MODELING LAND DEGRADATION FOR CONSERVATION PLANNING IN KALEHE TERRITORY, EASTERN D.R. CONGO

NACISHALI NTERANYA Jean

A THESIS SUBMITTED TO THE SCHOOL OF ENVIRONMENTAL SCIENCES AND NATURAL RESOURCE MANAGEMENT IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF DOCTOR OF PHILOSOPHY IN ENVIRONMENTAL STUDIES (ENVIRONMENTAL PLANNING AND MANAGEMENT), UNIVERSITY OF ELDORET, KENYA

2025

DECLARATION

Declaration by the Candidate

This thesis is my original work and has never been presented for the award of an academic degree in any other university and should not be copied, or reproduced in any format without written authority from the author and/or University of Eldoret.

NACISHALI NTERANYA Jean

________________________________ Date__________________________

SENV/EPM/P/001/21

Approval by the Supervisors

This thesis is submitted with our approval as the university supervisors.

________________________________ Date__________________________

Dr Andrew KIPLAGAT

School of Environmental Sciences and Natural Resource Management

Department of Environmental Planning, Sustainability and Geoinformatics

University of Eldoret, Kenya

________________________________ Date__________________________

Prof. Elias Ucakuwun

School of Environmental Sciences and Natural Resource Management

Department of Environmental Sciences

University of Eldoret, Kenya

________________________________ Date__________________________

Prof. Chantal KABONYI NZABANDORA

Faculty of Sciences

Université Officielle de Bukavu, D.R. Congo

DEDICATION

This thesis is dedicated to my family and friends for their love, prayers, supports, and encouragements throught my study.

ACKNOWLEDGEMENTS

My gratitude goes to the almighty God for the gift of life and for allowing me to pursuit this academic journey. I wish to express my gratitude to my university supervisors (Dr. Andrew Kiplagat, and Professor Elias K. Ucakuwun), and my home country supervisor (Professor Chantal Kabonyi), for their time, guidance, suggestions and critical reviews during the development of ideas, research activities, and thesis write-up. My profound gratitude goes to the faculty members of the School of Environmental Sciences and Natural Resources Management, in general, and the Department of Environmental Planning, Sustainability, and Geoinformatics in particular for their valuable inputs since the conception of this research. I am grateful to the University of Eldoret, the Université Officielle de Bukavu, and the RUFORUM for supporting my studies through the Graduate Teaching Assistantship (GTA) program. Support for this research was made possible through a capacity-building competitive grant (Grant number: RU/2024/GTA/CCNY/16) for training the next generation of scientists provided by Carnegie Corporation of New York through the RUFORUM. I owe many thanks to my field assistants and the people who agreed to provide their perspectives on the problem of land degradation in their communities. My appreciation goes also to all my colleagues, friends, and family for their support and encouragement during this study journey. More particularly, I would like to express my gratitude to Prof. Riziki Walumona, who helped me settle in Kenya when he was still pursuing his studies at University of Eldoret, for his valuable advice, and inspiration. I am also grateful to my peers GTA fellows (Nicole Nshobole from DR Congo, Dr. Sellu Mawundu from Siera-Leone, Dr. Ousman Sarlia, Dr. Emmanuel Pope, Dr. Henri Temba, Dr. Mandela Hinnes from Liberia, David Mugambi from Kenya) and other students and friends from various countries (Sofia Nifuma, Dr. Hosticks Ndozi, and Joseph Kabanze from Namibia, Felix

Lunanga, Atosha Byemba, and Joyeuse Mudagi from DR Congo, Bakarry Dibba and Momodou Sabaly from Gambia, Israel Mungira from Tanzania, Dr. Felix Muhizi from Rwanda, Annet Nanfuka and James Galambi from Uganda) with whom we lived in the campus as a family for their supports, discussions and the happy moment shared. I cannot finish this note without expressing my gratitude to my course mates and Kenyan friends (Brian Ambale, Kamimo Odiyo, Chelagat Juliet, Elija Kandie, Irene Chebon, Kelvin, Nickson Korir, Charity Barasa) for their hospitality and assistance when it was most needed. I also thanks all individuals, especially those who I have not been able to mention, who contributed to the success of this academic journey in one way or another.

ABSTRACT

The Eastern D.R. Congo is experiencing land degradation resulting from unsustainable land use which prevent the achievement of the land degradation neutrality in this region. This thesis aims to model the land degradation (LD) for conservation planning of natural resources in this region by using the Kalehe territory as a case study. Based on the system theory, a mixed approach combining field surveys, GIS, and remote sensing techniques was adopted. The geospatial data were used to assess the LULC changes, their implications on land productivity (LP), ecosystem service value (ESV), and soil erosion dynamics. Furthermore, a multi-criteria decision analysis (MCDA) based model was developed to assess the land degradation vulnerability (LDV). The results of these geospatial analyses were triangulated with community perception data to identify the DPSIR (Drivers-Pressures-State-Impacts-Responses) indicators toward the LD management. By analyzing the LULC changes from 1987 to 2020 using the Landsat images and forecasting the future LULC for 2030-2070 through Markov modelling, the study identifies trends of increasing built-up, shrub land, and cropland at the expense of forestland, grassland and wetland. These changes contributed to 34.17% of land cover degradation over the last three decades. The analysis of LP dynamics through the linear trend analysis of NDVI time series data reveals that 31.25% of the territory has experienced a decrease in LP. The assessment matrix was used to link the perceived ESV and the LULC categories. Through this approach, it was demonstrated that the potential supply of ecosystem services decreased in 28.44% of the land over the 1987-2020 period. The assessment of soil erosion dynamics through the RUSLE model indicated that the mean annual soil loss has increased over time from 32.08 t/ha/year in 1987 to 44.35 t/ha/year in 2020. Under the current LULC trend, the annual soil loss is projected to increase to 46.42 t/ha/year by 2030, 46.79 t/ha/year by 2050, and 48.38 t/ha/year by 2070. The adoption of conservation practices would result in the reduction of the current erosion rate by 86.56%, 62.28%, 54.05%, and 11.61% for bench-based terracing, agroforestry, strip cropping, and contouring, respectively. Moreover, the LD dynamic is influenced by the landscape characteristics since the decrease of forestland, and patch's shape complexity, the increase of patch's isolation, landscape heterogeneity, and fragmentation positively influenced the soil erosion dynamics. Hence, the need for land consolidation, connectivity and forest conservation during the future land use planning. This study also demonstrated that the LDV model based on MCDA can be used to predict the occurrence of physical LD processes in eastern DR Congo with an accuracy of 77.82%. Thus, it can be supplemented with the outcomes of land capability (LC) analysis for restoration planning and adaptive land use planning to reduce the LDV. To address the challenges of LD, this study proposes a conceptual model of LD management and a conservation action plan including the sustainable land use according to LC, implementation of conservations practices, environmental education, and improvement of community livelihoods.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACRONYMS AND ABBREVIATIONS

AfSIS: Africa Soil Information Service

AHP: Analytical Hierarchy Process

AI: Aggregated index

ANOVA: Analysis of Variance

AUC: Area under the ROC (Receiver Operating Characteristic) curve

DEM: Digital Elevation Model

DN: Digital Number

DPSIR: Driver, Pressure, State, Impact, and Response

ED: Edge density

ES: Ecosystem service

ETM+: Enhanced Thematic Mapper

FAO: Food and Agriculture Organization

FCPF: Carbon Fund of the Forest Carbon Partnership Facility

GEE: Google Earth Engine

GIS: Geographic Information System

GLASOD: Global Assessment of Soil Deterioration

GPW: Gridded Population of the World

GTAC: Geospatial Technology and Applications Center

IJI: Interspersion and juxtaposition index

I**PCC**: Intergovernmental Pannel on Climate Change

IPIS: International Peace Information

ISRIC: International Soil Reference and Information Centre

LCM: Modules for Land Change Modeler

LDN: Land Degradation Neutrality

LDVI: Land Degradation Vulnerability Index

LEDAPS: Landsat Ecosystem Distribution Adaptive Processing System

LP: Land productivity

LPI: Largest Patch Index

LSI: Landscape shape index

LULC: Land Use and Land Cover

MCDA: Multi-Criteria Decision Analysis

NDVI: Normalized Difference Vegetation Index

NGO: No Government Organization

OA: Overall Accuracy

OLI: Operational Land Imager

OTB: Orfeo Tool Box

PA: Producer Accuracy

PAFRAC: Perimeter-area fractal dimension

PCA: Principal Component Analysis

PD: Patch density

QA: Quality Assessment

QGIS: Quantum GIS

REDD+: Reducing Emissions from Deforestation and Forest Degradation

RGB: Red-Green-Blue

RGC: Référentiel Géographique Commun

ROC: Receiver Operating Characteristic

RUSLE: Revised Universal Soil Loss Equation

SEDAC: Socioeconomic Data and Application Center

SHDI: Shannon’s diversity index

SIDI: Simpson's diversity index.

SLM: Sustainable Land Management

SOTERCAF: Soil and Terrain Database for Central Africa

SPSS: Statistical Package for the Social Sciences

SRTM: Shuttle Radar Topography Mission

SWC: Soil and Water Conservation

TM: Thematic Mapper

TWI: Topographic Wetness Index

UN: United Nation

UNCCD: United Nations Convention to Combat Desertification

UNEP: United Nations Environment Programme

UNFCCC: United Nations Framework Convention on Climate Change

USDA: US Department of Agriculture

USGS: United State Geological Survey

USLE: Universal Soil Loss Equation

WOPR: WorldPop Open Population Repository

DEFINITIONS OF TERMS

Conservation planning: A set of processes to achieve conservation goals, prevent and reverse negative effects on nature, determine priority actions for the conservation of natural resources, and maintain areas that are managed to promote the persistence of natural value.

Ecosystem service: Material and immaterial benefits retrieved from the natural capital.

Land degradation vulnerability: The susceptibility of an area to loss of productivity or to be affected by land degradation processes due to biophysical and anthropogenic factors

Land degradation: Persistent reduction of land quality and its potential to supply the ecosystem service due to natural or anthropogenic disturbance which necessitates human intervention to recover the initial state

Land evaluation: A process of determining and predicting the performance, potential, and limitation of land for a specific use based on predefined criteria to guide the decision in land use allocation.

Land productivity: Capacity of the land to produce biomass

Land: The physical component of the earth's surface

Landscape modeling: Mathematical or conceptual simplification that represents the interrelations between the different components of the environment and simulates their changes over time and space at the landscape level.

Plan: A proposal for doing or achieving a desired goal.

Planning: A decision making process of thinking regarding the activities required to achieve a desired goal.

Patches: A homogeneous area in the landscape that is different from its surrounding

CHAPTER ONE

INTRODUCTION

1.1. Background to the study

Land-use and land cover change (LULC) can have positive benefits by enhancing the provision of essential ecosystem goods but if the land is poorly managed, it alters a range of other ecosystem functions and the continued supply of those goods (Yesuph & Dagnew, 2019; Zhang *et al*., 2022; Fang *et al*., 2022; Ersoy, 2025). This reduction of the productive capacity and alteration of ecosystem functions of the land is recognized as land degradation (Sirengo *et al*. 2018; Olsson *et al*., 2019; AbdelRahman *et al*., 2023).

Land degradation is a global environmental concern that contributes to biodiversity loss, climate change, food insecurity, alteration of water resources, alteration of the integrity of the ecosystem, and negatively affecting the livelihood of the population (Javed *et al*., 2012; Semenchuk *et al*., 2022; AbdelRahman *et al*., 2023; Ekka *et al*., 2023). It is the result of numerous factors including biophysical factors like climate change and anthropogenic factors such as unsustainable land use management (Mzuri *et al*., 2022; Ekka *et al*., 2023).

At the global level, the total number of people who are directly affected by land degradation is estimated to be 3.2 billion (von Keyserlingk *et al*. 2023). It is estimated that between 1983 and 2003, 22% of the land had been degraded (IUCN, 2015). The current rate of degradation reaches 12 million hectares per year (Thomas *et al*., 2017) and according to the second edition of the Global Land Outlook (GLO2) of UNCCD (2022), about 40% of global land are currently degraded. In Africa, the problem of land degradation constitutes an obstacle to economic development and its resilience to climate change as more than 700 million hectares of land are already being degraded (World Resources Institute, 2016; Koech *et al*., 2020). This degradation accounts for 46% of african land area and under the current trend, it is projected to render more than 50% of agricultural land unusable by 2050 in Africa (AGNES, 2020). In sub-Saharan Africa, water erosion is a major risk with more than 20% of land degraded, affecting more than 65% (485 million people) of the african population (FAO, 2015; AGNES, 2020). In Central and Eastern Africa, land degradation due to poor land management has reached catastrophic proportions at the level of agricultural land, particularly in Eastern DR Congo and Rwanda (Majaliwa *et al*., 2012; Heri-Kazi, 2020). In recent years, this region has experienced an accelerated degradation of its land resources due to climatic variations and the various pressures exerted on natural resources by humans to improve their well-being: agricultural activities, livestock, mining activities, forestry activities, etc. (COMIFAC and CEEAC, 2007; Achille *et al*., 2021). The territory of Kalehe, which is located in the highlands of the eastern DR Congo, in particular, has undergone deforestation in recent years and an upsurge in hydro-climatic risks (erosion, flooding, landslides, mudslides) that are often catastrophic (Depicker *et al*., 2021; Maki, 2023).

To halt the problem of land degradation, mitigation initiatives such as the Land Degradation Neutrality (LDN), introduced by the United Nations Convention to Combat Desertification (UNCCD) are being proposed through the environmental convention of United Nation (UNCCD, 2016) and its goal has been ratified in 2015 by the United Nations General Assembly as Target 15.3 of the Sustainable Development Goals (UN, 2017). Furthermore, several international initiatives with financial incentives such as the REDD+ (Reducing Emissions from Deforestation and Forest Degradation) mechanism, established by the Conference of Parties to the United

Nations Framework Convention on Climate Change (UNFCCC), and international funding initiatives such as the Carbon Fund of the Forest Carbon Partnership Facility and the Green Climate Fund developed by the UNFCCC were developed to assist developing countries to avoid the deforestation and improve the forest management as it is recognized that the degradation of forest ecosystem contributes to about 20% of the global carbon emission (Corbera & Schroeder, 2011; Rojas *et al*. 2021).

The DR Congo is being engaged in both the LDN scheme (Ministry of Environment and Sustainable Development of DR Congo, 2018) as well as the REDD+ mechanism to tackle the main drivers of deforestation and degradation since the adoption of its National REDD+ Framework strategy (Kengoum *et al*., 2020a). The implementation of such initiatives require participant countries to identify and characterize the drivers of LULC change, assess the condition favorable to land degradation, identify area at high risk of future land degradation based on historical observation pattern of LULC change, quantify the impact on ecosystem service or goods and use this information to the target area where mitigation actions are needed, design appropriate strategies for conservation and sustainable development (Orr *et al*., 2017; Cowie *et al*., 2018; Grinand *et al*., 2020). In this context, planning for LDN implies anticipating where future land degradation is likely to occur for effective implementation of an appropriate intervention to achieve the net loss across the landscape (Orr *et al*., 2017; Feng *et al*., 2022). Therefore, projecting the cumulative impacts of LULC change as well as the likely impact of land use management decisions and counterbalancing future land degradation or loss through planned measures to achieve equivalent gains within the same land unit are crucial processes for the planning of LDN (Cowie *et al*., 2018; Orr *et al*., 2017; Sims *et al*., 2021). Moreover, decision-support for choosing between alternate conservation actions, locating and implementing conservation actions can be provided through the conservation planning (McIntosh *et al*., 2017).

During the last decades, to do a balance between economic, social, and environmental values, landscape-scale modeling has appeared as an effective tool in the land use planning process (Colman *et al*., 2021). Modeling can be used to forecast change in the ecosystem and assess the outcomes of different alternatives in the allocation of appropriate use to land units. The integration of different scenarios of land management strategies into models can be helpful in the choice of an optimal mix of interventions to achieve the LDN in a given context. Therefore, policy actions to avoid future land degradation, conserve productive land and recover degraded land can be planned through a conservation planning process to achieve the LDN. Furthermore, conceptual model like the DPSIR (Driver, Pressure, State, Impact, and Response) model can be used to effectively describe the cause-effect relation between human development and environmental changes from drivers to responses by integrating both remote sensing data and community knowledge for sustainable land management (Obudu *et al*., 2022; Zhao *et al*., 2023). However, such models are less developed in Africa countries compared to developing countries (Obudu *et al*., 2022). It is against this background that this study will focus on the development of models that use biophysical and anthropogenic factors as independent variables to simulate the future LULC change and to determine the hotspot of land degradation where conservation measures such as the landscape restoration initiatives should be prioritized. Moreover, a participative approach through field surveys will be used to formulate the DPSIR model for land degradation management in this region.

1.2. Statement of the problem

During the last three decades, the DR Congo has been subjected to LULC changes and climate variations which have resulted in the degradation of land resources due to poor management practices (Molinario *et al*., 2020; Chishugi *et al*., 2021; Shapiro *et al*., 2021; Achille *et al*., 2021). This land degradation constitutes a serious obstacle to sustainable development in DR Congo (Bamba, 2010; Ministry of Environment and Sustainable Development of DR Congo, 2018; Heri-Kazi, 2020) as it alters the provision of ecosystem services. However, a quantitative understanding of land degradation dynamics under biophysical and socio-economic conditions is currently limited in DR Congo despite that the understanding of the extent and causative factors of this phenomenon is important to design the cause-targeted strategies. This lack of knowledge about the spatial dynamic of land degradation is an obstacle to providing a solution for the conservation planning and land resource use planning in DR Congo. Therefore, in the face of advancing human pressures on natural resources, the development of spatial explicit models of LULC changes and land degradation dynamics at the landscape scale, which takes into account their main drivers is important for determining priority actions for natural resources conservation and to support decision-making about land use allocation in DR Congo.

In the eastern DR Congo, the LULC changes associated with the anthropogenic pressure on the forest ecosystem (Kabonyi, 2011; Christensen & Jokar, 2020; Depicker *et al*. 2021; Maki, 2023) have contributed to the exacerbation of soil erosion (Karamage *et al*., 2016; Mahamba *et al*., 2023) which is the main source of soil degradation in this region (Majaliwa 2008; Adidja, 2014; Mashimango, 2015; Karamage *et al*., 2016; Heri-Kazi, 2020). This erosion contributes to the pollution and sediment loading in rivers (Ruzizi for example), Lake Kivu (Adidja, 2014; Mashimango, 2015; Majoro *et al*., 2020; Akayezu *et al*., 2020), and Lake Tanganyika (Ongezo *et al*., 2014; McGlue *et al*., 2021). This process endangers these ecosystems and the riparian populations that depend on their fishery resources (Majaliwa, 2008; Majaliwa *et al*., 2012; Majoro *et al*., 2020; McGlue *et al*., 2021). In addition, the erosion process leads to a loss of soil fertility with a consequent increase in food insecurity in this region where the depletion of resources due to the degradation of family farming agroecosystems endangers future generations (Byenda, 2016; Heri-Kazi, 2020). There is therefore a need for soil and water conservation to reverse the process of land abandonment and increase agricultural production to ensure food security, limit pressure on the forest, and contribute to biodiversity conservation. However, there is limited information about the spatio-temporal dynamic of soil erosion under current and possible future conditions of LULC change in mountainous areas (highland landscape) of eastern DR Congo despite evidence showing human activity and related LULC change as being the primary cause of accelerated soil erosion during the 21st century (Borrelli *et al*., 2017). Besides, the future climate scenario and the future land use scenario are likely to increase the rate of erosion at a global and local scale (Yang *et al*., 2003; Borrelli *et al*., 2020; Hateffard *et al*., 2021; Guder & Kabeta, 2025). In fact, the rainfall pattern in DR Congo is projected to change in near future due to climate change with an increase in frequency and intensity of extreme rainfall events (World Bank Group, 2021). Furthermore, due to an increasing population and LULC change, it is estimated that all the primary forest cover in DR Congo will be cleared by the year 2100 if the actual trend of deforestation continues into the future (Tyukavina *et al*. 2018). The question that arises then is how these changes will affect the soil erosion process and which conservation option should be adopted to reverse the problem of land degradation in the highland landscape of eastern DR Congo.

It is for the above reasons that it becomes very important to evaluate the spatiotemporal dynamic of soil erosion under current and possible future scenarios of LULC change to identify the priority areas for restoration and to evaluate the effectiveness of conservation measures in reducing the problem of erosion. In addition, the understanding of the relationship between the change in landscape pattern and soil erosion process is important for the implementation of intervention measures and for determining the optimal landscape structure to be adopted during the land use planning process to control the erosion process (Zhang *et al*., 2017; Li *et al*., 2022). However, only selected landscape metrics were considered for analysis of the relationship between the landscape pattern index (metrics) and soil erosion by using different statistical models in previous studies (Li *et al*., 2022). In consequence, these studies have arrived at different conclusions depending on the region, the scale, and the landscape metrics considered. Currently, there is no standard method of selecting landscape metrics and there is no universal conclusion about their relations with soil erosion (Zhang *et al*., 2017). Therefore, Li *et al*. (2022) preconized that future research should be focused on exploring the scale effects of landscapes on soil erosion and modifying the evaluation method of landscape indices to improve the evaluation accuracy in another region. In Eastern DR Congo, such research has not been done yet despite that the understanding of the response of soil erosion to changes in landscape patterns can provide a scientific basis for land use management and erosion control at different scales.

In the perspective of landscape restoration process, the pressing question which usually arises is: “where to restore first?” This question calls for an identification of priority areas for implementation of landscape restoration initiatives based on the biophysical constraints, socio-economics constraints and the preferences of stakeholders. This problem is spatial in nature and it can be handled in a GIS environment by weighting different environmental and socio-economic criteria for evaluating the land suitability through the Multi-Criteria Decision Analysis (MCDA). Then it is necessary to develop MCDA approach for identification of the most preferable sites for restoration where resources and efforts should be concentrated. Such approach have been developed in different part of the globe during the planning process (Uribe *et al*. 2014; Aguirre-Salado *et al*., 2017; Kouriati *et al*., 2024). However, in Eastern DR Congo, they have not been developed yet despite that this region is one of the most affected by land degradation in the country. To fill this gape, this study will develop MCDA based models for appraisal of land degradation vulnerability and identification of suitable areas for implementation of landscape restoration initiatives in eastern DR Congo. Moreover, the implementation of conservation measures and sustainable land use management to cope with the land degradation problem ought, to begin with an empirical and locally specific understanding of demographic, socio-economic, institutional, and biophysical factors that affect the conservation decision of local communities (Woldeamlak, 2007; Yifru & Miheretu, 2022). Cognizant of this, the identification of determinants factors that influence people's perception of land degradation and their decision to adopt conservation practices is of paramount importance for designing land use management strategies and conservation plans tailored to the local specific context (Tenge *et al*., 2004; Saguye, 2017a; Tesfahunegn *et al*., 2020; Yifru & Miheretu, 2022). These factors can be determined through the application of statistical models that have been implemented in different regions around the globe (Cherono *et al*., 2019; Wordofa *et al*., 2020; Yifru & Miheretu, 2022; Asfew *et al*. 2023). Although some studies have attempted to document the knowledge of local communities about the conservation practices in different regions of eastern DR Congo

(Adidja *et al*., 2016; Heri-Kazi, 2020; Chuma *et al*., 2022a), such models of adoption of conservation practices have not been developed yet at territorial level in Kalehe territory. Since each region around the word has its specificity in terms of agroecological and socio-economic conditions, it is difficult to generalize the community perception of land degradation and determinant factors of the adoption of conservation measures (Bekele & Drake, 2002). In addition to that, there's no consensus among the researchers about which factor should be targeted to enhance this adoption, implying that there is a need for locations-specific strategies to accelerate the implementation of conservation measures (Kumar *et al*. 2021). Hence the necessity to document the knowledge about the local community's perception of land degradation and to develop predictive models of this perception and decision to adopt conservation measures.

1.3. Objectives

a) General Objective

The main objective of this study is to assess the land degradation dynamics based on modeling approaches for the conservation of natural resources and optimization of the restoration plan of degraded lands at territorial level in eastern DR Congo.

b) Specific Objectives

The specific objectives assigned to this work are the following:

(1) To characterize the LULC change and its implication on land degradation,

(2) To assess the soil erosion dynamics under different land use scenarios,

(3) To develop a land degradation vulnerability model based on MCDA approach,

(4) To develop a conceptual model for land degradation management based on the DPSIR framework.

1.4. Research questions

This study will address the following concerns in accordance with the specific objectives (Table 1.1):

Table 0.1: Research questions for each specific objective

Objectives	Research question
Objective 1: Characterize the LULC change dynamic and its implication on land degradation	• What are the spatial and temporal trends of LULC change from the 1987–2020 period? • If these past trends continue in the future, what could be the situation for the 2030-2070 period? • What is the implication of these dynamics on the land degradation?
Objective 2: To assess the soil erosion dynamics under different land use scenarios	• What are the dynamics of soil erosion under the current and possible future situation of LULC changes? • How effective are conservation practices for reducing soil erosion under the current situation of LULC change? • What is the influence of landscape characteristics on soil erosion dynamics?
Objective 3: Develop MCDA-based models of land degradation vulnerability for landscape restoration planning	• What is the spatial pattern of land degradation vulnerability? • What are the priority areas for the implementation of Landscape Restoration Initiatives to reduce this vulnerability? • What is the accuracy of MCDA-based model in predicting the land degration vulnerability in Eastern DR Congo?
Objective 4: To develop a conceptual model for land degradation management	• What are the severity, causes, consequences, and preventive measures against land degradation? • What are the determinant factors of the adoption of conservation measures?

1.5. Research hypotheses

This study is based on the hypothesis that the Eastern DR Congo region is experiencing land degradation resulting from unsustainable land use which prevent the achievement of land degradation neutrality. Specifically, it is assumed that:

(1) There is a singnifican increase of land degradation due to LULC changes,

(2) There is a significant relation between soil erosion and landscape characteristics,

(3) The adoption of conservation practices significantly reduce the erosion risk,

(4) The MCDA model has the potential to predict the land degradation vulneravility,

(5) The adoption of conservation practices is influenced by socio-economics factors.

1.6. Justification and significance of the study

Through its National REDD+ Framework Strategy, DR Congo has committed to stabilizing its forest cover to 63.5% of the national territory and to reduce 56% of national greenhouse gas emissions associated with deforestation and degradation by 2030 (Kengoum *et al*., 2020). The DR Congo is also committed to reaching the Land Degradation Neutrality (LDN) by the year 2030 in light of target 15.3 of the Sustainable Development Goals which states that "By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought, and floods, and strive to achieve a land degradation-neutral world" (UN, 2017). The UNCCD has proposed that LDN should be integrated into the planning processes to avoid degradation in the land which are not degrading, implement sustainable management practices to reduce ongoing degradation, and reverse past degradation through restoration and rehabilitation practices in the land already degraded (Cowie *et al*., 2018). However, the lack of an accurate land use plan based on empirical data leads to poor decision-making in the management of natural resources in DR Congo. In consequence, there is a degradation of land resources which leads to an increase in environmental problems such as erosion, landslide, flood, loss of biodiversity, deforestation, water quality degradation, etc.

To reverse these environmental problems, there is a need to implement new policies towards the regulation of land use, conservation, and the promotion of sustainable natural resources management. Therefore, this study will focus on the development of models of land degradation to assess the impacts of changes in landscape patterns on ecosystem service and the response of soil erosion to changes in landscape structure in the current and possible future situation of LULC change. The development of such models is important for the implementation of REDD+ strategies and to achieve the land degradation neutrality (LDN) for which this country has been engaged. Furthermore, the development of models for predicting the erosion dynamic under different patterns of LULC constitutes an effective tool to assess the effectiveness of land use strategies in addressing the problem of land degradation. Indeed, the quantification of the effect of the spatial configuration of land cover (landscape pattern) on soil erosion can also help the planner to determine the optimal landscape structure and to design effective measures to control soil erosion by adjusting the landscape configuration. The DR Congo has also pledged to restore 8 million hectares of degraded and deforested land by the year 2030 in the framework of the Bonn Challenge and African Forest Restoration Initiative (AFR100), improve the land productivity in 5.4 million hectares of declining productive land (shrubland, grassland, cropland) with declining productivity, increase the stock of carbon soil content by 17% in the area where the 2.1 million hectares and 369 200 hectares of land with decreasing and slightly stability pattern of carbon soil content, respectively, and stop the conversion of forestland and wetland into others LULC types to reach the land degradation neutrality by 2030 (Ministry of Environment and Sustainable Development of DR Congo, 2018). However, key challenges such as the lack of national monitoring system of land degradation and appropriate conservation plans of natural resources have delayed progress.

