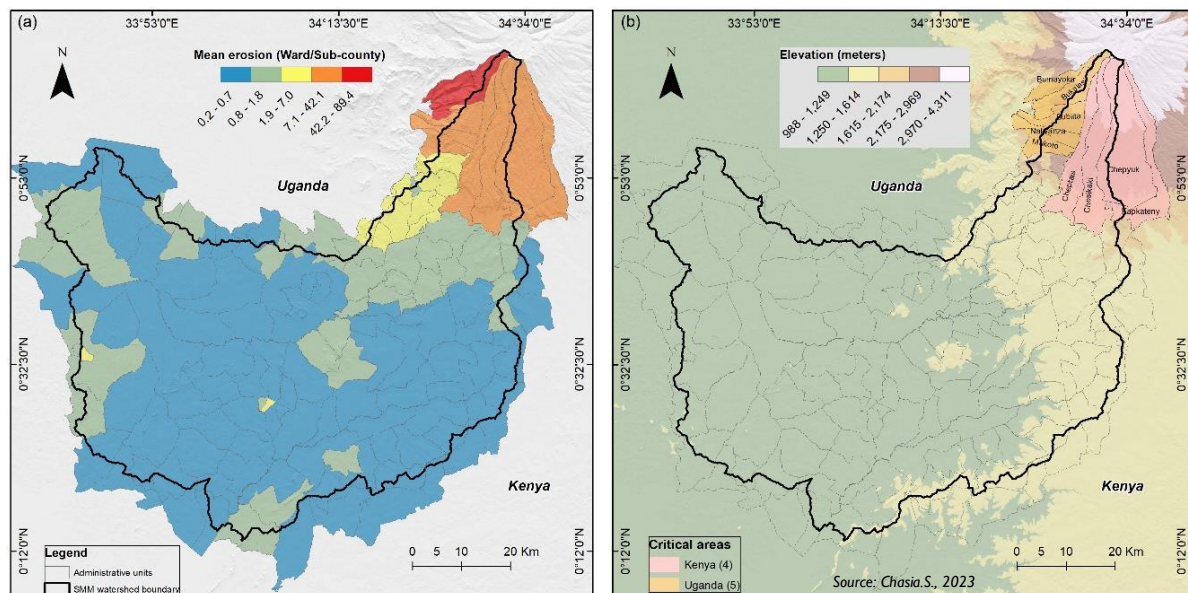


Figure 6-5. a) soil erosion critical areas, b) elevation levels for administrative units

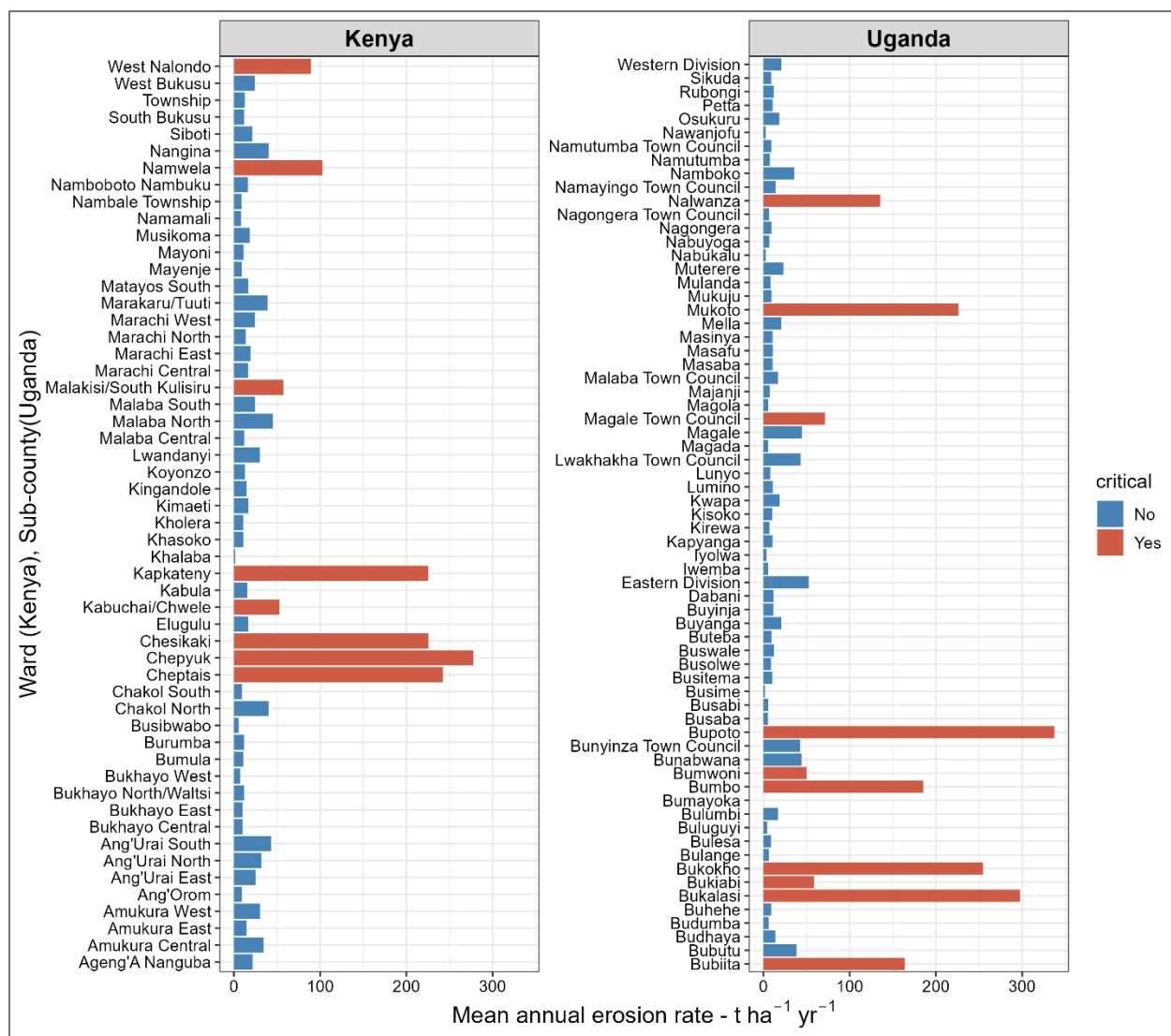


Figure 6-6. Mean annual soil loss for administrative units

6.4.2 Erosion Vulnerability Mitigation and Prioritization for SMM catchment

This study identified soil conservation priority areas based on the range of erosion that defined the severity levels (Table 6-6). Areas above $50\ t\ ha^{-1}\ yr^{-1}$ were categorized with a high severity class which require special soil and water conservation measures. Such areas in the study were mainly in Lwakhakha and Malakisi sub-catchments, which recorded maximum annual soil erosion rates of $1,777\ t\ ha^{-1}\ yr^{-1}$ and $1,482\ t\ ha^{-1}\ yr^{-1}$ respectively. Such zones located in high elevation areas are recommended to adopt several soil conservation practices such as strip farming and contour ploughing to reduce the amount of soil washed by surface runoff. Additionally, planting napier grass along soil conservation structures such as terraces, and vegetation strips along watercourses

could help reduce erosion by controlling the flow of water. Low-lying areas such as Mpologoma sub-catchment also recorded a significant amount of soil erosion rates at $1,297 \text{ t ha}^{-1} \text{ yr}^{-1}$. This could be attributed to the impact of floods during periods of heavy storms, as excess water from nearby streams flows to adjacent farms. In such areas, the study recommends the use of cover crops, which not only provides ground cover against soil erosion, it also helps in binding loose soil particles together which would improve soil structure and increase organic matter content. Further, adopting conservation tillage techniques, such as no-till, and reduced tillage, would minimize soil disturbance, while mulching would provide a protective layer against raindrop impact.

Table 6-6. Range of soil erosion values and severity class

Erosion vulnerability units (EVU)	Severity class	Range of erosion ($\text{t ha}^{-1} \text{ yr}^{-1}$)	Soil conservation priority
1	High	>50	Special soil and water conservation measures required
2	Moderate	20-50	High priority for soil conservation
3	Low	5-20	Medium priority for soil conservation
4	Very low	0-5	Less priority for soil conservation

6.5 Conclusion

The present study estimated the annual soil erosion rate in the Sio-Malaba-Malakisi catchment using RUSLE and physical datasets in a GIS. Thereafter, the AHP framework was applied to evaluate the influence of soil erosion driving factors in order to identify hotspot areas vulnerable to soil erosion. The annual soil erosion was estimated using standardized physical parameters, such as rainfall runoff erosivity, soil erodibility, slope length and steepness, crop management and support practice factors. On the other hand, AHP was used to identify critical areas affected by soil erosion in SMM catchment. Physical parameters, such as slope, precipitation, soil, vegetation cover, land-use/cover, and drainage density were used as weighted factors in determining the spatial location of soil erosion risk zones. The output was then used to identify areas susceptible to soil erosion at administrative and sub-catchment level in order to highlight areas severely affected by soil erosion. The study obtained a mean erosion rate of $4.3\text{-ton ha}^{-1} \text{ yr}^{-1}$, and a maximum soil loss of $1,777\text{-ton ha}^{-1} \text{ yr}^{-1}$ for catchments located on the upstream zones. Further, areas

recording soil erosion rates exceeding 50-ton ha⁻¹ yr⁻¹ were categorized as severe, which was above the tolerance value of 12-ton ha⁻¹ yr⁻¹ adopted for the study. Areas identified in the study recording soil loss above the tolerance value include Kapkateny, Chesikaki, Chepyuk and Cheptais wards in Kenya, and Nalwanza, Mukolo, Bumayoka, Bukalisi and Bubita sub-counties in Uganda. It should be noted that the determination of soil loss tolerance (*T* value) for SMM catchment was based on existing literature. However, in order to determine accurate and locally-appropriated *T* values that define the baseline soil tolerance levels for the transboundary catchment, the study recommends further research that incorporates other determining factors such as soil depth, top soil formation rate, loss of plant nutrients by erosion, sediment delivery and deposition. The study findings could therefore support decision makers within the vulnerable transboundary catchment in developing targeted soil erosion control measures in the affected areas, as well as guiding the adoption of appropriate soil conservation strategies.

CHAPTER 7

General Discussion, Conclusions and Recommendations

This chapter summarized the key chapters of the present study through an overall discussion and conclusion, also based on the research questions raised for the study. The chapter concludes by outlining key recommendations for further research.

7.1 Discussion

Generally, this study provides valuable insights into the investigated spatiotemporal patterns of land-use/cover changes, and their potential impact on the soil erosion process on the hydrology within the transboundary SMM basin. Through the analysis of historical land cover conditions, the land-use/cover statistics obtained could form the basis for preventing land degradation across the basin. Land-use/cover classes, such as open water, pasture, and open shrublands remain stable across the study period largely because of the availability of arable land. However, cropland areas showed a steady increase from 1995, while open land areas declined in the same period following the expansion of agriculture and consequently the conservation of open land to cropland. From 2008, built-up areas grew substantially leading up to the final analysis year partly due to population growth and urbanization. This trend in urban sprawl was concentrated mainly along the border towns of Busia and Malaba which acted as focal points of trade in the region. However, smaller towns and market centres generally continued to grow mainly along major transport corridors which provided economic opportunities for local traders. Whereas the conversion between the different land-use/cover classes was dynamic across the study basin, the study noted significant conversions of other land uses into cropland areas among the open land, pasture, and pockets of forested areas due to increasing demand for agriculture products, as well as weakness in enforcement by local environmental agencies. This observation is consistent with a previous study of the region by Opedes et al., (2022) who analyzed historical land cover changes and farming dynamics in the areas. Some areas under wetland cover type were also converted to agriculture; open land areas near existing built-up zones changed to urban due to eminent urban sprawl. In terms of potential future land-use change patterns plausible in the study region between 2017 and 2047 - a period prioritized by the local managers for conservation, this study revealed that the basin would still be vulnerable to soil erosion if urgent measures to regulate land-use activities to

prevent land degradation are not taken. The first case of study (i.e., Scenario 1), where it was assumed that crop production would be intensified across the basin as demand for agricultural products continues to grow, revealed that these activities could potentially accelerate further land degradation and worsen water pollution across the basin due to sedimentation and the overuse of chemical fertilizers especially in farms severely affected by soil fertility issues. In the second case (i.e., Scenario 2), where land reclamation strategies aimed at rehabilitating degraded soils across the basin were assumed, the study indicated that intensive afforestation programs targeted at regions previously affected by encroachment from agriculture could improve the overall vegetation cover and restore the local environment. In terms of soil erosion and deposition patterns consequent to the estimated land-use change patterns, the study indicated that regions experiencing deforestation and conversion of forest land to agriculture will continue to record high soil erosion rates. Conversely, a resurgence in vegetation cover as a result of the implementation of forest recovery programs in the region is likely to yield positive outcomes such as improvement in soil health and preventing land degradation. Under the potential for agricultural expansion scenario, for instance, the highest erosion rates were predicted in areas characterized by intensive agricultural practices, particularly those involving extensive tillage and monoculture cropping observed during field surveys. This could be because of the prevalent poor farming practices which damage the physical structure of the soils making them friable and hence susceptible to erosion. The results highlighted the vulnerability of the arable lands to soil erosion, especially within the highland zones due to factors such as soil compaction, reduced vegetation cover, and accelerated water runoff, as noted by other studies (Karamage et al., 2017; Mugagga et al., 2012). In contrast, areas with forest cover and natural vegetation exhibited significantly lower erosion rates for the period of study. Forested areas generally demonstrated the highest soil conservation capacity due to their dense root systems, which promote soil stabilization and water infiltration capacities (Jiang et al., 2014). The vegetation and the associated root zones generally reduce the erosive force from surface runoff water, thus protecting the surrounding soils from the erosion processes. Across the sub-basins, the regions within the upper reaches of the basin with steep slopes and high precipitation rates were found to be significantly affected by erosion due to the presence of young and mineral-rich volcanic soils that support farming throughout the year. The low-lying sub-regions on the other hand, were moderately affected by soil erosion mainly due to the topographic characteristics that favoured deposition over erosion.

Deposition areas were mainly observed in the southwestern regions of the basin where the Malaba and Mpologoma sub-catchments are located. This could be attributed to the prevailing low-altitude conditions in these regions which favour sediment deposition over erosion. Furthermore, the findings highlighted the importance of land management strategies that incorporate measures to control erosion. In the upper reaches of the study characterized by steep slopes, terracing, and contour ploughing were observed to be effective soil conservation practices in minimizing erosion rates. These practices help to intercept and slow down the flow of water, reducing the erosive forces and thus preventing soil loss. In mid to lower zones of the basin, the construction of gabions along stream banks with unstable soil structures would help prevent further destruction of infrastructure and reduce the deposition of sediments. The implications of this study suggest the need for adopting sustainable land management practices to mitigate soil erosion and land degradation. By promoting conservation tillage methods, implementing terracing techniques on sloping lands, and preserving or restoring natural vegetation cover, land managers and policymakers can help reduce soil erosion rates and maintain soil health.

7.2 Conclusion

This research study explored land-use/cover changes in the transboundary Sio-Malaba-Malakisi water catchment area to assess their impact on soil erosion vulnerability and recommend appropriate soil conservation measures for preventing further land degradation. The findings provide valuable insights into the repercussions of human activities on soil health and erosion potential. The analysis of historical land-use change revealed significant transformations in land cover over the past thirty years. This evolution, captured through a combination of remote sensing and archival data, served as the foundation of our subsequent investigations. The land-use modelling, utilizing a spatially explicit multi-scale land-use modelling framework, successfully projected future land-use scenarios, providing a foresight into potential shifts in landscape patterns. Further, the application of land use change scenarios in predicting erosion and deposition zones provided key insight into soil erosion vulnerable localities. Revisiting the initial research questions, we find that this study has addressed these queries comprehensively. This research set out to understand the historical trends in land use, model future scenarios, and assess the associated erosion and deposition patterns that define soil erosion vulnerability zones. In the first research question, the investigation by this study demonstrated that significant land-use changes have

occurred across the basin, particularly the expansion of cropland areas, which is intricately linked to heightened land degradation. Through a comprehensive analysis of land-use change, the study observed a period of steady growth in land-use activities beginning in the early years of analysis, followed by a period of intensification and conversion of land cover types. Delving into the intricacies of future land-use changes, this study explored the specific mechanism by which potential driving factors amplify land-use changes under the evaluated land-use scenarios. Biophysical conditions emerged as the key drivers of future LULC changes in both scenarios. Interestingly, the study also observed how land-use change restrictions affected conversion patterns across the basin, shedding light on the effectiveness of land management policy in preventing land degradation. Our analysis of the erosion and deposition patterns consequent of scenario land-use changes indicated that a sustained expansion in cropland cover across the study basin was correlated with soil erosion occurrence. Conversely, natural vegetation regeneration indicated a significant reduction in soil erosion especially in the regions susceptible to erosion. Overall, sediment deposition zones across the basin were recorded along stream banks and floodplains, indicating the influence of topographic characteristics on the erosion and deposition process. Soil erosion-vulnerable zones, on the other hand, were associated with regions characterized by steep slopes, and friable soils susceptible to surface runoff. Such regions exhibited severe erosion rates that exceeded the soil loss tolerance level indicating the need for urgent interventions. Our study aligns with existing literature on land-use change, but the integration of historical analysis, advanced modelling, and vulnerability assessment adds a unique dimension to the field. The nuanced understanding of the interaction between historical and simulated land-use patterns and contemporary vulnerabilities contributes to a more holistic perspective. The implications of this research therefore extend beyond the academic realm. By identifying areas prone to soil erosion and deposition based on historical trends and future land-use change trajectories, this study offers valuable information for land managers, policymakers, and conservationists. Proactive measures can be implemented to mitigate the risks in vulnerable regions across the Sio-Malaba-Malakisi basin, fostering sustainable land-use practices. While this study has advanced the understanding of future land-use change dynamics and their implications, we acknowledge certain limitations. The accuracy of our land-use model depends on the quality of input data and assumptions under which it operates. Additionally, the complexity of natural systems poses challenges in predicting with absolute certainty. Future research could thus explore

ways to refine modelling techniques and address these limitations. Building on our findings, the study would like to propose recommendations for sustainable land management. Integrating projected land-use analysis into future planning processes, adopting resilient land-use strategies, and implementing erosion control measures are critical steps toward mitigating the potential risks highlighted in our vulnerability assessment. In summary, this study contributes to the scientific community by offering a comprehensive understanding of the historical context of land-use changes in a transboundary watershed, predicting future scenarios, and assessing vulnerability to erosion and deposition. In revisiting the research questions, this study has successfully achieved its overarching objectives – to uncover the intricate relationship between land-use change and soil erosion vulnerability, and to provide practical insights for sustainable land management. These achievements underscore the relevance and contribution of our research to the broader field of hydrology.

7.3 Recommendations

This study would like to suggest the following recommendations in order to improve future land-use/cover change analysis and modelling, erosion and deposition modelling, and vulnerability assessment:

1. The use of high-resolution satellite data and advanced machine-learning classification algorithms would enhance the identification of land-use/cover classes at fine scale, thus improving classification accuracy, and the identification of small and spectrally similar objects.
2. To improve the prediction accuracy of the land-use model, more biophysical and socioeconomic data at finer-scale is required. This would support regionalization of the CLUE-S model and explore how different driving factors and specific demands for land use vary across the two geographies that define the transboundary SMM catchment.
3. Poor state and quality of hydrological data in the study region affected the calibration and validation of USPED's model performance. Therefore, future research could address these limitations by the installation of hydrological network across the basin for accurate sediment measurement.

4. Multi-scale modelling should be integrated with high-resolution remote sensing data to improve the predictive accuracy of the RUSLE model in order to capture complex erosion dynamics.

Other general recommendation aimed at mitigating soil erosion vulnerability, and promoting sustainable land management practices in the study region include:

1. Integrating soil erosion management intervention into land-use planning processes to safeguard environmental well-being.
2. Adoption of sustainable agricultural practices, such as conservation agriculture, that minimize soil erosion risks, especially in regions affected by severe erosion.
3. Transboundary collaboration between Kenya and Uganda, leading to the harmonization of the catchment management framework that guarantees long-term ecological benefits for the environment and local stakeholders in the catchment.

REFERENCES

- Abdulkareem, J. H., Pradhan, B., Sulaiman, W. N. A., & Jamil, N. R. (2019). Prediction of spatial soil loss impacted by long-term land-use/land-cover change in a tropical watershed. *Geoscience Frontiers*, 10(2), 389–403. <https://doi.org/10.1016/j.gsf.2017.10.010>
- Adenle, A. A., Boillat, S., & Speranza, C. I. (2022). Key dimensions of land users' perceptions of land degradation and sustainable land management in Niger State, Nigeria. *Environmental Challenges*, 8, 100544. <https://doi.org/10.1016/J.ENVC.2022.100544>
- African Union. (2017). *African Convention on the Conservation of Nature and Natural Resources*. The Africa Union.
- Agarwal, C., Green, G. M., Grove, J. M., Evans, T. P., & Schweik, C. M. (2002). *A Review and assessment of land-Use change models: dynamics of space, time, and human choice*. https://www.nrs.fs.fed.us/pubs/gtr/gtr_ne297.pdf
- Aiello, A., Adamo, M., & Canora, F. (2014). Modelling Spatially–Distributed Soil Erosion through Remotely–Sensed Data and GIS. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 8582 LNCS* (Issue PART 4, pp. 372–385). https://doi.org/10.1007/978-3-319-09147-1_27
- Aiello, A., Adamo, M., & Canora, F. (2015). Remote sensing and GIS to assess soil erosion with RUSLE3D and USPED at river basin scale in southern Italy. *Catena*, 131, 174–185. <https://doi.org/10.1016/j.catena.2015.04.003>
- Aksoy, H., Mahe, G., & Meddi, M. (2019). Modeling and practice of erosion and sediment transport under change. In *Water (Switzerland)* (Vol. 11, Issue 8). <https://doi.org/10.3390/w11081665>
- Alba-Fernández, M. V., Ariza-López, F. J., Rodríguez-Avi, J., & García-Balboa, J. L. (2020). Statistical methods for thematic-accuracy quality control based on an accurate reference sample. *Remote Sensing*, 12(5), 1–16. <https://doi.org/10.3390/rs12050816>
- Alemayehu, T., Griensven, A. van, Senay, G. B., & Bauwens, W. (2017). Evapotranspiration Mapping in a Heterogeneous Landscape Using Remote Sensing and Global Weather Datasets: Application to the Mara Basin, East Africa. *Remote Sensing*, 9(4), 390. <https://doi.org/10.3390/rs9040390>
- Alkama, R. Cescatti, A. (2016). Biophysical climate impacts of recent changes in global forest cover. *Science*, 351(6273), 597–600. <https://doi.org/10.1126/science.aad7270>
- Allafta, H., & Opp, C. (2022). Soil Erosion Assessment Using the RUSLE Model, Remote Sensing, and GIS in the Shatt Al-Arab Basin (Iraq-Iran). *Applied Sciences*, 12(15), 7776. <https://doi.org/10.3390/app12157776>
- Allen, T. R. (2000). Topographic normalization of landsat thematic mapper data in three mountain environments. *Geocarto International*, 15(2), 15–22. <https://doi.org/10.1080/10106049908542148>
- Alphan, H., Doygun, H., & Unlukaplan, Y. I. (2009). Post-classification comparison of land

- cover using multitemporal Landsat and ASTER imagery: The case of Kahramanmaras, Turkey. *Environmental Monitoring and Assessment*, 151(1–4), 327–336. <https://doi.org/10.1007/s10661-008-0274-x>
- Ambarwulan, W., Nahib, I., Widiatmaka, W., Suryanta, J., Munajati, S. L., Suwarno, Y., Turmudi, T., Darmawan, M., & Sutrisno, D. (2021). Using Geographic Information Systems and the Analytical Hierarchy Process for Delineating Erosion-Induced Land Degradation in the Middle Citarum Sub-Watershed, Indonesia. *Frontiers in Environmental Science*, 9(November), 1–10. <https://doi.org/10.3389/fenvs.2021.710570>
- Angima, S. ., Stott, D. ., O'Neill, M. ., Ong, C. ., & Weesies, G. . (2003). Soil erosion prediction using RUSLE for central Kenyan highland conditions. *Agriculture, Ecosystems & Environment*, 97(1–3), 295–308. [https://doi.org/10.1016/S0167-8809\(03\)00011-2](https://doi.org/10.1016/S0167-8809(03)00011-2)
- Asokan, A., & Anitha, J. (2019). Change detection techniques for remote sensing applications: a survey. In *Earth Science Informatics* (Vol. 12, Issue 2, pp. 143–160). <https://doi.org/10.1007/s12145-019-00380-5>
- Awange, J., Aluoch, J., Ogallo, L., Omulo, M., & Omondi, P. (2007). Frequency and severity of drought in the Lake Victoria region (Kenya) and its effects on food security. *Climate Research*, 33(2), 135–142. <https://doi.org/10.3354/cr033135>
- Badjana, H. M., Olofsson, P., Woodcock, C. E., Helmschrot, J., Wala, K., & Akpagana, K. (2017). Mapping and estimating land change between 2001 and 2013 in a heterogeneous landscape in West Africa: Loss of forestlands and capacity building opportunities. *International Journal of Applied Earth Observation and Geoinformation*, 63(February), 15–23. <https://doi.org/10.1016/j.jag.2017.07.006>
- Bai, Z., Dent, D., Olsson, L., & Schaepman, M. (2008). *Global assessment of land degradation and improvement: 1. identification by remote sensing*. <https://library.wur.nl/WebQuery/wurpubs/fulltext/40715>
- Ban, Y., Gong, P., & Giri, C. (2015). Global land cover mapping using Earth observation satellite data: Recent progresses and challenges. *ISPRS Journal of Photogrammetry and Remote Sensing*, 103, 1–6.
- Batista, P. V. G., Davies, J., Silva, M. L. N., & Quinton, J. N. (2019). On the evaluation of soil erosion models: Are we doing enough? *Earth-Science Reviews*, 197(June), 102898. <https://doi.org/10.1016/j.earscirev.2019.102898>
- Borrelli, P., Alewell, C., Alvarez, P., Anache, J. A. A., Baartman, J., Ballabio, C., Bezak, N., Biddoccu, M., Cerdà, A., Chalise, D., Chen, S., Chen, W., De Girolamo, A. M., Gessesse, G. D., Deumlich, D., Diodato, N., Efthimiou, N., Erpul, G., Fiener, P., ... Panagos, P. (2021). Soil erosion modelling: A global review and statistical analysis. *Science of the Total Environment*, 780, 146494. <https://doi.org/10.1016/j.scitotenv.2021.146494>
- Borrelli, P., Robinson, D. A., Fleischer, L. R., Lugato, E., Ballabio, C., Alewell, C., Meusburger, K., Modugno, S., Schütt, B., Ferro, V., Bagarello, V., Oost, K. Van, Montanarella, L., & Panagos, P. (2017). An assessment of the global impact of 21st century land use change on soil erosion. *Nature Communications*, 8(1). <https://doi.org/10.1038/s41467-017-02142-7>

- Brels, S., Coates, D., & Loures, F. (2008a). *Transboundary water resources management: the role of international watercourse agreements in implementation of the CBD*.
- Brels, S., Coates, D., & Loures, F. (2008b). Transboundary water resources management: the role of international watercourse agreements in implementation of the CBD. In A. Nollkaemper & I. Plakokefalos (Eds.), *The Practice of Shared Responsibility in International Law* (Issue 48, pp. 905–935). Cambridge University Press.
<https://doi.org/10.1017/9781316227480.035>
- Briassoulis, H. (2019). Combating Land Degradation and Desertification: The Land-Use Planning Quandary. *Land*, 8(2), 27. <https://doi.org/10.3390/land8020027>
- Brink, A. B., Bodart, C., Brodsky, L., Defourney, P., Ernst, C., Donney, F., Lupi, A., & Tuckova, K. (2014). Anthropogenic pressure in East Africa-Monitoring 20 years of land cover changes by means of medium resolution satellite data. *International Journal of Applied Earth Observation and Geoinformation*, 28(1), 60–69.
<https://doi.org/10.1016/j.jag.2013.11.006>
- Camberlin, P., & Okoola, R. E. (2003). The onset and cessation of the “long rains” in eastern Africa and their interannual variability. *Theoretical and Applied Climatology*, 75(1–2), 43–54. <https://doi.org/10.1007/s00704-002-0721-5>
- Capolongo, D., Pennetta, L., Piccarreta, M., Fallacara, G., & Boenzi, F. (2008). Spatial and temporal variations in soil erosion and deposition due to land-levelling in a semi-arid area of Basilicata (Southern Italy). *Earth Surface Processes and Landforms*, 33(3), 364–379.
<https://doi.org/10.1002/esp.1560>
- Cegielska, K., Noszczyk, T., Kukulska, A., Szylar, M., Hernik, J., Dixon-Gough, R., Jombach, S., Valánszki, I., & Filepné Kovács, K. (2018). Land use and land cover changes in post-socialist countries: Some observations from Hungary and Poland. *Land Use Policy*, 78, 1–18. <https://doi.org/10.1016/j.landusepol.2018.06.017>
- Chasia, S., Herrnegger, M., Juma, B., Kimuyu, J., Sitoki, L., & Olang, L. (2021). Analysis of land-cover changes in the Transboundary Sio-Malaba-Malakisi River Basin of East Africa: Towards identifying potential land-use transition regimes. *African Geographical Review*, 00(00), 1–17. <https://doi.org/10.1080/19376812.2021.2007143>
- Chasia, S., Olang, L. O., Juma, B., & Sitoki, L. (2024). Understanding the linkages between land-use transitions and soil erosion/sediment deposition: A case study of the transboundary Sio-Malaba-Malakisi watershed in Kenya and Uganda. *Physics and Chemistry of the Earth, Parts A/B/C*, 133(November 2023), 103529. <https://doi.org/10.1016/j.pce.2023.103529>
- Chasia, S., Olang, L. O., & Sitoki, L. (2023). Modelling of land-use/cover change trajectories in a transboundary catchment of the Sio-Malaba-Malakisi Region in East Africa using the CLUE-s model. *Ecological Modelling*, 476, 110256.
<https://doi.org/10.1016/j.ecolmodel.2022.110256>
- Chhabra, A., Geist, H., Houghton, R. A., Haberl, H., Braimoh, A. K., Vlek, P. L. G., Patz, J., Xu, J., Ramankutty, N., Coomes, O., & Lambin, E. F. (2006). Multiple Impacts of Land-Use/Cover Change. In *Land-Use and Land-Cover Change* (pp. 71–116). Springer Berlin

Heidelberg. https://doi.org/10.1007/3-540-32202-7_4

- Cimusa Kulimushi, L., Bigabwa Bashagaluke, J., Prasad, P., Heri-Kazi, A. B., Lal Kushwaha, N., Masroor, M., Choudhari, P., Elbeltagi, A., Sajjad, H., & Mohammed, S. (2023). Soil erosion susceptibility mapping using ensemble machine learning models: A case study of upper Congo river sub-basin. *CATENA*, 222, 106858. <https://doi.org/10.1016/J.CATENA.2022.106858>
- Claessens, L., Schoorl, J. M., Verburg, P. H., Geraedts, L., & Veldkamp, A. (2009). Modelling interactions and feedback mechanisms between land use change and landscape processes. *Agriculture, Ecosystems & Environment*, 129(1–3), 157–170. <https://doi.org/10.1016/j.agee.2008.08.008>
- Cohen, A. S., Kaufman, L., & Ogutu-Ohwayo, R. (2019). Anthropogenic Threats, Impacts and Conservation Strategies in the African Great Lakes: A Review. In *The Limnology, Climatology and Paleoclimatology of the East African Lakes* (pp. 575–624). Routledge. <https://doi.org/10.1201/9780203748978-33>
- Congalton, R. G., & Green, K. (2008). *Assessing the Accuracy of Remotely Sensed Data* (Vol. 20083968). CRC Press. <https://doi.org/10.1201/9781420055139>
- Congalton, R., Gu, J., Yadav, K., Thenkabail, P., & Ozdogan, M. (2014). Global Land Cover Mapping: A Review and Uncertainty Analysis. *Remote Sensing*, 6(12), 12070–12093. <https://doi.org/10.3390/rs61212070>
- Coral, C., Bokelmann, W., Bonatti, M., Carcamo, R., & Sieber, S. (2021). Understanding institutional change mechanisms for land use: Lessons from Ecuador’s history. *Land Use Policy*, 108, 105530. <https://doi.org/10.1016/j.landusepol.2021.105530>
- Coulter, L. L., Stow, D. A., Tsai, Y. H., Ibanez, N., Shih, H. chien, Kerr, A., Benza, M., Weeks, J. R., & Mensah, F. (2016). Classification and assessment of land cover and land use change in southern Ghana using dense stacks of Landsat 7 ETM+ imagery. *Remote Sensing of Environment*, 184, 396–409. <https://doi.org/10.1016/j.rse.2016.07.016>
- Das, B., Bordoloi, R., Thungon, L. T., Paul, A., Pandey, P. K., Mishra, M., & Tripathi, O. P. (2020). An integrated approach of GIS, RUSLE and AHP to model soil erosion in West Kameng watershed, Arunachal Pradesh. *Journal of Earth System Science*, 129(1), 94. <https://doi.org/10.1007/s12040-020-1356-6>
- de Sousa, K., Sparks, A., Ashmall, W., van Etten, J., & Solberg, S. (2020). chirps: API Client for the CHIRPS Precipitation Data in R. *Journal of Open Source Software*, 5(51), 2419. <https://doi.org/10.21105/joss.02419>
- de Vente, J., & Poesen, J. (2005). Predicting soil erosion and sediment yield at the basin scale: Scale issues and semi-quantitative models. *Earth-Science Reviews*, 71(1–2), 95–125. <https://doi.org/10.1016/j.earscirev.2005.02.002>
- DeFries, R., Achard, F., Brown, S., Herold, M., Murdiyarso, D., Schlamadinger, B., & de Souza, C. (2007). Earth observations for estimating greenhouse gas emissions from deforestation in developing countries. *Environmental Science and Policy*, 10(4), 385–394.

<https://doi.org/10.1016/j.envsci.2007.01.010>

- Desmet, P. J. J., & Govers, G. (1995). GIS-based simulation of erosion and deposition patterns in an agricultural landscape: a comparison of model results with soil map information. *CATENA*, 25(1–4), 389–401. [https://doi.org/10.1016/0341-8162\(95\)00019-O](https://doi.org/10.1016/0341-8162(95)00019-O)
- Di Gregorio, A., & Latham, J. (2009). AFRICOVER land cover classification and mapping project. *Encyclopedia of Life Support Systems (EOLSS)*; Werheve, W., Ed, 236–254.
- Djoumessi, Y. F. (2022). New trend of agricultural productivity growth in sub-Saharan Africa. *Scientific African*, 18, e01410. <https://doi.org/10.1016/j.sciaf.2022.e01410>
- Doetterl, S., Berhe, A. A., Nadeu, E., Wang, Z., Sommer, M., & Fiener, P. (2016). Erosion, deposition and soil carbon: A review of process-level controls, experimental tools and models to address C cycling in dynamic landscapes. *Earth-Science Reviews*, 154, 102–122. <https://doi.org/10.1016/j.earscirev.2015.12.005>
- Duveiller, G., Caporaso, L., Abad-Viñas, R., Perugini, L., Grassi, G., Arneth, A., & Cescatti, A. (2020). Local biophysical effects of land use and land cover change: towards an assessment tool for policy makers. *Land Use Policy*, 91, 104382. <https://doi.org/10.1016/j.landusepol.2019.104382>
- Ebabu, K., Tsunekawa, A., Haregeweyn, N., Tsubo, M., Adgo, E., Fenta, A. A., Meshesha, D. T., Berihun, M. L., Sultan, D., Vanmaercke, M., Panagos, P., Borrelli, P., Langendoen, E. J., & Poesen, J. (2022). Global analysis of cover management and support practice factors that control soil erosion and conservation. *International Soil and Water Conservation Research*, 10(2), 161–176. <https://doi.org/10.1016/j.iswcr.2021.12.002>
- Eddy, I. M. S., Gergel, S. E., Coops, N. C., Henebry, G. M., Levine, J., Zerriffi, H., & Shibkov, E. (2017). Integrating remote sensing and local ecological knowledge to monitor rangeland dynamics. *Ecological Indicators*, 82(May), 106–116. <https://doi.org/10.1016/j.ecolind.2017.06.033>
- Endalew, T., & Biru, D. (2022). Soil erosion risk and sediment yield assessment with Revised Universal Soil Loss Equation and GIS: The case of Nesha watershed, Southwestern Ethiopia. *Results in Geophysical Sciences*, 12, 100049. <https://doi.org/10.1016/j.ringps.2022.100049>
- Eric F. Lambin, H. G. (2006). *Land -Use and Land-Cover Change: Local Processes and Global Impacts* (H. G. Eric F. Lambin (Ed.)). Springer Berlin Heidelberg.
- Evans, B. (2006). Soil erosion and Conservation. Third edition. In R. P. . Morgan (Ed.), *Soil Use and Management* (3rd ed., Vol. 22, Issue 1). Blackwell Publishing Ltd. <https://doi.org/10.1111/j.1475-2743.2006.00013.x>
- Falcucci, A., Maiorano, L., & Boitani, L. (2007). Changes in land-use/land-cover patterns in Italy and their implications for biodiversity conservation. *Landscape Ecology*, 22(4), 617–631. <https://doi.org/10.1007/s10980-006-9056-4>
- FAO. (1997). *AFRICOVER land cover classification* (p. 76).