In the context of limited resources, it is then necessary to assess the status of land degradation and to identify priority areas for conservation where landscape restoration initiatives should be implemented. It is in this perspective that this study will provide a methodological framework for the assessment of land degradation vulnerability to identify priorities area for the implementation of landscape restoration initiatives and anticipating where future land degradation is likely to occur for effective implementation of an appropriate intervention to achieve the LDN in the context of the mountainous landscape of eastern DR Congo. The results of these studies will be presented as maps and models that will guide the policymaker in the management of the resources and identification of priority areas for restoration purposes.

1.7. Scope of the study

The scope of this study is to characterize the interrelation between the spatio-temporal dynamic of LULC change, the dynamic of land degradation, and their impacts on ecosystems services through spatial modeling to support informed decisions for the conservation of soil, water, and forest in the highland landscape of eastern DR Congo. The geographical coverage delimitation of this study is the Kalehe Territory.

Despite that, there are different forms of land degradation including biological, physical, and chemical degradation, this study will focus on physical land degradation such as soil erosion which is the main form of land degradation process in the eastern DR Congo. More specifically, the study is limited to the assessment of land degradation based on four indicators namely the LULC transition, the land productivity dynamics, the ecosystem services value, and the soil water erosion dynamics under past, current, and possible future situations of land use change.

The baseline for analysis is set to the year 1987 to take into account the state of the landscape before the population explosion in the Kalehe territory which occurred during the 1994-1996 period due to the arrival of Rwandan refugees invading any natural forest in search of land for cultivation, pasture or settlements. The year 2020 is considered the actual situation. For prediction, this study will provide a forecast of the degradation of ecosystem service and erosion dynamic under the future LULC projection for the years 2030 (short-term period), 2050 (medium-term period), and 2070 (long-term period). The selection of these years is following the international agreement in which DR Congo has taken part. The DR Congo has ratified the Kyoto Protocol in 2005, the Paris agreement in 2017, the Nagoya Protocol in 2015, and the Convention on Biological Diversity (CBD) in 1995 and signed the United Nations 2030 Agenda for the Sustainable Development Goals (SDGs) in 2015. In this context, prediction of future land-use change and its impact on ecosystem service as well as soil erosion will be done for the years 2030 which represent the deadline for the 2030 United Nation Agenda for Sustainable Development, 2050 which represent the deadline for the 2050 vision towards "Living in harmony with nature" of the CBD and the Paris climatic agreement to reduce the net-zero emission by 2050, years 2070 represent the baseline to reach the “carbon neutrality” and to avoid the global warming of more than 2°C (UNEP, 2014). For LULC classification, only 7 classes will be considered following the USGS first level of classification (Anderson *et al.*, 1976): wetland, forestland, grassland, shrubs, cropland, bare land, and built-up area.

CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

This chapter presents a review of the literature in accordance with the research objectives. Specifically, it presents the literature relevant to land degradation, LULC dynamics, its drivers and modeling, the impact of landscape dynamics on soil erosion and ecosystem service, conservation planning practices, soil erosion modeling for conservation planning, and the MCDA as a tool for land evaluation. Furthermore, it presents the theoretical framework and conceptual framework of the study which integrate the system theory and the decision theory in land degradation modeling and conservation planning.

2.2. Land degradation

The natural or anthropogenic disturbance of the environmental system has the potential to result in a long-term decline in ecosystem function and productivity. This permanent or temporary reduction of land productivity through the deterioration of physical, chemical, and biological characteristics of the land is recognized as land degradation (Bai *et al*., 2008; Tagore *et al*., 2012; Olsson *et al*., 2019; AbdelRahman *et al*., 2023). It includes all processes such as deforestation, biodiversity loss, soil degradation, and disruption of the water cycle that decrease the ability of natural resources such as soil, water, vegetation, and wildlife in their natural ecosystems to perform essential functions and services in those ecosystems (Hurni *et al*., 2010). The main types of land degradation are soil chemical degradation (including acidification, leaching, salinization, decreased fertility, chemical pollution, and decreased cation holding capacity), physical degradation (including soil crusting induced by the decline in soil structure, soil compaction, hard-setting, water and wind erosion, desertification), and biological degradation (long term loss of vegetation, reduced total carbon and biomass, and decreased biodiversity) (Lal *et al*., 1989, Zorn, 2013). These forms of land degradation can be seen as the consequence of the pressure on land resources due to the increasing demand for ecosystem services.

From the historical perspective, it is important to note that the definition of land degradation has evolved during the last three decades. For instance, in 1979, the FAO defined land degradation as a set of processes that diminish the current or potential productive capacity of the soil (Nachtergaele *et al*., 2010). In contrast, the LADA (2011) defined land degradation as the reduction of the capacity of the land to provide ecosystem services while the UNCCD defines the land degradation as the loss of economic or biological productivity of all land use categories resulting from human activities (UNCCD, 2016). In 2019 the IPCC defined land degradation as a negative trend of land conditions (long-term reduction of biological productivity, integrity of ecosystem, or value to humans) associated with human-induced process (anthropogenic process) (Olsson *et al*., 2019). All these definitions agree on the fact that land degradation can be a natural or human induced process that varies over time and space, negatively affect the land's natural function, leading to the decline in land productivity (Zorn, 2013).

2.2.1. Land degradation as a global environmental challenge

The imprint of human activities on the global environment has significantly impacted the functioning of the earth system so that the world has entered the Anthropocene (Steffen *et al*, 2011, Harfoot *et al*., 2021). Indeed, land resources are finite while the world population is still increasing in size. The world population has tripled in size since the twentieth century from 2.5 billion in 1950 to 7.9 billion in 2021 and it is projected to grow to 11 billion by the end of the twenty-first century (United Nations

Department of Economic and Social Affairs, Population Division, 2021). Furthermore, during the last 30 years, the consumption of natural resources has doubled and it is projected that the demand for the natural resource will still increase in the future so that they will be a need for the equivalent of 3 planets to meet the natural resource demand by 2050 (IRP, 2017; UNCCD, 2017). As a consequence of this pressure on natural resources, there is an emergence of land degradation processes that affect the well-being of about 3.2 billion worldwide and contribute to the loss of approximately 10% of the annual gross domestic product (von Keyserlingk *et al*. 2023) since there is an annual loss of 24 billion of fertile soil and 15 billion of trees, occasioning an economic cost of $40 billion (UNEP, 2016). From this perspective, several organizations have attempted to map the spatial extent of land degradation at a global scale but currently there are no reliable maps of global extent of land degradation due to conceptual (the way that land degradation is defined and the considered baseline) and methodological (diverging views about the spatial and temporal scale to consider, the quantification and mapping approaches) reasons (Olsson *et al*., 2019). The first map of land degradation at the global level was published in 1991 by the International Soil Reference and Information Centre (ISRIC), in cooperation with the United Nations Environment Programme (UNEP) and Food and Agriculture Organization (FAO) (Oldeman *et al*. 1990, Oldeman *et al*. 1991). This map was focused on human-induced soil degradation following the Global Assessment of Soil Deterioration (GLASOD) classification. For the United Nations Convention to Combat Desertification (UNCCD), three indicators were proposed to be used in the reporting mechanisms to monitor the progress toward the achievement of SDG 15.3.1 (proportion of degraded land to the total land area): the land productivity dynamics, the soil organic carbon, and the LULC change (Orr *et al*. 2017, Sims *et al*., 2019, Bär *et al*., 2023). However, currently, there is no single method that can be used to assess objectively the land degradation as the process is complex (Olsson *et al*. 2019) since more than one degradation type may occurs in the same place. Although it was estimated that 33% of land has already been affected by soil degradation at the global level (AbdelRahman, 2023) due to erosion, nutrient deplation of soil, soil acidification, salinization and compaction (UNEP, 2016), the current global extent and severity of land degradation are not yet well quantified (Olsson *et al*. 2019). For instance, the UNCDD (2022), estimate that up to 40% of earth's surface are affected by physical, biological of chemical land degradation process. However, the global assessment of land degradation based on NDVI during the 1983-2006 period indicated that between 22% and 24% ice free land have been degraded with about 10% of grasslands, 20% cultivated land and 30% of forests land undergoing degradation (Bai *et al.*, 2008). In the same perspective, by using the land productivity dynamics as an indicator of land degradation, de la Fuente *et al*. (2020) demonstrated that between 1999 and 2013, 15% of the land was characterized by a decrease in land productivity but there was a disparity among the continent with 37% of decline of productivity found in Australia and Oceania, 27% in South America, 22% in Africa, 18% in North America, 14% in Asia and 12% in Europe. However, because land degradation is complex, various indicators are used for assessment. Among these, soil erosion is the most common indicator. It is considered as the most dangerous type of land degradation worldwide (Alexandridis *et al.*, 2014). This issue has become a global environmental problem, accounting for 85% of all land degradation (Gurjeet & Rabindra, 2017). For instance, it is estimated that the soil erosion leads to the loss of 24 billion tons of fertile soil (UNCCD, 2017) and contributes to the degradation of water resources. This process threatens the sustainability of ecosystem services that soil provided, especially in the humid tropics where heavy rainfall increases its potential (Labrière, 2015).

Additionally, water erosion impacts ecology by destroying natural environments. It also affects social and economic life at local, regional, and global levels. The organic carbon constitutes another indicator of land degradation. In this context, it was estimated that around two-thirds of the organic carbon contained in soil and vegetation has been lost due to land degradation since the 19th century (Ekka *et al.*, 2023). This situation has some negative impacts on people's livelihoods at global scale. For example, the production of food is projected to decline by 12% in the next 25 years due to the loss of fertile land, which occurs at a rate of 20 million hectares per year. In consequence, the food insecurity will be exacerbated as the food prices will increase by 30% due to the degradation of fertile land (AbdelRahman, 2023). The land degradation affects also the global economy with its annual cost estimated to 3.4 trillion Euro (ELD, 2013. AbdelRahman, 2023), affecting half of humanity and threating about 50% of global population (UNCDD, 2022). In regards to this, the prevention of land degradation at global level constitutes one of the significant challenges of the 21st century (Mzuri *et al*., 2022). In this perspective, the UN declared the 2021-2030 the "decade on ecosystem restoration", highlighting the political commitment for restoration of degraded lands, achieving the SDG 15.3 and the land degradation neutrality by 2030 (Koech *et al*., 2020).

2.2.3. Land degradation: an issue for sustainable development in Africa

The rate of population in Africa is high and it is projected that the African population will increase from 1.1 billion in 2010 to 2 billion by 2040 and 4.2 billion by 2100 (UNDESA, 2014). At the same time, there is an increase in urbanization as it was estimated that only 40% of the population in Africa lived in urban areas in 2015 but this proportion is projected to be 56% by 2050 (UNDESA, 2014). Although that this population growth presents some advantages such as human capital, it come also with somes challenges considering that the demand for natural resources to reach the needs of this population will also increase.

In Africa, it is estimated that two third of the population depends on agriculture for their livelihood. However, only 55% of land in this continent is suitable for agriculture (Eswaran *et al*., 1997). In addition to this land suitability constraint, there are issues of land degradation that endanger the food security and livelihoods of the population. For instance, it is estimated that two-thirds of productive land in Africa is already affected by land degradation (UNCCD, 2013). More specifically, the trend of severity and extent of land degradation increase from the humid zones to the dry area in Africa. In the humid zone of the Congo and Zambezi basins, the extent of land degradation is estimated to vary between 24 and 29% while in the dry areas of the Nile, Niger, and Lake Chad basins it varies from 78 to 86% (Thiombiano & Tourino-Soto, 2007).

It is estimated that 715 million ha of productive land are degraded in Africa, with 65% of arables lands, 30% of grasing lands, and 20% of forestlands due to population growth, unsustainable land use practices, climate changes and institutional challenges (Koech *et al*., 2020). About 65% (485 million people) of the African population is affected by this situation (ECA, 2007, AGNES, 2020). More particularly in sub-Saharan Africa, 25% of 925 million people live in areas that are being degraded since the 1980s (Le *et al*., 2012). In addition to that, there are issues of climate change which is projected to increase the occurrence the rainfall variability and the incidences of extreme weather events (IPCC, 2014). Thus to achieve the sustainable development goals by the year 2030 and the African Agenda 2063, there is a need to implement sustainable land management. However, currently few updated accurate data regarding the extent, severity, and trend of land degradation are avalaible at continental level in

Africa (AGNES, 2020). In this context, the assessment of the spatial extent of land degradation processes and their drivers at national, regional, and local levels is essential to identify the land degradation hotspots where the restoration actions should be prioritized and to suggest potential management options. To address the land degradation in Africa, there are some regional initiatives such as the AFRI100, the Great Green Wall initiatives (Koech *et al*., 2020) and bilateral projects associated with the REDD+ mechanisms for instance.

2.2.4. Land degradation in DR Congo

The DR Congo is the biggest country in terms of the land surface in the Congo basin with almost two-thirds of the country's territory covered by dense humid forest (Mosnie *et al*., 2016, Kengoum *et al*., 2020). It is also the country with the highest population size in this region, with nearly 80 million inhabitants (Mosnie *et al*., 2016). This country is subject to land degradation, especially forest degradation, and erosion due to an increasing population, unsustainable management of the natural resource, and variation of climatic conditions. For instance, based on the UNCDD indicators of land degradation (LULC change, land productivity, and soil organic carbon stock), it was estimated that between 2000 and 2015, 5.8% (13.4 million of hectare) of the country have been degraded at an annual rate of 0.4%/year (8 294 hectares per year) (Ministry of Environment and Sustainable Development of DR Congo, 2018).

The deforestation and removal of natural vegetation, along with agriculture activities and over-exploitation of natural vegetation for domestic use are recognized as the relevant anthropogenic factors of land degradation in the DR Congo (Shapiro *et al*., 2021; Achille *et al*., 2021). Due to the anthropogenic pressure, forest degradation is increasing over time and the extent of degraded forest is estimated to be 27 million ha in DR Congo (Tchatchou *et al*., 2015; Shapiro *et al*., 2021). Moreover, the deforestation rate in DR Congo has doubled from 0.11% between 1990 and 2000 to 0.22% between 2000 and 2005 (Tchatchou *et al*., 2015). One of the consequences of the deforestation, is the decrease of the stock of soil organic carbon content. For instance, during the 2000-2015 period, there was a decrease of soil organic carbon stock by 17% and 0.2% due to conversion of 2 058 500 hectares of forestland into agricultural land and conversion of 369 200 hectares of forestland into pastureland, respectively. Furthermore, there is a decrease in biomass productivity which occurred in about 2.3% (5 394 806 hectares) of the national territory, especially in the province of Kinshasa, ex Katanga, and South-Kivu while the stability of land productivity is observed in 57.6% (135 104 700 hectares) of the national territory, especially in the central Congo basin which is covered by the remaining dense humid forest of the country (Ministry of Environment and Sustainable Development of DR Congo, 2018).

Among the different forms of soil degradation (soil erosion, physical and chemical degradation), soil erosion is ranked as the first form of soil degradation in DR Congo like in other countries of the Congo basin where the loss of topsoil through water erosion (sheet erosion) is occurring in 32% of the entire area, followed by loss of nutrients and organic matter through chemical degradation which occurs in 21% of area whereas 39% of the basin consists of stable terrain under natural conditions, without any human-induced erosion (Mushi *et al*., 2019). In particular, the highland region of eastern DR Congo is the most vulnerable to soil erosion due to its rugged topography, the nature of the soil, and the intensification of land use (Kamarage *et al*., 2016; Mahamba *et al*., 2023). This region has undergone LULC changes in recent years with increasing pressure on forest land (Institute for Environmental Security, 2008; Kabonyi *et al*., 2011; Musavandalo *et al*., 2024; Musavandalo *et al*., 2025). As an illustration, it has been estimated that the rate of deforestation in the Maiko-Tayna-Kahuzi-Biega landscape, one of the ecological landscapes of eastern DR Congo, is about 0.88% or 804km^2 of forest loss per year (Ngeleza, 2012) which is very high compared to the national level of deforestation of 0.2-0.3% (Kengoum *et al*., 2020). In this region, forests are under anthropogenic pressure due to mining, high population density, the presence of fertile volcanic soil for agriculture, armed conflicts that have caused massive displacement of the population, and the exploitation of wood energy even in national parks (Institute for Environmental Security, 2008; Kabonyi, 2011 Musavandalo *et al*., 2024; Musavandalo *et al*., 2025). These activities have contributed to land degradation, resulting in the exacerbation of soil erosion, sedimentation and nutrient deposition in Lake Kivu (Mashimango, 2015; Karamage *et al*., 2016).

Land degradation constitutes a serious obstacle to economic and social development in DR Congo (Bamba, 2010; Ministry of Environment and Sustainable Development of DR Congo, 2018). It affects the livelihoods of local community through the reduction of the supply of ecosystem services and upsurge of hydroclimatic risk such as erosion, landslides, and flooding. Therefore, efforts are needed to improve the livelihood of the Congolese people without degrading the land resource. It is in this context that in response to land degradation problems, the DR Congo is being engaged in both the LDN scheme by committing to restore all the degraded land by 2030 through the implementation of forest landscape restoration initiatives in 8 million hectares of degraded forest, 5.4 million hectares of area characterized by a decrease in land productivity, increasing the soil organic carbon (SOC) stock by 17% in 2.1 million hectares of land characterized by a decrease of SOC and 369 200 hectares where the SOC remained slightly stable during the 2000-2015, and prevent the conversion of forestland and wetland into others land uses categories (Ministry of Environment and Sustainable Development of DR Congo, 2018) as well as the REDD+ mechanism since the adoption of its National REDD+ Framework strategy (Kengoum *et al*., 2020) to tackle the main drivers of deforestation and land degradation, to stabilize the national forest cover to 63.5% and to reduce 56% of national greenhouse gas emissions associated with deforestation and degradation by 2030. The implementation of such initiatives require participant countries to identify and characterize the drivers of land-use change, assess the condition favorable to land degradation, identify the area at high risk of future land degradation based on historical observation pattern of land-use change, quantify the impact on ecosystem service or goods and use this information to the target area where mitigation actions are needed, design appropriate strategies for conservation and sustainable development (Orr *et al*., 2017; Cowie *et al*., 2018; Grinand *et al*., 2019). Moreover, the Government that enrolls in these policies is required to develop Reporting Verification and Monitoring (RVM) system and a set of indicators (Nampindo, 2014). Thus from a management and planning perspective, it is important to have a view of the driving factors of land degradation and to determine where land degradation is more likely to occur. One of the methods to do that is to perform spatial-scale modeling of land degradation processes by considering the environmental factors that influence them as dependent variables. Besides, the mapping data of land degradation trends is an important tool for the development of natural resource management policies and the environmental safeguarding (Sirengo *et al*., 2018). Therefore, there is a necessity for the identification of areas which are vulnerable to land degradation over different times in both current and possible future situations in the ecological landscape of DR Congo.

2.3. Land use and land cover dynamics

The UNCCD (2017) defines the land as the bio-productive system of the earth that includes the soil, vegetation, other biota, and the ecological and hydrological processes that operate within the earth system. Although land cover and land use (LULC) are often used interchangeably, there is a difference between the two terms (Wang & Yang, 2020). Indeed, the land cover describes the biophysical attributes or characteristics of the earth's surface while land use describes how land is used by humans or the intent applied to these attributes (De Jong, 2012; Wang & Yang, 2020).

To ensure survival, meet economic needs, and accelerate development, people in developing countries, use land resources unsustainably through practices such as overgrazing, deforestation, unplanned urban expansion, etc. In consequence, the land use and land cover change occurs (Mashame & Akinyemi, 2016; Tadesse *et al*., 2017; Wang & Yang, 2020).

Despite some economic and social benefits resulting from LULC changes, such conversion often has unintended consequences on the environment (Leh *et al*., 2013). Consequently, some environmental issues related to landscape transformations concerning land use change emerge (Casado, 2007; Wang & Yang, 2020). These changes affect ecosystems, biodiversity, and the services they provide to society (Maitima, 2009; Mburu, 2015; Davison *et al*., 2021; Ersoy Tonyaloğlu, 2025). They are a complex and dynamic process that can be exacerbated by human activities (Leh *et al*., 2013) and their magnitudes vary depending on the period examined and the geographical area considered (Mburu, 2015). Thus the knowledge about the type and location of land use and occupancy change provides important information that is commonly used to assess landscape conditions, inventory the status and trend of change in the ecosystem for a given period (Javed *et al*., 2012). Detecting this change is then a critical requirement for assessing potential environmental impacts of anthropgenic activities and developing land management plans and strategies.

The analysis of land use and land cover change dynamics requires current geospatial technologies such as Geographic Information Systems (GIS) and remote sensing through the analysis of aerial photographs and satellite images at different scales ranging from local to regional and global (Zeleke & Hurni, 2001; Maitima *et al*., 2004; Mame *et al*., 2016; Wang & Yang, 2020). These techniques have emerged as important tools for the assessment of natural resource degradation and monitoring of their spatio-temporal dynamics following the provision of reliable, accurate, and up-to-date information at an acceptable cost (Javed *et al*., 2012). These techniques are based on the detection of multi-temporal and multi-spectral digital change from remote sensing data as a means of understanding landscape dynamics, detecting, identifying mapping, and monitoring land use/occupation change on a time scale (Mashimango, 2015). Without additional information, remote sensing detects land cover but, in most cases, land use is derived from land cover (De Jong, 2012).

2.3.1. Impact of LULC change on land degradation

Land degradation is among the environmental and anthropogenic problems caused by land use change and climate change (Elgubshawi, 2008; Mashame & Akinyemi, 2016; Hermans & McLeman, 2021). Indeed, The Millennium Ecosystem Assessment (2005) showed that poor land use practices and management choices are increasing land degradation around the world (Labrière, 2015; Hermans & McLeman, 2021). LULC change directly impacts global biodiversity, contributes to climate change, is the main source of soil degradation, and by altering ecosystem services, affects the capacity of biological systems to support human needs (Marques *et al*., 2019; Wang & Yang, 2020; Semenchuk *et al*., 2022, Ersoy Tonyaloğlu, 2025).

The implications of these LULC changes could be positive (convey desirable changes) or negative (bring undesirable changes) (Yesuph & Dagnew, 2019). Thus, it is possible to use the LULC change as a proxy for land degradation (Sims *et al*., 2019). Indeed, some negatives impacts on ecosystems are associated with LULC changes at local, regional and global level (Alemu, 2015). This is the case of biodiversity loss which is likely to occurs when there is a transformation of undisturbed land such as natural forest into more intensive land use such as farming, grazing and timber harvesting (Marques *et al*., 2019, Semenchuk *et al*., 2022), the soil erosion associated to the increase of intensity of LULC change (Borrelli *et al*., 2017, Borrelli *et al*., 2020), the reduction of carbon sequestration potential associated to forestry activities (Marques *et al*., 2019) and associated CO_2 emission which account for 13-21% of global total anthropogenic greenhouse gaz emission during the 2010-2019 period (Nabuurs *et al*., 2022).

Land degradation models can then be applied to indicate whether the change in LULC has been sustainable or unsustainable. Such analyses are essential for planning and decision-making that focus on environmental rehabilitation actions and the development of awareness programs (Zeleke & Hurni, 2001). Thus, many studies combine remote sensing, GIS, and modeling techniques to investigate the link between landscape dynamics and land degradation. For instance, there is a link between land use change and erosion risk (Wijitkosum, 2012; Borrelli *et al*., 2017; Guder & Kabeta, 2025), biodiversity loss (Maitima *et al*., 2009; Davison *et al*., 2021), habitat degradation (Msoffe *et al*., 2011; Fumy *et al*., 2021), degradation of soil physicochemical properties (Elgubshawi, 2008; Assefa, 2020) and flow of ecosystem service (Msofe *et al*., 2020; Ersoy Tonyaloğlu, 2025). Other studies show that land use change can be beneficial for the restoration of degraded lands. This is the case of the work of Wijitkosum (2012) who demonstrated the link between reforestation and a decrease in soil loss through erosion.

2.3.2. LULC change modeling

The knowledge about the type, location and temporal changes of LULC can provides important information that is commonly used to assess landscape conditions, and inventory the status and trend of change in the ecosystem for a given period (Javed *et al*., 2012; Gomes *et al*., 2021). In order to properly analyse the state of environmental changes, it is important to understand the spatial and temporal dynamics of LULC and identify the mechanisms associated with these dynamics. These mechanisms are related to natural and anthropogenic factors (Mame *et al*., 2016; Wang & Yang, 2020; Christensen & Jokar Arsanjani, 2020).

The LULC change constitutes as an important driver of environmental change on all spatial and temporal scales and contributes significantly to earth-atmosphere interactions, forest fragmentation, and biodiversity loss (Fu *et al*., 2000). Thus, analysis of past and present trends of land-use changes through geospatial techniques and community perception approach can elucidate the relative vulnerability of areas of high conservation priority to anthropogenic pressure and habitat fragmentation (Nackoney & Williams, 2012). LULC change is also considered as one of the factors which contribute to local environment disturbance by influencing surface water runoff, soil loss by erosion, and stream flows (Woldeamlak, 2002; Guder & Kabeta, 2025). Due to these, modeling the dynamic of LULC change is an imperative for environmental management (Gashaw *et al*., 2017; Wang *et al*., 2022).

The detection and prediction of LULC change over time constitute a powerful tool for natural resources management, environmental modelling, sustainable land use planning, spatial plannig and conservation planning (Wang *et al*., 2022; Tahir *et al*., 2025). It is in that perspective that different studies have been conducted around the world to assess the pattern of LULC change at different spatial scales using different methods (Wang *et al*., 2022). For instance, various models including logistic regression (Bavaghar, 2015), machine learning tools (Grinand *et al*., 2019), and MCDA-based models (Monjardin-Armenta *et al*., 2020) have been developed to simulate the future scenario of LULC change and to assess alternative scenario of land management. Based on these studies, it have been demonstrated that the LULC changes study should be location specific as the interaction among theirs drivers varies from one place to another (Kindu, 2017). In addition, there is an interrelation of drivers of LULC change at different scales (local, national, and global) and it is improper to make generalizations of other places around the globe (Munthali, 2020). However, the understanding of divers of LULC change at the local level is still limited in several region around the word. Therefore, further research is needed to determine the location-specific interactions among driving forces of LULC change (Beilin *et al*., 2014).

Indeed, the integration of drivers of LULC changes into models can be helpful to predict future trends and enhance our ability to predict outcomes and interventions (Mottet *et al*., 2006; Christensen & Jokar, 2020). Therefore, quantitative and qualitative analyses of the drivers of LULC change are needed to develop predictive models of the future pattern of LULC change in a given area (Veldkamp & Lambin, 2001). These data can be used in the development of effective land use planning and strategies for sustainable resource use planning, management, and conservation (Kindu, 2017) considering that the modeling approach can help to predict the future demand in land. It give also some insights into the area where and why LULC change is likely to occur in the future due to the changing in environmental factors or human interventions (Bhattacharjee & Ghosh, 2015). Furthermore, the LULC change models can be used to simulate different scenarios of management strategies before a decision can be made.