- Fenta, A. A., Tsunekawa, A., Haregeweyn, N., Poesen, J., Tsubo, M., Borrelli, P., Panagos, P., Vanmaercke, M., Broeckx, J., Yasuda, H., Kawai, T., & Kurosaki, Y. (2020). Land susceptibility to water and wind erosion risks in the East Africa region. *Science of the Total Environment*, 703, 135016. <https://doi.org/10.1016/j.scitotenv.2019.135016>
- Fenta, A. A., Yasuda, H., Shimizu, K., Haregeweyn, N., Kawai, T., Sultan, D., Ebabu, K., & Belay, A. S. (2017). Spatial distribution and temporal trends of rainfall and erosivity in the Eastern Africa region. *Hydrological Processes*, 31(25), 4555–4567. <https://doi.org/10.1002/hyp.11378>
- Fleitmann, D., Dunbar, R. B., McCulloch, M., Mudelsee, M., Vuille, M., McClanahan, T. R., Cole, J. E., & Eggins, S. (2007). East African soil erosion recorded in a 300 year old coral colony from Kenya. *Geophysical Research Letters*, 34(4), L04401. <https://doi.org/10.1029/2006GL028525>
- Friedl, M. A., & Brodley, C. E. (2002). Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment*, 61(3), 399–409. [https://doi.org/10.1016/S0034-4257\(97\)00049-7](https://doi.org/10.1016/S0034-4257(97)00049-7)
- Friedl, M. A., McIver, D. K., Hodges, J. C. F., Zhang, X. Y., Muchoney, D., Strahler, A. H., Woodcock, C. E., Gopal, S., Schneider, A., Cooper, A., Baccini, A., Gao, F., & Schaaf, C. (2002). Global land cover mapping from MODIS: Algorithms and early results. *Remote Sensing of Environment*, 83(1–2), 287–302. [https://doi.org/10.1016/S0034-4257\(02\)00078-0](https://doi.org/10.1016/S0034-4257(02)00078-0)
- Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A., & Michaelsen, J. (2015). The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2(1), 150066. <https://doi.org/10.1038/sdata.2015.66>
- Ganasri, B. P., & Ramesh, H. (2016). Assessment of soil erosion by RUSLE model using remote sensing and GIS - A case study of Nethravathi Basin. *Geoscience Frontiers*, 7(6), 953–961. <https://doi.org/10.1016/j.gsf.2015.10.007>
- García-Ruiz, J. M., Beguería, S., Nadal-Romero, E., González-Hidalgo, J. C., Lana-Renault, N., & Sanjuán, Y. (2015). A meta-analysis of soil erosion rates across the world. *Geomorphology*, 239, 160–173. <https://doi.org/10.1016/j.geomorph.2015.03.008>
- Gelagay, H. S., & Minale, A. S. (2016). Soil loss estimation using GIS and Remote sensing techniques: A case of Koga watershed, Northwestern Ethiopia. *International Soil and Water Conservation Research*, 4(2), 126–136. <https://doi.org/10.1016/j.iswcr.2016.01.002>
- Ghosal, K., & Das Bhattacharya, S. (2020). A Review of RUSLE Model. *Journal of the Indian Society of Remote Sensing*, 48(4), 689–707. <https://doi.org/10.1007/s12524-019-01097-0>
- Gil Pontius Jr, R., & Schneider, L. C. (2001). Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. In *Ecosystems and Environment* (Vol. 85).
- Gioia, D., Amodio, A. M., Maggio, A., & Sabia, C. A. (2021). Impact of land use changes on the

- erosion processes of a degraded rural landscape: An analysis based on high-resolution DEMs, historical images, and soil erosion models. *Land*, 10(7). <https://doi.org/10.3390/land10070673>
- Giri, C. (Ed.). (2012). *Remote sensing of land use and land cover. Principles and applications*. Taylor & Francis.
- Gleyzer, A., Denisyuk, M., Rimmer, A., & Salingar, Y. (2004). A fast recursive GIS algorithm for computing Strahler stream order in braided and nonbraided networks. *Journal of the American Water Resources Association*, 40(4), 937–946. <https://doi.org/10.1111/j.1752-1688.2004.tb01057.x>
- Greenland, S., Senn, S. J., Rothman, K. J., Carlin, J. B., Poole, C., Goodman, S. N., & Altman, D. G. (2016). Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations. *European Journal of Epidemiology*, 31(4), 337–350. <https://doi.org/10.1007/s10654-016-0149-3>
- Guerra, C. A., Rosa, I. M. D., Valentini, E., Wolf, F., Filipponi, F., Karger, D. N., Nguyen Xuan, A., Mathieu, J., Lavelle, P., & Eisenhauer, N. (2020a). Global vulnerability of soil ecosystems to erosion. *Landscape Ecology*, 35(4), 823–842. <https://doi.org/10.1007/s10980-020-00984-z>
- Guerra, C. A., Rosa, I. M. D., Valentini, E., Wolf, F., Filipponi, F., Karger, D. N., Nguyen Xuan, A., Mathieu, J., Lavelle, P., & Eisenhauer, N. (2020b). Global vulnerability of soil ecosystems to erosion. *Landscape Ecology*, 35(4), 823–842. <https://doi.org/10.1007/s10980-020-00984-z>
- Guzha, A. C. C., Rufino, M. C. C., Okoth, S., Jacobs, S., & Nóbrega, R. L. B. L. B. (2018). Impacts of land use and land cover change on surface runoff, discharge and low flows: Evidence from East Africa. *Journal of Hydrology: Regional Studies*, 15(November 2017), 49–67. <https://doi.org/10.1016/j.ejrh.2017.11.005>
- Haidara, I., Tahri, M., Maanan, M., & Hakdaoui, M. (2019). Efficiency of Fuzzy Analytic Hierarchy Process to detect soil erosion vulnerability. *Geoderma*, 354(September 2018), 113853. <https://doi.org/10.1016/j.geoderma.2019.07.011>
- Hansen, M. C., & Loveland, T. R. (2012). A review of large area monitoring of land cover change using Landsat data. *Remote Sensing of Environment*, 122, 66–74. <https://doi.org/10.1016/j.rse.2011.08.024>
- Hoover, J. D., Leisz, S. J., & Laituri, M. E. (2017). Comparing and Combining Landsat Satellite Imagery and Participatory Data to Assess Land-Use and Land-Cover Changes in a Coastal Village in Papua New Guinea. *Human Ecology*, 45(2), 251–264. <https://doi.org/10.1007/s10745-016-9878-x>
- Huang, X., Lu, Q., Zhang, L., & Plaza, A. (2014). New postprocessing methods for remote sensing image classification: A systematic study. *IEEE Transactions on Geoscience and Remote Sensing*, 52(11), 7140–7159. <https://doi.org/10.1109/TGRS.2014.2308192>
- Igad. (2007). *IGAD Environment and Natural Resources Strategy*. April, 60.

- IGAD. (2019). *Kenya and Uganda cooperate on trans-boundary water matters under IGAD auspices*.
- Institute of Water Research. (2002). *RUSLE - an online soil erosion assessment tool*. Michigan State University. <http://www.iwr.msu.edu/rusle/kfactor.htm>
- IPPC. (2007). Summary for Policymakers. *Ippc*, May, 1–19. <https://doi.org/10.1017/CBO9781139177245>
- Irwin, E. G., & Geoghegan, J. (2001). Theory, data, methods: Developing spatially explicit economic models of land use change. *Agriculture, Ecosystems and Environment*, 85(1–3), 7–24. [https://doi.org/10.1016/S0167-8809\(01\)00200-6](https://doi.org/10.1016/S0167-8809(01)00200-6)
- Jazouli, A. El, Barakat, A., Khellouk, R., Rais, J., & Baghdadi, M. El. (2019). Remote sensing and GIS techniques for prediction of land use land cover change effects on soil erosion in the high basin of the Oum Er Rbia River (Morocco). *Remote Sensing Applications: Society and Environment*, 13, 361–374. <https://doi.org/10.1016/j.rsase.2018.12.004>
- Jiang, B., Bamutaze, Y., & Pilesjö, P. (2014). Climate change and land degradation in Africa: A case study in the Mount Elgon region, Uganda. *Geo-Spatial Information Science*, 17(1), 39–53. <https://doi.org/10.1080/10095020.2014.889271>
- Jing, S., Liao, L., Du, M., & Shi, E. (2022). Assessing the effect of the joint governance of transboundary pollution on water quality: Evidence from China. *Frontiers in Environmental Science*, 10(October), 1–13. <https://doi.org/10.3389/fenvs.2022.989106>
- Judex, M., & Menz, G. (2006). Modelling of land-use changes in a West African catchment. *ISPR Archives*, 36(7), 18.
- Juma, B., Olang, L. O., Hassan, M., Chasia, S., Bukachi, V., Shiundu, P., & Mulligan, J. (2021). Analysis of rainfall extremes in the Ngong River Basin of Kenya: Towards integrated urban flood risk management. *Physics and Chemistry of the Earth, Parts A/B/C*, 124(August), 102929. <https://doi.org/10.1016/j.pce.2020.102929>
- Kabo-bah, K. J., Guoan, T., Yang, X., Na, J., & Xiong, L. (2021). Erosion potential mapping using analytical hierarchy process (AHP) and fractal dimension. *Heliyon*, 7(6), e07125. <https://doi.org/10.1016/j.heliyon.2021.e07125>
- Karamage, F., Zhang, C., Liu, T., Maganda, A., & Isabwe, A. (2017). Soil Erosion Risk Assessment in Uganda. *Forests*, 8(2), 52. <https://doi.org/10.3390/f8020052>
- Kiage, L. M., Liu, K. B., Walker, N. D., Lam, N., & Huh, O. K. (2007). Recent land-cover/use change associated with land degradation in the Lake Baringo catchment, Kenya, East Africa: Evidence from Landsat TM and ETM+. *International Journal of Remote Sensing*, 28(19), 4285–4309. <https://doi.org/10.1080/01431160701241753>
- Kidane, M., Bezie, A., Kesete, N., & Tolessa, T. (2019). The impact of land use and land cover (LULC) dynamics on soil erosion and sediment yield in Ethiopia. *Heliyon*, 5(12), e02981. <https://doi.org/10.1016/j.heliyon.2019.e02981>
- Koomen, E., Stillwell, J., Bakema, A., & Scholten, H. J. (2007). *Modelling land-use change*:

Progress and applications (Vol. 90). Springer Science & Business Media.

- Kucsicsa, G., Popovici, E.-A., Bălteanu, D., Grigorescu, I., Dumitraşcu, M., & Mitrică, B. (2019). Future land use/cover changes in Romania: regional simulations based on CLUE-S model and CORINE land cover database. *Landscape and Ecological Engineering*, 15(1), 75–90. <https://doi.org/10.1007/s11355-018-0362-1>
- Kucuker, D. M., & Cedano Giraldo, D. (2022). Assessment of soil erosion risk using an integrated approach of GIS and Analytic Hierarchy Process (AHP) in Erzurum, Türkiye. *Ecological Informatics*, 71, 101788. <https://doi.org/10.1016/j.ecoinf.2022.101788>
- Kulimushi, L. C., Choudhari, P., Maniragaba, A., Elbeltagi, A., Mugabowindekwe, M., Rwanyiziri, G., Byizigiro, R. V., Pingale, S. M., & Singh, S. K. (2021). Erosion risk assessment through prioritization of sub-watersheds in Nyabarongo river catchment, Rwanda. *Environmental Challenges*, 5, 100260. <https://doi.org/10.1016/J.ENVC.2021.100260>
- Kumar, P., Pandey, P. C., Singh, B. K., Katiyar, S., Mandal, V. P., Rani, M., Tomar, V., & Patairiya, S. (2016). Estimation of accumulated soil organic carbon stock in tropical forest using geospatial strategy. *Egyptian Journal of Remote Sensing and Space Science*, 19(1), 109–123. <https://doi.org/10.1016/j.ejrs.2015.12.003>
- Kumar, S., & Kushwaha, S. P. S. (2013). Modelling soil erosion risk based on RUSLE-3D using GIS in a Shivalik sub-watershed. *Journal of Earth System Science*, 122(2), 389–398. <https://doi.org/10.1007/s12040-013-0276-0>
- Lal, R. (2001). Soil degradation by erosion. *Land Degradation & Development*, 12(6), 519–539. <https://doi.org/10.1002/ldr.472>
- Lal, R. (2005). Soil erosion and carbon dynamics. *Soil and Tillage Research*, 81(2), 137–142. <https://doi.org/10.1016/j.still.2004.09.002>
- Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Folke, C., Bruce, J. W., Coomes, O. T., Dirzo, R., George, P. S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E. F., Mortimore, M., Ramakrishnan, P. S., Richards, J. F., Steffen, W., ... Veldkamp, T. A. (2001). *The causes of land-use and land-cover change: moving beyond the myths* (Vol. 11).
- Leh, M., Bajwa, S., & Chaubey, I. (2011). Impact of land use change on erosion : An integrated remote sensing , Geographic Information Systems and modeling methodology. *Land Degradation & Development*, n/a-n/a. <https://doi.org/10.1002/ldr.1137>
- Li, L., Du, S., Wu, L., & Liu, G. (2009). An overview of soil loss tolerance. *CATENA*, 78(2), 93–99. <https://doi.org/10.1016/j.catena.2009.03.007>
- Liao, C., Zhou, T., Xu, D., Cooper, M. G., Engwirda, D., Li, H., & Leung, L. R. (2023). Topological Relationship-Based Flow Direction Modeling: Mesh-Independent River Networks Representation. *Journal of Advances in Modeling Earth Systems*, 15(2), 1–19. <https://doi.org/10.1029/2022MS003089>
- Lillesand T.M., Kiefer R.W., and C. J. W. (2015). *Remote sensing and image interpretation* (7th

ed.). John Wiley & Sons.

- Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PLoS ONE*, 13(7), 1–23. <http://10.0.5.91/journal.pone.0200493>
- Liu, D., Zheng, X., & Wang, H. (2020). Land-use Simulation and Decision-Support system (LandSDS): Seamlessly integrating system dynamics, agent-based model, and cellular automata. *Ecological Modelling*, 417(December 2019), 108924. <https://doi.org/10.1016/j.ecolmodel.2019.108924>
- Liu, J., Liu, S., Tieszen, L. L., & Chen, M. (2007). *Estimating soil erosion using the USPED model and consecutive remotely sensed land cover observations*. January 2007, 16:1–16:6. <https://doi.org/10.1145/1357910.1358122>
- Liu, J., Sleeter, B., Selman, P. C., Diao, J., Zhou, Q., Worstell, B., & Moritsch, M. (2021). Modeling watershed carbon dynamics as affected by land cover change and soil erosion. *Ecological Modelling*, 459(650), 109724. <https://doi.org/10.1016/j.ecolmodel.2021.109724>
- Liu, S., Bliss, N., Sundquist, E., & Huntington, T. G. (2003). Modeling carbon dynamics in vegetation and soil under the impact of soil erosion and deposition. *Global Biogeochemical Cycles*, 17(2), n/a-n/a. <https://doi.org/10.1029/2002GB002010>
- Lizaga Villuendas, I., Latorre, B., Gaspar, L., & Navas, A. (2022). Effect of historical land-use change on soil erosion in a Mediterranean catchment by integrating 137 Cs measurements and WaTEM/SEDEM model. *Hydrological Processes*, 36(5). <https://doi.org/10.1002/hyp.14577>
- Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, 28(5), 823–870. <https://doi.org/10.1080/01431160600746456>
- Ma, S., Li, Y., Zhang, Y., Wang, L.-J., Jiang, J., & Zhang, J. (2022). Distinguishing the relative contributions of climate and land use/cover changes to ecosystem services from a geospatial perspective. *Ecological Indicators*, 136, 108645. <https://doi.org/10.1016/j.ecolind.2022.108645>
- Maitima, J. M., Mugatha, S. M., Reid, R. S., Gachimbi, L. N., Majule, A., Lyaruu, H., Pomery, D., Mathai, S., & Mugisha, S. (2009). The linkages between land use change, land degradation and biodiversity across East Africa. *African Journal of Agricultural Research*, 3(10), 310–325. <https://doi.org/10.5897/AJEST08.173>
- Makaya, N., Dube, T., Seutloali, K., Shoko, C., Mutanga, O., & Masocha, M. (2019). Geospatial assessment of soil erosion vulnerability in the upper uMgeni catchment in KwaZulu Natal, South Africa. *Physics and Chemistry of the Earth*, 112(January), 50–57. <https://doi.org/10.1016/j.pce.2019.02.012>
- Malek, Ž., Verburg, P. H., R Geijzendorffer, I., Bondeau, A., & Cramer, W. (2018). Global change effects on land management in the Mediterranean region. *Global Environmental Change*, 50, 238–254. <https://doi.org/10.1016/j.gloenvcha.2018.04.007>

- Marcos-Martinez, R., Bryan, B. A., Connor, J. D., & King, D. (2017). Agricultural land-use dynamics: Assessing the relative importance of socioeconomic and biophysical drivers for more targeted policy. *Land Use Policy*, 63, 53–66. <https://doi.org/10.1016/j.landusepol.2017.01.011>
- Mather, P., & Tso, B. (2010). Classification methods for remotely sensed data. In *Vasa*. Vasa.a. In *Vasa*.
- Mati, B. M., Morgan, R. P. C., Gichuki, F. N., Quinton, J. N., Brewer, T. R., & Liniger, H. P. (2000). Assessment of erosion hazard with the USLE and GIS: A case study of the Upper Ewaso Ng'iro North basin of Kenya. *International Journal of Applied Earth Observation and Geoinformation*, 2(2), 78–86. [https://doi.org/10.1016/S0303-2434\(00\)85002-3](https://doi.org/10.1016/S0303-2434(00)85002-3)
- Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G., & Gotts, N. M. (2007). Agent-based land-use models: a review of applications. *Landscape Ecology*, 22(10), 1447–1459. <https://doi.org/10.1007/s10980-007-9135-1>
- Maxwell, A. E., Warner, T. A., & Fang, F. (2018). Implementation of machine-learning classification in remote sensing: an applied review. *International Journal of Remote Sensing*, 39(9), 2784–2817. <https://doi.org/10.1080/01431161.2018.1433343>
- McCormack, D. E., Young, K. K., & Kimberlin, L. W. (2015). Current Criteria for Determining Soil Loss Tolerance. In *Determinants of Soil Loss Tolerance* (pp. 95–111). <https://doi.org/10.2134/asaspecpub45.c9>
- Memarsadeghi, N., Mount, D. M., Netanyahu, N. S., & Le Moigne, J. (2007). A fast implementation of the isodata clustering algorithm. *International Journal of Computational Geometry and Applications*, 17(1), 71–103. <https://doi.org/10.1142/S0218195907002252>
- Mengistu, D. A., & Waktola, D. K. (2016). Monitoring land use/land cover change impacts on soils in data scarce environments: a case of south-central Ethiopia. *Journal of Land Use Science*, 11(1), 96–112. <https://doi.org/10.1080/1747423X.2014.927011>
- Merritt, W. S., Letcher, R. A., & Jakeman, A. J. (2003). A review of erosion and sediment transport models. *Environmental Modelling and Software*, 18(8–9), 761–799. [https://doi.org/10.1016/S1364-8152\(03\)00078-1](https://doi.org/10.1016/S1364-8152(03)00078-1)
- Michetti, M. (2012). Modelling Land Use, Land-Use Change, and Forestry in Climate Change: A Review of Major Approaches. *Ssrn*. <https://doi.org/10.2139/ssrn.2122298>
- Midekisa, A., Holl, F., Savory, D. J., Andrade-Pacheco, R., Gething, P. W., Bennett, A., & Sturrock, H. J. W. (2017). Mapping land cover change over continental Africa using Landsat and Google Earth Engine cloud computing. *PLoS ONE*, 12(9), 1–15. <https://doi.org/10.1371/journal.pone.0184926>
- Ministry of Lands, H. and U. D. (2013). *Republic of Uganda the Uganda National Land Policy* (Issue 13). <http://extwprlegs1.fao.org/docs/pdf/uga163420.pdf>
- Ministry of Lands Housing and Urban Development. (2006). *The National Land Use Policy* (Issue Idc).