2.3.3. LULC dynamics in DR Congo, its drivers, and impacts

DR Congo hosts one of the largest rainforest covers in the world which account for about 155 million hectares of forest covering almost 67% of the country's land area (De Wasseige *et al*., 2009). Although DR Congo is home to 60% of the remaining Congo Bassin rainforest (Mayaux *et al*., 2013), during the last decades, this country has been subjected to several LULC changes due to population pressure, conflicts, and insecurity which threaten the integrity of this ecosystem. For instance, during the 2000-2015 period, the annual deforestation rate of DR Congo was among the highest in the Congo Basin and was estimated at around 0.2-0.3% (Kengoum *et al*., 2020). According to Tyukavina *et al*. (2018), there is a correlation between the annual rate of forest cover loss and population growth in DR Congo. Under the assumption that this trend will continue in the future, the study estimated that all of the primary forests of DR Congo could be cleared by 2100 as the population will reach 197 million people by 2050 and 379 million by 2100 concerning (Tyukavina *et al*. 2018). In consequence, sustainable forest management will be challenging due to the increasing population, especially in the Eastern part of the country where the population density is high. To address these challenges, there is need to understand the spatiotemporal dynamic of LULC change for effective resource use and conservation planning.

Studies conducted on LULC dynamics, using GIS and remote sensing approaches in DR Congo have shown the link between LULC change and forest degradation (Bamba, 2010; Kabonyi *et al*., 2011; Achille *et al*., 2021). However, knowledge of the link between land use change, terrain physiography, land productivity, ecosystem supply potential, and soil erosion dynamics is fragmentary in DR Congo. Only a few studies including Ongezo *et al* (2014) in the Lac Tanganyika basin, Ekaka Azanga *et al*. (2016) in the Ruzizi basin, Ndolo (2015) in the Ndjili River basin, Mashimango (2015) in the

Lwiro sub-watershed, Kamarage *et al*. (2016) in the Lake Kivu basin, Eisenberg & Muvundja (2020) in a portion of Ruzizi basin, and Chuma *et al*. (2022b) in Chisheke watershed (Territory of Walungu) for instance, have attempted to address this issue. Nevertheless, none of these studies have attempted to forecast the impact of possible future LULC change on soil erosion in this region, nor the impact of LULC change on the flow of ecosystem services. Thus, in the context of land use planning, it is important to extend these studies, especially in the mountainous areas of Kivu that present a high susceptibility to water erosion and where there is pressure on the forest ecosystem due to high population density.

Although the assessment of the driving force behind the LULC change is fundamental for building realistic models of LULC change (Veldkamp & Lambin, 2001; Wang *et al*, 2022), quantifiable and spatially explicit data about this driving factor are still limited in DR Congo. Most of the LULC research in DR Congo has been focused on the changing pattern and qualitative analysis of driving factors with an emphasis on the local communities' perception (Megevand *et al*., 2013; Tchatchou *et al*., 2015; Ciza *et al*. 2015; Moonen *et al*. 2016) but without a spatial quantification of the underlying factors and modeling to support future LULC change analysis. This lack of knowledge about the spatial prediction of future LULC change constitutes an obstacle to providing a solution for conservation planning and land resource use planning in the ecological landscape of DR Congo. Indeed, studies on LULC dynamics in DR Congo have focused on the evaluation of the impact of anthropogenic activities on the Spatio-temporal dynamics of forest landscapes (Bamba, 2010; Tyukavina *et al*. 2018; Kabuanga *et al*., 2019; Shapiro *et al*., 2021; Musavandalo *et al*., 2024), the spatial analysis of the impact of mining activities and armed conflicts on deforestation (Butsic *et al*., 2015, Musavandalo *et al*., 2025), and the actor identification of the driving factors of LULC change based on the local community perception (Ciza *et al*. 2015; Moonen *et al*. 2016). From these studies, it is clear that agricultural practices, unsustainable logging, urbanization, fuelwood collection, mining activities, and development of urban infrastructure are direct drivers of forest cover loss whereas demography, economic factors, socio-political, proximity to the road, and biophysical factors are indirect drivers of landscape dynamics in DR Congo (Tchatchou *et al*., 2015). These driving factors can be integrated into spatially explicit models to identify potential degradation hotspots where mitigation measures should be taken to prevent further degradation. However, only few studies, including the work of Bamba (2010), Tyukavina *et al*. (2018) and Shapiro *et al*. (2021) attempted to quantitatively assess the underlying drivers of deforestation in DR Congo based on a spatially explicit approach but they didn't quantitatively assess the underlying drivers of others LULC changes such as the built-up area expansion and the cropland expansion. To contribute to the understanding of drivers of LULC change in this area, this study assesses the impact of biophysical and socio-economic factors on the pattern of landscape dynamics by combining GIS processing and regression techniques. This analysis is necessary to identify the main drivers of LULC change which can be integrated into spatially explicit models to predict future scenarios of LULC change in this area. Despite that several models including statistical models and machine learning technics have been developed in the prediction of LULC change (), their applications are constrained by the availability of data for the calibration of models and the complexity of divers of LULC change (Munthali, 2020). Due to this constraint, few studies (Christensen & Jokar (2020) in the Virunga landscape for instance) have been focused on the forecasting of LULC change in Eastern DR Congo. To overcome this challenge, this study will assess the ability to use open access and remote sensing data and their integration into a statistical model to simulate the possible future LULC dynamics in Eastern DR Congo.

2.4. Landscape dynamics

The landscape is the spatial manifestation of the relations between societies and their environment, whose current structure is the result of a dynamic evolving in time (Casado, 2007). It has two main dimensions: a "cultural" dimension where the landscape represents the sensitive link of individuals with their environment, mainly through visibility (but also through other senses such as hearing); a "natural" dimension, where the landscape offers a set of biotic and abiotic resources favorable to certain biodiversity (Foltête *et al.*, 2015). This landscape can be transformed by human activities (Munyemba, 2010) such as land-use change, which influences land resources (Javed *et al.*, 2012; Labrière, 2015). Thus, understanding the functioning of environmental systems, their evolution over time, and the response of their structure to disturbance processes is necessary to define future lines of action and management (Casado, 2007). The landscape pattern can be characterized by determining the landscape structure and composition index (Kupfer, 2012). They are useful for assessing fragmentation, connectivity, richness, etc. In particular, landscape fragmentation is used as an indicator of land degradation (Sklenicka *et al.*, 2014). It is then important to determine the drivers of land fragmentation (Pueyo *et al.*, 2006; Jaege *et al.*, 2016).

2.4.1. Impact of landscape dynamics on soil erosion

At the global level, various studies have analyzed the relationship between the landscape pattern index (metrics) and soil erosion by using different statistical models including the linear regression and partial least-concessions regression models to understand the response of soil erosion dynamic to the change in landscape pattern

(Zhang *et al*., 2017; Li *et al*., 2022). In these studies, only selected landscape metrics were considered for analysis. In consequence, these studies have arrived at different conclusions depending on the region, the scale, and the landscape metrics considered. Currently, there is no standard method of selecting landscape metrics and there is no universal conclusion about their relations with soil erosion (Zhang *et al*., 2017). Therefore, Li *et al*. (2022) preconized that future research should be focused on exploring the scale effects of landscapes on soil erosion and modifying the evaluation method of landscape indices to improve the evaluation accuracy in another region. In Eastern DR Congo, such research has not been done yet despite that the understanding of the response of soil erosion to LULC change and change in landscape pattern can provide a scientific basis for land use management and erosion control at different scales.

2.4.2. Impact of landscape dynamics on the flow of ecosystem service

The ecosystem service refers to the value and service that people benefits directly or indirectly from nature (Wallace, 2007). According to the Millennium Ecosystem Assessment (2005), this service can be categorized into provisioning, cultural, support, and regulating services (Brown, 2013). The evaluation of this service can be done through different approaches including biophysical, economic, and social evaluation (Kindu *et al*. 2016; Zhou *et al*., 2020; Hasan *et al*., 2020). Therefore, it is possible to assess the impact of land use change on ecosystem service (Hasan *et al*., 2020, Zhang *et al*., 2022, Fang *et al*., 2022). It is also possible to model the impact of the change in landscape structure and composition on the ecosystem service (Lamy *et al*., 2016, Ersoy Tonyaloğlu, 2025). Such studies are useful in determining the optimal landscape structure that can be adopted during the planning process to minimize the negative impact of land use change in the provisioning of ecosystem service. Such studies have been done in different parts of the world but in DR Congo such models are still missing. Different approaches are employed to assess the ecosystem service value: the non-monetary value and the monetary value. The non-monetary value is based on the empirical data from modeling approaches such as the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) tool (Fang *et al*., 2022; Ersoy Tonyaloğlu, 2025) or stakeholder rating of the ecosystem value potential of LULC types to provide the ecosystem service through the assessment matrix (Hasan *et al*., 2020; Fang *et al*., 2022; Esmail *et al*., 2023). Two types of monetary ecosystem value coefficient (in USD per hectare and per year) for each LULC type have been widely used: the global ecosystem service value for each biome represented by the LULC type as proposed by Costanza *et al*. (1997) and the ecosystem service value from The Economics of Ecosystems and Biodiversity (TEEB) database (Van der Ploeg & de Groot, 2010) as adapted in others tropical environment by Kindu *et al*. (2016) and Sharma *et al*. (2019). Based on the LULC maps, the surface (in hectares) of each LULC type is multiplied by the corresponding ecosystem value coefficient to obtain the total ecosystem value (in USD) for the considered LULC type. Based on the review of the impact of LULC on ecosystem service, Hasan *et al*. (2020) found that most of the research has revealed a negative impact of LULC change on ecosystem service. However, there exist “research gaps related to methods for valuing ecosystem services more accurately and for collecting social responses to the impacts of LUC on different ecosystem services” (Hasan *et al*. 2020). Thus further research for the development of quantification of ecosystem service is still needed. In the data-deficient area, the assessment of ecosystem service value through the transfer matrix approach is done based on global value coefficients or modified value coefficients developed by other schools (Msofe *et al*., 2020). Since the context can be different, it is important to develop an ecosystem service value index adapted to the specificities of each region. From this perspective, an evaluation of ecosystem service value based on the land user perspective will be assessed in this study.

2.4.3. State of the art on landscape dynamics assessment in DR Congo

Studies on landscape dynamics in DR Congo have focused on the evaluation of the impact of anthropization on the spatiotemporal dynamics of forest landscapes (Bamba, 2010, Kabulu *et al*., 2008, Kabuanga *et al*., 2020) and its impact on soil physicochemical properties (Alongo *et al*., 2013), the dynamics of urban green infrastructure (Balandi *et al*., 2024), the dynamic of urban and peri-urban area due to rapid population growth (Balandi *et al*., 2023), the quantification and modeling of landscape dynamics to assess the ecological impact of deposits resulting from hydrometallurgy (Munyemba, 2010), and the analysis of the impact of landscape characteristics on the domestic water vulnerability (Chishugi *et al*., 2021). These studies show that demography, urbanization, agricultural practices, mining activities, roads, and armed conflicts are important factors influencing landscape dynamics and leading to the loss of forest cover, degradation of soil physicochemical properties, and water quality in DR Congo. These studies do not analyze the influence of physiography on landscape dynamics. Nevertheless, topographical factors guide human land use choices. Understanding this relationship is fundamental to the implementation of conservation measures (Li *et al*., 2013). Furthermore, it is not clear how the change in landscape characteristics (structure and composition) may influence the earth's surface process (soil erosion, sedimentation, surface water runoff) and the potential supply of ecosystem services. This lack of information leads to poor decisions on land use allocation during land use planning. It is then necessary to develop models that predict the impact of changes in landscape characteristics on the land degradation vulnerability to predict the optimal landscape characteristics that should be adopted during the land use planning to reduce the land degradation vulnerability.

2.5. Conservation planning

Conservation planning is a "science and practice dedicated to preventing, stopping, and reversing negative effects on nature" (Milt, 2015). Conservation planning is also defined as "the process of locating, configuring, implementing and maintaining areas that are managed to promote the persistence of biodiversity and other natural values" (Pressey *et al*., 2007). The conservation planning is not only about biodiversity conservation but the resource concerns are soil erosion, soil quality degradation, degraded plant condition, inadequate habitat for fish and wildlife, excessive water, livestock production limitation, inefficient energy use, insufficient water, water quality degradation, air quality impacts, etc. (Book, 2019; Bennett *et al*., 2019). Therefore, the conservation planning constitutes a process of making informed decision support about the conservation of natural resources. It is a holistic problem-solving approach of natural resource management issues which implies to make a choice between different conservations alternatives by considering the environmental, economic, and social factors in the land use management process to meet the human needs and protect the natural resources. Therefore, the conservation planning emphasizes the identification of desired future conditions for improved natural resource management, the minimization of resource use conflicts, and the identification of opportunities for more efficient use of natural resources.

2.5.1. Conservation planning process

According to the Natural Resource Conservation Service (NRCS) of the USDA (Bennett *et al*., 2019), the process of conservation planning can be implemented by following 9 steps (Figure 2.1): the identification of problems, the determination of objectives, the inventory of resources, the analysis of resource data, the formulation of alternatives, the evaluation of alternatives, the decision making, the implementation of the plan and the evaluation of the plan (Book, 2019, Bennett *et al*., 2019). The purpose of these steps is to develop and implement a natural resource conservation plan for the protection, conservation and enhancement of natural resource use to meet the human needs. This natural resource conservation plan presents and analyses the major issues and problems of natural resource management, and proposes action plans for conservation of natural resources as well as the protection of the ecosystem and their components.

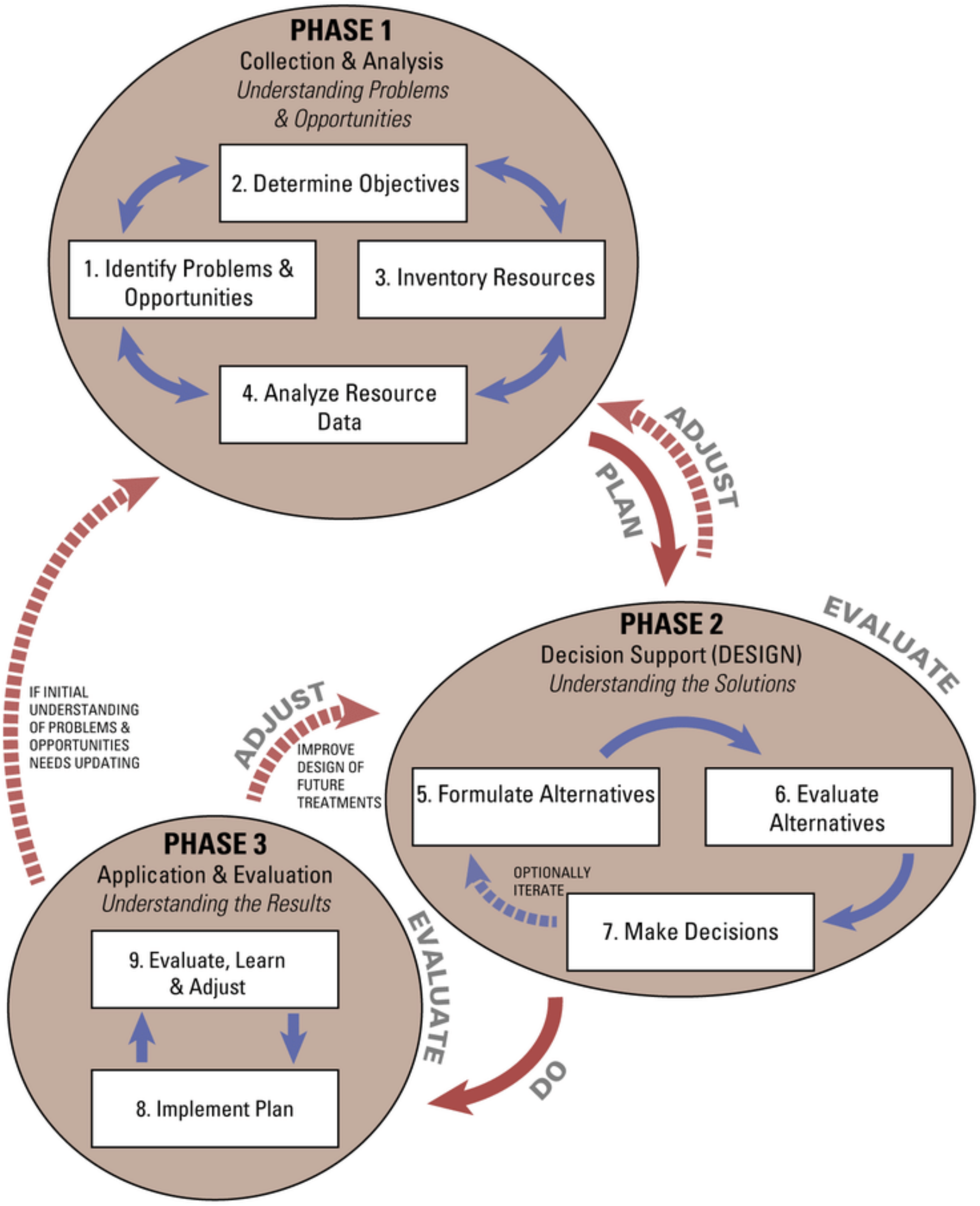


Figure 2.1: Conservation Planning Process.

Source: Bennett *et al*. (2019)

2.5.2. Land conservation practices

Sustainable land management consists of technical and institutional measures initiated by individuals or societies to maintain land productivity and other natural resource functions for present and future generations (Hurni *et al*., 2010). To maintain and improve land productivity, priorities must be taken for natural resource conservation.

Among the land conservation practices, there are agronomic practices (such as intercropping, contour cropping or contour farming, mulching, tillage practices, ridging, conservation cropping system, crop residues management, etc.), vegetative measures (such as grass strips, hedgerows or contour vegetative hedges, windbreaks, etc.), physical or mechanical (such as terraces, benches, bunds, vegetated waterways, constructions of permanent and no permanent conservation structures to control gullies erosion, construction of palisades and retaining walls for sediment retention, construction of check dam, etc.), management practices (such as land use change, fenced areas, rotational grazing, etc.) as well as combinations of different practices under conditions of complementarity and mutually reinforcing efficiency such as agroforestry (Hurni *et al*., 2008, Srivastava *et al*., 2010). Furthermore, agroforestry which implies the combination of shrubs or trees, and crops (annual or perennial) or livestock (Gold, 2009), is recognized as one of the solutions to land degradation (Cooper *et al*., 1996) which can be integrated into conservation strategies to create resilient multifunctional landscapes that provide a range of socio-economic benefits (Dumont *et al*., 2019). Indeed, agroforestry has the potential to contribute to the increase of agriculture productivity, soil fertility restoration (Dollinger & Jose, 2018), food security improvement (Kiptot *et al*., 2014), climate change mitigation (Verchot, 2007), biodiversity conservation (McNeely & Schroth, 2006), soil conservation (Young, 1989) and water resources conservation (Bekele-Tesemma, 1997). Consequently, in the context of the expansion of human activities due to population growth, the implementation of agroforestry can reduce the pressure on natural resources and contribute to the preservation of land for future generations. In DR Congo, agroforestry has been adopted as a resource management strategy (Dumont *et al*., 2019). However, there is little information about the location of suitable land for the implementation of agroforestry and the factors affecting the adoption of agroforestry as a conservation practice, especially in the highland region of eastern DR Congo.

2.5.3. Determinant factors for adoption of conservation measures

The adoption of conservation measures is influenced by a set of factors (Kumar *et al*. 2021, Yifru & Miheretu, 2022) including the socio-demographic characteristics (age of decision makers, education level of farmers, family size, marital status, gender), physical factors (farmland size, tenure security, fertility of the land, slope of plot, distance to farmland), economics characteristics (farm assets, main activity, access to credit facility, number of livestock units, income from off-farm activities), institutional characteristics (access to extension services, membership of an organization and participation in conservation programs which indicates the social capital, land tenure, accessibility to market facilities, participation in training on conservation measures) and attitudinal factors (perception on erosion, perception on effectiveness of conservation measures, perception on crop yield productivity). Based on an extensive review of the literature, Kumar *et al*. (2021) demonstrated that there are no universally significant factors affecting the adoption of conservation measures and there's no consensus among the researchers about which factor should be targeted to enhance this adoption. To assess the influence of these factors on the adoption of conservation measures, different modeling approaches including the binary logistic (Yifru & Miheretu, 2022, Asfew *et al*. 2023), logit and multinomial logit (Bekele & Drake, 2003, Mekuriaw *et al*., 2018), the ordered and multivariate probit (Kpadonou *et al*., 2017), tobit (Anley *et al*., 2017) and Poisson regression (Jara-Rojas *et al*., 2012) were employed around the word. Despite that some studies have attempted to inventory the conservation practices in selected watersheds in the Kivu region (Adidja *et al*., 2016, Heri-Kazi, 2020, Chuma *et al*., 2022a), few studies have been focused on the development of models to identify the determinant factors of the adoption of conservation measures at territorial level in this region.

2.6. Soil erosion modeling for conservation planning

There is a need for soil and water conservation to reverse the process of land abandonment and increase agricultural production to ensure food security (Gurjeet & Rabindra, 2017), limit pressure on the forest, and contribute to biodiversity conservation. Thus, it is crucial to identify critical areas of soil degradation to provide information related to the conservation strategy. Indeed, the identification of area susceptible to soil erosion constitute a benchmark for water and soil conservation planning (Tadesse *et al*., 2020). The implementation of soil and water conservation measures at the landscape level is important to stop or mitigate rivers, lakes, and estuaries' erosion and siltation process (Rinos *et al*., 2003). However, due to financial and organizational constraints, it is difficult to implement conservation measures in large spaces in less time (Jhariya *et al*., 2018). To optimize the economic funds during the implementation of ecosystem restoration practices, it is vital to do a careful and detailed plan (Aguirre-Salado *et al*., 2017). Therefore, the watersheds prioritization which indicates the order in which different sub-watersheds have to be taken for treatment under the soil, and water conservation measures constitute a good management strategy to derive the maximum benefit out of any such money-time-effort making scheme (Deepak Khare & Dhore 2007; Jhariya *et al*., 2018). In this context, an assessment of the watershed vulnerability to land degradation due to anthropogenic and natural factors is done through the application of a spatial modeling approach.

2.6.1. Soil erosion models

During the soil and water conservation planning process, the soil erosion models are commonly used as decision tools to investigate the physical processes and mechanisms that govern the rate of erosion, identify areas at high risk of soil loss and perform scenario analysis of adoption of conservation practices. A distinction is made between empirical models (statistical or regression model for instance) that estimate erosion rate based on the regression of soil loss with biophysical properties and climatic characteristics, conceptual models (partially empirical), and physical (or mechanistic) models that simulate the physical process of erosion by solving the fundamental equations that describe runoff flow and sediment generation (Espiritu, 1997, Ganasri & Ramesh, 2015). However, these quantitatives methods present some shortcomings as they require a lot of data which are scarce, especially in developing countries, or they are limited to the area for which the method has been developed (Vulević *et al*., 2015). Furthermore, some quantitatives methods of erosion modelling are designed to account for one type of erosion and require a large amount of data which restraint their application in a data-poor context (Zhang *et al*., 2020). In consequence, qualitative methods have been proposed to address these constraints due to the fact they require fewer data, they can be used to assess various types or forms of erosion at the same time and to identify priority areas with a high risk of erosion (hotspot) based on the key driving factors of erosion process (Zhang *et al*., 2020).

Trough the development of GIS techniques and Remote Sensing in recent years, it has become possible to analyse the spatial dynamics of soil erosion in conjuction with the natural and socioeconomic factors that influence it for a given period (Yahya *et al*., 2015). It is also possible to predict the soil erosion rate under different conditions of land use (Shi *et al*., 2004; Guder *et al*., 2025) through the application of spatially distributed models like the Erosion Potential Method (EPM, Gavrilovic, 1988), Revised Universal Soil Loss Equation (RUSLE; Renard *et al*., 1997); the Soil and Water Assessment Tool (SWAT; Arnold *et al*., 1998); the European Soil Erosion Model

(EUROSEM; Morgan *et al*., 1998), and the Water Erosion Prediction Project (WEPP; Flanagan *et al*., 2001) for instance. These models allow the assessment of soil erosion spatial variability and they can be used in the planning of conservation measures at the landscape scale (Lulseged *et al*., 2017, Tessema *et al*., 2020). These models can be used to predict the trend of erosion changes in the future by considering the future rainfall erosivity (Hateffard *et al*., 2021), land-use changes (Loukrakpam & Oinam, 2021), and impacts of policies which are dynamics factors influencing soil loss by erosion (Panagos *et al*., 2017).

The Universal Soil Loss Equation (USLE) (Wischmeier, 1987) and its derived version (RUSLE) (Renard *et al*., 1997) are the most popular because of their simple computational requirement and factors that are available on-site (Espiritu, 1997). The (R) USLE has also advantage as the parameters of this model can be easily integrated into a GIS for better analysis (Ganasri & Ramesh, 2015). That's how they are most widely used in soil erosion modeling with a considerable degree of certainty. For instance, they are applied during the the assessment of soil erosion spatial variability and they can be used in the planning of soil and water conservation measures at the landscape scale level (Lulseged *et al*., 2017, Tessema *et al*., 2020).

In the conservation planning process, the R(USLE) model is applied at a very low cost and the results are used to provide valuable assistance to decision-makers and land planners. More particularly, it helps to simulate evolution scenarios and subsequently to target the priority areas that require conservation and erosion control actions. Indeed, this model provides a good understanding of the relationships between erosion and land management through the analysis of spatial and temporal variability in erosion risk (Gashaw *et al*., 2017).

This model is helpfull during the soil erosion susceptibility mapping to identify areas at high risk of erosion and assist in prioritizing areas for conservation. Thus, the integration of (R)USLE model, GIS, and multi-temporal satellite imagery are commonly used to monitor changes in the environment, specifically to assess the rate of erosion at local, regional, and global scales. Then, the assessment of spatial variability of soil erosion can be done and these data can be used in the planning of soil and water conservation measures at the landscape scale level (Lulseged *et al*., 2017, Tessema *et al*., 2020). It also offers a possibility to predict the soil erosion rate under different conditions of land use (Shi *et al*., 2004), climatic change projection (Hateffard *et al*., 2021, Borrelli *et al*., 2020), land-use changes (Loukrakpam & Oinam, 2021; Panagos *et al*., 2017; Borrelli *et al*., 2020), and impacts of policies which are dynamics factors influencing soil loss by erosion (Panagos *et al*., 2017).

Soil erosion rate can be assessed at different scales ranging from plot level to watershed level by applying different empirical, conceptual, and physical models but these methods present some shortcomings as they require a lot of scarce data, especially in developing countries, or they are limited to the area for which the method has been developed (Vulević *et al*., 2015). Moreover, the quantitative method is designed to account for one type of erosion and requires a large amount of data which contains their application in a data-poor context (Zhang *et al*., 2020). For instance, the RUSLE model has been criticized for "its inability to account for soil loss from gully erosion, mass wasting events, or predicting potential sediment yields to streams" (Benavidez *et al*., 2018). Thus, qualitative methods have been proposed to address these constraints as they require fewer data, they can be used to assess the different types of erosion at the same time and identify priority areas with a high risk of erosion based on the key driving factors of erosion process (Zhang *et al*., 2020). Therefore, a combination of both quantitative and qualitative approaches is often recommended for systematic conservation planning (Berliner, 2009). In this context, a rule-based modeling approach that integrates both quantitative analyses with qualitative expert judgments can be used to overcome the data scarcity challenge and to facilitate the incorporation of local and expert knowledge (Berliner, 2009). The integration of experts' judgments in an MCDA model can provide a rapid and cost-effective approach to identifying priority areas for conservation, performing land suitability maps, and assessing the vulnerability of land to degradation (Amdihun *et al*., 2014). In this context, this study will attempt to develop an MCDA-based model for zoning the physical land degradation at the landscape level and using erosion as a proxy of land degradation.

2.6.2. Status of soil erosion modeling for conservation planning in DR Congo

Different scholars have attempted to assess the erosion phenomenon through the modeling approach in DR Congo using the RUSLE model, Remote Sensing data, and GIS (Karamage *et al*. 2016; Tshikeba *et al*. 2018; Nacishali, 2021, Eisenberg & Muvundja, 2020, Chuma *et al*., 2022b). However, there is limited information about the patterns of the Spatio-temporal dynamic of soil erosion under different conditions of land-use change in mountainous areas of eastern DR Congo despite that it being reported as the primary cause of accelerated soil erosion during the 21st century is human activity and related land-use change (Borrelli *et al*., 2017). Unfortunately, there is a paucity of data on the impact of possible future land-use changes on water erosion in DR Congo. In addition, the impact of landscape structure on soil erosion dynamics has not been assessed yet despite that this information is crucial for conservation planning to cope with the problem of erosion. This lack of information leads to some uncertainty in the management of natural resources in DR Congo. Therefore, it is necessary to estimate the spatial-temporal dynamic of soil erosion under different scenarios of land-use change, climate projection, and management practices to identify priority measures for soil conservation planning in DR Congo.

2.7. MCDA approach as a tool for land evaluation

The land evaluation is defined as the process of predicting land performance, potential, and limitations for changing use over time according to specific types of use to guide strategic land use during the decision-making process (Nwer, 2005, Gebre *et al*., 2021). It includes the land suitability, land potential or capability analysis and land vulnerability analysis which are necessary in the spatial planning process for allocation of land to a specific use.

The determination of land suitability or land use potential implies the use of a range of biophysical and socio-economic information, the identification of criteria, their ranking, as well as an evaluation of the influencing factors before a decision can be made. The above steps are handled through a Multi-Criteria Decision Analysis (MCDA) approach based on qualitative and quantitative data. The integration of biophysical and socio-economic factors known to influence the future land use allocation in a GIS-based MCDA model can constitute a valuable tool in modeling future land use scenarios for resource planning and management (Nyeko, 2012, Kouriati *et al*., 2024). The prediction of the potential and limitation of land for changing use is necessary as it can guide strategic land-use decision-making (Nwer, 2005, Gebre *et al*., 2021) and prevent adverse impacts on natural resources.

The application of a quantitative approach in conservation planning can be challenging due to the paucity of available environmental data. Therefore, a combination of both quantitative and qualitative approaches is often required for systematic conservation planning of natural resources (Berliner, 2009). In this context, a rule-based modeling approach, like the MCDA approach, which integrated both quantitative analyses with qualitative expert judgments can be used to overcome the data scarcity challenge and to facilitate the incorporation of local and expert knowledge (Berliner, 2009). The integration of experts' judgments into an MCDA approach, which takes into account both direct biophysical and socio-economic factors in the land evaluation, can provide a rapid and cost-effective tool for identifying priorities areas for conservation, to perform land suitability analysis (Nwer, 2005) and to assess the effectiveness of land degradation responses for enhanced land use planning and restoration strategies (Pandit *et al*., 2020).

The MCDA is a valuable tool for decision-making in a data-poor context as it seeks to find a compromise solution that satisfices decision makers rather than an illusory optimum solution (Farashi *et al*., 2016). There are various ranges of MCDA approaches that have been applied around the globe to address different problems and to make the best decision in natural resource and environment management. However, the Analytical Hierarchy Process (AHP) was highlighted as one of the best MCDA approaches (Mardani *et al*., 2015). AHP involves the identification of criteria, their weighting and a paired comparison of criteria based on expert knowledge to derive a priority scale (Saaty, 2008). This method is robust, requires data that is easily obtained, and constitutes a flexible decision-making tool that can be used to find solutions to multi-criteria problems. It has been widely used in land resource use planning (Nyeko, 2012, Kouriati *et al*., 2024), land suitability analysis for the implementation of forest landscape restoration initiatives (Kadan *et al*., 2021), land suitability analysis for the implementation of agriculture (Herzberg *et al*., 2019), land degradation vulnerability analysis (Amdihun *et al*., 2014, Sandeep *et al*., 2021, Yadav *et al*. 2022, Mzuri *et al*. 2022, Tolche *et al*. 2022) and prioritization of conservation planning (Abuzaid *et al*., 2021). However, the MCDA is often criticized for arbitrary criteria selection and weighting based on experts' judgments as experts often differ in judgments and the accuracy of their judgment may also be difficult to determine (Berliner, 2009).

2.8. Theoretical and conceptual framework

2.8.1. Theoretical framework

Two theories related to the modification of the land degradation process are employed in this study: the system theory and the decision theory.

2.8.1.1. System Theory for conservation planning

The system theory is based on system thinking and considers the region as a system composed of different but connected components which are in constant flux (Checkland 1994; Faludi, 2013; Margules & Pressey, 2000). The relationship between the different components is dynamic, thus creating a positive or negative effect on the community. Therefore, from a planning perspective, the planner has a function to understand the relationships between the different components so that he can be able to guide, control and change their composition in specific ways to achieve certain objectives. To do this, the planning process is concerned with the prediction of the behavior of the system. For an effective control of the system, it is advisable to consider it as a whole, so that its dynamism can be controlled. An understanding of the system is important as it helps the planner to anticipate its dynamics holistically and plan accordingly (Hersperger, 1994; Faludi, 2013). In fact, in the system approach, there is an emphasis on the interactions between the components of the system and their interrelations by considering that everything is related to everything else. Based on this principle, it become possible to theorize and predict the dynamics of a system through the application of models which take into account the totality of elements (components) in the system under study, as well as their interaction and interdependence. It is in this context that the landscape scale spatial and conceptual models can be developed for conservation planning purposes. For instance, the systematic conservation planning (the process of locating and managing conservation zones with explicit objectives) constitutes an example of the application of the system approach (Margules & Pressey, 2000). This conservation planning approach can be used to identify new potential areas for conservation and to assess the effectiveness of existing protection measures (Hersperger, 1994; Margules & Pressey, 2000). It has been applied in the conservation of natural resources including water, soil, forest, and biodiversity.

The main advantage of the systems approach is that it gives a holistic view of the phenomena under study even in complexe landscape. Thus proving as an objective, transparent, and goal-oriented technique for conservation planning. However, the application of this approach requires a lot of data to model the system. The availability of low-cost satellite images constitutes an opportunity to apply the system approach for conservation planning in regions where data are scarce. Therefore, in this study, the system approach will be used to develop models of land degradation which take into account both the biophysical and socio-economic variables as independent variables to predict the most vulnerable area to land degradation where conservation actions should be prioritized at the landscape level in Eastern DR Congo.

The quantitative assessment of land degradation through geospatial and modeling approaches is necessary to control and manage the problem of land degradation at a landscape level. It is in this perspective that an assessment of land degradation that take into account all the dimension of ecological status and trend can be done based on the system theory of thinking. More specifically, the DPSIR (drivers, pressure, state, impact, response) approach (Carr *et al*., 2007; Obubu *et al*., 2022; Zhao *et al*., 2023) can be applied to determine the drivers and impacts of environmental changes (LULC change and land degradation for instance) on the community livelihoods at landscape level in the study area to suggest sustainable mitigation measures. In this context, the landscape is considered an open system that can be well understood only if all the components of the system are considered. Therefore, this study will focus on the ecosystem theory (Müller, 1997) which is one of the landscape ecology theories for a quantitative assessment of land degradation at a landscape scale level.

The landscape ecological approach focuses on the interrelation and heterogeneity of different components which define the landscape (Hersperger 1994; Menon & Bawa, 1997; Lee *et al*., 2009). In this approach, the landscape is characterized by three attributes: the structure of the landscape which represents the component of the ecosystem and refers to the variation of composition and configuration of the components of the landscape, the function that represents the flow of energy and material among the component of the system and the change representing the variation of the composition and function of the ecosystems over time (Walz, 2011). The landscape structure dynamics has an impact on the flow of ecosystem services (Hasan *et al*., 2020). As a result, there can be a degradation or aggradation of the land due to the changes in landscapes structure (composition and configuration). These changes can be apprehended by considering the landscape metrics or index. Therefore, it is possible to assess the relationship between the landscape structure and the land degradation dynamics. In the context of conservation planning, this study develops models to assess the relationship between the landscape characteristics, ecosystem service value, and soil erosion at a landscape scale level in eastern DR Congo. The developed models are essential in determining the optimal landscape structure and composition which can be adopted during the planning process to enhance the ecosystem service value and reduce the land degradation vulnerability in general and soil loss by erosion, in particular at the territorial level in this region.

2.8.1.2. Decision Theory for conservation planning

The decision theory is a set of methods or organized approaches for reaching optimal decisions by taking into account the uncertainty related to the initial conditions of the decision problem, the choice of actions to solve that problem, and the consequences of actions considered (Hansson, 1994). This theory requires clearly stated objectives, decision alternatives, and outcomes to allow the separation of values such as conservation and other societal objectives from beliefs. It can be applied in the domain of conservation and management of natural resources as they imply to make decisions on appropriate actions from a range of options (Dee & Gerber, 2012). For instance, the decision-makers need to know effective conservation actions by distinguishing the actions which work and the one that does not work. This assesment can be done through scenario planning (Amer *et al*., 2013). It constitutes an effective tool to make conservation decisions about how, when, and where to act based on our expectations for the future. It consists in using a set of contrasting scenarios or potential future conditions to explore the uncertainty surrounding the future consequence of a decision in a decision-making process (Peterson *et al*., 2003). The utilization of scenario planning is beneficial for conservationists as it increases the understanding of key uncertainties, helps to incorporate alternative perspectives into conservation planning, and presents greater resilience of decisions to surprise (Dee & Gerber, 2012; Peterson *et al*., 2003). The steps in the implementation of scenarios planning include the identification of central issues or problem, the assessment of the system, the identification of key alternatives, and the development of the alternative to building scenarios or predictions about what would happen if different future conditions came to be, testing scenarios and screen policies by selecting the plan which is more resilient based on the tested scenarios (Peterson *et al*., 2003). In the context of this study, based on the decision theory, the soil erosion dynamic under different LULC and conservation practices scenarios will be analyzed to determine the effective conservation option to be adopted. Furthermore, there is competition between different land uses options (agricultural production and conservation of forest for instance) in the highland of eastern DR Congo. To make an informed decision about the optimal land use allocation to either production or protection, this study relies on the decision theory to perform the land suitability analysis to determine the priority area for implementation of landscape restoration initiatives by using an MCDA approach.

2.8.2. Land degradation analytical framework

To understand the cause, and consequences and to provide mitigation measures for land degradation, this study will rely on a set of frameworks which include the sustainable development framework, the land degradation neutrality framework, the DPSIR framework, and the IPCC vulnerability assessment framework.

2.8.2.1. Sustainable development framework

The need to prevent land degradation and to restore the degraded land is of global concern. Therefore, since the Rio+20 conference in 2012 to the adoption of UN sustainable development goals in 2015, there is an am emphasis to tackle the land degradation problem which has increased. The restoration of degraded land is important as it presents many benefits such as the improvement of food security, the improvement of resilience to climate change, and biodiversity conservation. It is in line with the above that the combat against land degradation and desertification has been listed as goal 15 of the United Nations 2030 Sustainable Development Agenda. SDG 15 is to: "Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss" (Mohieldin & Caballero, 2015). More specifically, target 15.3 of this goal aims to: "By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought, and floods, and strive to achieve a land degradation-neutral word". To monitor the progress toward this goal, the 15.3.1 indicators ("Proportion of land that is degraded over the total land area") are used. Furthermore, SDG 15.4.2 which refers to the green cover index (Proportion of green cover) in mountainous landscapes constitutes a proxy for assessing the progress of conservation actions in highland landscapes which are prominent in Eastern DR Congo. From a conservation planning perspective, these indicators can be put in to assist in tracking the progress of land mitigation initiatives such as the REDD+ mechanisms through which the DR Congo has made commitment to stabilize its forest cover to 63.5% of the national territory by 2030 and to ensure that the Land Degradation Neutrality (LDN) will be reached by the year 2030. In addition to that, in the year 2022, through the 2022 UN biodiversity conference (COP 15), DR Congo adopted the post-2020 Global Biodiversity Framework (30 by 30 plan). This plan implies that, by the year 2030, there will be effective conservation and management of 30% of the world's lands, inland waters, and oceans, and the restoration of at least 30% of natural ecosystems. Currently, the DR Congo has made progress toward the conservation of its natural resources as 12% of its land has been converted to protected areas at a national level (Butsic *et al*., 2015). However, to reach the 30% percent target by the year 2030, an investigation of priority areas for conservation is needed and the effectiveness of conservation action should be assessed. In this context, the assessment of the land degradation status through a modeling approach constitutes assets to investigate the land condition and to predict its future pattern so that conservation actions can be implemented to ensure that the country aligns with the Sustainable Development Goals.

2.8.2.2. Land degradation neutrality (LDN) framework

Land Degradation Neutrality is defined as "a state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems" (UNCCD, 2016). The goal of Land Degradation Neutrality has been ratified in 2015 by the United Nations General Assembly as target 15.3 of the Sustainable Development Agenda which state: "By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought, and floods, and strive to achieve a land degradation-neutral world" (UN, 2017). The UNCCD has proposed that land degradation neutrality (LDN) should be integrated into the planning processes to avoid degradation in the land which are not degrading, implement sustainable management practices to reduce ongoing degradation, and reverse past degradation through restoration and rehabilitation practices in the land already degraded (Cowie *et al*., 2018; Sims *et al*., 2021; Feng *et al*., 2022). In a hierarchical perspective, the priorities of LDN imply avoiding, reducing, and reversing land degradation so that there is no net loss of the land-based natural capital between the baseline (reference's time, t_0) and the target date (t_1 which is set to the year 2030 which is the target date to achieve the SDGs) (Cowie *et al*., 2018). However, an inappropriate decision about land use or natural resource use that does not take into account the biophysical, and socio-economic aspects and their interactions can lead to the poor decision in the planning processes. Consequently, inappropriate land use allocation contributes to land degradation.

2.8.2.3. Driver-Pressure-State-Impact-Response (DPSIR) framework

The DPSIR framework was established by the European Environment Agency (EEA) in 1991 to provide an integrated approach that enables the policymaker to have feedback on environmental quality and impact resulting from political choices based on different indicators (Kristensen, 2004; Agyemang *et al*., 2007; Obubu *et al*., 2022). This framework assumes that causal-effects links is starting from the *driving forces* of environmental changes (biophysical and socio-economic factors which contribute to the increase or mitigation of pressure on the environment) through *pressure* (a set of proximate causes or direct anthropogenic pressure on the environment) to *states* (current state and condition of the environment determined by the extent and magnitude of land degradation) and environmental *impacts* (biological, social and economic effects of environmental changes on human and ecosystem) which can lead to *responses* (choices or what the society perceive that should be done, improved or mitigate to have a better environment) (Kristensen, 2004; Agyemang *et al*., 2007). The DPSIR framework constitutes an environmental impact assessment tool and it is useful for the establishment of environmental policies. This model is particularly useful in the assessment of land degradation (Agyemang *et al*., 2007; Gessesew, 2017; Zhao *et al*., 2023) and has implications for the elaboration of sustainable land management policies (Obubu *et al*., 2022). The DPSIR framework is illustrated on figure 2.2.

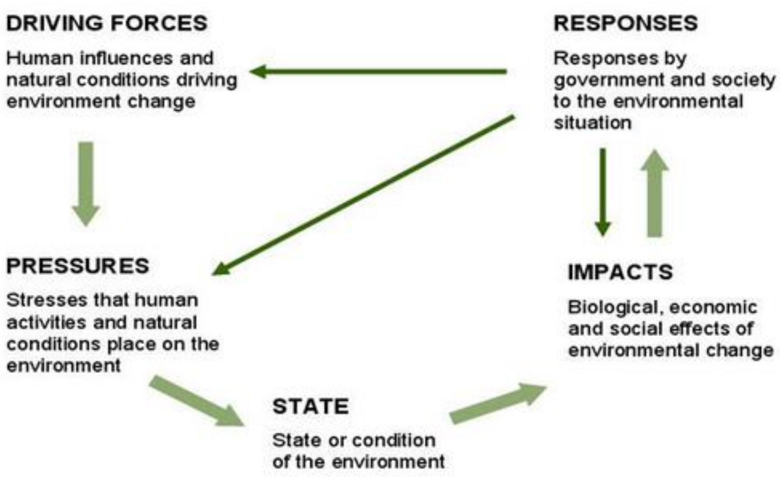


Figure 2.2: DPSIR framework for land degradation assessment.

Source: adapted from Kristensen (2004)

2.8.2.4. IPCC vulnerability assessment framework

The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as "the propensity or predisposition to be adversely affected" (Sharma *et al*., 2019). In their framework of vulnerability assessment (IPCC 2007; IPCC 2014) they consider vulnerability as a function of exposure, sensitivity, and adaptability (Sharma *et al*., 2019; Yu *et al*., 2021). The IPCC framework for vulnerability assessment was found to be useful in the identification of drivers of vulnerability and to find a way to reduce this vulnerability by acting on the drivers (Sharma *et al*., 2019). This framework has been used in many studies for the assessment of vulnerability to natural disasters (hydro-meteorological and geological) (Sharma *et al*., 2019, Zhao *et al*., 2020). The application of this approach has been found useful in the assessment of the spatial variability of vulnerability to natural disasters and the prioritization of actionable areas for adaptation (Sharma *et al*., 2019; Zhao *et al*. 2020). Although there are some advances in the assessment of land degradation risk, von Keyserling *et al*. (2023), based on an extensive review of literature on the approach for assessing the land degradation risk, found that there is currently no consistent conceptual framework for the assessment of land degradation risk. She advocates that a clear distinction between the different components of risk (hazard, vulnerability and risk) should be done during the assessment of land degradation as these concepts (hazard, vulnerability and risk) were used interchangeably in the previous studies. In this study, we will focus on the IPCC framework to develop a model for the assessment of land degradation vulnerability at the landscape level in the study area. Land degradation vulnerability is defined as the susceptibility of an area to lose productivity (Sandeep *et al*., 2021) due to a synergy of biophysical and socio-economic factors. It refers to the degree to which the land is suspected to be affected given the risk exposure. In the context of this study, we focused on the physical land degradation processes and adapted the IPCC concept to land degradation vulnerability assessment as follows: the risk exposure was defined as the degree to which the land and communities are exposed to the impact of ongoing physical degradation processes such as erosion, landslides, and flooding. Sensitivity is defined as the degree to which they could be harmed by that exposure considering the biophysical factors of vulnerability and adaptability as the capacity to respond, adapt, or reduce the exposure or sensitivity considering the socio-economics factors of vulnerability. Following the approach adopted by Zaho *et al*. (2020), in this study, the socioeconomic factors and accessibility factors are considered indicators of adaptability while the biophysical factors are considered indicators of sensitivity, and the risk of erosion is considered the indicator of exposure to define the overall land degradation vulnerability.

2.8.3. Conceptual framework

The framework of this study (Figure 2.3) is based on the system theory in general and the landscape ecological approach in particular. It considers that the land degradation (dependent variable) is caused by a synergy of biophysical and socio-economics factors (independent variables) which constitutes also the underlying drivers of landscape pattern (LULC dynamics and landscape structure) but its effects (alteration of ecosystem service and acceleration of dynamic of earth surface processes) can be accentuated or attenuated through the adoption or no adoption of appropriate policies actions against land degradation such as the implementation of sustainable land use management, adoption of conservation measures, landscape restoration and appropriate land use allocation (intervening variables). These variables are interconnected and constitute the component of a system that can be modeled to assess the outcomes of land use management options under different scenarios ("What if scenario” and “business as usual scenario”) for conservation planning purposes (identification of priority area for conservation, sustainable land use planning, determination of best conservation options).

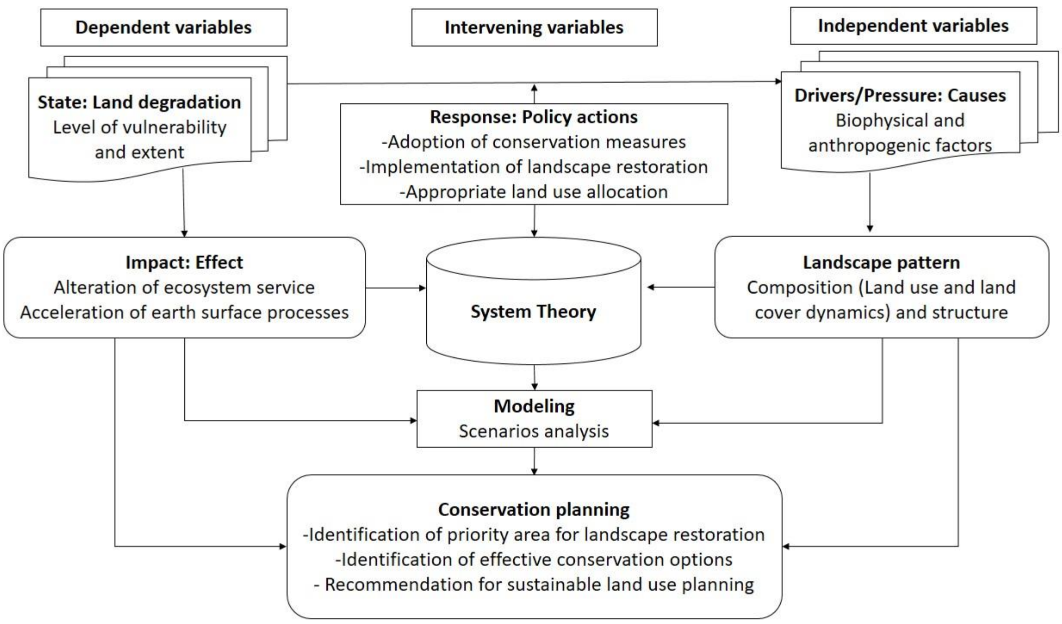


Figure 2.3: Conceptual framework of the study.

The definition and relation among the key concepts are presented below:

The landscape is a mosaic of ecosystems that can be represented by different LULC type and their spatial heterogeneity. The spatial arrangement, shape, and proportion of the ecosystem or LULC type represent the landscape pattern. The change in landscape patterns can affect the supply of ecosystem services. This change implies a flow of energy and matter between the human development systems and the environmental systems (Liu *et al*., 2020). Therefore, the resurgence of anthropogenic disturbance in the ecosystem can result in the alteration of ecosystem services and acceleration of the dynamics of the earth's surface processes. This degradation is the resultant of a synergy of natural causes (biophysical factors) and anthropogenic causes (socio-economic factors). The understanding of these causes and their interactions is essential for identifying appropriate policy actions to cope with the problem of land degradation. The non-adoption of these actions against land degradation will result in the acceleration of land degradation and its impacts on both human well-being and the environment. The ultimate goal of this framework is to develop models that predict the outcomes of the interactions among these factors based on the system theory in general and the landscape ecological approach in particular.

The landscape ecological approach refers to the pattern of the ecosystem, their interactions, the effect of these interactions on ecological processes, and the effects of spatial heterogeneity of these interactions (Grober-Dunsmore *et al*. 2009; Halbac-Cotoara-Zamfir *et al*. 2022). It is in this context that this study focuses on the analysis of the effects of the conversion of natural ecosystems (natural forest landscape for instance) into human-dominated systems such as agriculture, bare land, and human settlements expansion in eastern DR Congo. This transformation of the natural forest ecosystem due to anthropogenic activities is likely to alter the landscape in both the composition (LULC area) and the configuration (spatial pattern of patches). This landscape transformation affects the provision of ecosystem service and dynamics of the earth's surface processes such as erosion, surface water runoff, and sedimentation.

The understanding of the landscape transformation due to anthropogenic and biophysical factors as well as the response of the earth's surface processes to landscape pattern change and changes of ecosystem service in response to LULC dynamics can be apprehended through the system theory by considering that everything is related to everything else. It is in this framework that this study will develop realistic models for predicting the susceptibility of the transformation of natural forest landscape into the anthropogenic landscape as well as the response of earth surface process (erosion) and ecosystem service to this landscape transformation under different land use management scenarios ("scenario of adoption of conservation options" and "business as usual scenario"). These models can be applied in the planning process to identify priority areas for the implementation of landscape restoration initiatives, determine the most effective options for soil and water conservation, and determine the optimal configuration of the LULC for controlling the land degradation process. The outcomes of these model are essential for Sustainable Land Use Planning which consist of the selection of the appropriate land use allocation for a given biophysical and socio-economic conditions to achieve Sustainable Land Management.

Sustainable Land Management is the use of land resources (soil, water, biodiversity) in a way to maximize the production of goods and services to meet the needs of human beings while maintaining the long-term productivity of the land and enhancing their environmental or ecological support functions (Woodfine, 2009). The implementation of the sustainaible land management system is essential for reducing the vulnerability to land degradation, restoring or rehabilitating degraded land, and ensuring the sustainable use of land resources.

CHAPTER THREE

MATERIALS AND METHODS

3.1. Introduction

The previous chapter provided general information about the research topic and the theoretical and conceptual framework of the study. This chapter presents the study area and the methods that was adopted to reach the assigned objectives and to provide responses to the research questions outlined in chapter 1. This chapter is subdivided into two parts. The baseline information about the geographical and geological context of the Kalehe territory is first presented to justify its selection as a case study. Secondly, the research design, the data source, data tools, and the analysis approach adopted to solve the research question are detailed. Due to the complexity of the land degradation, a mixes approach combining remote sensing, GIS modeling, land users' perspectives through the semi-structured interview, and spatial modeling were used.

3.2. Study Area Description

3.2.1 Location of the study area

The Territory of Kalehe is located in the South Kivu province of the Democratic Republic of Congo. It is bounded in the north by the province of North-Kivu (territories of Masisi and Walikale), in the east by Lake Kivu, in the west by the territory of Mwenga, and in the south by the territory of Kabare (Figure 3.1). It is the 4th territory of the province in terms of area which is 5057km^2 representing 8% of the South-Kivu province surface. It is subdivided into two collectivities (chiefdoms) namely Buhavu and Buloho. The Buhavu chiefdom (collectivity) encompasses most of the territory with an area of 3535.25km^2. It is made up of 7 administrative groups (Groupement) which are Buzi, Kalima, Kalonge, Mbinga North, Mbinga Sud, Mubugu, and Ziralo villages. The collectivity of Buloho is made up of 8 administrative groups (Bitale, Ndando, Mulonge, Lubengera, Munyandjiro, Bagana, Musenyi, and Karali villages) and which covers only a small portion of the territory in its central part, representing some 546.52km^2.

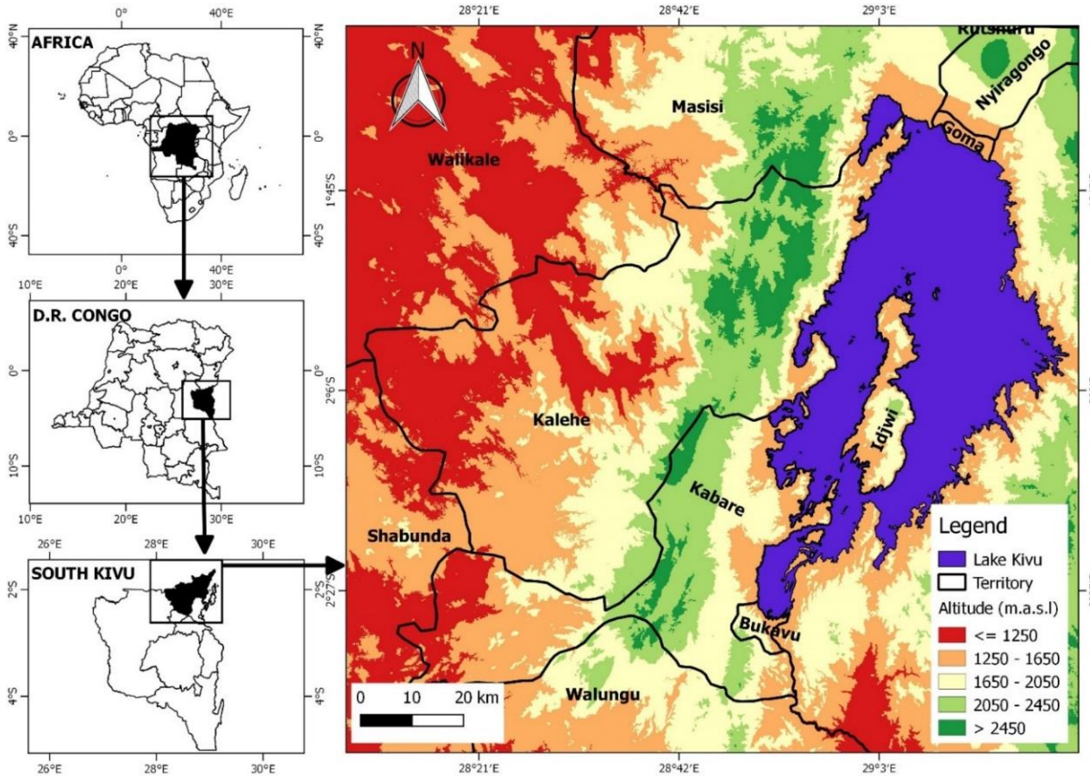


Figure 3.1: Localization of the study area.