- Ministry of Water and Irrigation. (2008). The National Water Resources Management Strategy (NWRMS). *Ministry of Water and Irrigation Water Kenya, January 2006*, 21.
<http://wstf.go.ke/watersource/Downloads/006>. Water Resources Management Strategy.pdf
- Mitasova, H., Hofierka, J., Zlocha, M., & Iverson, L. R. (1996). Modelling topographic potential for erosion and deposition using GIS. *International Journal of Geographical Information Systems*, 10(5), 629–641. <https://doi.org/10.1080/02693799608902101>
- Mitasova, H., & Mitas, L. (2011). Multiscale Soil Erosion Simulations For Land Use Management. *Landscape Erosion and Evolution Modeling*, 321–347.
https://doi.org/10.1007/978-1-4615-0575-4_11
- Mitasova, H., Mitas, L., & Brown, W. M. (2001). Multiscale Simulation of Land Use Impact on Soil Erosion and Deposition Patterns. *Sustaining the Global Farm*, 1163–1169.
- Moore, I. D., & Wilson, J. P. (1992). Length-slope factors for the revised universal soil loss equation: simplified method of estimation. *Journal of Soil & Water Conservation*, 47(5), 423–428.
- Moore, T. R. (1979). Rainfall erosivity in East Africa. *Geografiska Annaler: Series A, Physical Geography*, 61(3–4), 147–156. <https://doi.org/10.1080/04353676.1979.11879987>
- Mugagga, F., Kakembo, V., & Buyinza, M. (2012). Land use changes on the slopes of Mount Elgon and the implications for the occurrence of landslides. *Catena*, 90, 39–46.
<https://doi.org/10.1016/j.catena.2011.11.004>
- Muhati, G. L., Olago, D., & Olaka, L. (2018). Land use and land cover changes in a sub-humid Montane forest in an arid setting: A case study of the Marsabit forest reserve in northern Kenya. *Global Ecology and Conservation*, 16, e00512.
<https://doi.org/10.1016/j.gecco.2018.e00512>
- Mwanake, H., Mehdi-Schulz, B., Schulz, K., Kitaka, N., Olang, L. O., Lederer, J., & Hernegger, M. (2023). Agricultural Practices and Soil and Water Conservation in the Transboundary Region of Kenya and Uganda: Farmers’ Perspectives of Current Soil Erosion. *Agriculture*, 13(7), 1434. <https://doi.org/10.3390/agriculture13071434>
- Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J., Choimes, A., Collen, B., Day, J., De Palma, A., Díaz, S., Echeverria-Londoño, S., Edgar, M. J., Feldman, A., Garon, M., Harrison, M. L. K., Alhusseini, T., ... Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, 520(7545), 45–50. <https://doi.org/10.1038/nature14324>
- Noszczyk, T. (2019). A review of approaches to land use changes modeling. *Human and Ecological Risk Assessment: An International Journal*, 25(6), 1377–1405.
<https://doi.org/10.1080/10807039.2018.1468994>
- Olang, L. O., Kundu, P., Bauer, T., & Fürst, J. (2011). Analysis of spatio-temporal land cover changes for hydrological impact assessment within the Nyando River Basin of Kenya. *Environmental Monitoring and Assessment*, 179(1–4), 389–401.
<https://doi.org/10.1007/s10661-010-1743-6>

- Olang, L. O., Kundu, P. M., Ouma, G., & Fürst, J. (2014). Impacts of land cover change scenarios on storm runoff generation: A basis for management of the Nyando Basin, Kenya. *Land Degradation and Development*, 25(3), 267–277. <https://doi.org/10.1002/ldr.2140>
- Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, 148, 42–57. <https://doi.org/10.1016/j.rse.2014.02.015>
- Omondi, L., & Musula, P. (2011). Land Degradation of the Mau Forest Complex in Eastern Africa: A Review for Management and Restoration Planning. In *Environmental Monitoring*. InTech. <https://doi.org/10.5772/28532>
- Omonge, P., Feigl, M., Olang, L., Schulz, K., & Herrnegger, M. (2022). Evaluation of satellite precipitation products for water allocation studies in the Sio-Malaba-Malakisi river basin of East Africa. *Journal of Hydrology: Regional Studies*, 39(December 2021), 100983. <https://doi.org/10.1016/j.ejrh.2021.100983>
- Ongoma, V., Chen, H., & Omony, G. W. (2018). Variability of extreme weather events over the equatorial East Africa, a case study of rainfall in Kenya and Uganda. *Theoretical and Applied Climatology*, 131(1–2), 295–308. <https://doi.org/10.1007/s00704-016-1973-9>
- Opedes, H., Mächer, S., Baartman, J. E. M., Nedala, S., & Mugagga, F. (2022). Land Cover Change Detection and Subsistence Farming Dynamics in the Fringes of Mount Elgon National Park, Uganda from 1978–2020. *Remote Sensing*, 14(10), 2423. <https://doi.org/10.3390/rs14102423>
- Orgiazzi, A., Bardgett, R. D., Barrios, E., & others. (2016). *Global soil biodiversity atlas*. European Commission.
- Panagos, P., Borrelli, P., Meusburger, K., Alewell, C., Lugato, E., & Montanarella, L. (2015). Estimating the soil erosion cover-management factor at the European scale. *Land Use Policy*, 48, 38–50. <https://doi.org/10.1016/j.landusepol.2015.05.021>
- Panagos, P., Borrelli, P., Meusburger, K., van der Zanden, E. H., Poesen, J., & Alewell, C. (2015). Modelling the effect of support practices (P-factor) on the reduction of soil erosion by water at European scale. *Environmental Science and Policy*, 51, 23–34. <https://doi.org/10.1016/j.envsci.2015.03.012>
- Panagos, P., Borrelli, P., Poesen, J., Ballabio, C., Lugato, E., Meusburger, K., Montanarella, L., & Alewell, C. (2015). The new assessment of soil loss by water erosion in Europe. *Environmental Science & Policy*, 54, 438–447. <https://doi.org/10.1016/j.envsci.2015.08.012>
- Pandey, A., Himanshu, S. K., Mishra, S. K., & Singh, V. P. (2016). Physically based soil erosion and sediment yield models revisited. *Catena*, 147, 595–620. <https://doi.org/10.1016/j.catena.2016.08.002>
- Pelacani, S., Märker, M., & Rodolfi, G. (2008). Simulation of soil erosion and deposition in a changing land use: A modelling approach to implement the support practice factor. *Geomorphology*, 99(1–4), 329–340. <https://doi.org/10.1016/j.geomorph.2007.11.010>
- Phiri, D., Simwanda, M., Salekin, S., Nyirenda, V., Murayama, Y., & Ranagalage, M. (2020).

- Sentinel-2 Data for Land Cover/Use Mapping: A Review. *Remote Sensing*, 12(14), 2291. <https://doi.org/10.3390/rs12142291>
- Pistocchi, A., Cassani, G., & Zani, O. (2002). Use of the USPED model for mapping soil erosion and managing best land conservation practices. *Proceedings of the First Biennial Meeting of the International Environmental Modelling and Software Society on Integrated Assessment and Decision Support*, 3, 163–168. <http://www.iemss.org/iemss2002/>
- Sessional Paper No. 01 of 2017 on National Land Use Policy, (2017).
- Poesen, J. (2018). Soil erosion in the Anthropocene: Research needs. *Earth Surface Processes and Landforms*, 43(1), 64–84. <https://doi.org/10.1002/esp.4250>
- Potapov, P., Hansen, M. C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X.-P., Baggett, A., Kommareddy, I., & Kommareddy, A. (2022). The Global 2000-2020 Land Cover and Land Use Change Dataset Derived From the Landsat Archive: First Results. *Frontiers in Remote Sensing*, 3(April), 1–22. <https://doi.org/10.3389/frsen.2022.856903>
- Pradeep, G. S., Krishnan, M. V. N., & Vijith, H. (2015). Identification of critical soil erosion prone areas and annual average soil loss in an upland agricultural watershed of Western Ghats, using analytical hierarchy process (AHP) and RUSLE techniques. *Arabian Journal of Geosciences*, 8(6), 3697–3711. <https://doi.org/10.1007/s12517-014-1460-5>
- Pricope, N. G. (2009). Assessment of spatial patterns of sediment transport and delivery for soil and water conservation programs. *Journal of Spatial Hydrology*, 9(1), 21–46.
- Qian, Y., Zhang, K., & Qiu, F. (2005). *Spatial Contextual Noise Removal for Post Classification*. 524–528. <http://dl.acm.org/citation.cfm?id=1066795>
- Qiu, F., Chastain, B., Zhou, Y., Zhang, C., & Sridharan, H. (2014). Modeling land suitability/capability using fuzzy evaluation. *GeoJournal*, 79(2), 167–182. <https://doi.org/10.1007/s10708-013-9503-0>
- Rajbanshi, J., & Bhattacharya, S. (2020). Assessment of soil erosion, sediment yield and basin specific controlling factors using RUSLE-SDR and PLSR approach in Konar river basin, India. *Journal of Hydrology*, 587(April), 124935. <https://doi.org/10.1016/j.jhydrol.2020.124935>
- Ramirez Gómez, S. O. I. (2019). *Local voices in land use decisions: Co-producing spatial knowledge on ecosystem services with indigenous and tribal communities in intact forest regions*. Utrecht University.
- Raza, A., Ahrends, H., Habib-Ur-rahman, M., & Gaiser, T. (2021). Modeling approaches to assess soil erosion by water at the field scale with special emphasis on heterogeneity of soils and crops. *Land*, 10(4). <https://doi.org/10.3390/land10040422>
- Reed, M. S., & Clokie, M. R. J. (2000). Effects of grazing and cultivation on forest plant communities in Mount Elgon National Park, Uganda. *African Journal of Ecology*, 38(2), 154–162. <https://doi.org/10.1046/j.1365-2028.2000.00234.x>

- Renard, K. G., Yoder, D. C., Lightle, D. T., & Dabney, S. M. (2011). Universal Soil Loss Equation and Revised Universal Soil Loss Equation. *Handbook of Erosion Modelling*, 135–167. <https://doi.org/10.1002/9781444328455.ch8>
- Reyers, B., O’Farrell, P. J., Cowling, R. M., Egoh, B. N., Le Maitre, D. C., & Vlok, J. H. J. (2009). Ecosystem Services, Land-Cover Change, and Stakeholders: Finding a Sustainable Foothold for a Semiarid Biodiversity Hotspot. *Ecology and Society*, 14(1), art38. <https://doi.org/10.5751/ES-02867-140138>
- Riquetti, N. B., Beskow, S., Guo, L., & Mello, C. R. (2023). Soil erosion assessment in the Amazon basin in the last 60 years of deforestation. *Environmental Research*, 236, 116846. <https://doi.org/10.1016/J.ENVRES.2023.116846>
- Robert Rangeley, Bocar M. Thiam, Randolph A. Andersen, C. A. L. (1994). *International River Basin Organizations in Sub-Saharan Africa, Volumes 23-250*. <http://books.google.com/books?id=-gHMB8MPOBoC&pgis=1>
- Rosas, M. A., & Gutierrez, R. R. (2020). Assessing soil erosion risk at national scale in developing countries: The technical challenges, a proposed methodology, and a case history. *Science of the Total Environment*, 703, 135474. <https://doi.org/10.1016/j.scitotenv.2019.135474>
- Roussel, J.-M. (2012). *Feasibility study and preparation of an integrated watershed management program and investment proposal for Sio-Malaba-Malakisi sub basin* (Issue May). <http://nileis.nilebasin.org>
- Russell G. Congalton, K. G. (2009). *Assessing the accuracy of remotely sensed data. Principles and Practices* (Second). Taylor & Francis.
- Sano, E. E., Rosa, R., Brito, J. L. S., & Ferreira, L. G. (2010). Land cover mapping of the tropical savanna region in Brazil. *Environmental Monitoring and Assessment*, 166(1–4), 113–124. <https://doi.org/10.1007/s10661-009-0988-4>
- Santos, C. A. G., Watanabe, M., & Suzuki, K. (1998). A Conceptual Soil Erosion Model. *Proceedings of Hydraulic Engineering*, 42, 1033–1038. <https://doi.org/10.2208/prohe.42.1033>
- Schneider, L. C., & Gil Pontius, R. (2001). Modeling land-use change in the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems and Environment*, 85(1–3), 83–94. [https://doi.org/10.1016/S0167-8809\(01\)00189-X](https://doi.org/10.1016/S0167-8809(01)00189-X)
- Schulp, C. J. E., Levers, C., Kuemmerle, T., Tieskens, K. F., & Verburg, P. H. (2019). Mapping and modelling past and future land use change in Europe’s cultural landscapes. *Land Use Policy*, 80, 332–344. <https://doi.org/10.1016/j.landusepol.2018.04.030>
- Schürz, C., Mehdi, B., Kiesel, J., Schulz, K., & Herrnegger, M. (2020). A systematic assessment of uncertainties in large-scale soil loss estimation from different representations of USLE input factors-a case study for Kenya and Uganda. *Hydrology and Earth System Sciences*, 24(9), 4463–4489. <https://doi.org/10.5194/hess-24-4463-2020>
- Serdeczny, O., Adams, S., Baarsch, F., Coumou, D., Robinson, A., Hare, W., Schaeffer, M.,

- Perrette, M., & Reinhardt, J. (2017). Climate change impacts in Sub-Saharan Africa: from physical changes to their social repercussions. *Regional Environmental Change*, 17(6), 1585–1600. <https://doi.org/10.1007/s10113-015-0910-2>
- Serneels, S., & Lambin, E. F. (2001). Proximate causes of land-use change in Narok District, Kenya: a spatial statistical model. *Agriculture, Ecosystems & Environment*, 85(1–3), 65–81. [https://doi.org/10.1016/S0167-8809\(01\)00188-8](https://doi.org/10.1016/S0167-8809(01)00188-8)
- Sharma, A., Tiwari, K. N., & Bhadoria, P. B. S. (2011). Effect of land use land cover change on soil erosion potential in an agricultural watershed. *Environmental Monitoring and Assessment*, 173(1–4), 789–801. <https://doi.org/10.1007/s10661-010-1423-6>
- Song, X.-P., Hansen, M. C., Stehman, S. V., Potapov, P. V., Tyukavina, A., Vermote, E. F., & Townshend, J. R. (2018). Global land change from 1982 to 2016. *Nature*, 560(7720), 639–643. <https://doi.org/10.1038/s41586-018-0411-9>
- Swarnkar, S., Malini, A., Tripathi, S., & Sinha, R. (2018). Assessment of uncertainties in soil erosion and sediment yield estimates at ungauged basins: an application to the Garra River basin, India. *Hydrology and Earth System Sciences*, 22(4), 2471–2485. <https://doi.org/10.5194/hess-22-2471-2018>
- Tadesse, L., Suryabagavan, K. V., Sridhar, G., & Legesse, G. (2017). Land use and land cover changes and Soil erosion in Yezat Watershed, North Western Ethiopia. *International Soil and Water Conservation Research*, 5(2), 85–94. <https://doi.org/10.1016/j.iswcr.2017.05.004>
- Tairi, A., Elmouden, A., & Aboulouafa, M. (2019). Soil Erosion Risk Mapping Using the Analytical Hierarchy Process (AHP) and Geographic Information System in the Tifnout-Askaoun Watershed, Southern Morocco. *European Scientific Journal ESJ*, 15(30), 338–356. <https://doi.org/10.19044/esj.2019.v15n30p338>
- Tamene, L., & Vlek, P. L. G. (2008). Soil Erosion Studies in Northern Ethiopia. In A. K. Braimoh & P. L. G. Vlek (Eds.), *Land Use and Soil Resources* (pp. 73–100). Springer Netherlands. https://doi.org/10.1007/978-1-4020-6778-5_5
- Tavana, M., Soltanifar, M., & Santos-Arteaga, F. J. (2023). Analytical hierarchy process: revolution and evolution. *Annals of Operations Research*, 326(2), 879–907. <https://doi.org/10.1007/s10479-021-04432-2>
- Tekwa, I. J., Laflen, J. M., Kundiri, A. M., & Bala Alhassan, A. (2021). Evaluation of WEPP versus EGEM and empirical model efficiencies in predicting ephemeral gully erosion around Mubi area, Northeast Nigeria. *International Soil and Water Conservation Research*, 9(1), 11–25. <https://doi.org/10.1016/j.iswcr.2020.08.003>
- Thenkabail, P. S. (2015). Remotely sensed data characterization, classification, and accuracies. In *Remotely Sensed Data Characterization, Classification, and Accuracies* (Vol. 1).
- Torri, D., Poesen, J., & Borselli, L. (1997). Predictability and uncertainty of the soil erodibility factor using a global dataset. *CATENA*, 31(1–2), 1–22. [https://doi.org/10.1016/S0341-8162\(97\)00036-2](https://doi.org/10.1016/S0341-8162(97)00036-2)
- Tucker, G. E., Catani, F., Rinaldo, A., & Bras, R. L. (2001). Statistical analysis of drainage

- density from digital terrain data. *Geomorphology*, 36(3–4), 187–202.
[https://doi.org/10.1016/S0169-555X\(00\)00056-8](https://doi.org/10.1016/S0169-555X(00)00056-8)
- Uitto, J. I., & Duda, A. M. (2002). Management of transboundary water resources: Lessons from international cooperation for conflict prevention. *Geographical Journal*, 168(4), 365–378.
<https://doi.org/10.1111/j.0016-7398.2002.00062.x>
- UNCCD. (2019). *Land degradation, poverty and inequality*. 1–12.
- Vagen Tor-Gunnar, Winowiecki, L. A. (2019). Predicting the Spatial Distribution and Severity of Soil Erosion in the Global Tropics using Satellite Remote Sensing. *Remote Sensing*, 1–18.
- Vaidya, O. S., & Kumar, S. (2006). Analytic hierarchy process: An overview of applications. *European Journal of Operational Research*, 169(1), 1–29.
<https://doi.org/10.1016/j.ejor.2004.04.028>
- Van Breugel, P., Kindt, R., Lillesø, J. P. B., Bingham, M., Demissew, S., Dudley, C., Friis, I., Gachathi, F., Kalema, J., & Mbago, F. (2015). Potential Natural Vegetation Map of Eastern Africa (Burundi, Ethiopia, Kenya, Malawi, Rwanda, Tanzania, Uganda and Zambia). Version 2.0. *Forest & Landscape Denmark and World Agroforestry Centre (ICRAF)*. URL: <Http://Vegetationmap4africa.Org, Version 2>.
- van der Knijff, J. M., Jones, R. J. A., & Montanarella, L. (2000). Soil erosion risk assessment in Europe. *Luxembourg: Office for Official Publications of the European Communities, EUR 19022*, 32.
- Van Oost, K., Beuselinck, L., Hairsine, P. B., & Govers, G. (2004). Spatial evaluation of a multi-class sediment transport and deposition model. *Earth Surface Processes and Landforms*, 29(8), 1027–1044. <https://doi.org/10.1002/esp.1089>
- Van Oost, K., Govers, G., & Desmet, P. (2000). Evaluating the effects of changes in landscape structure on soil erosion by water and tillage. *Landscape Ecology*, 15(6), 577–589.
<https://doi.org/https://doi.org/10.1023/a:1008198215674>
- Van Soesbergen, A. (2016). A review of land-use change models. *UNEP World Conservation Monitoring Centre*.
- van Vliet, J. (2013). Calibration and validation of land-use models [Wageningen University]. In *Wageningen University*. <https://www.wur.nl/en/Publication-details.htm?publicationId=publication-way-343332353934>
- Vancutsem, C., Marinho, E., Kayitakire, F., See, L., & Fritz, S. (2013). Harmonizing and combining existing land cover/land use datasets for cropland area monitoring at the African continental scale. *Remote Sensing*, 5(1), 19–41. <https://doi.org/10.3390/rs5010019>
- Vanmaercke, M., Panagos, P., Vanwalleghem, T., Hayas, A., Foerster, S., Borrelli, P., Rossi, M., Torri, D., Casali, J., Borselli, L., Vigiak, O., Maerker, M., Haregeweyn, N., De Geeter, S., Zgłobicki, W., Bielders, C., Cerdà, A., Conoscenti, C., de Figueiredo, T., ... Poesen, J. (2021). Measuring, modelling and managing gully erosion at large scales: A state of the art. *Earth-Science Reviews*, 218(April), 103637.

<https://doi.org/10.1016/j.earscirev.2021.103637>

- Veldkamp, A., & Verburg, P. H. (2004). Modelling land use change and environmental impact. In *Journal of Environmental Management* (Vol. 72, Issues 1–2, pp. 1–3). Elsevier.
- Verburg, P. H., Kok, K., Pontius Jr, R. G., & Veldkamp, A. (2006). Modeling land-use and land-cover change. In *Land-use and land-cover change: local processes and global impacts* (pp. 117–135). Springer.
- Walsh J. Stephen, C.-M. A. K. (Ed.). (2002). *Linking People, Place and Policy - A GIScience Approach*. Spring science + Business Media, LLC.
- Walsh, S. J., & Crews-Meyer, K. A. (2002). *Linking people, place, and policy: A GIScience approach*. Springer Science & Business Media.
- Wang, F., Yuan, X., & Xie, X. (2021). Dynamic change of land use/land cover patterns and driving factors of Nansihu Lake Basin in Shandong Province, China. *Environmental Earth Sciences*, 80(5), 180. <https://doi.org/10.1007/s12665-021-09476-y>
- Wang, T., Shi, J., Letu, H., Ma, Y., Li, X., & Zheng, Y. (2019). Detection and Removal of Clouds and Associated Shadows in Satellite Imagery Based on Simulated Radiance Fields. *Journal of Geophysical Research: Atmospheres*, 124(13), 7207–7225. <https://doi.org/10.1029/2018JD029960>
- Wanyama, D., Moore, N. J., & Dahlin, K. M. (2020). Persistent vegetation greening and browning trends related to natural and human activities in the mount Elgon ecosystem. *Remote Sensing*, 12(13). <https://doi.org/10.3390/rs12132113>
- Warren, S. D., Mitsova, H., Hohmann, M. G., Landsberger, S., Iskander, F. Y., Ruzyski, T. S., & Senseman, G. M. (2005). Validation of a 3-D enhancement of the Universal Soil Loss Equation for prediction of soil erosion and sediment deposition. *CATENA*, 64(2–3), 281–296. <https://doi.org/10.1016/j.catena.2005.08.010>
- Warren, S. D., & Ruzyski, T. S. (2022). Validation of the USPED Erosion and Deposition Model at Schofield Barracks, O’ahu, Hawai’i. *Pacific Science*, 76(1), 43–51. <https://doi.org/10.2984/76.1.4>
- Wasige, J. E., Groen, T. A., Smaling, E., & Jetten, V. (2012). Monitoring basin-scale land cover changes in Kagera Basin of Lake Victoria using: Ancillary data and remote sensing. *International Journal of Applied Earth Observation and Geoinformation*, 21(1), 32–42. <https://doi.org/10.1016/j.jag.2012.08.005>
- Wasonga, D. V., & Opiyo, J. (2018). Biodiversity status of Mount Elgon Forest ecosystem. *Biodiversity Status of Mount Elgon Forest Ecosystem. Component 4: Science to Inform Design of Community-Level Actions and Policy Decisions, February*, 80. [http://kefriwatertowers.org/PDF/Biodiversity status report _ Mt Elgon FF.pdf](http://kefriwatertowers.org/PDF/Biodiversity%20status%20report%20_Mt%20Elgon%20FF.pdf)
- Waturu, M., Sitoki, L., Lalah, J., Chasia, S., & Mbao, E. (2023). Effect of land use/land cover changes on water quality in the Upper Athi River sub-catchment in Kenya. *African Journal of Aquatic Science*, 1–14. <https://doi.org/10.2989/16085914.2023.2207098>

- Were, K. O., Dick, T. B., & Singh, B. R. (2013). Remotely sensing the spatial and temporal land cover changes in Eastern Mau forest reserve and Lake Nakuru drainage basin, Kenya. *Applied Geography*, 41, 75–86. <https://doi.org/10.1016/j.apgeog.2013.03.017>
- Williams, J. R. (1995). The EPIC model. Computer models of watershed hydrology. In *Water Resources Publication* (pp. 909–1000). <https://www.cabdirect.org/cabdirect/abstract/19961904785>
- Wischmeier, W., & Smith, D. (1978). *Predicting rainfall erosion losses: a guide to conservation planning* (No. 537). Department of Agriculture, Science and Education Administration.
- Wu, Q., Chen, Y., Wilson, J. P., Tan, H., & Chu, T. (2021). A new approach for calculating the slope length factor in the Revised Universal Soil Loss Equation. *Journal of Soil and Water Conservation*, 76(2), 153–165. <https://doi.org/10.2489/jswc.2021.00085>
- Wu, Y., & Chen, J. (2012). Modeling of soil erosion and sediment transport in the East River Basin in southern China. *Science of The Total Environment*, 441, 159–168. <https://doi.org/10.1016/j.scitotenv.2012.09.057>
- Wuepper, D., Borrelli, P., & Finger, R. (2019). Countries and the global rate of soil erosion. *Nature Sustainability*, 3(1), 51–55. <https://doi.org/10.1038/s41893-019-0438-4>
- Wynants, M., Kelly, C., Mtei, K., Munishi, L., Patrick, A., Rabinovich, A., Nasser, M., Gilvear, D., Roberts, N., Boeckx, P., Wilson, G., Blake, W. H., & Ndakidemi, P. (2019). Drivers of increased soil erosion in East Africa's agro-pastoral systems: changing interactions between the social, economic and natural domains. *Regional Environmental Change*, 19(7), 1909–1921. <https://doi.org/10.1007/s10113-019-01520-9>
- Yang, W., Seager, R., Cane, M. A., & Lyon, B. (2015). The annual cycle of East African precipitation. *Journal of Climate*, 28(6), 2385–2404. <https://doi.org/10.1175/JCLI-D-14-00484.1>
- Yao, Y., Kong, W., Wang, Z., Zhao, Z., Shao, M., & Wei, X. (2023). Distribution of soil physical and hydraulic properties between erosion and deposition topographies in five small catchments from north to south on the Loess Plateau of China. *CATENA*, 222, 106891. <https://doi.org/10.1016/J.CATENA.2022.106891>
- Yigini, Y., & Panagos, P. (2016). Assessment of soil organic carbon stocks under future climate and land cover changes in Europe. *Science of the Total Environment*, 557–558, 838–850. <https://doi.org/10.1016/j.scitotenv.2016.03.085>
- Yirgu, T. (2022). Assessment of soil erosion hazard and factors affecting farmers' adoption of soil and water management measure: A case study from Upper Domba Watershed, Southern Ethiopia. *Heliyon*, 8(6), e09536. <https://doi.org/10.1016/j.heliyon.2022.e09536>
- Zacharia, M. (2013). Assessment of Land Cover Changes in Lake Olbolosat Region of the Central Kenyan Highlands using Landsat Satellite Imagery Aided by Indigenous Knowledge. *Journal of Biodiversity Management & Forestry*, 02(02). <https://doi.org/10.4172/2327-4417.1000107>
- Zaehring, J. G., Llopis, J. C., Lathachack, P., Thein, T. T., & Heinemann, A. (2018). A novel

- participatory and remote-sensing-based approach to mapping annual land use change on forest frontiers in Laos, Myanmar, and Madagascar. *Journal of Land Use Science*, 13(1–2), 16–31. <https://doi.org/10.1080/1747423X.2018.1447033>
- Zhang, F., Zhan, J., Zhang, Q., Yao, L., & Liu, W. (2017). Impacts of land use/cover change on terrestrial carbon stocks in Uganda. *Physics and Chemistry of the Earth*, 101, 195–203. <https://doi.org/10.1016/j.pce.2017.03.005>
- Zhang, H., Wei, J., Yang, Q., Baartman, J. E. M., Gai, L., Yang, X., Li, S., Yu, J., Ritsema, C. J., & Geissen, V. (2017). An improved method for calculating slope length (λ) and the LS parameters of the Revised Universal Soil Loss Equation for large watersheds. *Geoderma*, 308(July), 36–45. <https://doi.org/10.1016/j.geoderma.2017.08.006>
- Zhang, Y., Qin, X., Qiu, Q., Yu, R., Yao, Y., Li, H., Shao, M., & Wei, X. (2023). Soil and water conservation measures reduce erosion but result in carbon and nitrogen accumulation of red soil in Southern China. *Agriculture, Ecosystems & Environment*, 346, 108346. <https://doi.org/10.1016/J.AGEE.2023.108346>
- Zhao, S., Liu, S., Sohl, T., Young, C., & Werner, J. (2013). Land use and carbon dynamics in the southeastern United States from 1992 to 2050. *Environmental Research Letters*, 8(4). <https://doi.org/10.1088/1748-9326/8/4/044022>
- Zhou, F., Xu, Y., Chen, Y., Xu, C. Y., Gao, Y., & Du, J. (2013). Hydrological response to urbanization at different spatio-temporal scales simulated by coupling of CLUE-S and the SWAT model in the Yangtze River Delta region. *Journal of Hydrology*, 485, 113–125. <https://doi.org/10.1016/j.jhydrol.2012.12.040>

APPENDICES

Appendix A. Similarity Index Report

Turnitin Originality Report

Processed on: 22-Aug-2023 16:56 EAT
 ID: 2149436933
 Word Count: 48753
 Submitted: 1

Assessing land-use/cover changes and their im... By Stanley Chasia

[Document Viewer](#)

Similarity Index
16%

Similarity by Source
 Internet Sources: 12%
 Publications: 12%
 Student Papers: 3%

Include quoted

Include bibliography

excluding matches < 10 words

mode: quickview (classic) report print refresh download

1% match (student papers from 23-Jun-2022) Submitted to Kenyatta University on 2022-06-23	
1% match (Internet from 17-Feb-2023) https://preview.carpentries.org/r-raster-vector-geospatial/aio.html	
<1% match (student papers from 22-Sep-2020) Submitted to Kenyatta University on 2020-09-22	
<1% match (student papers from 08-Feb-2023) Submitted to Kenyatta University on 2023-02-08	
<1% match (Internet from 06-Aug-2018) https://d-nb.info/1163665126/34	
<1% match (Internet from 17-Sep-2022) https://d-nb.info/1103135171/34	
<1% match (Internet from 04-Apr-2021) https://d-nb.info/1228535701/34	
<1% match (Internet from 19-Jul-2023) https://d-nb.info/1296547574/34	
<1% match (Internet from 27-Jan-2023) https://www.researchgate.net/publication/318090546_Integrating_remote_sensing_and_local_ecological_knowledge_to_monitor_rangeland_dynamics	
<1% match (Internet from 13-May-2023) https://www.researchgate.net/publication/349519148_Geospatial_modelling_of_soil_erosion_and_risk_assessment_in_Indian_Himalayan_region-A_study_of_Uttarakhand_state	
<1% match (Internet from 25-Mar-2023) https://www.researchgate.net/publication/364837448_tqdyr_kmyt_altrbt_almnjrft_walrwasb_fy_hwd_nhr_alabrsh_bastkhdam_alastshar_n_bd_w_walnmadrj_alryadyt_Gis	
<1% match (Internet from 07-Feb-2023) https://www.researchgate.net/publication/262806484_Assessing_the_effects_of_land_use_and_topography_on_soil_erosion_on_the_Loess_Plateau_in_China	
<1% match () de Sousa, Kauã. "Agrobiodiversity and climate adaptation: insights for risk management in small-scale farming", 2020	
<1% match () Echtaie, Rawad S.. "Investigation into land-use change in two contrasting areas in the Nile Delta, Egypt", University of Plymouth	
<1% match () Munch, Zahn. "Towards land change management using ecosystem dynamics and land cover change in rural Eastern Cape", Stellenbosch : Stellenbosch University, 2019	
<1% match ()	

Appendix B. Theory of Land-use/Cover Change Scenarios

Considering both physiographic and biophysical conditions existing in the SMM catchment, this study explored two land-use/cover change scenarios with the greatest impact on the local hydrology, including soil erosion and sediment deposition patterns in the study area. The SMM catchment is largely an agricultural basin, and therefore, most human activities are centred around farming and cultivation of mainly seasonal crops. Therefore, the following three scenarios were explored.

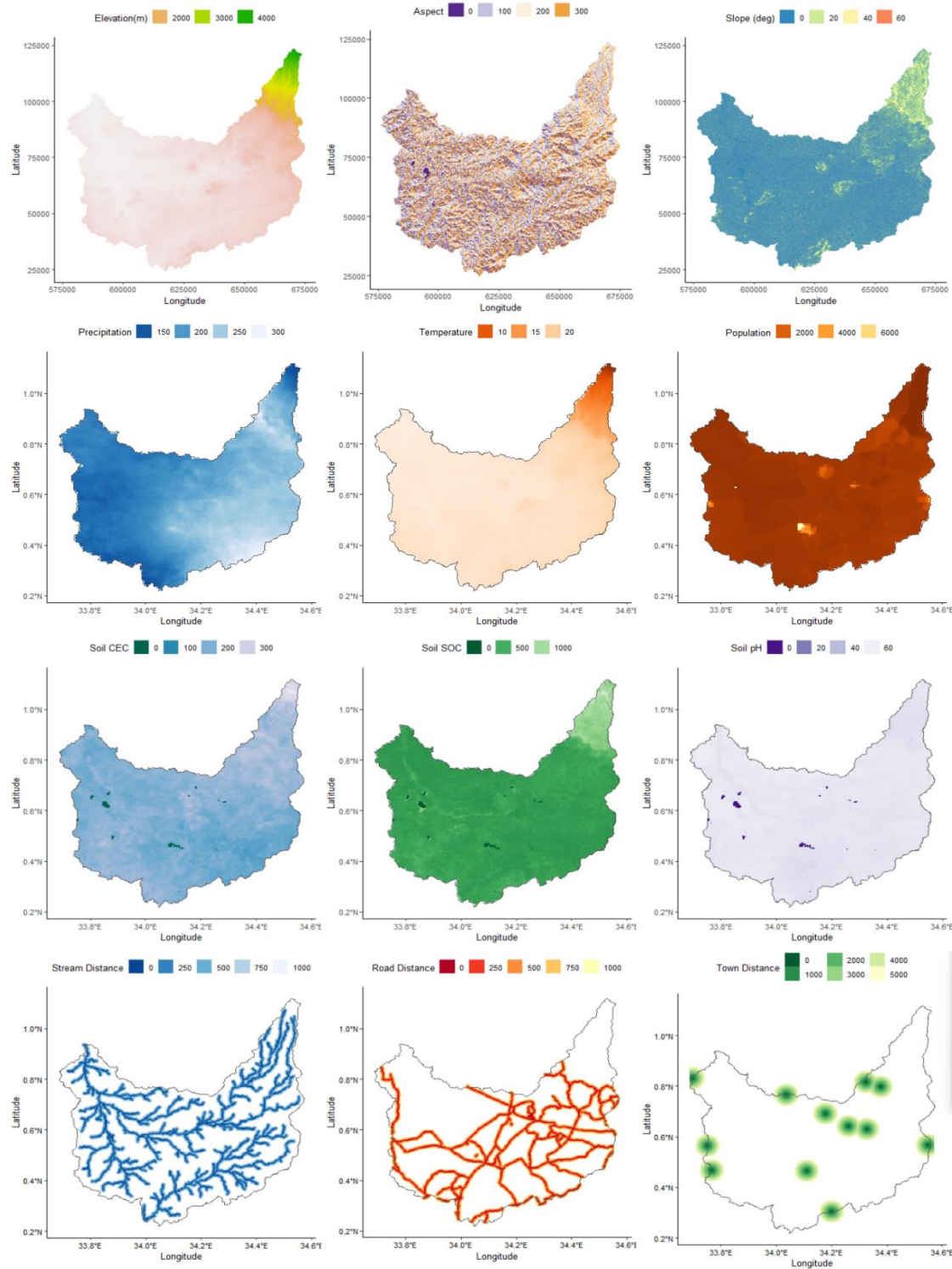
(i) *Agricultural Expansion – (S1)*

This scenario assumes an environment where there's a combination of weak legislation and or complete lack of enforcement of existing laws protecting fragile ecosystems, coupled with an increase in human population in the basin which exerts pressure on limited land resources. In addition, it is assumed that an increase in demand for cash crops in the area i.e., rice which grows in wetlands, and a corresponding improvement market price, would incentivize the people to encroach into wetlands to cultivate rice while those living near the edges of Mount Elgon Forest would clear trees for agriculture. In this scenario, the conversion elasticity values in the model would be relaxed to allow the transformation of pixels under these land cover types, especially in accessible areas with potential for agriculture. Therefore, the expansion of agriculture in this case would mainly be constraint by prevailing physiographic and climatic factors.