For planning purposes, the territories of DR Congo are subdivided into health zones or health areas which represents a catchment comprising a population of approximately 50,000 to 100,000 people in rural areas and 100,000 to 250,000 people in urban areas. The health zone constitutes in the DR Congo the basic operational level for the organization, planning and development of health activities and humanitarian actions. A health zone is a well-defined geographical space, included within the territorial limits of a municipality or territory. The territory of Kalehe was subdivided into four health zone namely the Kalehe, Bunyakiri, Kalonge, and Minova. For this study, the analysis was done at the territorial level considering all territory of Kalehe and at a sub-territorial level, the health zones were considered as a case study.

3.2.2. Climate

The climate of the Kalehe territory is tropical but moderated by the altitude (Subtropical highland climate). It is characterized by the annual temperature ranging from 18 to 22ºC (USAID, 2018) and the annual rainfall varying between 1284 and 1970mm with a mean of 1720mm$\pm$ 145mm according to Wordclim data. The high precipitation regime is observed in the high plateau characterized by an altitude greater than 2000m in the eastern and southern parts of the territory where the annual precipitation rainfall is more than 1700mm. The climate is characterized by two seasons: the rainy season and the dry season (USAID, 2018). The region is characterized, especially in the Lake Kivu basin by a bimodal climate with two rainfall seasons per year. The first rainy season goes from March to May and the second from September to December (Karamage *et al*., 2016). In this region, there are 2 growing seasons: season 'A' which goes from September to December, and cropping season 'B' from February to May, and a short intermediate season from June to August favorable to market gardening (Blomme *et al*., 2020).

3.2.3. Soil

About the soil group classification of the Food and Agriculture Organization (Nachtergaele, 2017), three groups of soils characterized by different degrees of weathering are identified in the Kalehe territory: the acrisols characterized by subsurface accumulation of low activity clays and low base saturation, the ferrasols which are deep and strongly weathered soils with a chemically poor, but physically stable subsoil and cambisols which are weakly to moderately developed soils.

3.2.4. Vegetation and Biodiversity

Formerly, the territory of Kalehe was covered by diversified vegetation going from the meadow, and savannah to the dense forest. However, with the population explosion invading any natural forest in search of land for cultivation and pasture for livestock, there is deforestation leaving behind grassland and shrubs. The Kalehe territory is part of the Maiko-Tayna-Kahuzi-Biega ecological landscape. It contains the eastern part of Kahuzi-Biega National Park, a UNESCO World Heritage Site since 1980 (Kabonyi *et al*., 2011) and the southern part of the Forest Reserve of Sud-Masisi. The forest cover of the Kahuzi-Biega National Park is characterized by a stratified vegetation according to the variation of altitude (elevation). This national park surrounds the territory of Kalehe in its western and southwestern parts (Bunyakiri). The territory of Kalehe comprises high biological diversity area including the ecosystems of Lake Kivu and the ecological corridor of the Kahuzi-Biega National Park. These ecological landscapes are localized in the Albertine rift region (Western branch of East African Rift), one of the hotspots of biodiversity in Africa (Stattersfield *et al*.,1998; Burgess *et al*., 2004), which is home to endangered species such as lowland gorillas (*Gorilla beringei graueri*), chimpanzee (*Pan troglodytes*), and forest elephants (*Loxodonta africana*) as well as a rich and diverse flora (Crawford, 2017).

3.2.5. Geology

The geology of the Kivu region is characterized by Proterozoic formations and Phanerozoic covers (Ilunga., 1991, Lefévère, 2003). Proterozoic formations include those of the Ubendian-Ruzizian range (Paleoproterozoic); those of the Kibarian chain (Mesoproterozoic) and those of the Synclinorium chain of Itombwe (Neoproterozoic). The Phanerozoic formations include sedimentary covers and volcanic formations. In the territory of Kalehe, the alkaline complex and metasedimentary formations from the Itombwe synclinorium are characteristics of the Neoproterozoic. In this area, the Neproterozoic formation is essentially constituted by shales, diamictites (sedimentary rocks of glacial origin), and quartzites. The Mezoproterozoic formations are predominant in the area. They are constituted by the metasedimentary rocks of the Kibarian age, including pelites and quartzopelites, granite intrusions, and ring dykes. The Paleoproterozoic formations are located only in the western part of the territory. The Precambrian basement of Kalehe is composed of rocks such as schist, shale, sandstones, quartzite, granites, amphibolite, diorite, and pegmatite. The Phanerozoic formation of Kalehe is constituted by volcanic formations of the Cenozoic age belonging to the volcanic area of Cibinda-Kalehe in the East and the volcanic area of Kahuzi-Biega in the West (Ilunga, 1991). In the Cibinda-Kalehe area, the Cenozoique volcanic formation is constituted by basaltic rocks associated with the extension of the rift while the Kahuzi-Biega Massif is constituted by rhyolite and trachytes rocks.

3.2.4. Geomorphology

The relief of Kalehe is very rugged, such is characteristic of the western regions of the Kivu rift of the Democratic Republic of Congo. The relief is dominated by unevenness including mountains, hills, plateaus, steep slopes, and marshes that are crossed by streams. One can find small flat surfaces that are at the edge of Lake Kivu at the low bottom of towards the Western slopes of Mount Mitumba. The mountains of the Kahuzi-Biega surround the territory of Kalehe in its western part while the northern part is characterized by high plateaus (altitude >2000m) as opposed to the low plateaus (altitude <2000m) which border Lake Kivu to the east. Finally, in the southwestern part of the territory (Bunyakiri), there is a mountainous area adjacent to the Kahuzi-Biega Park. The geomorphology of this region is linked to the formation and evolution of the western branch of the Eastern African Rift. Therefore, the Kalehe territory is crossed by NE-SW oriented faults (Albertian orientation) and NW-SE oriented faults (Tanganyikian orientation) characteristic of the western branch of the East African Rift

(Ilunga, 1991, Lefévère, 2003). Additionally, there is an occurrence of N-S oriented fault in this territory.

3.2.6. Hydrology and drainage

The Kalehe territory is characterized by a high drainage density (Figure 3.2).

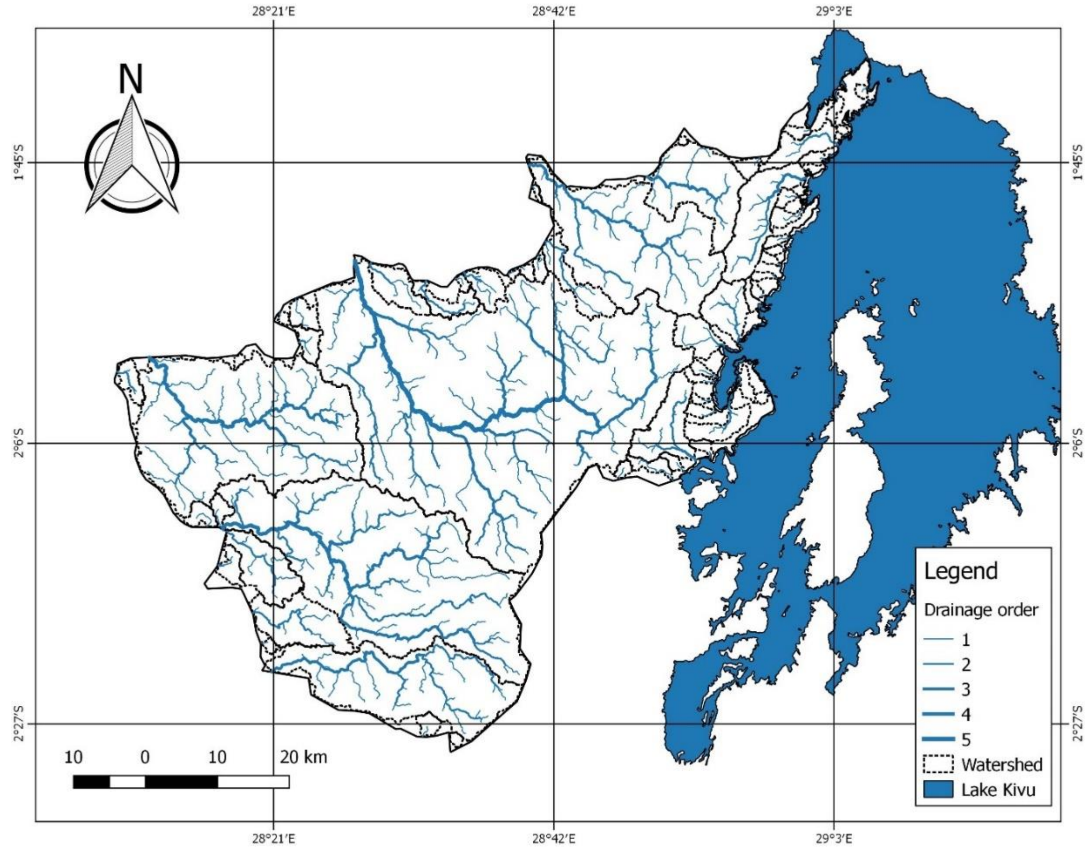


Figure 3.2: Channels network and drainage basins of the Kalehe Territory.

Apart from Lake Kivu, the territory of Kalehe benefits from a very rich hydrographic network of watercourses, some of which constitute the real exploitable potential for the production of electricity. Based on the analysis of SRTM-DEM, 59 hydrological basins (watersheds) were delineated in the Kalehe territory (Figure 3.2). These watersheds vary in size, stream order, and stream density as illustrated on Figure 3.2 and Table 3.1. The minimum size area of watershed is 1.35km^2 while the maximum is 1289.46km^2. The cumulative stream length of the entire territory of Kalehe is 1759.35km for an area of 4152.33km^2, implying that the drainage density at territorial level is about

0.42km/km^2. These watersheds have about 742 streams which vary in term of stream order ranging from 1 to 5 following the Strahler classification. The number of stream (stream count) and stream length of the same order decrease with the increase of stream order (Table 3.1).

Table 3.1: Stream number and stream length for the Kalehe territory.

Stream order	**1**	**2**	**3**	**4**	**5**	**Grand Total**
Stream number	400	186	99	30	27	742
Stream length	913.18	469.93	254.66	68.12	53.46	1759.35

3.2.8. Population and Demography

The Kivu region, located in the eastern DR Congo, is characterized by a high population density reaching 300 inhabitants/km^2 compared to the western part which has a density of around 30 inhabitants/Km^2 (Ngeleza, 2012). However, this population is unequally distributed spatially in this region. This population is concentrated along the coastal zone of Lake Kivu in the eastern part of the territory and the central part of the territory due to road accessibility and diversity of economic activities. However, the western part of the territory has the lowest population density due to the dense forest coverage (National Park of Kahuzi-Biega), inaccessibility, and insecurity. The total population is estimated, according to 2020 statistics of the population projected based on the 1984 census (the last which has been done at the country level), to be 856819 people who are inequally distributed in four health zones namely Kalehe, Bunyakiri, Kalonge, and Minova (Table 3.2). The annual increase rate of population in this territory is 3.3%[1].

[1] https://data.humdata.org/dataset/rdc-statistiques-des-populations, accessed on 30 May 2022

Table 3.2: Population distribution per health zone in Kalehe territory.

Health zone	Population 2019	Population 2020	Population 2021	Population 2022
Bunyakiri	223614	230993	238616	246490
Kalehe	177160	183006	189045	195283
Kalonge	168000	173544	179271	185187
Minova	260674	269276	278162	287341

The population of Kalehe is divided into six main communities: the Bahavu, the Batembo, the Barongeronge, the two Rwandophone communities (Hutu and Tutsi), and the Batwa (or Bambuti or Pygmies). The Rwandophones live in the high plateaus where the climatic conditions are favorable for their pastoral activities (raising cattle), while the other communities more generally live in the low plateaus: the Batembo are largely found in Bunyakiri, the Bahavu are mainly located in the low plateaus and the Batwa are scattered throughout the territory, but mainly in areas far from major centers. Finally, the Barongeronge lives in the Kalonge area, south of Bunyakiri. Note, however, that North Kivu communities such as Bahunde are also found in the territory of Kalehe, (mainly in Minova). Bashi and Barega populations are also present in the major agglomerations of this territory.

3.2.9. Economics activities

Agriculture, livestock, petty trade, and fishing are the main economic activities of the Kalehe territory. Currently, agriculture mainly concerns cassava, peanuts, beans, and oil palm. Small livestock is widespread throughout the territory, while the breeding of large livestock (cows) is currently a specificity of the high plateau. As for fishing, it is mainly done by the Bahavu populations of the territory's coast. As regards small-scale operations, the exploitation of wood is highly developed in the forest parts of Bunyakiri and Kalonge, while the exploitation of minerals such as cassiterite, gold, and coltan is carried out in several sites spread over the territory but particularly concentrated in the high plateaus of Kalehe (Numbi, Shanje, Nyabibwe, Katasomwa, Nyawaronga). The wood is mainly transported to the markets of Bukavu, while the minerals are brought either to Goma or to Bukavu depending on the origin of the traders and the agreements often contracted by these traders with the various purchasing counters in Goma and Bukavu. However, the isolation from which the territory of Kalehe suffers constitutes a serious disadvantage on the economic level: two national roads cross the territory, namely National Road 2 which connects Bukavu to Goma via the east of the territory of Kalehe (Groupements of Mbinga South, Minga North, and Buzi) and National Road 3 (NR 3) which connects Bukavu to Kisangani and crosses the western part of the territory (Bunyakiri and Kalonge). However, these two roads are in very poor condition.

3.2.10. Contextualization of land degradation in Kalehe territory

The territory of Kalehe, in the Eastern DR Congo, is full of numerous natural resources including forest land, wildlife biodiversity, fisheries resources, arable lands, and minerals resources. However, the overexploitation of these resources following the population growth, the aggressiveness of the climate coupled with the mountainous relief characteristic of the East African Rift region as well as the change in land use, make this territory vulnerable to land degradation problems. As a result, there is an increase in problems of erosion, landslides, and flooding in this area with catastrophic impacts. As an illustration, following heavy rains which fell between 2nd and 5th May 2023 in Luzira, Bushushu, Chabondo and Nyamukubi villages in Kalehe territory, the Lukungula rivers, Kabushungu and Kanyunyi came out of their beds as a consequence of high surface water runoff and heavy river siltation, leading to flooding, sinking mud and stones in the villages. This catastrophic flash flood event coupled with landslides and erosion led to the death of at least 411 people and the destruction of nearly 3,000 houses and six schools in Kalehe territory[2]. Furthermore, soil degradation through water erosion remains a danger for agricultural production in this area (Heri-Kazi, 2020), and forest degradation poses a threat to the biodiversity of this region. This region is also affected by landslides as a consequence of biophysical and anthropogenic constraints such as deforestation, population growth, associated with high demand of food and development of economic activities. These factors, in conjunction with conflicts as well as economics pull factors such as mining have constrained people to settle in steeper areas that are more prominent to erosion and landslides at the expanse of the natural ecosystem (Depicker *et al*. 2021). It is, therefore, more than urgent to determine the hotspots of land degradation in this territory to implement land conservation plans that take into account the specificities of this region. In this regard, this study is focused on modeling land degradation and earth surface process (soil erosion) under the current and possible future patterns of land use change to determine the priority area for conservation and to assess the effectiveness of conservation actions in the highlands landscapes of Eastern DR Congo by using the Kalehe territory as a case study.

3.3. Data Requirements and Sources

This study adopted a case study approach where both primary and secondary data were required to achieve its objectives.

[2] https://reliefweb.int/attachments/65f82d9e-c1ef-455f-a868-8a2dfe3bfdcd/Flash%20Update%205%20-%20Sud-Kivu_15%20juin_FINAL.pdf, accessed on 30 June 2023

3.3.1. Primary source of data

The primary source of data includes the ground truth survey about the land use type obtained through direct observation, and the data about the occurrence of erosion collected on the field and by analyzing of high-resolution images of Google Earth. Other primary data were acquired through the administration of a questionnaire (household survey) to collect information about the land users' perception of land degradation, the conservation practices, and the importance of each LULC type to providing ecosystem services.

3.3.2. Secondary source of data

The secondary data include the remote sensing images (Landsat images, Google Earth images, and Digital Elevation Model/DEM). The Landsat images and the DEM derived from Shuttle Radar Topography Mission (SRTM) was acquired from the USGS (United State Geological Survey) website[3]. Others secondary data were retrieved from national databases such as the Congolese National Forest atlas database from the Ministry of Environment and Sustainable Development[4] and the Référentiel Géographique Commun (RGC) for geographic data[5], the International Peace Information (IPIS) Open database of Artisanal mining Sites in D.R. Congo[6] from the International Peace Information System (IPIS) and Congolese Ministry of mining and the WorldPop Open Population Repository (WOPR) for population (demography) data[7], Regional databases such as the Soil and Terrain Database for Central Africa (SOTERCAF) and the Africa Soil Information Service (AfSIS) of the International Soil Reference and Information

---

3 https://earthexplorer.usgs.gov/
4 https://cod.forest-atlas.org/
5 www.rgc.cd
6 https://ipisresearch.be/
7 https://wopr.worldpop.org/?COD/Population

Centre (ISRIC) for soil data[8] and Global database such as the WordClim database[9] for climatic data. Furthermore, other relevant data were acquired through extensive reading from textbooks, journals, periodicals, seminar reports, newsletters, newspaper reports, dissertations, government documents, legislation, population data, workshop papers, and other relevant documents.

3.4. Research design

The correlational research design and quantitative analysis were used in this study to examine the relationship between independent and dependent variables according to the objectives of the study (Figure 3.3). The designed methodology of this study involves the utilization of a triangulated approach (mixed approach) that includes field observation, remote sensing, GIS, spatial modeling, and community perception (community truthing) on land degradation processes in the highland landscape of Eastern DR Congo.

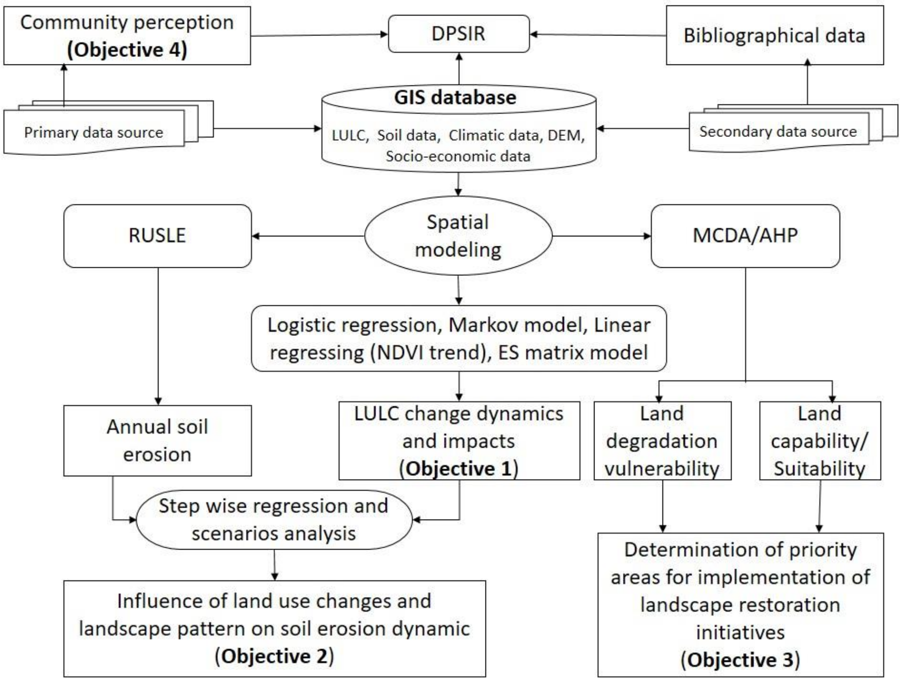


Figure 3.3: Schematic summary of methodological approach.

[8] https://data.isric.org/
[9] https://www.worldclim.org/

This research was performed in three stages. The first phase of the methodological framework is to use remote sensing data, field observation, and GIS techniques to analyze the spatiotemporal pattern of land degradation dynamics in terms of LULC changes, land productivity dynamics, ecosystem service supply dynamics, and soil erosion dynamics. For this stage, the multi-source data, either primary data from field observation (ground truth data about the LULC change and occurrence of land degradation features), or secondary data related to the climate, topography, soil, and socio-economic data retrieved from national and global geodatabase or analysis of satellite images (Landsat) were integrated into a GIS environment for geospatial analysis. The LULC dynamics during the 1987-2020 period were determined based on the change detection analysis of LULC maps derived from the supervised classification of Landsat images. The output of this analysis was used as a baseline to forecast the LULC changes for the 2030-2070 period under the business-as-usual (BAU) scenario using the Markov-chain simulation model. Before this prediction, a binary logistic modeling approach was used to quantify the underlying drivers of LULC change. The impact of LULC change on the dynamic of ecosystem service supply potential was assessed by using the ecosystem service matrix model. The analysis of land productivity dynamics during the 1987-2020 period was done through the trend analysis of Landsat-based NDVI time series by using the linear regression model for NDVI trend analysis. This analysis allows us to identify the area with a decreasing pattern of land productivity which depicts the occurrence of vegetation degradation processes and to identify its underlying drivers. The Revised Universal Soil Loss Equation (RUSLE) model (Renard *et al*., 1997) was used to simulate the risk of soil loss by erosion under different modes of land-use change and conservation scenarios. The multiple linear regression model was used to assess the spatial relation between the potential soil loss by erosion as dependent variables with landscape pattern metrics (structure and composition) as independent variables.

In the second stage, the Multi-criteria Decision Analysis (MCDA) approach was used to identify the priority area for implementation of landscape restoration initiatives based on land capability and land degradation vulnerability. This was done through the application of the Analytical Hierarchy Process (AHP) and by considering both the biophysical and the socio-economic factors.

In the third stage, the results of the GIS-based spatial modeling approach and community perception (community truthing) were triangulated using the DPSIR framework (Kristensen, 2004; Agyemang *et al*., 2007; Obudu *et al*., 2022; Zhao *et al*., 2023) to identify the driver, pressure, state, impact, and response toward the land degradation mitigation and sustainable land management. To achieve this, a participative research approach including informal interviews and a household-based questionnaire survey was used to collect information about the local knowledge (community perception) on the causes, consequences, and strategies that they have adopted to cope with the problem of land degradation in their entities. Both quantitative and qualitative data regarding the experience of the local community on land degradation were collected during the household interview. The perception data were analyzed using descriptive and inferential statistics in Excel, SPSS, and R. The socio-economic determinants factors of this perception were determined using the binary logistic regression model.

3.5. Materials and equipment

This section presents the data collections tools and data analysis tools adopted in this study.

3.5.1. Data collection tools

Remote sensing tools such as Landsat images covering the 1987-2020 period, the Digital Elevation Model derived from SRTM (Shuttle Radar Topography Mission) data, and Google Earth images were used for a quantitative assessment of the spatiotemporal dynamics of landscape in the study area. A structured questionnaire consisting of closed-ended questions was used for the collection of information about the land user perspective on LULC change and land degradation. The evaluation or assessment matrix was used to assess the perceived ecosystem service value of the LULC using a Likert Scale ranging from 0= Not important (no service provided) to 3= Very important (high service). The Global Positioning System (GPS) and camera were used during the field observation. Field visits involved the observation of land use type, land degradation features, and conservation practices in the area. Direct observation and photographs were used for the validation of information provided by remote sensing tools and to obtain some points that were not captured during the questionnaire interviews. The secondary data information was acquired through document analysis and national, regional, and global databases.

3.5.2. Data analysis tools

For the spatial data analysis, the QGIS (Quantum GIS Development Team 2022) and SAGA GIS 7.8.2 software were used for handling, preparing, and visualization of the spatial data. The Monteverdi-Orfeo Tool Box (OTB)-6.0.2-Win64 was used to perform the supervised classification of Landsat images by using the random forest algorithm. The Modules for Land Change Modeler (LCM) of TerrSet 20 software (formerly known as IDRISS) was used to simulate the future land-use change while the Fragstat software was used to calculate the landscape metrics, Finally, the Easy AHP module of QGIS which provides Analytic Hierarchy Process (AHP) and Weighted Linear

Combination (WLC) analysis in QGIS was used for the development of Multi-Criteria Decision Analysis based models. The R software (R Core Team 2022) and SPSS 16 were used for the statistical analysis and development of regression models. Apart from the LCM, the MCDA models based on the AHP approach, and regression models, and the RUSLE model was also used for the simulation of soil loss to erosion under different conditions of land-use change and management practices.

3.6. Description of data sets and collection procedure

3.6.1. Land degradation features data

In the framework of this study, the mass movement features such as erosion and shallow landslide were considered as a proxy of physical land degradation. The inventory of mass movement features was based on documentary data from the shallow landslide inventory database for North Tanganyika-Kivu Rift Region (eastern DR Congo, Rwanda, and Burundi) which contains 7944 shallow landslide features for the 2000-2019 period (Depicker & Dewitte, 2021), direct observation in the field and through 3D visualization in Google Earth Pro.

3.6.2. LULC data

Field observation was conducted to collect data about the LULC type. The main LULC type was described in the field and their geographic coordinates were captured using a GPS Garmin 64S with an accuracy of 3m. Subsequently, the high-resolution images of Google Earth were used to complete the information on LULC collected in the field. This data was used as control points for the classification of Landsat images and the accuracy assessment of the LULC maps. Seven (7) land use types were considered in this study: forest land, cropland, grassland, shrub land, bare land, settlement, and wetland (Figure 3.4).

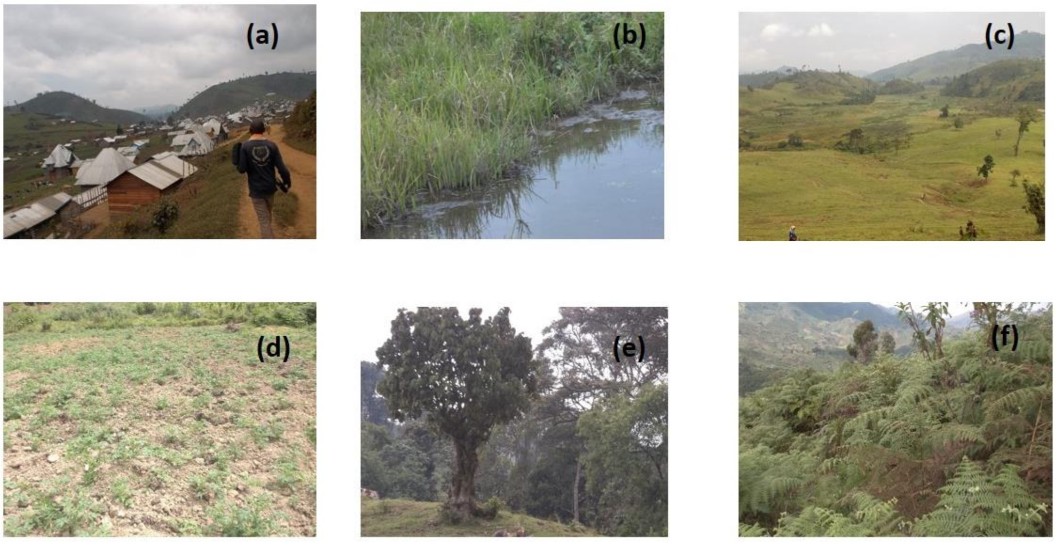


Figure 3.4: Land use and land cover type in Kalehe territory.