(ii) *Land Reclamation Scenario - (S2)*

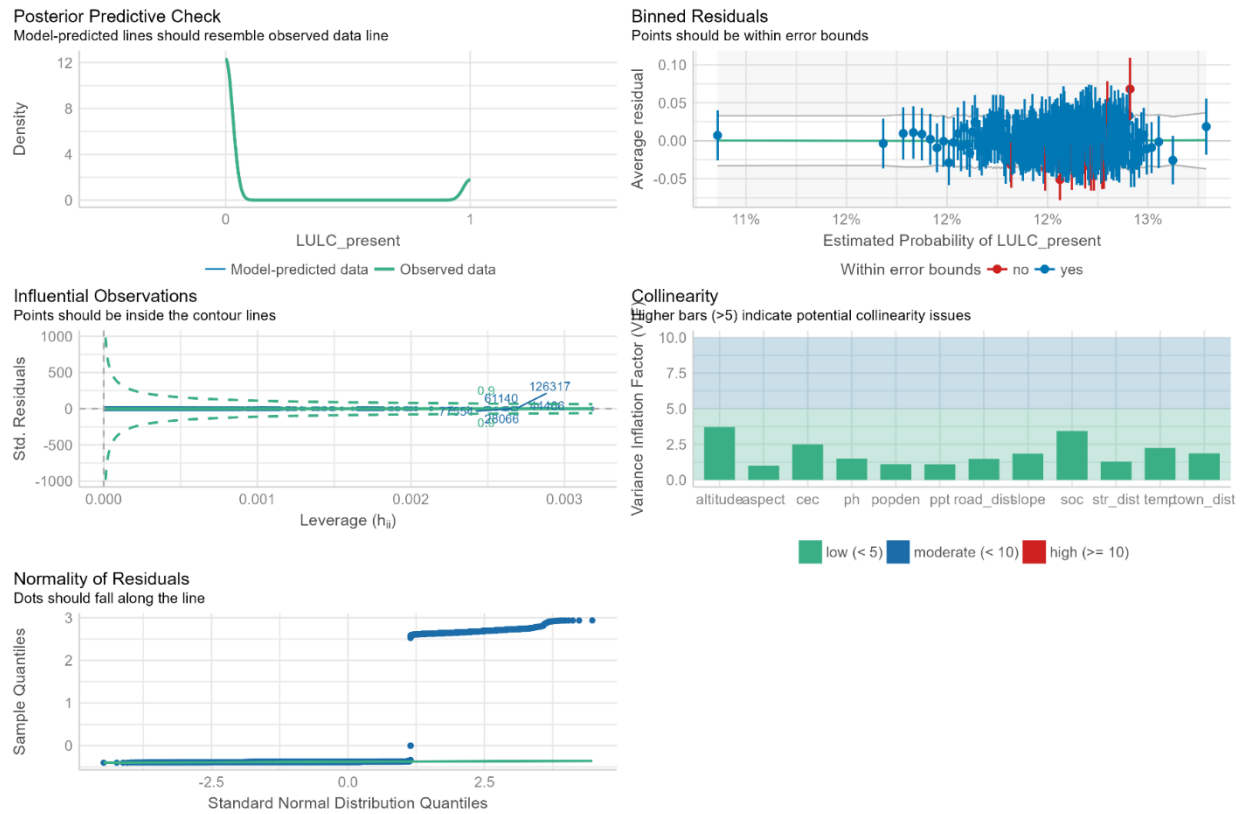
The land reclamation scenario represents a condition where, due to deforestation as a result of gradual expansion of agricultural land, especially on the fringes of Mount Elgon Forest and other areas covered by indigenous trees and shrubland, there would be a corresponding increase in the rate of soil erosion, leading to sedimentation of reservoirs and severe land degradation. This in turn would affect water quality and soil productivity with consequences on both the health and livelihood of the people. Therefore, areas previously under primary forest would be reclaimed back, while open and fallow land areas would be converted to tree plantations. During the conversion process by the model, areas under cropland were assigned conversion elasticity values (<0.5) which allowed some pixels under cropland with conditions suitable for tree growth to change to tree cover.

Appendix C. Potential LULC Driving Factors used in the Regression Equation



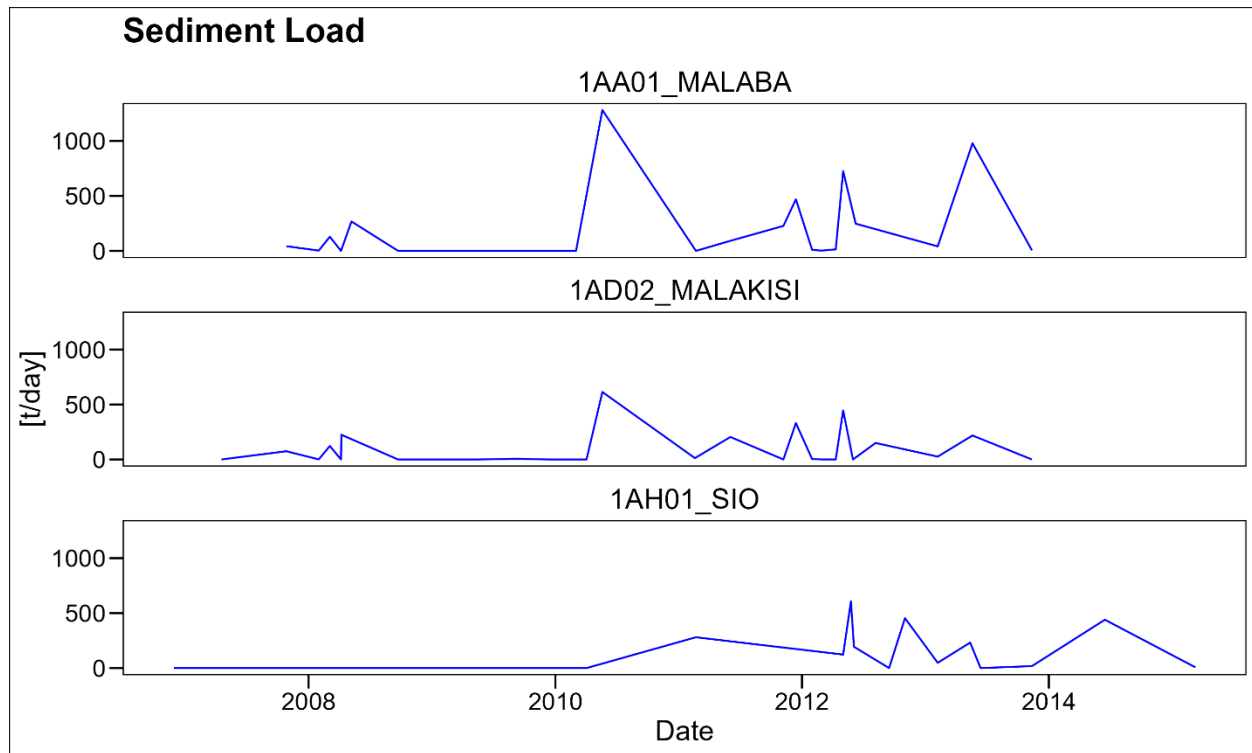
Appendix Figure 1 Potential driving factors used to model land-use cover change in the study area

Appendix D. Logistic Regression Model Performance

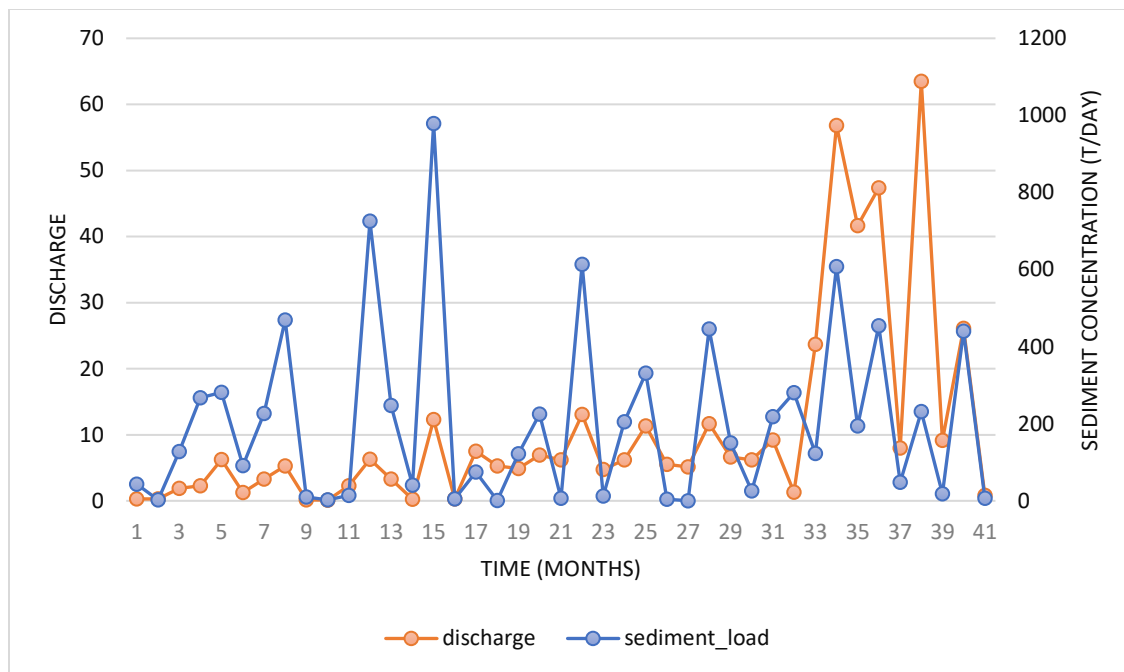


Appendix Figure 2. Logistic Regression Model Performance plot

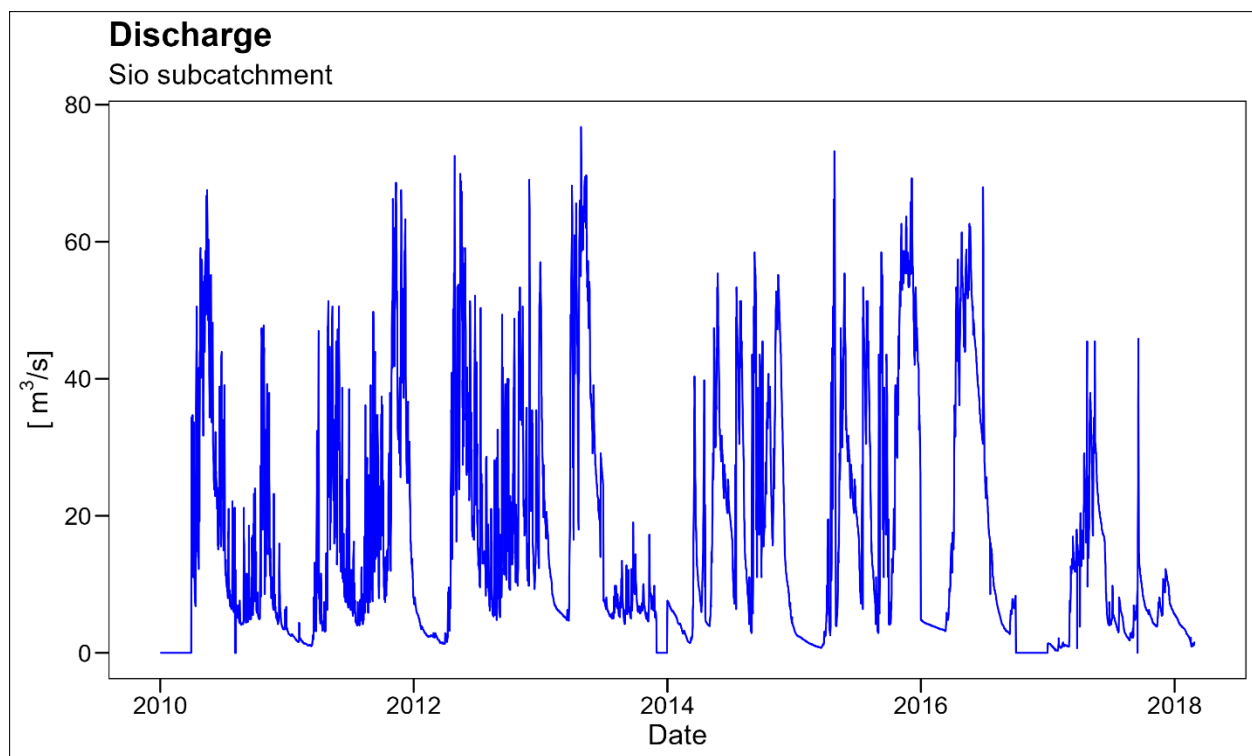
Appendix E. Hydrometeorological Timeseries from available data in SMM



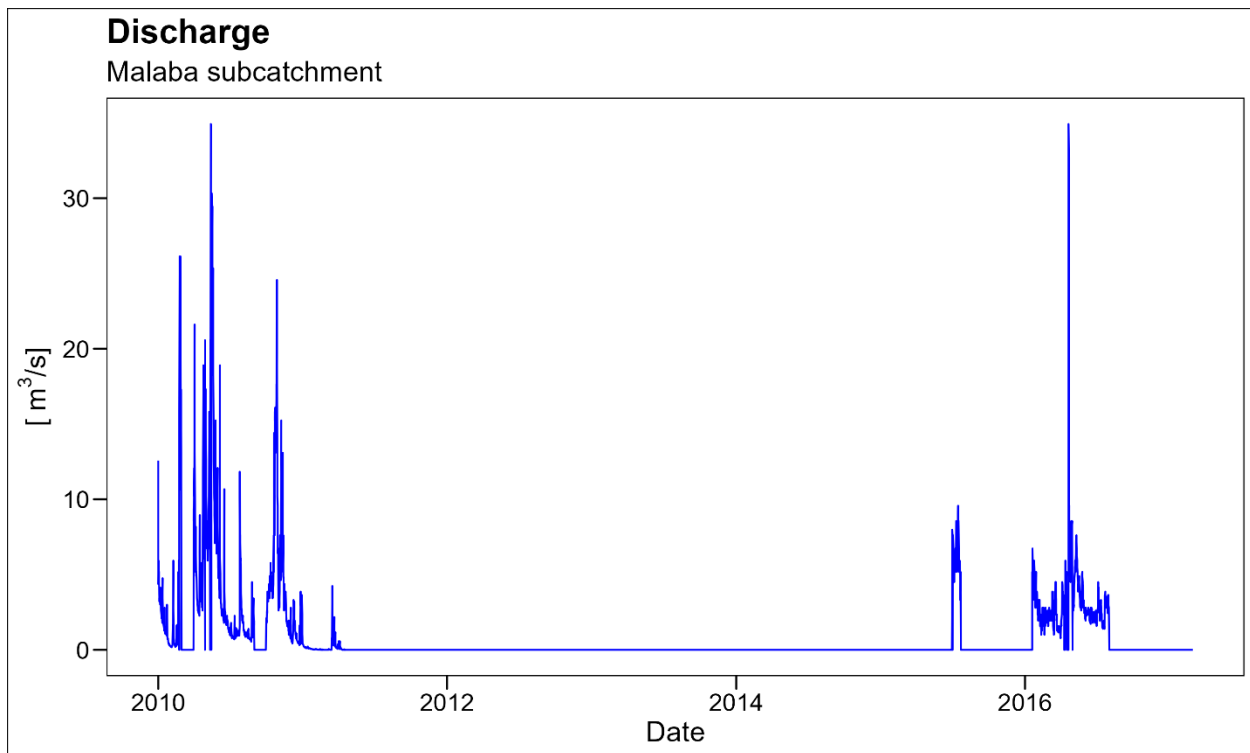
Appendix Figure 3. Daily sediment load concentration



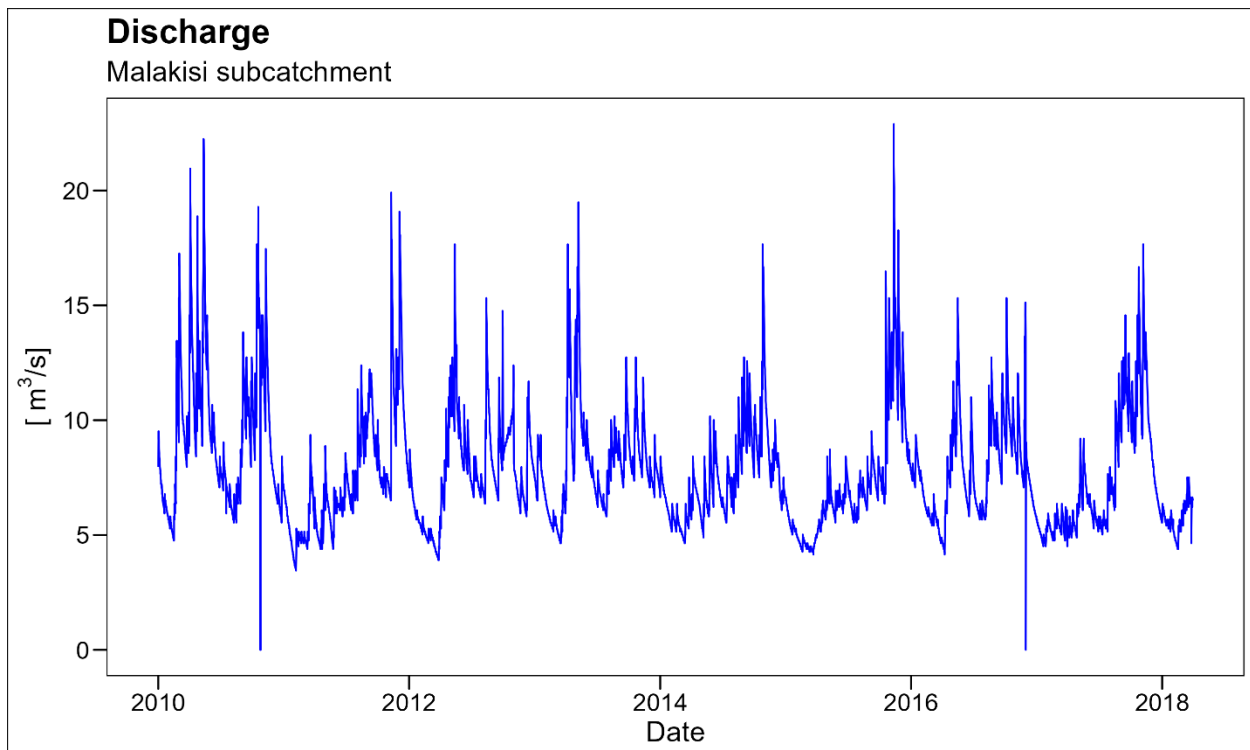
Appendix Figure 4. Sediment concentration and discharge SMM (2007 - 2015)



Appendix Figure 5. Mean daily discharge - Sio



Appendix Figure 6. Mean daily discharge - Malaba



Appendix Figure 7. Mean daily discharge - Malakisi

Appendix F. Data Collection Questionnaire sample



Questionnaire

ID:.....

Date of interview:.....

Time of interview:.....

XCOORD (UTM):.....

YCOORD (UTM):.....

ELEV (m.a.s.l):.....



Part A1: Respondent's Identification/Background

Country COCODE:

County COUCODE:

Sub-county SCOCODE:

Ward WACODE:

District DISCODE:

Location LOCCODE:

Sub country SCCODE:

Village VCODE:

Household HHCODE:

Respondent's name:.....

Gender:.....

Age:.....

Contacts mobile phone number:.....

PART A2. Type of household

1. Are you a native of this village? [] 1=Yes [] 0=No
2. If No, which year did you migrate in to this village?.....
3. How many parcels do you have/own?
4. What are the sizes of your 3 main parcels
 - a) Parcel 1.....
 - b) Parcel 2.....
 - c) Parcel 3.....
5. Are the parcels sub-divided among different family units? [] 1=Yes [] 0=No
6. In which year did you start farming?.....
7. Other income generating activities (off-farm employment)-----

PART B. Input for all Crops grown by the Household during the FIRST season of 2017 (MAR – JUN) & SECOND season (JUL-OCT)

Parcel ID	Plot ID	Plot area (ha)	Land ownership (see codes)	Year started cultivation	Crops cultivated 1 st season	Yield season 1 (kg)	Crops cultivated 2 nd season	Yield season 2 (kg)	Type of multi-season crop(s) cultivated – more than one year % of land under seasonal crop	% of land under permanent crop	Tillage system (see codes)	Use of fertilizer (1=Yes, 2=No)	Type of fertilizer used (see codes)	Quantity of fertilizer per acre (Kg)	Use of irrigation (1=Yes, 2=No)	Type of irrigation (see codes)	Frequency of irrigation (see codes)	Use of farm mechanization (1=Yes, 2=No)	Type of farm mechanization (see codes)
		B1	B2	B3	B4	B5	B6	B7			B8	B9	B10	B11	B12	B13	B14	B15	B16
											S1 S2		S1 S2	S1 S2		S1 S2	S1 S2		S1 S2

Codes for B2: 1= Family/ancestral land; 2= Leasehold; 3= Purchase (personal/private); 4= other specify

Codes for B4: Grains: 1=Rice, 2=Maize, 3 = Sorghum, 4 = Millet; **Tuber & Roots:** 5= Banana, 6=Cassava, 7=Yams, 8=Irish potatoes, 9=Sweet potatoes; **Legumes:** 10=Beans, 11=Peas, 12=Groundnuts, 13=Soybeans; **Vegetables:** 14=Kale, 15=Cabbage, 16=Onions, 17=Amaranth, 18=Tomatoes 19=Other (specify); 20 =Other (specify)

Codes for B5: 1 = Mango; 2 = Banana; 3 = Avocado; 4 = Jack fruit; 5 = Coffee; 6 = Sugarcane; 7 = Water melon; 8 = Orange; 9 = Cotton; 10 = Pawpaw

Codes for B8: 1 = No till, residues burnt; 2 = Ploughing, residues incorporated; 3= Ploughing, residues incorporated plus mulch; 4 = Other (specify)

Codes for B10: 1=Diammonium Phosphate (DAP); 2=UREA; 3=NPK; 4=Calcium Ammonium Nitrate (CAN); 5=Mono Ammonium Phosphate (MAP); 6= Triple Super Phosphate (TSP); 7=Single Super Phosphate (SSP); 8= Compose manure; 9 = NA; 10 = Other (specify)

Codes for B12: 1=Drip irrigation; 2= Sprinkler system; 3= Hydroponics 4= Watering can/Bucket; 5 = NA; 6 = Other (specify)

Codes for B13: 1= Everyday; 2. Once a week; 3= Twice a week; 4= NA; 5 = Other (specify)

Codes for B16: 1= Tractor; 2= Ox-drawn plow; 3 = Cotton picker; 4= Sickle; 5= coffee crusher; 6 = NA; 7 = Other (specify)

PART C. Input for Animal Husbandry and Dairy Farming

Parcel ID	Plot ID	Practice of animal husbandry (1=Yes, 2=NO)	Types of animal reared (see codes)	Number of animals in C2	Year started C1	Source of animal feeds C2	For dairy, number of liters/cow/day	For dairy, number of liters/goat/day	Availability of refrigeration/milk cooling fertilities (1=Yes, 2=No)	Storage costs for C6 (KES/UGS)	For cow: cost of milk/liter (KES/UGSH)	For goat: cost of milk/liter (KES/UGSH)	Market access (travel time to nearest market) (see codes)	Availability of extension services (1=Yes, 2=No)	Frequency of extension services (see codes)
		C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14

Codes for C2: 1 = Cattle; 2 = Goat; 3 = Sheep; 4 = Pig; 5 = Poultry; 6= Donkey; 7 = Other (specify)

Codes for C5: 1 = Own farm; 2 = Free range grazing; 3 = Purchase feeds; 4 = Cooperative Society Feeds; 5 = Other (specify)

Codes for C11: 1= <1hour; 2 = >1 hour<2 hours; 3= >2 hours; 4= Other (specify)

Codes for C14: 1 = Once a week; 2 = Twice a month; 3 = Once every three months; 4 = NA; 5 = Other (specify)

**Animal Husbandry – the practice of breeding and keeping farm animals*

General comments.

.....

Part Di: input for Socio-economic data (*Income, Energy options*)

Parcel ID	Plot ID	Off-farm employment (OFE) (1=Yes; 2=No)	Nature of off-farm employment (see codes)	Primary source of income (see codes for D2)	Household expenditure priorities (see codes)	Ownership of mobile phone (1=Yes; 2=No)	Primary use of mobile phone	Membership of savings/ Cooperative society (SACCO)	Duration of membership (months/years)	Benefits of membership (see codes)	Highest level of education (Household head)	Type of cooking energy	Source of cooking energy
		D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12

Part Dii: input for Socio-economic data: *Health, Water, Hygiene and Sanitation*

Parcel ID	Plot ID	Type of healthcare facility	Distance to nearest HCF	Water sources	Accessibility (Distance to nearest WS)	Cost of 1 liter of water (KES/UGS)	Water treatment method(s)	Type of ablution facility	Waste disposal methods & management
		D13	D14	D15	D16	D17	D18	D19	D20

Codes for D2: 1=Formal employment (government, private sector); 2=Self-employment (*bodaboda*, market vender, brick making); 3= Farming; 4=Other(specify)

Codes for D4: 1= Food; 2=Medical; 3= Education; 4=Farm inputs; 5= Utility bills; 6 = Other (specify)

Codes for D6: 1 = Calling; 2 = Calling and texting; 3 = Mobile banking;

Codes for D9: 1=Loans (low interest); 2=Subsidized farm inputs; 3=Market for commodities; 4=Free training/access to information; 5=Other(specify)

Codes for D10: 1=No formal education; 2= Primary (complete); 3=Primary (incomplete); 4=Secondary; 5=Tertiary (TVET, college, university); 6=Other(specify)

Codes for D11: 1=Firewood; 2= Charcoal; 3=Paraffin; 4= Gas; 5 = Electricity; 6 = Biogas; 7 = Solar; 8 = Other (specify)

Codes for D12: 1= Generate from own farm; 2 = Buy from dealers/ local market; 3 = Other(specify)

Codes for D13: 1 = Health Centre2; 2 = Health Centre3; 3 = Health Centre4; 5 = Regional Hospital; 6 = Dispensary; 7 = Clinic; 8 = Provincial General Hospital

Codes for D15: 1 = Bore hole; 2 = Rain water harvesting; 3 = Streams and Rivers; 4 = Taps (National Water); 5 = Well; 6 = Spring; 7 = Other(specify)

Codes for D18: 1= Chemical (Chlorine); 2 = Boiling; 3 = Filtration; 4 = Solar (reverse osmosis; 5 = None; 6 = Other(specify)

Codes for D19: 1 = Pit-latrine 2 = Open defecation; 3 = Flashing toilet 4 = Other(specify)

Codes for D20: 1 = Burn; 2 = Burry; 3 = Recycle and re-use; 4 = None; 5 = Other(specify)

Part E: Input for Land-use and Management Requirements

Parcel ID	Plot ID	Plot area (ha)	Primary land-use (see codes)	Total cultivated land (ha)	Total area under temporary crops (ha)	Total area under permanent crops (ha)	Year started cultivating plot	Land-use type last 10 years	Perception of LULC change drivers (see codes)	Training on soil and water conservation practice: (1=Yes; 2= No)	Major soil & water conservation practice (SCP) (see codes)	Frequency of use of SCP (see codes)	Determinants of household land-use
		E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12

Codes for E3: 1=Cultivate (annual crops); 2=cultivated (seasonal crops); 3=Grazing land; 4=Woodlots; 5=Other (specify)

Codes for E8: 1=Agriculture (food crops); 2=Agriculture (cash crops); 3=Agriculture (food crop & cash crop); 4=Bush & shrubs; 5=Forested land; 6=Swamp; 7=Grazing/grass land; 8=Other (specify)

Codes for E9: 1= Changes in weather pattern; 2= Improvement in commodity prices; 3=Improvement in farming technology; 4=Demographic changes; 5=Changes in land value; 6= Changes in soil fertility; 7=Other(specify)

Codes for E11: 1=Mulching; 2=Trenches; 3= Contour ploughing; 4=Minimum tillage; 5=cover crops; 6=Other(specify)

Codes for E12: 1=Before tilling; 2= After tilling; 3= When rains begin; 4 = NA; 5 = Other (specify)

Codes for E13: 1=Soil characteristics (fertility); 2=Cultural norms; 3= Market demand for crop; 4 = Government policy; 5=Other (specify)

Fi: Input for Historical Land use/land Cover State

Parcel ID	Plot ID	Current LULC state year 2017 (see codes)	Total area (Ha) OR % under current LULC	LULC State (Last five years) – 2012 (see codes)	Total area (Acre)/ % under LULC - 2013	LULC State_2007 (Last 10 years) (see codes for F3)	Total area (Acre)/ % under LULC - 2017	What factors influenced changes in LULC state on the parcel	What factors would influence future changes in LULC on the parcel (seed codes)
		<i>F1</i>	<i>F2</i>	<i>F3</i>	<i>F4</i>	<i>F5</i>	<i>F6</i>	<i>F7</i>	<i>F8</i>

Codes for F1: 1=Mixed farming; 2= Agroforestry; 3=Grazing land; 4=Built-up (homesteads); 5=Woodlot; 6=Bare soil; 7=Wet land/swamp; 8= Other (specify)

Codes for F3: 1=Agricultural field (maize, beans, sorghum); 2=Bare soil; 3= Grassland/Grazing land; 4= Wetland/swamp; 5= Forest; 6=Other (specify)

Codes for F7: 1= Reduced soil fertility; 2=Soil erosion; 3=Changes in income (increase/decrease); 4= Changes in weather patterns; 5= Government policy; 6= Infrastructural development (new road, power lines); 7= Pests & diseases; 8 = Population increase; 9 = Increase in HH size; 9= Other (specify)

Codes for F8: 1= Improvement in weather patterns; 2= Training in modern farming; 3= Soil fertility; 4 = Improvement in seed variety; 5 = Government subsidies on farm inputs; 6 = Improvement in commodity prices; 7 =Improvement of infrastructure (refrigeration, roads, power); 8 = Increase in farm size; 9 = Changes in Government policy; 10 = Reduction in land prices; 11 = Other (specify)

General comments.

.....

.....

.....

R Code Compilation for the PhD study

OBJECTIVE #1

Time series trends in LULC change (1986-2017)

```
# Set working directory
setwd("G:/My Drive/CapNex_2021/Cpx2/LULC mapping_2021")

# Load library
library(readr)
library(ggplot2)
library(dplyr)
library(scales)
library(ggrepel)

# Read data
lc <- read_csv("Classification_stats_20210725_combo.csv", col_names = TRUE)

# Extract data
labs <- filter(lc, Year==2017) %>%
  mutate(lucode=c('Br', 'Mf', 'Os', 'Pw', 'Cp', 'Bu', 'Wt', 'Ol', 'Ps'))

# Plot
ggplot(lc, aes(Year, area_ha, colour = classname))+
  theme_classic() +
  geom_point(shape = 18, size = 3) +
  geom_line() +
  geom_label_repel(data = labs, aes(Year, area_ha, label=lucode), show.legend=FALSE) +
  geom_rect(aes(xmin = 1995, xmax = 2008, ymin = -Inf), ymax = Inf, alpha = 0.05, fill = 'green') +
  geom_rect(aes(xmin = 2008, xmax = 2017, ymin = -Inf), ymax = Inf, alpha = 0.07, fill = 'red') +
  labs(x = "Year", y = "Area [Hectares]") +
  scale_y_continuous(labels = comma) +
  scale_x_continuous(breaks = c(1986, 1995, 2008, 2017)) +
  geom_label(
    aes(Year, area_ha, label = lucode, colour = classname),
    data = labs, size = 3.5, vjust = 0, hjust = 0, nudge_x = 0.25, show.legend = FALSE) +
  geom_label(aes(x = 2001, y = 300000), label = 'Phase-I', colour = 'gray20', fontface = 'bold') +
  geom_label(aes(x = 2012, y = 300000), label = 'Phase-II', colour = 'gray20', fontface = 'bold') +
  theme(
    legend.position = 'top',
    legend.text = element_text(size = 12),
    legend.title = element_text(size = 14),
```

```
axis.text = element_text(size = 14),
axis.title = element_text(size = 16)
) +
guides(color=guide_legend(title = 'LULC Classes'))
```

Land-use/Cover Change

```
# Load Library
library(ggplot2)
library(readr)
library(scales)
library(tidyr)
library(viridis)
library(ggpattern)
library(ggthemes)

# Set working directory
setwd('G:/My Drive/CapNex_2021/Cpx2/LULC mapping_2021')

# Read data
luc <- read_csv('lulc_change_2b.csv', col_names = TRUE)

# Plot
ggplot(luc) +
  geom_col_pattern(
    aes(lulc, per, pattern_fill = lulc),
    pattern = 'stripe',
    fill = 'white',
    colour = 'black'
  ) +
  theme_hc() +
  labs(x = 'Land-use/Cover class', y = 'Percentage (Total area)') +
  facet_grid(.~yr) +
  theme(
    strip.text = element_text(size = 18),
    axis.title = element_text(size = 17, vjust = 1),
    axis.text = element_text(size = 15),
    legend.text = element_text(size = 14),
    legend.title = element_text(size = 17),
    legend.position = "none"
  ) +
  guides(fill=guide_legend(title = 'LULC Classes')) +
  scale_y_continuous(labels = scales::percent_format(accuracy = 1))
```

OBJECTIVE #2

Correlation analysis

```
#Load library
library(readr)
library(Hmisc)
library(corrplot)
library(dplyr)

# Set working directory
data_file <- "G:/My Drive/CapNex_2021/Cpx2/Rscripts/R_plots"
setwd(data_file)

# Read data
lulc <- read_csv(file = "all_lulc_drivers.csv", col_names = TRUE)

# create a correlation matrix
lucorr <- cor(lulc)

# Plot standard correlation matrix
corrplot(lucorr, method = "shade", shade.col = NA, tl.col = "black", tl.srt = 45)

# Modify corr plot - include correlation coefficients w/o Legend
col <- colorRampPalette(c("#BB4444", "#EE9988", "#FFFFFF", "#77AADD", "#4477AA"))

corrplot(lucorr, method = "shade", shade.col = NA, tl.col = "black", tl.srt = 45,
         col = col(200), addCoef.col = "black", cl.pos = "n", order = "AOE")
```

Trends in demand from LULC change scenarios

```
# Set working directory
file_path <- "G:/My Drive/CapNex_2021/Cpx2/Manuscript/Publications/Obj2/Ecological Modelling"
setwd(file_path)

# Read data
LULC <- read_csv("scenario_analysis.csv", col_names = TRUE)

# Plot
ggplot(data = LULC, aes(x = area, y = LU, fill = scenario)) +
  geom_col(position = "dodge", color = "gray30") +
  facet_wrap(~year) +
  labs(x = "Area (Ha)", y = "Land use type") +
  scale_x_continuous(labels = comma) +
  scale_fill_manual("Scenario", values = c("lavenderblush3", "darkseagreen", "khaki")) +
  theme_few() +
  theme()
```

```

axis.title = element_text(size = 14, colour = "black"),
axis.text = element_text(size = 12, colour = "black"),
strip.text = element_text(size = 16, colour = "black"),
legend.position = "bottom",
legend.title = element_text(size = 14, color = "black"),
legend.text = element_text(size = 12, color = "black"),
legend.background = element_rect(color = "black")
)

```

Regression analysis

```

# Load library
library(haven)
library(readr)
library(dplyr)
library(reshape2)
library(ggplot2)

# Read spss data
data <- read_sav('G:/My Drive/CapNex_2021/Cpx2/SPSS_Database_CapNex/clues_
data.sav')

# Read data
beta <- read_csv('G:/My Drive/CapNex_2021/Cpx2/Clues_model_inputs/beta_val
ues.csv', col_names = TRUE)

# Reshape data
melt_beta <- melt(beta)
melt_beta

# add column for LU name
melt_beta$lu <- rep(row.names(beta),5)
head(melt_beta)

# Plot
ggplot(melt_beta, aes(variable, Driver)) +
  geom_tile(aes(fill=value), colour = 'white') +
  scale_fill_gradient(low = 'white', high = 'red')

# rescale values for all variables in melted data frame
library(plyr)
library(scales)
library(ggthemes)
melt_beta <- ddply(melt_beta, .(variable), transform, rescale = round(resc
ale(value),3))
head(melt_beta)

# Plot heatmap for beta values using re-scaled values
ggplot(melt_beta, aes(variable, Driver)) +
  geom_tile(aes(fill = rescale), color = 'white') +
  scale_fill_gradient(low = 'whitesmoke', high = 'red4') +

```

```

labs(x = "Land-use/cover", y = "Drivers", fill = "Beta value") +
theme_few() +
theme(axis.title.y = element_text(size = 13, face = 'bold'),
      axis.title.x = element_text(size = 13, face = 'bold', vjust = 0.75)
,
      axis.text = element_text(size = 12, colour = 'black'),
      legend.title = element_text(size = 14, color = 'black', vjust = 3),
      legend.text = element_text(size = 13, color = 'black'))

```

Erosion and Deposition using USPED

```

# Load library
library(raster)
library(rasterVis)
library(ggplot2)
library(dplyr)
library(sf)
library(maptools)

# Set working directory
setwd("G:/My Drive/CapNex_2021/Cpx2/Datasets")

# Load USPED inputs
flowacc <- raster("Raster datasets/USPED/usped_30m/input files/flowacc.tif")
dem <- raster("Raster datasets/USPED/usped_30m/input files/dem30_fill.tif")
slope <- raster::terrain(dem, opt = "slope")
aspect <- raster::terrain(dem, opt = "aspect")
kfac <- raster("Raster datasets/USPED/usped_30m/input files/soils_kfac.tif")
cfac <- raster("Raster datasets/USPED/usped_30m/input files/cover_cfac.tif")
rfac <- raster("Raster datasets/USPED/usped_30m/input files/r_moore_rfac.tif") #280 #constant
cell_res <- 30

# Read-in basin shapefile as simple feature
basins_layer <- read_sf("shapefiles/smm_catchments_utm.shp")
subcatchments_shp <- shapefile("shapefiles/smm_catchments_utm.shp")
subcatchments_sp <- readShapeSpatial("shapefiles/smm_catchments_utm.shp")

# Compute topographic component(factor) of sediment transport capacity (LST) for prevailing rill erosion
sflowtop_r <- (flowacc * cell_res)^0.6 * sin(slope * 0.01745)^1.3

# Calculate LST for prevailing sheet erosion
sflowtop_s <- flowacc * cell_res * sin(slope * 0.01745)

# Standardize input dimensions and extent to DEM raster
sflowtop_r <- raster::projectRaster(from = sflowtop_r, to = dem, method = "ngb")
sflowtop_s <- raster::projectRaster(from = sflowtop_s, to = dem, method =