A. Built-up area B. Wetland C. Grassland D. Cropland E. Forest F. Shrub land.

3.6.3. Landsat data

Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) for the year 2020 acquired from the USGS Earth Explorer website[10] and available in the Google Earth Engine platform were selected for the for the1987, 2002 and 2020 years respectively. The choice of the year was constrained by data availability based on the cloud coverage constraint (< 15% of cloud coverage). The Landsat 7 ETM+ acquired after the year 2003 was avoided due to imperfection observed in the images because after this date the Scan Line Corrector (SLC)[11] fails. Only Landsat Collection 2 Level 2 images with minimum cloud coverage of less than 15 percent were selected. This threshold of 15 percent was adopted in this study despite that some authors think that the cloud cover should be less than 10 percent (Zaidi *et al*., 2017). However, the study area is located in a tropical region which is covered by clouds most of the time (Basnet & VodaceK,

---

[10] https://earthexplorer.usgs.gov/, accessed on 10 December 2022
[11] https://www.usgs.gov/faqs/what-landsat-7-etm-slc-data , accessed on 17 December 2022

2015) and it was hard to get images with less than 10 percent of cloud-free images covering the entire study area which falls over four sets of Landsat scenes (path/row: 173/061, 173/062, 174/061 and 174/062). Therefore, a cloud coverage of 15 percent which has been adopted in other tropical areas (Zaidi *et al*., 2017) was used in this study. These images have a spatial resolution of 30 m and have been projected in the system WGS 84 (ESPGS: 4326, UTM Zone 35S).

3.6.4. Climatic data

Climatic data variables were derived from the WorldClim database for the long-term average precipitation. The Wordclim database consists of monthly total precipitation, monthly mean, minimum and maximum temperature, and 19 derived bioclimatic variables with a spatial resolution of 30 arc seconds (1km). These climatic data have a resolution of 1km and represent the average monthly climatic data from 1950 to the nearly recent period (Fick and Hijmans, 2017).

3.6.5. Topographic and hydrological data

The Digital Elevation Model (DEM) derived from the void-filled Shuttle Radar Topography Mission (SRTM) version 3 with 30m of spatial resolution (1 arc-second) from the United States Geological Survey (USGS) Earth Explorer website[12] was used to determine the topographic factors such as the altitude, slope, Topographic component index/Topographic wetness index, Aspect and the implementation of the watershed and stream analysis. The SRTM data were used to delineate the watershed in the study area, determine the morphological characteristics of the watershed, and generate a stream network. Before the extraction of hydrological parameters, the SRTM data was corrected by filling the sink and modifying elevation values to remove drainage discontinuity and imperfection in the data. After that, the flow direction, flow

[12] http://earthexplorer.usgs.gov

accumulation, slope, and other hydrological processes were computed using the hydrological function of SAGA GIS 7.8.2 to extract the drainage network and delineate the watershed in the study area. These watersheds derived from the analysis of SRTM-DEM was considered as the planning unit or hydrological response unit in the context of this study.

3.6.6. Soil data

Soil data was compiled from the Soil and Terrain Database for Central Africa (SOTERCAF) available at the ISRIC website[13] and compiled by the FAO (Batjes, 2007). This database includes a shapefile of soil units whose attribute table contains soil properties of Central African countries (DR Congo, Burundi, and Rwanda) that were compiled by different organizations from 1940 to 2001 (Batjes, 2007). The physicochemical properties of the soil were extracted from the Africa Soil Information Service (AfSIS) database[14] with a spatial resolution of 250 m (Hengl *et al*., 2015).

3.6.7. Demographic data

The demographic data (population density) from the WorldPop Open Population Repository (WOPR) (WorldPop - School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville; Departement de Geographie, Universite de Namur) and Center for International Earth Science Information Network (CIESIN), Columbia University (2018)) available at WordPop website[15] for the year 2020 was used in this study to estimate the spatial dynamics of the population. This data has a spatial resolution of 1km and contain the total population count per squarekm. It was collected through micro census and metrics derived from building footprints. Data collection was led by

[13] https://data.isric.org/
[14] https://www.isric.org/projects/africa-soil-information-service-afsis
[15] https://wopr.worldpop.org/?COD/Population

the Flowminder Foundation, the École de Santé Publique de Kinshasa, the WorldPop Research Group at the University of Southampton, and the Bureau Central du Recensement, which is part of the Institut National de la Statistique (INS) of DR Congo (Boo *et al*., 2021).

3.6.8. Geographic and socioeconomic data

The spatial data about the roads, rivers, mining concessions and permits, forest concession, protected area, community management area (community forest reserve), and majors centers (villages, ports) was derived from the Forest Atlas of DR Congo[16] elaborated in 2018 by the Ministry of Environment and Sustainable Development (MESD) of DR Congo and the Referential Geographic Commun (RGC) database[17] compiled by a different humanitarian organization working in DR Congo. The data about the location of the artisanal mining sites were derived from the International Peace Information (IPIS) Open database of Artisanal mining Sites in DR Congo[18] elaborated by the IPIS and Mining Ministry of DR Congo in 2018.

3.6.9. Data harmonization

The multisource spatial data in digital format (raster or vector) retrieved from different databases were clipped to the extinct of the study area. As they have different spatial resolutions, they were harmonized at a 30 m cell of spatial resolution through the nearest neighbor resampling method and re-projected to the Universal Transverse (UTM) (zone 35S) map projection and coordinate system, the Word Geodetic System 1984 (WGS84) datum and spheroid. The function *align*s raster available in QGIS 2.18 was used for this purpose. The continuous and categorical variables were spatialized

[16] https://cod.forest-atlas.org/
[17] www.rgc.cd
[18] https://ipisresearch.be/

(alphanumeric variables), and standardized (legend of classes and uses), and the vector data were rasterized with a pixel size of 30 m.

3.6.10. Land user's perception data

The semi-structured household questionnaire was used to assess the land user's perception of land degradation with an emphasis on forest degradation and erosion, the perceived ecosystem value of each land cover, and the drivers of changes that occurred during the study period (1987-2020). The questionnaire consisted of the socio-economic characteristics of the households, the perception of the degradation of farmland, the perception of degradation of forest land, the perception of erosion and adoption of conservation practices, and the perception of change in the supply of ecosystem services regarding LULC change-related questions. A semi-structured questionnaire that contained closed and open-end questions was used to obtain the information on these attributes. Before the data collection, a pilot survey was done in the field and four field assistants (enumerators) were trained to understand the logic of the questionnaire. The pilot survey was realized for pretesting the household questionnaire and to familiarize with the study area landscape. A total of 31 households were selected randomly in the territory of Kalehe to pretest the questionnaire. This pilot survey helped to readjust the questionnaire as various items which were inconsistent and unnecessary were removed. Furthermore, some questions were reformulated to make them clear in eliciting desired information in according to the purpose of the study. From a data collection perspective, the questionnaire was translated into French language and four enumerators who live in the area, and know both French and at least one local community's language (Kihavu, Mashi, Kirongeronge or Kiswahili) was recruited and trained in data collection. Each household interview had a duration between 40 minutes and 60 minutes. The collection of data was done in 2 months (July and August 2022). Before doing the server, the purpose of the study was explained to the respondent and the verbal consent was requested to participate in the study. To avoid incomplete questionnaires, during the interview, if the person failed to respond to questions or refuse to continue to respond, at any time, the interview was stopped and the respondent was replaced until the target number was attained.

3.6.10.1. Target population

The targeted population comprised all the land users (inhabitants) of the territory of Kalehe who were estimated to 856 819 people in 2020[19]. This population is distributed into four health zones namely Kalehe, Bunyakiri, Minova, and Kalonge as earlier seen in Table 3.2.

3.6.10.2. Sample size

The sample size was estimated using the equation 3.1 proposed by Kothari (2004):

$$n = \frac{Z^2pqN}{e^2(N-1)+Z^2pq} \quad \text{(Equation 3-1)}$$

where n= the number of households to be interviewed (sample size), Z equal to 1.96 is the score at 0.95 level of significance from the normal curve, e equal to 0.05 is the precision desired, p is the expected proportion of household having the knowledge of land degradation and conservation practices in the area and q= 1-p is the expected proportion of household who don't have this knowledge, N is the total number of the population and equal to 857 012. Since p is not known in the area, a value of p=q=0.5 was considered. Therefore, the estimated number of households to be considered for the interview is

$$n = \frac{(\mathbf{1.96})^{\mathbf{2}}\boldsymbol{X}\mathbf{0.5}\boldsymbol{X}\mathbf{0.5}\boldsymbol{X}857012}{\mathbf{0.05^2}(857012-1)+(\mathbf{1.96})^{\mathbf{2}}\boldsymbol{X}\mathbf{0.5}\boldsymbol{X}\mathbf{0.5}} = 384 \text{ households.}$$

[19] https://data.humdata.org/dataset/rdc-statistiques-des-populations , accessed on 30 May 2022

These households were distributed proportionately to the four Health Zones as can be seen in Table 3.3.

Table 3.3: Targeted population and sample size per health zone and collectivity.

Health zone	Sampled village	Population 2020	Sample size	Proportion (%)
Bunyakiri	Kalima	230993	103	26.8
Kalehe	Mbinga Sud	183006	82	21.4
Kalonge	Kalonge	173544	78	20.3
Minova	Mbinga Nord	269276	121	31.5
Total		**857012**	**384**	**100**

The criteria for the selection of households to be interviewed are described in the next section.

3.6.10.3. Sampling selection

The sample selection of the target population was done through a multi-stage cluster sampling which is a random sampling approach. The territory of Kalehe was purposively selected as it is one of the highland areas which is affected by land degradation (forest degradation, landslides, and soil erosion) in eastern DR Congo (Maki, 2014, Heri-Kazi, 2020). In the first stage, the four health zones of the Kalehe territory (Kalonge, Kalehe, Bunyakiri, and Minova) are considered clusters (groups). In the second stage in each health zone, one village was selected according to accessibility and security criteria (Figure 3.5).

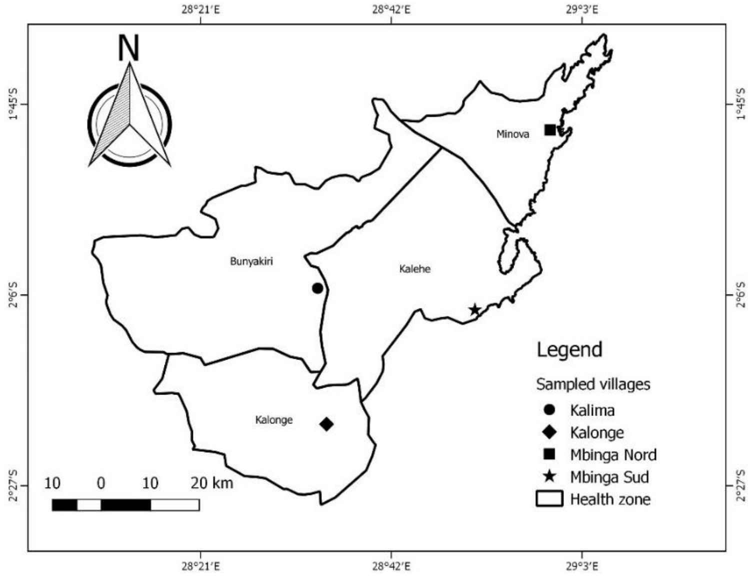


Figure 3.5: Location map of the selected villages for the household survey.

In the third stage, in each village, several households were randomly selected proportionally to the total population of the health zone (Table 3.3). In the last stage, the choice of the household was done through a systematic random sampling technique by the enumerator to conduct the interviews. Therefore every 3rd household head who meet the inclusion criteria was interviewed. At the household level, the questionnaire was administrated only to the household or family head who have an age which is above 20 years and has lived in the area for at least 10 years by assuming that in 10 years, a person can still remember the important events which have contributed to the evolution and modification of the natural environment. Furthermore, these inclusion criteria were adopted in the context of this study because the process of land degradation is slow. Thus, people who have lived in an area for a long time can potentially experience it. The questionnaire was administrated only to the household head or family head as they are the decision-maker in the household.

3.7. Data analysis and processing

3.7.1. Analysis of the spatiotemporal dynamic of LULC change

The analysis of the spatial and temporal dynamic of LULC changes has been done through the application of the following steps as illustrated in Figure 3.6: (1) Landsat images preprocessing to obtain cloud-free images composite using the Google Earth Engine and supervised classification to obtain LULC maps for the 1987-2020 period, (2) accuracy assessment of image classification based on the ground truth data collected on field by using the GPS and through observation of Google Earth images, (3) analysis of past trend of LULC changes during the 1987-2020 period, (4) LULC change susceptibility modeling using the logistic regression model and identification of its underlying drivers, (5) Accuracy assessment of LULC projection model based on the observed and simulated LULC map for 2020 using the Markov-SVM model, (6) Future LULC projection for the 2030-2070 period.

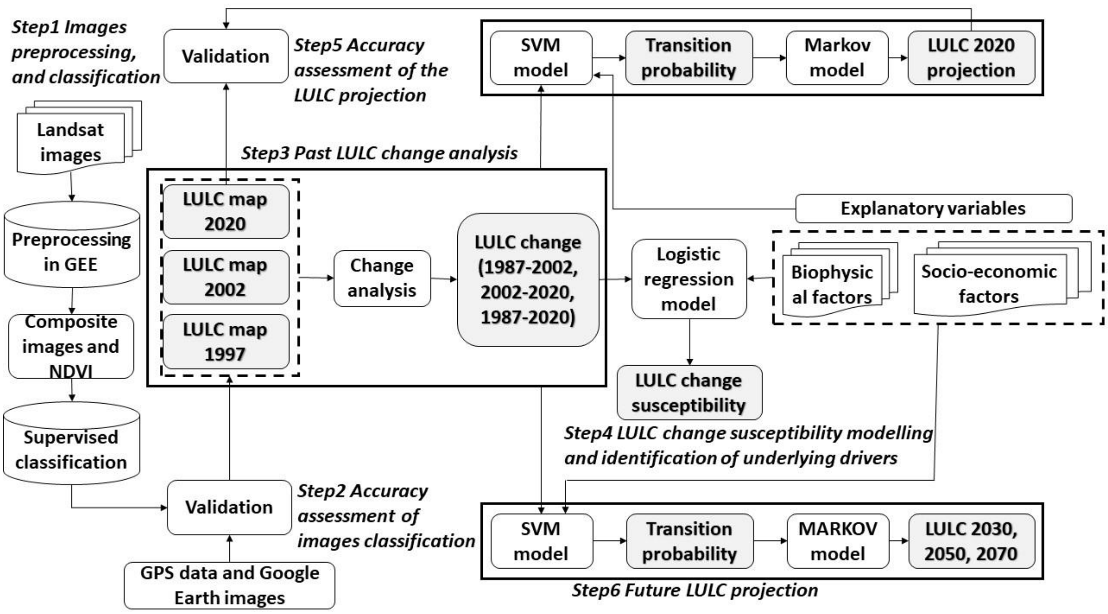


Figure 3.6: Methodological framework applied in the analysis of LULC dynamics.

3.7.1.1. Images preprocessing

The Landsat images used in this study belong to the Landsat Collection 2, Level 2 surface reflectance which was preprocessed for geometrical correction and atmospheric correction (Xu *et al*., 2021) when downloaded from the USGS website[20] . The surface reflectance of the Landsat Level 2 Collection 2 (Landsat L2 C2) sciences products was generated based on data from Landsat Collection 2 level 1 products by using the Landsat Ecosystem Distribution Adaptive Processing System (LEDAPS) algorithm (Version 3.4.0) for Landsat 4-5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (ETM+) while the Land Surface Reflectance Code (LaSRC) algorithm (Version 1.5.0) was used for the Landsat 8 Operational Land Imager (OLI). Furthermore**,** for the enhancements of surface reflectance a scaling factor of "0.0000275 × DN − 0.2" for the optical bands and "0.00341802 × DN + 149.0" where DN is the Digital Number or pixel value[21] was applied to convert the DN value into surface reflectance. Subsequently, the cloud was masked on the selected images using the QA bands, and shadows were masked using the sum of the specified bands (nir, swir1, and swir2') of Landsat L2 C2. Then the annual composite was obtained by using the 50% percentile (Median value) of all pixel values obtained from the atmospherically corrected and cloud-masked Landsat surface reflectance images. For all these steps, the workflow for preparing and exporting annual Landsat cloud-free images in GEE (Google Earth Engine) developed by the Geospatial Technology and Applications Center (GTAC, 2002) of USDA (US Department of Agriculture) was used. The final composite contains the standard Landsat bands (blue through swir2). The output is a

[20] https://earthexplorer.usgs.gov/, accessed on 10 December 2022
[21] https://www.usgs.gov/core-science-systems/nli/landsat/landsat-collection-2-level-2-science-products, accessed on 28 December 2022

mosaic of bands 1, 2, 3, 4, 5, 6 and 7. In addition, the NDVI bands scaled by 10,000 and namely p10NDVI (the tenth percentile NDVI value scaled by 10,000), p50NDVI (the fiftieth percentile NDVI value scaled), and p90NDVI (the ninetieth percentile NDVI value) were used to assess the quality and assist in the classification of images. The annual Landsat multiband composites were mosaicked and clipped according to the geographical extent of the study area with a shape file of the administrative boundary of the Kalehe territory.

3.7.1.2. NDVI analysis

The NDVI was derived from Landsat images to quantify the trend of vegetation and land productivity over the 1987-2020 period. The NDVI consists of calculating a ratio between the pixel values of red bands and the near-infrared of the same image. It is based on the fact that vegetation reflects very little in the red and is very strong in the near-infrared. This calculation is very effective in determining the presence of vegetation, but also to assess the importance of plant biomass and the intensity of photosynthetic activity. The NDVI is computed using the equation 3.2:

$$NDVI = \frac{\mathrm{LIR-LR}}{\mathrm{LIR+LR}} \text{ (Equation 3-2)}$$

where NDVI = Normalized Difference Vegetation Index bounded between -1 and +1, LIR = the spectral luminance at the sensor measured for infrared band or near-infrared Landsat band 4 (0.77–0.90 µm) for Landsat 5 TM, Landsat 7 ETM+ and bands 4 (0.64–0.67 µm) and 5 (0.85–0.88 µm), respectively of Landsat8 OLI/TIRS spectral wavelengths, LR = the spectral luminance at the sensor measured for red band or visible red Landsat band 3 (0.63–0.69 µm) (Fokeng *et al*., 2022). For the time series data, the annual composite NDVI data archived in the Google Earth Engine catalog was considered.

3.7.1.3. Satellites images classification

The annual composite Landsat was used to analyze the LULC for the entire study area. The images from 1987, 2002, and 2020 were considered for this analysis. The images were processed employing the false-color composite by combining different bands of the Landsat images for the first interpretation before the image classification. The False-color composite RGB (Red, Green, Blue) was used to discriminate the characteristic or spectral reflectance of earth surface materials like vegetation, water, bare land, etc. For the Landsat 5 TM (Thematic Mapper) and Landsat 7 ETM+ (Enhanced Thematic Mapper Plus), the RGB band composition is 3-2-1 was used whilst for the Landsat 8 OLI (Operational Land Imager) the RGB band 4-3-2 was considered. The ground truth points about the LULC collected on the field and through the high-resolution image of Google Earth was used for the classification of Landsat images and accuracy assessment of classification. The reference data generated were used to define the spectral class and to check if the reference data are matching with the false-color composite for LULC classification. Based on ground data about the main LULC type observed in the area through field survey utilizing the Global Positioning System (GPS), the analysis of high-resolution Google Earth images and the visual interpretation of the false color composite RGB, a total of 238, 238 and 240 referencing's zones were gathered for 1987, 2002 and 2020 years, respectively, to perform a supervised classification of Landsat images and to confirm the accurateness of the LULC maps. The Random Forests Classifier algorithm of supervised classification was used to establish the LULC map for each period. The Landsat composites images and the training area were carried out in the Monteverdi-Orfeo Tool Box (OTB)-6.0.2-Win64 software to perform the LULC classification. A training and validation sample ratio of 0.5 was applied. Following the recommendations of Gao (2009) for Landsat image classification, a minimum of 5 to 10 polygons is considered as training samples for each LULC class. Therefore, the minimum number of samples in each LULC class considered in this study was 10. Furthermore, a maximum of 2000 trees was considered to perform the Random Forests classification of LULC. All pixels of the Landsat image were assigned to a LULC class based on the first order Land use classification scheme of Anderson *et al*. (1976). Consequently, 7 LULC classes were considered according to field observation: wetland, forestland, grassland, shrubs land, cropland (agriculture), bare land (fallow land), and settlements (Built-up area). After the classification, the majority filter (3x3 pixel size) was applied to the LULC map to eliminate the isolated pixels in the final maps.

3.7.1.4. Accuracy assessment of the satellite's images classification

The evaluation of the agreement between the LULC type on the classified images and ground truth observation was done through an accuracy assessment as image classifications usually contain some errors. For the accuracy assessment of the output classification, 50% of the referencing data obtained from field observation and Google Earth images were randomly selected. Based on this data an error or confusion matrix for 1987, 2002, and 2020 years, generated in the Monteverdi-Orfeo Tool Box (OTB)-6.0.2-Win64 software, was used to evaluate the accuracy of LULC classification. Four indices were used: the percentage of user's accuracy representing the probability that a predicted value to be in a certain class is truly in that class (the number of reference points which are correctly classified divided by the total number of reference points classified within that class), the producer's accuracy which represents the probability to classify a value in a class correctly (the total number of correctly classified reference points by the total number of reference points truly in that class), overall accuracy (sum of the number of correctly classified values divided by the total number of values) and the Kappa indices. Thus, the following formula was used to compute the user accuracy (UA), producer accuracy (PA), and overall accuracy (OA):

$$UA = \frac{C_{aC}}{C_C} * 100 \text{ (Equation 3-3)}$$

$$UA = \frac{C_{aR}}{C_R} * 100 \text{ (Equation 3-4)}$$

$$OA = \sum_{a=1}^{n} \frac{C_{cc}}{T} * 100 \text{ (Equation 3-5)}$$

With, C_{aC} the number of correctly classified reference points for a given class, C_C is the total number of reference points considered within that class, C_{aR} is the total number of reference points correctly classified in that class, C_R is the total number of reference points in that class, C_{cc} is the total number of reference points that are correctly classified, and T is the total number of reference points in the error matrix.

The Kappa indices vary between 0 and 1, with a value less than 0.4 indicating a poor agreement while a value between 0.4 and 0.8 indicates a moderate agreement and a value higher than 0.8 denotes a strong agreement (Mishra *et al*., 2016). Considering the rows number in the confusion matrix (r), the number of diagonal elements observed in row I and column i (Xii), the totals for rows i (X+i), the total for column i (Xi+), and the number of observations N, the Kappa index (K) is calculated using the equation (Lucia *et al*., 2019):

$$K = \frac{N * \sum_{i=1}^{r} Xii - \sum_{i=1}^{r} (Xi+) * (X+i)}{N^2 - \sum_{i=1}^{r} (Xi+) * (X+i)}$$

$$= \frac{(Total * sum\ of\ correct) - sum\ of\ all\ the\ (row\ total * column\ total)}{Total\ squared - sum\ of\ all\ the\ (row\ total * column\ total)} \text{ (Equation 3-6)}$$

3.7.1.5. Analysis of LULC change

The method of post-classification comparison was applied to analyze the LULC change in the three time periods (1987, 2002, and 2020). The LULC maps for consecutive periods were cross-tabulated and compared to each other to have a vision of the LULC changes patterns for the 1987-2002, 2002-2020, and 1987-2020 periods. The surface was calculated using the Semi-Automatic Classification Plugin (SCP) of QGIS (Congedo, 2016; Pereira *et al*., 2019). A subtraction of the surface covered by a specific LULC (in ha) type at the initial period (A_0) and the final period (A_1) was used to assess the change in the area. Using the initial area as a reference, the difference of surface was converted to assess the temporal change (TC) in percentage during the entire period by using the equation 3.7 (Ebrahim *et al*., 2017). Subsequently, considering the time interval T (in years) between A_0 and A_1, the rate of changes (RC) for different LULC categories was estimated in ha/year using the equation 3.8 and the annual rate of change (AC) in percentage/year using the equation 3.10. This later equation is specifically used to determine the annual rate of deforestation (Temesgen *et al*., 2014, Ebrahim *et al*., 2017, Shirvani *et al*., 2017).

$$TC(\%) = \frac{A_1 - A_0}{A_0} * 100 \text{ (Equation 3-7).}$$

$$RC\ (Ha/year) = \frac{A_1 - A_0}{T} \text{ (Equation 3-8)}$$

$$AC\ (\%/year) = \frac{A_1 - A_0}{A_0 * T} * 100 \text{ (Equation 3-9)}$$

Furthermore, to quantify the overall LULC gains and losses, the transition maps and cross-transitions matrices were generated. This analysis helps us to determine the persistent area (area characterized by no change for a specific LULC type) located at the diagonal of the matrix, the gross gain (the total area which was converted to a specific LULC class) which is calculated as by deducing the persistence through the column total, and the gross loss (total area of specific LULC classes which was converted to other LULC classes) which is calculated by deducing the persistence through the rows total for each LULC categories. The net change was obtained through a difference between the gain and loss for each LULC type. The total change is obtained by adding the loss and the gain (Yesuph & Dagnew, 2019). In addition, the trajectory of LULC changes during the 1987-2020 periods was based on the LULC transition which represents the area of LULC types that have been converted from one LULC to another between 1987 and 2020.

3.7.1.6. Analysis of proximate drivers of LULC change

The proximate drivers represent human activities such as urbanization, deforestation, or agriculture expansion which directly influence the LULC change was identified through the analysis of the transition matrix. The LULC maps for the 1987-2020 periods were used to identify the main conversion of one class to another and to determine the proximate drivers of land-use change during the 1987-2020 period. The identification of prominent LULC change was identified by adopting the approach suggested by Sims *et al*. (2019) to the context of the study area.

In the context of this study, we elaborated four conversion maps based on the prominent LULC change occurring in the study area: the deforestation map (showing the transformation of forest land to any other land), the shrub land expansion map (showing the conversion of another land to shrub land), the built-up area expansion map showing the extension of the built-up area, and the cropland expansion map showing the expansion of agricultural land between the year 1987 and 2020. The conversion maps were transformed into binary maps variables with a value of 0 indicating the absence of change and a value of 1 indicating the presence of change. These maps with binary variables were used as dependent variables for Logistic regression modeling to show the probability of conversion of a given LULC category to another.

3.7.1.7. Selection and analysis of underlying driving factors of LULC change

In the context of this study, we analyzed and quantified the relationship between the driving factors and LULC change between 1987-2020. This analysis was done to identify the driving factors that have great explanatory power for the LULC change in the landscape.

The Socio-economic factors related to accessibility (distance to roads, distance to administrative groups' center, distance to the village/locality, proximity to rivers, distance to the artisanal mining sites), population dynamics (population density), and zoning policy (protected area and mining concession) were considered as explanatory data (independent variables). In conjunction, the biophysical factors such as altitude gradient or elevation, slope gradient, slope aspect (exposition), and soil types were also identified as independent variables. The topographic variables including altitude, slope gradient (percent), and slope aspect were derived from the SRTM-DEM of 30 m of spatial resolution which was preprocessed by fillings gape before its integration in the LULC models. The proximity variables like the distance from the road was calculated using the data about the road network of the DR Congo while the distance from rivers was calculated using the rivers networks dataset available in the DR the RGC database. For the artisanal mining sites and the mining concession, the IPIS open database which contains data from the Mining Ministry of DR Congo was considered. For all the distance data, the Euclidian distance in meter was calculated using the proximity function of QGIS 2.18 software. For categorical variables that include the protected area, obtained from the National Forest Atlas of DR Congo and the mining concession, a binary classification was done to determine whether a pixel falls in a given land or not.