```

```

"ngb")

# Standardize kfactor and cfactor to DEM raster
kfacs <- raster::projectRaster(from = kfacs, to = dem, method = "ngb")
cfacs <- raster::projectRaster(from = cfacs, to = dem, method = "ngb")
#rfacs <- raster::projectRaster(from = rfacs, to = dem, method = "ngb")

# Compute components of change in sediment flow in x&y direction - sheet erosion
qsx_r <- sflowtop_r * (kfacs*100) * (cfacs*100) * 280 * cos(((aspect * (-1))
+ 450) * 0.01745)
qsy_r <- sflowtop_r * (kfacs*100) * (cfacs*100) * 280 * sin(((aspect * (-1))
+ 450) * 0.01745)

# Compute components of change in sediment flow in x& direction - rill erosion
qsx_s <- sflowtop_s * (kfacs*100) * (cfacs*100) * 280 * cos(((aspect * (-1))
+ 450) * 0.01745)
qsy_s <- sflowtop_s * (kfacs*100) * (cfacs*100) * 280 * sin(((aspect * (-1))
+ 450) * 0.01745)

# Rill Erosion inputs
qsx_slope_r <- raster::terrain(qsx_r, opt = "slope")
qsx_aspect_r <- raster::terrain(qsx_r, opt = "aspect")
qsy_slope_r <- raster::terrain(qsy_r, opt = "slope")
qsy_aspect_r <- raster::terrain(qsy_r, opt = "aspect")

# Sheet Erosion inputs
qsx_slope_s <- raster::terrain(qsx_s, opt = "slope")
qsx_aspect_s <- raster::terrain(qsx_s, opt = "aspect")
qsy_slope_s <- raster::terrain(qsy_s, opt = "slope")
qsy_aspect_s <- raster::terrain(qsy_s, opt = "aspect")

# Rill erosion - compute components of change in sediment flow in x&y direction as partial derivatives of sediment flow field
qsx_dx_r <- cos(((qsx_aspect_r * (-1)) + 450) * 0.01745) * tan(qsx_slope_r * 0.01745)
qsy_dy_r <- sin(((qsy_aspect_r * (-1)) + 450) * 0.01745) * tan(qsy_slope_r * 0.01745)

# Sheet erosion - compute components of change in sediment flow in x&y direction as partial derivatives of sediment flow field
qsx_dx_s <- cos(((qsx_aspect_s * (-1)) + 450) * 0.01745) * tan(qsx_slope_s * 0.01745)
qsy_dy_s <- sin(((qsy_aspect_s * (-1)) + 450) * 0.01745) * tan(qsy_slope_s * 0.01745)

# Calculate net erosion and deposition patterns
erdep_rill <- qsx_dx_r + qsy_dy_r # rill erosion
erdep_sheet <- 10 * (qsx_dx_s + qsy_dy_s) # sheet erosion

```

OBJECTIVE #3

Relationship between observed values and ED values

```
# Load library
library(ggplot2)
library(readr)
library(scales)
library(ggthemes)
library(dplyr)

ed <- read.csv("G:/My Drive/CapNex_2021/Cpx2/Manuscript/Publications/Obj3/
ed_data.csv")

fill_shape = c(4, 8, 15, 16, 17)

library(extrafont)
loadfonts(device = "win")

# Plot
ggplot() +
  geom_point(data = ed,
             aes(x = samples, y = usped,
                 shape = basin),
             size = 2.5) +
  scale_shape_manual(name = "SMM sub-catchments",
                     values = fill_shape) +
  xlab("Observed values") +
  ylab("USPED - ED estimates(t.ha/yr)") +
  theme_economist_white(gray_bg = FALSE, base_family = "serif") +
  theme(
    text = element_text(family = "serif"),
    axis.title.x = element_text(size = 16, colour = "black", vjust = -1.5)
  ,
    axis.title.y = element_text(size = 16, color = "black", vjust = 1.5),
    axis.text = element_text(size = 14, colour = "black"),
    legend.title = element_text(size = 16, colour = "black"),
    legend.text = element_text(size = 14, colour = "black"),
    legend.box.background = element_rect()
  ) +
  geom_smooth(data = ed,
             aes(x = samples, y = usped),
             method = "loess",
             se = TRUE)
```

Manuscript 1 – African Geographical Review

AFRICAN GEOGRAPHICAL REVIEW
<https://doi.org/10.1080/19376812.2021.2007143>



Routledge
Taylor & Francis Group

RESEARCH ARTICLES



Analysis of land-cover changes in the Transboundary Sio-Malaba-Malakisi River Basin of East Africa: Towards identifying potential land-use transition regimes

Stanley Chasia^{a,b}, Mathew Herrnegger^c, Benard Juma^{a,b,d}, Jacinta Kimuyu^e, Lewis Sitoki^a and Luke Olang^{d,f}

^aDepartment of Geosciences and the Environment, Technical University of Kenya, Nairobi, Kenya; ^bDepartment of Civil Engineering, Technical University of Kenya, Nairobi, Kenya; ^cInstitute for Hydrology and Water Management, Department of Water, Atmosphere and Environment, University of Natural Resources and Life Sciences, Vienna, Austria; ^dCenter for Integrated Water Resource Management, Faculty of Applied Sciences and Technology, Technical University of Kenya, Nairobi, Kenya; ^eDepartment of Geography and Spatial Science, Technical University of Kenya, Nairobi, Kenya; ^fDepartment of Biosystems and Environmental Engineering, Technical University of Kenya, Nairobi, Kenya

ABSTRACT

This study evaluated historical land-cover states in order to identify potential land-use transition regimes leading to land degradation. Landsat satellite datasets were used to characterize land-cover states for 1986–2017 period. The multinomial probability distribution was used to establish sample size for training and accuracy assessment. Using a hybrid image classification approach, individual satellite images were initially clustered using the ISODATA technique, and spectral classes later transformed posteriori into respective thematic classes. Maximum Likelihood Function was subsequently used to assign pixels into classes with highest probability. Approximately 12% of mixed forest declined, while cropland increased by 30% between 1995–2008.

ARTICLE HISTORY

Received 15 June 2021
Accepted 27 October 2021

KEYWORDS

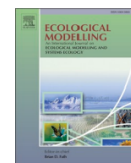
Land-use land-cover change; Landsat imageries; catchment management; transboundary river basin; sio-malaba-malakisi; East Africa

1. Introduction

Human-induced processes often leading to changes in land-cover conditions continue to render many landscapes susceptible to accelerated land degradation across the globe (Abdulkareem et al., 2019), (Briassoulis, 2019). While such changes are predominantly at localized scales, their cumulative effects have important feedbacks on regional climate and desertification (Briassoulis, 2019). Adverse land-cover changes are often pervasive, exacerbating not only changes in climate through global warming but also degradation of detracted lands through decrease in soil organic carbon (Yigini & Panagos, 2016), loss of biodiversity and terrestrial habitats (Liping et al., 2018), and negative effects on hydrology and water resource systems (Guzha et al., 2018)–(Olang et al., 2014). Consequently, several global studies, coordinated through global environmental accords have attempted to quantify and assess the effects of land-cover changes with a view to providing information to support environmental conservation and management at various scales (Ban et al., 2015), (Falcucci et al., 2007). The Africover and the Global Land Cover mapping projects exemplify such global initiatives (Ban et al., 2015). However, their lumped spatial coverage, coupled with inconsistent updates with time (Vancutsem et al., 2013), still limits their applications for hydrological impact assessment at localized scales.

CONTACT Stanley Chasia  stanley.chasia@tukenya.ac.ke

© 2021 The African Specialty Group of the Association of American Geographers



Modelling of land-use/cover change trajectories in a transboundary catchment of the Sio-Malaba-Malakisi Region in East Africa using the CLUE-s model

Stanley Chasia^{a,d,*}, Luke O. Olang^{b,c}, Lewis Sitoki^{a,c}

^a Department of Geosciences and The Environment, Technical University of Kenya (TUK)

^b Department of Biosystems and Environmental Engineering, TUK, Nairobi, Kenya

^c Centre for Integrated Water Resource Management (CIWRM), TUK, Nairobi, Kenya

^d Department of Civil Engineering, TUK, Nairobi, Kenya

ARTICLE INFO

Keywords:

Land-use change modeling
Transboundary catchment
East Africa
Sio-malaba-malakisi catchment
CLUE-s model
Scenario analyses

ABSTRACT

A comprehensive understanding of land-use change processes and their future trajectories is essential for the development of land-use management plans required for conservation of ecological resources. In East Africa, however, there is still limited information on historical, current and future land cover change trends within the vulnerable watersheds. In such data constrained areas, a few studies have adapted spatial models, employing historical land cover change trends derived from satellite remote sensing to provide the requisite landscape metrics for ecological modelling and management. In this study, the ensemble Conversion of Land Use and its Effects at Small regional extent (CLUE-s) model was used to model potential land-use/cover change trajectories in the transboundary Sio-Malaba-Malakisi Watershed of Kenya and Uganda. Historical change trends were obtained from consistently classified land cover datasets. The model parameters, which included climatic, biophysical and human factors were estimated from physical datasets in a Geographical Information System (GIS). Two scenarios that represented options for agricultural expansion (Scenario I), and land reclamation (Scenario II) were investigated for the period between 2027 and 2047 to support ongoing regional initiatives towards ecological resource conservation and watershed management across the transboundary region. From the results, Scenario I indicated an increase in the cropland area by 24%, covering approximately 62% of the whole basin area by 2047. A Scenario II indicated a 30% increase in forest cover, indicating an improvement in forest recovery and restoration of ecosystem area. The results obtained can be used to support baseline studies on the management of the transboundary region with varied country-management options.

1. Introduction

Land use changes are universal earth processes of global importance and environmental change research (Cegielska et al., 2018; Duveiller et al., 2020). This is largely because changes in land-use are often dynamic and pervasive at localised scales but collectively affect the sustainability, and proper functioning of atmospheric and land surface processes across the globe (Lambin et al., 2001; Midekisa et al., 2017; Song et al., 2018). In most developing countries, the effects of land-use change are today manifesting through accelerated rates of soil erosion (Duveiller et al., 2020; Schürz et al., 2020), habitat and biodiversity loss (Ban et al., 2015; Du and Huang, 2017; Liu et al., 2020), and alteration of hydrological regimes (Guzha et al., 2018; Mati et al., 2008; Olang

et al., 2014). Consequently, several initiatives aimed at coordinating conservation and management of the affected ecosystems have been established at global levels to support comprehensive understanding of the land-use change processes, their trends and future trajectories, requisite for the conservation and sustainable utilization of ecological resources. The Convention on Biological Diversity (Chandra and Idrisova, 2011) for instance, aims at promoting sustainable utilization of biodiversity, while the Kyoto Protocol (Böhlinger, 2003) and UNFCCC (Kuyper et al., 2018), aim at reducing greenhouse gas emissions and combating climate change respectively. In East Africa, such initiatives include the Nile Basin Initiative (Khorbotly, 2003) and the Mt. Elgon Regional Ecosystem Conservation Programme (Batvik et al., 2002), both aiming at ensuring efficient land and water resource conservation,

* Corresponding author at: P.O. Box 52428 – 00200, Nairobi, Kenya.
E-mail address: stanley.chasia@tukenya.ac.ke (S. Chasia).

<https://doi.org/10.1016/j.ecolmodel.2022.110256>

Received 12 October 2022; Accepted 16 December 2022

Available online 24 December 2022

0304-3800/© 2022 Elsevier B.V. All rights reserved.



Understanding the linkages between land-use transitions and soil erosion/sediment deposition: A case study of the transboundary Sio-Malaba-Malakisi watershed in Kenya and Uganda

Stanley Chasia^{a,d,*}, Luke O. Olang^{b,c}, Benard Juma^{a,c,d}, Lewis Sitoki^a

^a Department of Geosciences and the Environment, Technical University of Kenya (TUK), Nairobi, Kenya

^b Department of Biosystems and Environmental Engineering, TUK, Nairobi, Kenya

^c Centre for Integrated Water Resource Management, TUK, Nairobi, Kenya

^d Department of Civil Engineering, TUK, Nairobi, Kenya

ARTICLE INFO

Keywords:

Soil erosion and sediment deposition
Soil management
USPED model
Land-use scenarios
Sio-Malaba-Malakisi watershed
Kenya & Uganda

ABSTRACT

Soil erosion consequent of unsustainable land-use practices represents one of the world's most pressing environmental problems affecting many watersheds. An assessment of sediment sources and delivery paths is essential for the development of site-specific soil management strategies for curbing environmental degradation. The present study employed a physically-based lumped approach to estimate soil erosion and sediment deposition patterns across the transboundary Sio-Malaba-Malakisi (SMM) watershed. The Unit Stream Power-based Erosion Deposition (USPED) model was adopted for the study, and integrated with physically-based parameters derived in a Geographical Information System (GIS). A land-use map for 2017 was used for simulating the reference soil erosion and deposition status of the basin. Furthermore, the impacts of two land-use scenarios representing options for cropland expansion (Scenario-I), and land reclamation (Scenario-II), were evaluated for the period 2047, corresponding to a thirty-year period used in assessing catchment management planning for SMM. The annual soil erosion ranged between 0 and 460 t ha⁻¹yr⁻¹, with a mean erosion rate of 160 t ha⁻¹yr⁻¹ for the baseline condition. Deposition zones were mainly concentrated along stream banks and floodplain in low-lying sub-catchments. The mean soil erosion rate increased by 61 % and 16 % for scenarios I and II respectively. Overall, the modelled erosion/deposition values were correlated with available sediment data for the basin, realizing a coefficient determination (R^2) value of 0.74. These results could serve as a benchmark against which future trends in land-use changes can be compared in the region and hence support the development of regional soil erosion conservation strategies.

1. Introduction

Land use changes, including deforestation, urbanization, and agricultural expansion are recognized as significant drivers of environmental alterations with potential implications for soil erosion and deposition (Borrelli et al., 2017; Chhabra et al., 2006; Cimusa Kulimushi et al., 2023). Off-site sediment loads emanating from disturbed soils in many catchment areas often affect water quality, channel morphology and riverine habitat, leading to further environmental degradation of the ecological systems (Aksoy et al., 2019; Poesen, 2018). Globally, approximately 24–75 billion tons of fertile soil are lost annually from

arable lands due to unsustainable agricultural practices (Zhang et al., 2023). The situation is likely to worsen due to a projected increase in population, and economic growth which is estimated to result in a 50 % increase in demand for food by 2050 (FAO¹ and OECD,² 2018). Already, an estimated 1.1 billion hectares of global land are degraded through soil erosion, translating to about US \$400 billion financial losses annually (Bai et al., 2008; Borrelli et al., 2021; Ebabu et al., 2022). This could potentially threaten the livelihood of approximately 3.2 billion people, especially those living in rural communities, smallholder farmers and the very poor (Newbold et al., 2015).

In Sub-Saharan Africa (SSA), where agriculture remains the mainstay

* Corresponding author. P.O. Box 52428 – 00200, Nairobi, Kenya.

E-mail address: stanley.chasia@rukenya.ac.ke (S. Chasia).

¹ Food and Agricultural Organization of the United Nations.

² Organization for Economic Co-operation and Development.

<https://doi.org/10.1016/j.pce.2023.103529>

Received 19 June 2023; Received in revised form 26 October 2023; Accepted 28 November 2023

Available online 2 December 2023

1474-7065/© 2023 Elsevier Ltd. All rights reserved.

Journal of Environmental Management Assessment of soil erosion risk and vulnerability in the transboundary Sio-Malaba-Malakisi watershed in Kenya and Uganda --Manuscript Draft--	
Manuscript Number:	
Article Type:	Research Article
Section/Category:	Environmental Assessment and Monitoring
Keywords:	Analytical Hierarchy Process; Environmental management; Soil erosion modelling; Transboundary catchment; Sio-Malaba-Malakisi catchment; Kenya and Uganda
Corresponding Author:	Stanley Chasia Technical University of Kenya Nairobi, Nairobi KENYA
First Author:	Stanley Chasia
Order of Authors:	Stanley Chasia Luke O. Olang Claudia Bess Jacinta Kimuyu Lewis Sitoki
Abstract:	Persistent soil erosion poses a significant threat to water quality, ecosystem viability and soil health in many regions of the world. Addressing this challenge requires a comprehensive understanding of local soil erosion rates, including the identification of vulnerable areas, to facilitate effective and integrated environmental management. In East Africa, however, many affected regions are data poor and lack measured hydrological data from which soil erosion estimates can be derived. This study used the physically based Revised Universal Soil Loss Equation (RUSLE) model to estimate the annual rate of soil erosion in the transboundary Sio-Malaba-Malakisi catchment, straddling Kenya and Uganda. Soil erosion events were quantified by integrating input factors derived from physical datasets using a Geographical Information System (GIS). The Analytical Hierarchy Process (AHP) technique was then used to assess the importance of selected physical factors influencing the soil erosion process in order to identify regions of increasing environmental vulnerability. The results obtained indicate a wide range of soil erosion rates across the region, with an estimated mean annual rate of 250 t ha⁻¹yr⁻¹ for the whole catchment. Upstream areas characterized by intensive agricultural activity had erosion rates of up to 2,000 t ha⁻¹yr⁻¹, while downstream areas indicated erosion rates below 600 t ha⁻¹yr⁻¹. Areas with intensive agriculture, unprotected soils, and a soil loss tolerance value above 12 t ha⁻¹yr⁻¹ were found to be most vulnerable. Rainfall and vegetation cover were identified as key factors influencing erosion susceptibility. Regions with soil erosion rates above 50 t ha⁻¹yr⁻¹ were identified as high priority regions for targeted soil and water conservation measures. The identification of vulnerability zones, including the classification of their severity, provides an opportunity to prioritize sustainable environmental management interventions; a process that can be replicated for such affected regions elsewhere.
Suggested Reviewers:	Cosmo Ngongondo Professor, University of Malawi cngongondo@cc.ac.mw Professor Ngongondo's research interests are in the scientific assessments of the impacts of climate change on water resources and other related natural resources as well as hydrological and climatic sciences. His insights and experience within sub-Saharan Africa would be valuable in shaping and improving our work. Prof. Jean-Marie Kileshye Onema Executive Director, WaterNet, Amsterdam Institute for the Urban Water Cycle, Division of Technology Research & Engineering jmkileshye-onema@wateronline.org

Powered by Editorial Manager® and Production Manager® from Aries Systems Corporation