Before the integration of the explanatory variable in the models, the potential drivers of LULC change were checked for multicollinearity by the mean of Pearson's correlation coefficient and Variance Inflation Factor (VIF). The Pearson correlation among the quantitatives variables was done using a bivariate correlation to check the collinearity among variables, avoid redundancy of data, and for reduction of the variable. All variables which have a significant correlation coefficient of 0.8 at $p\text{-value} < 0.05$ were reconsidered as they were not used together in the model (one was excluded). Only the continuous variables related to distance (proximity), altitude, slope gradient, and aspects were analyzed for multicollinearity. The binary variables such as the occurrence (presence/absence) of mining concession and protected area, as well as the category variable (soil type), were not concerned by this correlation analysis. Complementary to the Pearson correlation, the multicollinearity of all the independent variables was tested using the VIF. All variables which have a VIF higher than 10 were not integrated into the models as they could cause the problem of multicollinearity.

To perform the correlation and VIF analysis, a total of 1000 points were randomly selected in the Kalehe territory using the *Research Tool* of QGIS 2.18. The values of the selected underlying drivers of LULC change were extracted from each spatial variable in raster format using the *Point Sampling Tool* extension of QGIS 2.18. Then the value stored in the attribute table of the sample point layer's was transferred to Excel for further statistical analysis. The correlation table was obtained using the function *pairsrp ( )* of the package *pgirmess* in R 3.6.

3.7.1.8. LULC change modeling and susceptibility mapping

To measure the importance of drivers of LULC change, a binary map for the four major LULC changes occurring in the study area between 1987 and 2020 with a value of 1 corresponding to the area where the LULC change is present and 0 to the area where the LULC change is considered as absent was performed. For each map representing the major LULC which have occurred between 1987 and 2020, 1000 sites considered as a representative sample to model the spatial relationship between the LULC changes and theirs potential underlying drivers, were selected randomly to extract the point which exhibit the occurrence of LULC change and those that lay in the area where there is no change. A minimum distance of 200m was considered between pairs of points samples to minimize the problem of autocorrelation or spatial dependency among samples pairs (Kipkulei *et al*., 2022). For each point, the value of the LULC change occurrence data and their potential driver was extracted using the Point Sampling Tool extension of QGIS 2.18 and transferred to an Excel spreadsheet. These points' samples were split in two: 70% of points to train the model and 30% to test the model. Then a Logistic Regression Model (LRM) was performed using each LULC change binary data set to 0 for no converted land and 1 for converted land as the dependent or explained variables and the potential driving factor of LULC change as independents or explanatory variables. In logistic regression, the logit U is assumed to be a linear combination of the independent variables and formulated as follows $P_i = \frac{e^U}{1+e^U}$ With Logit U= $\ln(\frac{P_i}{1-P_i})$= $\beta 0 + \beta 1X1 + \beta 2X2 + \cdots \beta iXi$. Hence the probability of change varies between 0 and 1 and it is given by the function 3-12

$$P_i = \frac{exp(\ \beta 0 + \beta 1X1 + \beta 2X2 + \cdots \beta iXi)}{1 + exp(\ \beta 0 + \beta 1X1 + \beta 2X2 + \cdots \beta iXi)} \text{ (Equation 3-10)}$$

In this formula, P_i represents the probability of occurrence of a certain LULC change in the landscape, and U is the independent variable which is a linear combination of the explanatory factors X_i, β_0 the intercepts or constant of the model β_i is the correlation coefficient between each explanatory factor X_i and the LULC change. The value of the correlation coefficient was used to assess the relationship between the LULC change and the driving factors. It also helped to determine the direction (positive or negative) of this relationship. The statistical significance of the regression coefficient was tested using the Walid chi-square test.

For each prominent LULC change (deforestation, cropland expansion, built-up area expansion, shrub land expansion), a full logistic regression model considering all the potential drivers is established to determine their effects on LULC change. After that, a backward stepwise logistic regression model was performed. This allows us to determine the best-fit model based on the most influential environmental drivers of the LULC change. As a result, the best-fit model was used to predict the LULC change susceptibility. The application of the best-developed model and its integration in the GIS environment (QGIS) along with the spatial variables help to produce the LULC change susceptibility maps. This map was classified into 5 classes based on the quantile interval to depict the zones with very low, low, moderate, high, and very high susceptibility to LULC change. For the accuracy assessment of the predictive model, the overall accuracy of the classification, the pseudo-R-square, and the Area under the ROC (Receiver Operating Characteristics) curve (AUC) was used. The pseudo-R-square (Nagelkerke's R coefficient) which is an adjusted value of the Cox and Snell's R square coefficient was used to determine the percentage of variability of the dependent variable explained by the independent variable. It varies between 0 and 1, with a maximum value of 1 indicating a perfect prediction. Nagelkerke's R squared indicates the power of explanation of the developed model. In addition, the Area under the ROC (Receiver Operating Characteristics) curve (AUC) was used to evaluate the performance of the logistic regression model in predicting the LULC change. The ROC was calculated by comparing the predicted probability of the LULC change by the logistic model and the observed change. The null hypothesis is that the true area under the ROC curve is 0.5 for a random classification. For overall accuracy, the classification table which summarizes the observed and the predicted group was used by considering a cutoff of 0.5. The ROC curve plot helps to assess the predictive capacity of a classifier model. This graphical representation plots the sensitivity (true positive rate) against the 1-specificity (false positive rate). The area under the ROC curve (AUC) helps to assess the accuracy of the model. The values of the AUC range from 0 to 1 with the value of 1 considered as the perfect discrimination and a value below 0.5 considered as random (Hossein, 2019). The explanatory driving factors were considered to have great explanatory power when the area under the ROC curve (AUC) is greater than 0.6.

3.7.1.9. Modeling the LULC change transition potential

The transition potential modeling of LULC classes represents the probability of transformation of one LULC class to another over time. It was performed through the Land Change Modeler (LCM) integrated with the TerrSet Geospatial Monitoring and Modeling Software (IDRISI). Modeling of the spatiotemporal change transition potential was performed by considering the LULC change map within the studied period (1987-2020) and explanatory variables which are the biophysical and socio-economic variables that are responsible for the change in the landscape. For the transitional potential modeling, the Support Vector Machine (SVM) was used to obtain a transition probability maps which gives the likelihood of transformation of a given LULC class from the initial year to another LULC from the final year. The SVM is a machine learning technique that establishes a linear or no linear Kernel plane to separate classes in a variable space.

3.7.1.8. Prediction of the future LULC dynamics

The prediction of future LULC was based on the assumption that the historical trend in the LULC pattern continued in the future and was influenced by the same factors (Business-As-Usual scenario). Under this scenario, it is assumed that the communities continue to do their socio-economic activities under the prevailing development and conservation policy. Considering the transition probability maps obtained previously and the transition matrix, the Markov chain simulation modeling which is integrated into the Land Change Modeler (LCM), was used to predict the LULC for 2030, 2050, and 2070 based on the observed trend from 1987 to 2020. The year 2020 was considered as the baseline for projection. This model is used to simulate or predict the future state of a system by considering the immediately preceding state through the development of a transition probability matrix which shows the probability of change from an initial time to a final time. The outputs of the model are the "hard prediction" maps which show the likely LULC which can occur in the future based on the past trend and the "soft prediction" map which represent the probability of transformation of the LULC observed during the baseline to another LULC in the future. The LULC map of 2020 was used as a base map to predict the LULC for the years 2030, 2050, and 2070. The choice of these periods for the prediction of LULC type was done in line with the deadline for the 2030 United Nations Agenda for Sustainable Development, the 2050 vision towards "Living in harmony with nature" of the CBD, and the Paris climatic agreement to reduce the net-zero emission by 2050, the 2070 baseline to reach the "carbon neutrality" and to avoid the global warming of more than 2°C (UNEP, 2014).

3.7.1.9. Accuracy of the future prediction

The accuracy of the projection was tested by comparing the simulated LULC of 2020 based on the observed trend during the 1987-2002 period and the observed LULC of the same year. To compare the amount of change between the two LULC maps, the chi-square goodness of fit test was performed at a 5% significance level under the null hypothesis that the observed and simulated areas of the different LULC classes in 2020 are in the same proportion. Furthermore, the Kappa validation technic integrated with the Semi-Automatic Classification Plugin for QGIS (SCP) was used to compare the predicted and the classified maps.

3.7.2. Implication of LULC dynamics on land cover degradation

To foster the LDN operationalization within the study area, the LULC change was used as a proxy of land degradation during the baseline period (1987-2020) and the monitoring period (2020-2070). The land cover degradation was inferred from the LULC changes using a decision matrix containing the criteria for determining the land condition (degradation, stability, improvement) based on the trend of LULC changes and following the approach proposed by Sims *et al*. (2021). Furthermore, using the biophysical and socio-economic factors as independent variables and the occurrence of land cover degradation during the 1987-2020 as dependent variables, a binary logistic regression model was developed to identify the determinant factors of land cover degradation and to map the land cover degradation susceptibility at territorial level in Eastern DR Congo. Figure 3.7 presents an overview of the developed methodology.

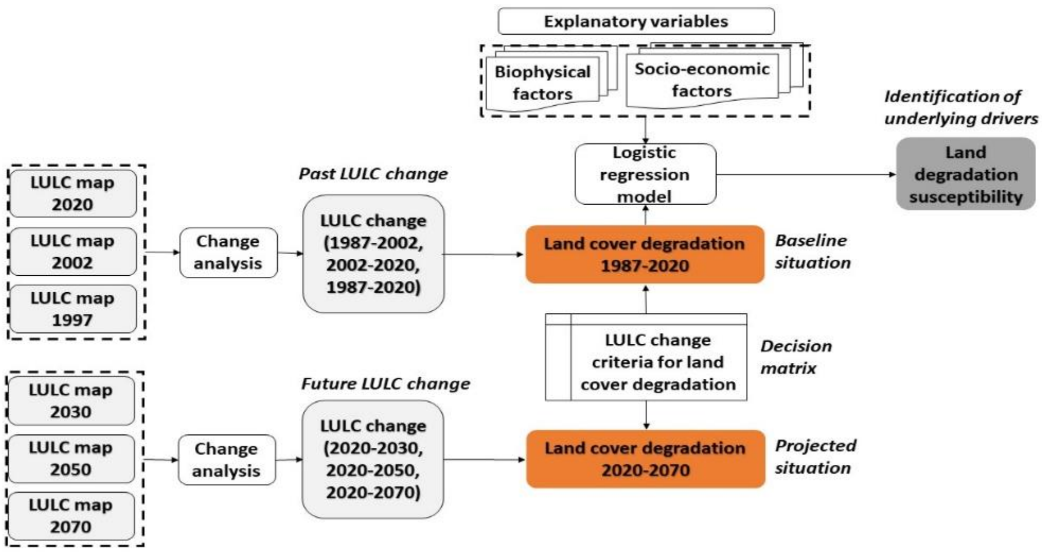


Figure 3.7 Methodological framework for assessing the implication of LULC change on land cover degradation.

3.7.2.1. Analysis of land cover degradation status

The sub-indicators of SDG 15.3.1 "Proportion of land that is degraded over the total land area" which was proposed in the Good Practice Guidance for Sustainable

Development Goal (SDG) indicator 15.3.1 (Sims *et al*., 2019, Sims *et al*., 2021) of the UNCCD (United Nations Convention to Combat Desertification) include the land productivity dynamics, the land use change and the soil carbon organic. To understand the land cover degradation status using the LULC change as an indicator (Bär *et al*., 2023) and to assess the potential to reach the land degradation neutrality target, the decision matrix approach for the evaluation of land cover degradation was proposed by Sims *et al*. (2019) was adapted to the study area context. Based on this approach, the area characterized by land cover degradation (negative land use transition), stability (no change), and improvement (positive) was delineated. To evaluate if the land degradation neutrality target should be reached by the years 2030, 2050, and 2070, the status of land cover degradation at the baseline period (2020) was compared to that of the future.

3.7.2.2. Modelling the land cover degradation and susceptibility mapping

A quantitative assessment of the underlying drivers of LULC degradation status (negative land use transition) was done through a logistic regression model approach. To assess the driver of negative LULC transition, 1000 random sites were sampled and their land cover condition (land cover degradation occurrence and no occurrence) were determined. This binary variable was used as a dependent variable to develop a logistic regression model and to understand the factors which contribute to the land cover degradation or the negative land use transition in the study area. In this context, the model of land cover degradation occurrence was defined as

$$Logit\ Yn = \beta_0 + \sum_{i=1}^{n} \beta_i\, x_i \quad \text{(Equation 3-11)}$$

Where Yn is the dependent variable representing the land condition, with Yn =1 indicating the land cover degradation (negative land change transition) and Yn =0 indicating the land cover improvement or stability (positive or neutral land change transition). Xi represents the independent variables or explaining factors of the land cover condition in the study area. In the context of this study, both the biophysical and socio-economic drivers of land cover degradation were assessed as the land condition may be influenced by natural and anthropogenic factors. Therefore we assessed how the natural factor such as topography (altitude and slope), the edaphic factor (type of soil), demographic factors (population density), the socio-economic factors of accessibility (distance to road, distance to artisanal mining sites, distance to majors rivers, distance to majors centers and village), the conservation and development policy (presence of protected areas such as national park and forest reserve, presence of mining concession) may influence the occurrence of land cover degradation in the study area.

A stepwise backward Logistic regression model was performed in SPSS 16 to determine the best-fit model of prediction of land cover degradation as a function of the determinant underlying drivers. This model was integrated into QGIS 2.18 along with the spatial raster file of the underlying drivers to produce a susceptibility map of land cover degradation. This land cover degradation susceptibility map of the study was categorized into 5 classes based on the quantile interval of probabilities to show the area with a very low, low, moderate, high, and very high probability of degradation. The accuracy of the goodness-of-fit and predictive efficiency of models was tested using the area under the ROC (Receiver Operating Characteristic) curve (AUC) and the pseudo-R-square (Nagelkerke's R coefficient).

3.7.3. Quantification of the landscape pattern

The quantification of the landscape change pattern form from 1987-2020 period was done through the landscape metrics (index). The landscape composition and configuration metrics were determined at 2 levels of analysis: the class-level metrics which integrate all the patches of a given class (LULC type or category) and landscape-level metrics which considers all the patches or classes over the entire landscape (Kevin, 2015). These metrics were calculated based on the LULC maps for each period using the FRAGSTATS v4.2.1 software and by considering the watersheds delineated in the study area as basics environmental units of analysis. In this study, the description of the landscape structure was done based on 15 landscape metrics (Table 3.4) which reflect the major component of land use planning (Shi *et al*., 2013). These components include the shape, distance, connectivity, and diversity of patches (McGarigal *et al*., 2012). The 15 metrics have been selected to understand the ecological process and the ecological effects of anthropogenic activities at the landscape level (Table 3.4).

Table 3.4: Landscape configuration metrics used in the present study

Metrics	Code	Rationale
Fragmentation and aggregation metrics		
Patch density	PD	The ratio between the number of patches and unit area of the landscape (number per 100 ha). The high value of PD reflects the high level of landscape fragmentation.
Largest patch index	LPI	Percentage of the largest patch in the landscape (unit:%). The smaller the LPI, the higher the fragmentation
Edge density	ED	The ratio between the total length of all edge segments and the unit area of the landscape (unit: m/ha). It indicates the nature of edge or patches boundary in a landscape.
Landscape shape index	LSI	A ratio between the total edge length or edge and the minimum edge length in the landscape (unit: none). It takes a value of 1 when there is only one square patch and increases as the patch becomes less compact.
Interspersion and juxtaposition index	IJI	Indicates the patch adjacencies and measures the interspersion or intermixing of classes (unit: %).
Aggregation index	AI	A ratio between the number of like adjacencies involving the corresponding land use type and the maximum possible number of like adjacencies involving the corresponding land use class for the entire landscape (unit: %).
Patch cohesion index	COHESION	Characterizes the physical connectedness of a patch belonging to a specific land use class (unit: none).
Contagion	CONTAG	It is based on the cell advances and indicates the tendency of the patch types to be aggregated (unit: %).
Shape metrics		
Mean patch size	AREA_MN	The average area of a patch in the landscape (unit: ha)
Mean shape index	SHAPE_MN	The ratio between the actual perimeter of the patch and the minimum perimeter for a maximally compact patch (unit: none). If all patches are square, it takes a value of 0, otherwise, it increases when the patches are complex
Mean perimeter-area ratio	PARA_MN	The mean perimeter-to-area ratio of a particular class describes the complexity of the landscape (unit: none). Its value increases as the patch becomes more complex.
Mean Euclidian nearest neighbor distance	ENN_MN	Average distance to the nearest neighboring patch of the same class based on the edge-to-edge distance (unit: m). Take a value close to 0 when the patch of the same class becomes aggregated and increases indefinitely when they become more isolated.
Perimeter-area fractal dimension	PAFRAC	Characterize the complexity of the patch in the landscape (unit: none). It takes a minimum value of 1 if the shape of the patch is simple and a maximum value of 2 when the shape becomes irregular.
Diversity metrics		
Shannon's diversity index	SHDI	Indicates the patch diversity in a landscape based on the number of classes and abundance of each class (unit: none)
Simpson's diversity index	SIDI	Represent the probability that two selected random patches belong to the same class (unit: none).

Source : McGarigal *et al*. (2012), Shi *et al*. (2013)

The landscapes metrics which were computed are:

(1) Composition indices: proportion of Forest land (FL), Grassland (GL), Shrub land (SL), Built-up area (BA), Cropland (CL), Wetland (WL), and Bare land (BL)

(2) Configuration indices: the landscape fragmentation index which reflects the subdivision of the larger land unit into small patches, the landscape patches metrics which reflects the size and shape of patches, the landscape diversity index which provides information on the number of classes (landscape richness) and their distribution (landscape evenness), were considered.

3.7.4. Analysis of land productivity dynamics

The analysis of the land productivity was done by determining the trend of Landsat-based NDVI over the 1987-2020 period. Additionally, using the biophysical and socio-economic factors as independent variables and the occurrence of persistent decrease of land productivity during the 1987-2020 as dependent variables, a binary logistic regression model was developed to identify the determinant factors of land productivity degradation and to map the land productivity degradation susceptibility at territorial level in Eastern DR Congo

3.7.4.1. Analysis of land productivity status

The multitemporal remote sensing data plays a great role in the assessment of land productivity (Traore *et al*., 2014). More particularly, the vegetation index such as the NDVI is commonly used as a proxy for the assessment of vegetation dynamics (vegetation greenness) as the linear trend analysis of NDVI times series data can distinguish the degraded land from no degraded lands (Muhoyi *et al*., 2023). Indeed, the spatial trend of NDVI is widely used as a proxy of land productivity to understand the vegetation pattern and by extension the dynamics of land improvement, stability, and degradation (Kirui *et al*., 2021, Muhoyi *et al*., 2023). Therefore, the land condition (degradation, improvement or stability) associated with LULC change and other environmental factors during the past three decades (1987-2020) was assessed based on the linear trend of NDVI derived from the Landsat images to capture the land with declining, stable and increasing biomass in the study area. By considering the dynamic of biomass as a proxy of land productivity, the NDVI data enables us to identify the areas which undergone the degradation, stability, and improvement of land productivity.

The time series of multi-temporal annual composite NDVI value derived from Landsat images during the 1987-2020 period was extracted from the Google Earth Engine platform. These remote sensing observations provided an insight into the past and present land conditions of the Kalehe territory. Considering the spatio-temporel trend of NDVI as an indicator of change in land productivity, the Mann-Kendall monotonic trend test (monotonicity refers to a consistency of increasing or decreasing observations) which quantifies the direction and strength of two variables was used.

The Mann-Kendall test helped to determine if a trend exist or not in the NDVI time series data during the last 33 years of analysis. It is a non-parametric test which does not require the normality of data or homoscedasticity of variance. That is why this test has been used widely for trend analysis of remote sensing data. It is used to test two hypotheses: the null hypothesis (H0) which suggest that there is no trend present in the data and the alternative hypothesis (H1) which suggest that there is a trend in the data. This trend could be positive or negative. Thus, the correlation coefficient (τ) of the Mann-Kendall test varies between +1 and -1 indicating, respectively a positive (consistency increasing) or negative (consistency in decreasing) trend. For a value of 0, there is no consistent trend. The evidence of a statistically significant trend in the data is passed through the p-value of the test at the confidence level of 90% as suggested in other studies (Traore *et al*., 2014). For the spatial analysis of the annual NDVI trend, the function MKraster ( ) developed by Abdi *et al*. (2019) was used in this study. This function was executed in R 3.5 and required two packages: Raster and Kendall.

3.7.4.2. Modelling the land productivity degradation and susceptibility mapping

The Mann Kendall's monotonic trend coefficient (τ) of the NDVI during the 1987-2020 period was used to establish a land degradation (decrease of NDVI) occurrence map with two classes: 1 indicating the presence of land degradation when $\tau < 0$ and 0 indicating the absence of land degradation (stability or improvement of land productivity) $\tau \geq 0$. 1000 random sites were sampled and their land condition (degradation occurrence and no occurrence) were determined. This binary variable was used as a dependent variable to develop a logistic regression model and to understand the factors which contribute to the land productivity degradation in the study area. In this context, the model of land productivity degradation was defined as

$$Logit\ Yn = \beta_0 + \sum_{i=1}^{n} \beta_i\, x_i \text{ (Equation 3-12)}$$

Where Yn is the dependent variable representing the land condition, with Yn =1 indicating the land degradation and Yn =0 indicating the land improvement or stability based on the Mann-Kendall's monotonic trend coefficient (τ) of NDVI between the years 1987 and 2020. Xi represents the independent variables or explaining factors of the land condition in the study area. In the context of this study, both the biophysical and socio-economic drivers of land degradation were assessed as the land condition may be influenced by natural and anthropogenic factors. Therefore an assessment of how the natural factors such as topography (altitude and slope), the edaphic factor (type of soil), demographic factors (population density), the socio-economic factors of accessibility (distance to road, distance to artisanal mining sites, distance to majors rivers, distance to majors centers and village), the conservation and development policy (presence of protected areas such as national park and forest reserve, presence of mining concession) may influence the occurrence of land productivity degradation in the study area was done.

A stepwise backward Logistic regression model was performed in SPSS 16 to determine the best-fit model of prediction of land productivity degradation as a function of the determinant underlying drivers. This model was integrated with QGIS 2.18 along with the spatial raster file of the underlying drivers to produce a susceptibility map of land productivity degradation. This land productivity degradation susceptibility map of the study was categorized into 5 classes based on the quantile interval of probabilities to show the area with a very low, low, moderate, high, and very high probability of land productivity degradation. The accuracy of the goodness-of-fit and predictive efficiency of models was tested using the area under the ROC (Receiver Operating Characteristic) curve (AUC) and the pseudo-R-square (Nagelkerke's R coefficient).

3.7.5. Analysis of the dynamics of ecosystem service supply potential

The evaluation matrix was used to monitor the perceived ecosystem service potential. The rank provided by local community were linked to the LULC maps to obtain the perceived ecosystem service value maps. A change analysis of those maps was done to determines the area with an increasing, decreasing and increasing potential of ecosystem services based on the perception of local communities. Furthermore, the influence of landscape metrics (composition and structure) was asses by developing multiple linear regression models. The Figure 3.8 provides an overview of the methodological framework applied to the analysis of the land cover dynamic in the context of this study.

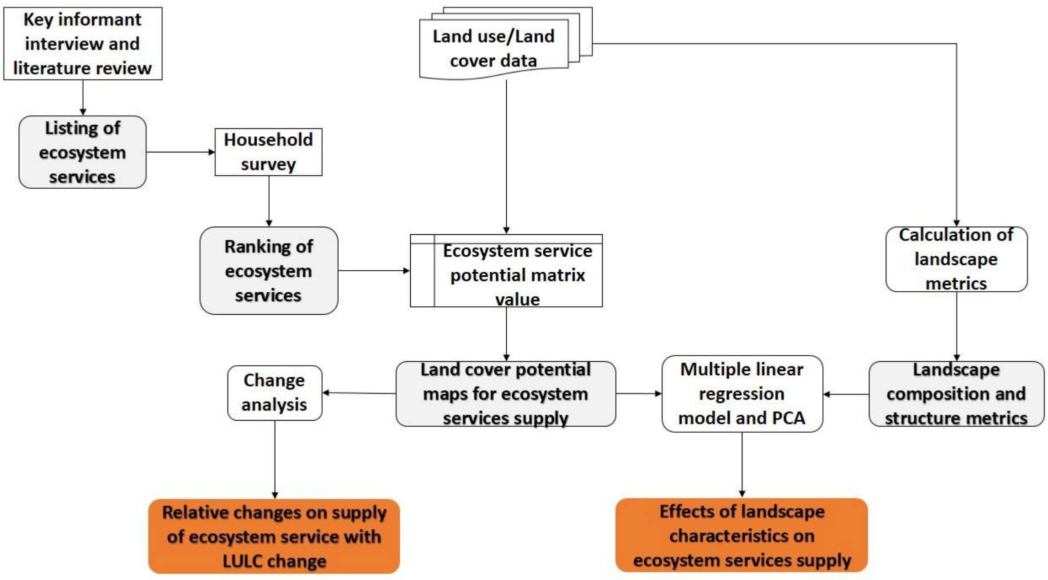


Figure 3.8: Methodological framework applied in the analysis of ecosystem service dynamics.

3.7.5.1. Assessment of the perceived ecosystem service value

The "Matrix model" approach to the evaluation of no monetary value of ecosystem services (Chaudhary *et al*., 2016; Burkhard, 2017; Esmail *et al*., 2023) was adopted in this study. The evaluation matrix of the perceived value of ecosystem services provided by each LULC type was used for an in-depth analysis of the impact of LULC change on the ecosystem service as perceived by the local community. A list of potential ecosystem services available in the territory of Kalehe was elaborated based on the knowledge about the study areas. These potential ecosystem services were completed and validated by the community knowledge during the pilot survey. During the pilot survey, 7 people who were considered as elders in the community (age >50 years), who have lived in the area for more than 30 years were purposively selected and considered as key informants as they were supposed to have a good knowledge of the environmental changes that occurred in their locality through the last three decades. This key informant was involved in the validation of the evaluation matrix for the assessment of the perceived value of the ecosystem service provided by each LULC type in the Kalehe territory. A total of 30 ecosystem services was validated by the local community during the pilot survey and then incorporated in the final evaluation matrix that consisted of 4 sections, each section corresponding to one ecosystem service category (supply services, regulation services, support services, and cultural services) as defined by the Millennium Ecosystem Assessment (2005). To establish the assessment matrix, the ecosystem services were placed in the rows matrix while the LULC type was inserted in columns (Burkhard, 2017). To complete the evaluation matrix, the enumerator has to formulate a simple question addressed to the respondent: "How do you rate the importance or capacity of the LULC type $LULC_k$ to supply a service ES_i?" Therefore, the stakeholders were asked to rate the importance or value of each LULC type in terms of availability, accessibility, or potential supply to each ecosystem service based on the ecosystems services indicators recognized by the local community in their locality by using a Likert like the scale of four levels ranging from 0 to 3 with 0= Not important (no service provided by the LULC type), 1= least important (low supply of service by the LULC type), 2= moderately important (medium supply of the service by the LULC type) and 3= Very important (high supply of the service by the LULC type). In addition to the evaluation matrix, questions related to the trend of provisioning services and the main drivers of change in the provisioning of ecosystem services were asked of local people during the household interview.

3.7.5.2. Statistical analysis of the perceived ecosystem service value

Based on the score provided by the land users, descriptive statistics including mean and standard variation of the ecosystem service value index was done. Bare plots and boxplots were used for the visual representation of the data. Inference statistics including the ANOVA test and Chi-square test of independence were also used to test the hypothesis. For instance, the chi-square test was used to assess if there is a significant dependency between the LULC type and perceived ecosystem service. The ANOVA statistics were used to assess if the perceived value of ecosystem service varies according to the LULC type and ecosystem service category at a confidence level of 95%. Furthermore, the multivariate statistics including the Principal Component Analysis (PCA) was applied using the packages *FactormineR* and *Factorextra* of R 3.3. The PCA was used to quantitatively assess the association between the perceived value of ecosystem services and the LULC types. These statistical analyses were done in R 3.3.

3.7.5.3. Spatial and temporal dynamics of the ecosystem service value

To map the ecosystem service value, the mean ecosystem service score from the ecosystem service matrix during the interview was linked with the LULC maps. Using the spatial analysis tools of QGIS 2.18, the LULC maps for the respective years were merged with the mean value of the provisioning, regulating, supporting, and cultural ecosystems services using the approach proposed by Burkhard (2017) as illustrated in the Figure 3.9 and by adapting to the specificity of the study. Using this approach, we produced 8 maps representing the four categories of ecosystem services for the years 1987 and 2020 respectively. For each year, an overall ecosystem service potential map was generated by summing and standardizing the results of the fours ecosystems services as suggested by Esmail *et al*. (2023). The standardization and rescaling of the sum of the fours ecosystem services categories maps were done through the application of the following equation to have values ranging from 0 to 3:

$$x_s = \frac{(x - xmin)*3}{(Xmax - Xmin)} \text{ (Equation 3-13)}$$

The maps were classified according to the final score obtained as follows to discriminate the area with high ecosystem service supply potential for those with low potential: 0 (No potential/No relevant supply)-1 (low potential/ low supply), 1-2 (moderate potential/Moderate supply) and 2-3 (high potential/High supply). Subsequently, the ecosystem service supply potential maps were individually analyzed using the zonal statistic tool of QGIS 2.18 to compute the mean ecosystem service value at the territorial level, health zone level, and watershed level.

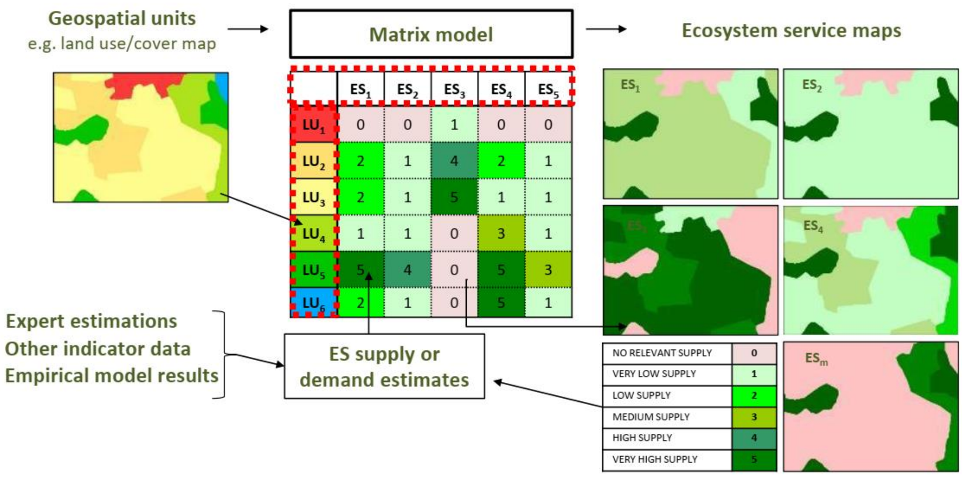


Figure 3.9: Spatial representation of the ecosystem services supply potential based on the ecosystem evaluation matrix model.

Source: Burkhard (2017)

The quantification of the change in ecosystem service value about the LULC change during the 1987-2020 periods was done through the comparison of the spatially aggregated mean of ecosystem service value index per unit area for different years using the zonal statistics according to the administrative boundary (Esmail *et al*., 2023). The spatial aggregated mean value per unit area was computed based on the ecosystem service map using the zonal statistic tool of QGIS 2.16. The percentage of change (PC) for the mean ecosystem service value between two years T1 and T0, was calculated by using the formula (Equation 3.15):

$$PC\ (\%) = \frac{ES_1 - ES_0}{ES_0} * 100 \text{ (Equation 3-14)}$$

With ES_0 and ES_1being the mean or the total ecosystem service value at T0 and T1 respectively.

In addition, to obtain the map showing the trend of supply of ecosystem service value between the1987-2020, the overall ecosystem service potential map for the initial year T0 (ES_0) and the final year T1(ES_1) was subtracted and classified as follows to show the trend in the ecosystem service supply during the period T1-T2: PC (%) $= 0$: No change (stability), PC (%) > 0: Increase (Improvement), and PC (%) < 0: Decrease (Degradation).

Based on the maps of the trend in the supply of ecosystem service between 1987 and 2020, the percentage of area with decreasing trend was quantified per health zone and per watershed to do a prioritization zoning for conservation in the study area. This was helpful to produce the map of the degradation of the ecosystem service supply in the study area due to LULC change and to quantify its extent under the current and possible future situation of LULC change.

3.7.5.4. Modelling the impact of landscape pattern on ecosystem services

The regression models were used to predict the effect of landscape patterns on ecosystem service value (perceived value). For this, the average ecosystem service value for each watershed delineated in the study area was considered a dependent variable while the landscape pattern index (metrics) was considered an independent variable. Pearson's correlation analysis was done to assess the relationship among the variables. Stepwise multivariate regression was done through the stepAIC ( ) [MASS package] function of R 3.3 to select the best model that describes the relationship between the landscape pattern metrics and the ecosystem service value. The best model was chosen based on the AIC (Akaik Information Criterion) and both forward and backward directions were considered to choose the best model. Additionaly, the

Principal Componnent Analysis (PCA), a multivariate statistical technique, was uded to obtain information about the most important landscape metrics that influence the variability in the perceived ecosystem service value. Thus the PCA approach was used to analyse the relationship between the perceived ecosystem service value, the landscape composition and the landscape structure metrics at watershed level. For this, the FactoMineR and factorextra packages of R 3.3 were used.

3.7.6. Analysis of soil erosion dynamics

This study adopted the RUSLE model (Renard *et al*. 1997) to assess the dynamics of land degradation at territorial level within the study area. Figure 3.10 presents an overview of the RUSLE model adapted to the study area.

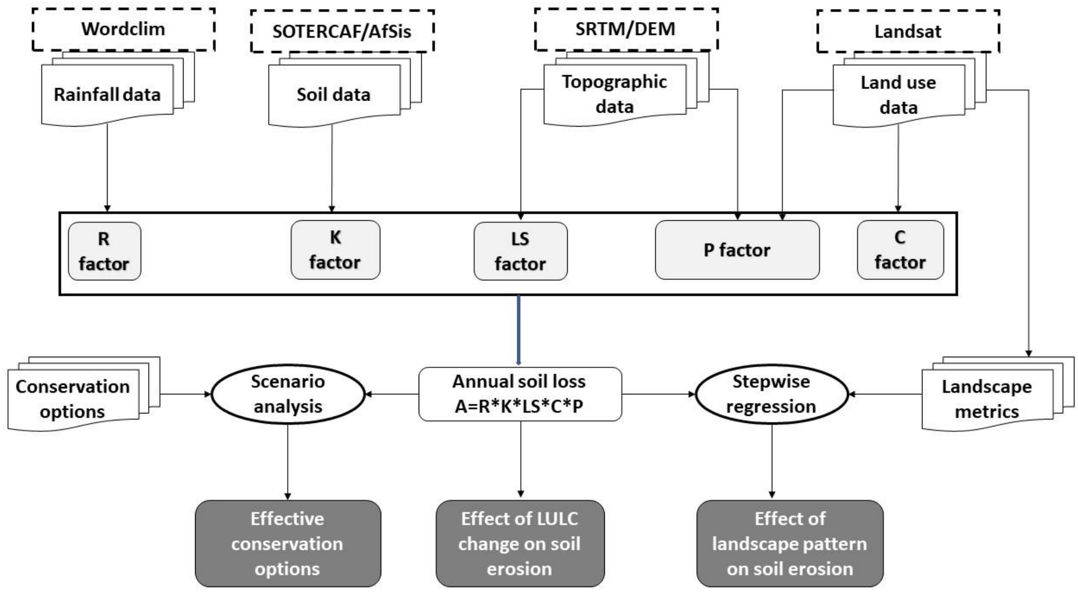


Figure 3.10: Methodological framework applied in the analysis of soil erosion dynamics.

As can be seen from the above figure 3.10, the parameters of the model were estimated using available soil data (SOTERCAF data, AfSIS data) for the K factor, rainfall data (WordClim data) for the R factor, topographic data (SRTM-DEM) for the LS factor, and remote sensing data (Landsat) for the C and P factors which were integrated into a GIS environment for analyzing the spatial pattern of the soil loss under different LULC change and conservation management scenarios. Furthermore, the effect of landscape pattern of soil erosion was determined through the regression analysis of annual soil loss and landscape metrics.

3.7.6.1. Overview of the RUSLE model

The Revised Universal Soil Loss Equation (RUSLE) developed by Renard *et al*. (1997) was integrated into a GIS environment to evaluate the spatiotemporal dynamic of soil erosion under different conditions of LULC change and conservation practices scenarios. The RUSLE model is given by the equation 3.15

$$A = R * K * LS * C * P \quad \text{(Equation 3-15)}$$

, where A expresses the possible long-term average annual soil losses (t/ha/yr), R, the rainfall erosivity factor (MJ.mm/ha.h.yr), K, the soil erodibility factor (t.ha.h/ha.MJ.mm), LS, the topographic factor (dimensionless), C, the vegetation factor (dimensionless), P. is the support practice factor or protection factor (dimensionless).

3.7.6.2. Determination of the RUSLE model parameters

a) Rainfall erosivisity factor (R)

The rainfall erosivity factor R (MJ.mm/ha.h.yr) refers to the erosive force of a specific rainfall event which could significantly affect the stability of the soil and lead to soil loss (Wischmeier & Smith, 1978; Gashaw *et al*., 2017). The R-factor was calculated using the long-term mean annual rainfall derived from the WordClim database. This climate data area is reliable for estimating the erosivity factor R and is widely used around the world to estimate the current mean value of R based on the average long-term precipitation (Claessens *et al*., 2008) and the projected future value of R under different climate change scenarios (Panagos *et al*., 2017, Hateffard *et al*., 2021). The equation 3.16 proposed by Lo *et al*. (1985) which is commonly used in the Kivu region (Karamage *et al*., 2016) was considered for the computation of the R factor.

$$R = 38.46 + 3.48 * P \text{ (Equation 3-16)}$$

Where R represents the rainfall erosivity factor (MJ mm ha^{-1} h^{-1} per year) and P is the annual precipitation (mm) calculated using the Wordclim climate data from the recent period (from 1970 to the nearest period) and the future period.

b) Soil erodibility factor (K)

The soil erodibility index K (t.ha.h/ha.MJ.mm) is a numerical value that represents the susceptibility of soil to water erosion based on its physicochemical characteristics (Ganasri & Ramesh, 2015). In this study, the erodibility (K) for the different soil textural classes was calculated using the equation of William (1995). This equation determines the K-factor using soil properties such as clay, sand, silt, and organic carbon fraction. These data were extracted from the Afsis (African Soil Information System) which is a gridded mapping of soil Properties of Africa at 250 m resolution (Hengl *et al*., 2015). The equation 3.17 of Willian (1995) is given by the relationship:

$$K = fcsand * fcl - si * forgc * fhisand \text{ (Equation 3-17)}$$

Where fcsand (Equation 3.18) is a parameter that confers a low erodibility factor for soils with high sand content and a high erodibility for soils with little sand, fcl-si (Equation 3.19) is a factor that considers a low erodibility value for soil with a large clay to silt ratio, forgc (Equation 3.20) is a factor that reduces erodibility for soils with high organic carbon content, fhisand (Equation 3.21) is a factor that reduces soil erodibility for soils with extremely high sand contents. The obtained value from the original equation of William was standardized from the American system units to the International System Units with a multiplying factor of 0.1317 (Bamutaze *et al*., 2021).

$$fcsand = 0.2 + 0.3 * exp\left[-0.256 * ms * \left(1 - \frac{msilt}{100}\right)\right] \text{ (Equation 3-18)}$$

$$fcl - si \ = \left(\frac{msilt}{mc+msilt}\right)^{0.3} \text{ (Equation 3-19)}$$

$$forgc \ = 1 - \frac{0.036*orgC}{orgC+exp[3.72-(2.95*orgC)]} \text{ (Equation 3-20)}$$

$$fhisand \ = 1 - \frac{0.7*\left(1-\frac{ms}{100}\right)}{\left(1-\frac{ms}{100}\right)+exp\left[-5.51+22.9*\left(1-\frac{ms}{100}\right)\right]} \text{ (Equation 3-21)}$$

Where ms is the percentage of sand (particle of 0.05 to 2.00 mm diameter), msilt is the percentage of silt content (particle of 0.002 to 0.05 mm diameter), mc is the percentage of clay content (particle of less than 0.002 mm diameter), and orgC is the organic carbon content (%).

c) Topographic factor (LS)

The topographic factor LS considers both slope length (L) and slope gradient or steepness (S) value which influence surface runoff velocity and play an important role in erosion occurrence (Moore & Wilson, 1992; Sarathi & Pani, 2015, Panagos *et al*., 2015). The LS factor was calculated by using the equation proposed by Desmet and Govers (1996) which is appropriate for terrain with complex topography (Panagos *et al*., 2015). The Desmet and Govers (1996) equation is given by the formula

$$L_{i,j} = \frac{(A_{i,j-in}+D^2 \ )^{m+1}-A_{i,j-in}^{m+1})}{(D^{m+2}*x_{i,j}^{m}*22.13^{m}} \text{ (Equation 3-22)}$$

with $L_{i,j}$, the slope length factor for a (i,j) coordinate grid cell; $A_{i,j-in}$ being the flux accumulation area or contributing area to the input (i,j)-chordinate grid cell measured in m^2 ; D is the size of the grid cell in meters, $X_{i,j}=sina_{i,j}+cosa_{i,j}$ (Equation 3-23); $a_{i,j}$ is the direction of the aspect of the grid cell of coordinates (i,j); m varies between 0 and 1 and is given by the relation $m = \frac{\beta}{\beta+1}$ (Equation 3-24) with $\beta = \frac{\frac{Sin\theta}{0.0896}}{[0.56+3*(sin\theta)^{0.8}]}$ (Equation 3-25); θ is the slope angle in degrees. This equation is integrated into the geoprocessing toolbox (Terrain analysis) of SAGA GIS 7.8.2 (System for Automated Geoscientific Analyses). A preprocessing of the Digital

Elevation Model (DTM) derived from an SRTM image of 30m spatial by filling the pits was performed in the QGIS software using the fill sink tool before the calculation of the LS factor.

d) Soil cover-management factor (C)

The soil cover-management factor C (dimensionless) represents the effects of vegetation cover and land use management practices on soil erosion (Ndolo, 2015; Belayneh *et al*., 2019). This factor denotes the influence of LULC on the runoff as the vegetation influences the runoff through the interception of precipitation, the enhancement of rainfall infiltration, and the reduction of rainfall energy. It is the ratio of bare soil losses under specific conditions to soil losses corresponding to soils under farming systems (Alexandridis *et al*., 2014). The C value is strongly related to LULC and varies between 1 for no protected soils to 0 for well-protected soils. In the context of this study, the C was determined based on the past (1987 and 2002), recent (2020), and predicted (2030, 2050, and 2070) LULC data. The C value of each LULC type (Table 3.5) was evaluated from the literature and weighted following field observation (Yang *et al*., 2003; Adidja *et al*., 2016; Eisenberg & Muvundja, 2020).

e) Support or conservation practice factor (P)

The support or conservation practice factor P (dimensionless) expresses the effect of soil and water conservation practices (mulching, afforestation, contour cultivation, terracing, etc.) on soil erosion reduction (Ganasri et Ramesh, 2015, Eisenberg & Muvundja, 2020). It is based on the fact that the conservation actions undertaken by the land user have the potential to reduce the runoff concentration and flow velocity thus reducing the entrainment of soil. It varies between 0 and 1, with effective conservation actions for the lowers value and no effective conservation actions for the highest value. During the field survey, the land users reported that they undertake some soil and water conservation measures such as mulching and fallow which was most predominant but the scale is limited and these practices are not effective to control the erosion in the study area. Through field observation, it was noted that farmer continues to practice intensive tillage without the implementation of resistant erosion control techniques. Therefore, a value of 0.5 was assigned to the factor P for the cropland and a value of 1 for no agricultural lands as suggested by Yang *et al*. (2003).

Table 3.5: C and P factors assigned for the different LULC in the study area

LULC	C factor	P factor	C*P
Forestland	0.001	1	0.001
Cropland	0.5	0.5	0.25
Wetland (Swamps)	0.05	1	0.05
Settlement	0.1	1	0.10
Grassland	0.08	1	0.08
Shrub land	0.08	1	0.08
Bare land	0.35	1	0.35
Mixed forest and cropland	0.1	0.8	0.08

Source: Yang *et al*. (2003)

3.7.6.3. Analysis of the spatial and temporal trend of erosion

The annual soil loss was computed by multiplying the 6 factors of erosion according to the RUSLE model. The soil erosion produced for the year 2020 was considered as the representation of the current situation of erosion in the study area. The analysis of the spatial variation of erosion intensity was done by classifying the soil loss by erosion according to the classification proposed by FAO-PNUMA-UNESCO (Hernando & Romana, 2015): <10 t/ha/year (low), 10-50 t/ha/year (Moderate), 50-200 t/ha/year (High) and 200 t/ha/year (very high). Furthermore, to determine the watershed which presents a high level of severity to water erosion according to the present situation of erosion, the average soil loss of erosion to each watershed in the study area was calculated and classified according to the different classes of severity.

The past trend of erosion dynamics was analyzed for the 1987-2020 period. The erosion map from 1987, 2002, and 2020 were categorized into 4 areas: slight, moderate, severe, and extreme degrees of severity to water erosion according to the classification proposed by FAO-PNUMA-UNESCO (Hernando & Romana, 2015). To evaluate the rate of change in erosion intensity for a given period, the equation 3.26 was used:

$$RC=\frac{Ub-Ua}{Ua} * \frac{1}{T} * 100 \ (\%) \text{ (Equation 3-26)}$$

with RC the change in erosion intensity during the study period, Ua and Ub represent, respectively, the initial and final phase of erosion intensity, and T the time in years (Li *et al.*, 2016). The change in soil erosion intensity between the years 1987 and 2020 was used to determine the hotspot of physical soil degradation. The erosion maps of the two dates (1987 and 2020) were subtracted to identify areas with a decreasing, stability, or increasing erosion risk. In this context, the percentage of change (PC) of the soil loss between two years T1 and T0, was calculated by using the formula (Equation 3-27) at the spatial level:

$$PC\ (\%) = \frac{E_1 - E_0}{E_0} * 100 \text{ (Equation 3-27)}$$

With E_0 and $E_1$the soil loss at T0 and T1 respectively. The maps of soil erosion trend between the two years were classified as follows: $PC\ (\%) = 0$: No change (stability), $PC\ (\%) > 0$: Increase (Degradation), and $PC\ (\%) < 0$: Decrease (Improvement). Based on this map, the spatial extent of the area with decreasing pattern of erosion was determined and the delineated watershed in the study area was classified according to the extent of increasing trend of erosion for conservation prioritization.

3.7.6.4. Scenario analysis of erosion dynamic

The scenario analysis was done to evaluate the effect of LULC change and climate change on soil erosion and the effectiveness of conservation measures under the current and possible future situation of LULC change. The following scenarios were developed by using the RUSLE:

a) Baseline scenarios

The 2020 erosion risk map which reflects the current situation of erosion was considered as the baseline for comparison to prioritize area for implementation of soil and water conservation measure in the landscape. Therefore, a soil erosion severity map was established to identify the vulnerable area (erosion hotspots) for conservation priority in the Kalehe territory. Based on the erosion severity maps, the territory was classified into three soil loss severity classes such as low risk (0-10 t/ha/year), moderate (30-50 t/ha/year), and high (>50 t/ha/year). Since the rate of erosion can be influenced by the site physical characteristics such as the slope, altitude, LULC types, and soil characteristics, the zonal statistics toolset of QGIS 2.18 was used to quantify the relation between the mean soil loss and the physical characteristics of the sites. The LULC categories, the soil types, the slopes classes, and altitudes classes were used as zones to extract and quantify the mean soil loss, the total soil loss, and the area coverage of each zone.

b) Conservation practices scenarios

It is possible to understand how changing farming practices may mitigate or exacerbate soil loss in a given area by using the P factors in scenario analysis (Benavidez *et al*., 2018). The soil conservation planning was based on the tolerable soil loss limit which represents the maximum soil loss by erosion that can occur in the region and still permit crop productivity in the region. In the highland of the tropical region, an annual value of 11 tons per ha is considered a tolerable soil loss (Gashaw *et al.*, 2017). Based on this value, the 2020 erosion risk map was classified into two categories to discriminate areas with soil loss below the tolerable limit and areas with soil loss high than the tolerable limit where the conservation measure should be prioritized. After identifying the land units having a soil loss higher than the tolerable limit, the P factor of these units was adjusted to simulate the effectiveness of conservation measures. Four scenarios of conservation management practices (contouring, strip cropping. bench terracing, and broad-based terracing) were tested based on the value of the P (Table 3.6) factor to determine the best management practices for soil and water conservation in cultivated lands. In the conservation scenario analysis, the R, K, LS, and C factors were fixed while we changed the value of P according to the conservation practice that proposed.

Table 3.6: P values for various soil conservation support practice factors

Slope (%)	Bench Terracing	Broad base Terracing	Contour farming	Strip cropping
1–2	0.1	0.12	0.6	0.3
3–8	0.1	0.1	0.5	0.15
9–12	0.1	0.12	0.6	0.3
13–16	0.1	0.14	0.7	0.35
17–20	0.12	0.16	0.8	0.4
21–25	0.12	0.18	0.9	0.45
> 25	0.14	0.2	0.95	0.5

Source: David (1988), Shi *et al*. (2004), Karamage *et al*. (2016)

The agroforestry implies the combination of shrubs or trees, and crops or livestock (Gold, 2009). It is recognized as one of the solutions to land degradation (Cooper *et al*., 1996). Therefore, it can be integrated into conservation strategies. In order to assess the impact of the adoption of agroforestry and forest plantation as a conservation practice on the soil erosion rate, the soil loss was estimated for the scenario that the total area of cropland is turned into agroforestry system while the forest plantation is expanded into shrubland, grassland, and bare land. Therefore, the value of P and C factors for the cropland was adjusted by considering the parameters proposed by Yang *et al*. (2003) for mixed cropland and forestland (Table 3.5). In this scenario, the values of C and P factors for the forestland, wetland, and built-up land remained unchanged while it is considered that there is an afforestation of bare land, shrubland, and grassland. The forest plantation's C (0.02) and P (0.8) values was assigned to the bare land, shrubland, and grassland following the approach adapted by Lee *et al*. (2017).

c) LULC changes under the Business-as-Usual scenarios

According to Ramankutty & Foley (1998), the scenarios of land-use change must take into account the historical land uses of the twentieth century, the future land uses and potential land uses under present climate conditions. Therefore, we considered a business-as -usual scenario to simulate the future trend of erosion risk under the assumption that the historic trend (1987-2020) of LULC change due to biophysical and socio-economic factors will continue in the future. The rainfall erosivity and the LULC are the two most dynamic factors in erosion which can be used in modeling scenarios to evaluate the trend of erosion under possible future climate change and land use change (Panagos *et al*., 2017). However, the future climate change impact on soil erosion goes beyond the scope of this study which focuses on the impact of LULC change. Therefore, the estimation of future erosion scenarios was based on an association of the RUSLE factor C to the predicted LULC data for 2030, 2050, and 2070. In the scenario of erosion dynamics due to land-use change, the C factor calculated based on future LULC was integrated into the RUSLE model to predict the future soil loss by erosion for the years 2030, 2050, and 2070.

3.7.6.5. Development of the soil erosion management plan

The suitability analysis of soil and water conservation measures was conducted based on the erosion rate derived for the application of the RUSLE model, the actual LULC derived for the supervised classification of the Landsat images and the slope gradient derived from the SRTM-DEM to develop a soil erosion management plan that target the area with moderate to high erosion rate that exceed the tolerable limit of 10t/ha/year. In order to provide a solution to the issues of erosion in the territory of Kalehe, the management plan was prepared for prioritizing area with high erosion rate by considering the threshold of 10t/ha/year which is the acceptable limits for tropical context. The approach developed by Srivastava *et al*. (2010) and Das *et al*. (2020) was adapted to the study area context. Since this study target the area with moderate and high risk of erosion, the soil erosion map derived from the RUSLE model for the 2020 year was categorized into two priority zone for implementation of conservation measures: the high priority zone with soil loss > 10 t/ha/year and the low priority zone with erosion rate ≤ 10 t/ha/year. The best soil and water management practices was determined based on the suggestion of Srivastava *et al*. (2010) considering the existing LULC type and slope gradient. Therefore, for the land with slope gradient of 0-5% under moderate to high erosion risk, the contour bunding or strip cropping which is suitable for mild slopes was considered. In the same way, the agricultural the land with slope gradient of 5-15%, the broad base terracing which are suitable for this area was recommended. Similarly, the bench terracing was suggested for land with a slope gradient of 15-30%. Likewise for agricultural land, shrubland, grassland, and bare land with a slope gradient of more than 30% and contributing to the high erosion rate, the afforestation or agroforestry was suggested. Based on the current LULC maps, the forest cover and wetland were not considered for the above conservation practices, since this area should be protected against.

3.7.6.6. Analysis of the impact of landscape pattern on the soil erosion

The Pearson correlation analysis was performed to assess the statistical relationships between landscape pattern metrics and soil erosion loss to determine which landscape metric has a significant influence on soil erosion. To identify the relationship between landscape dynamics and soil erosion, the Pearson correlation of the potential soil loss based on the RUSLE model and the landscape metrics was examined at the initial phase.

In the second phase, the landscape pattern metrics (landscape composition and structure metrics) were considered as independent variables and the mean yearly soil loss by erosion per watershed was considered as dependent variables. Then the stepwise multivariate linear regression model was applied using the MAS package of R 3.3 to determine the best-fit model which explains the relationship between the erosion dynamic and the landscape metrics in the study area. Thirdly, the Principal Componnent Analysis (PCA), a multivariate statistical technique, was uded to determine the most important landscape metrics that influence the dynamic of erosion by analyzing the relationship between the mean annual soil loss based on the RUSLE model, the landscape composition and the landscape structure metrics at watershed level. For this, the *FactoMineR* and *factorextra* packages of R 3.3 were used.

3.7.7. Development of a multi-criteria spatial models for conservation planning

From the perspective of conservation planning, it is essential to determine the priority area for the implementation of landscape restoration initiatives and to adapt the land use to its capability to avoid further degradation. To attain the objective of making land use decisions based on land capability and land degradation vulnerability level for conservation planning, this study adopted the Analytical Hierarchy Process (AHP), a MCDA approach, to compare different criteria and proposed a methodology based on the following steps: (1) using the Landsat images to elaborate the map of the current LULC in the study area, (2) assessment of land degradation vulnerability to identify the hotspot of degradation where restoration should be prioritized, (3) Validation of the land degradation vulnerability model through field observation, (4) Assessment of the land capability (5) overlay of the land capability map and the current LULC map to obtain the land adequacy map which determines the adequacy or inadequacy of the current land use management (7) Adaptation of the current land use to the land capability, and suggestion of conservation measures. Therefore, a land degradation vulnerability model (LDVM) as well as a land capability model (LCM) were developed. Figure 3.11 summarizes the general process in the MCDA approach adopted in this study.

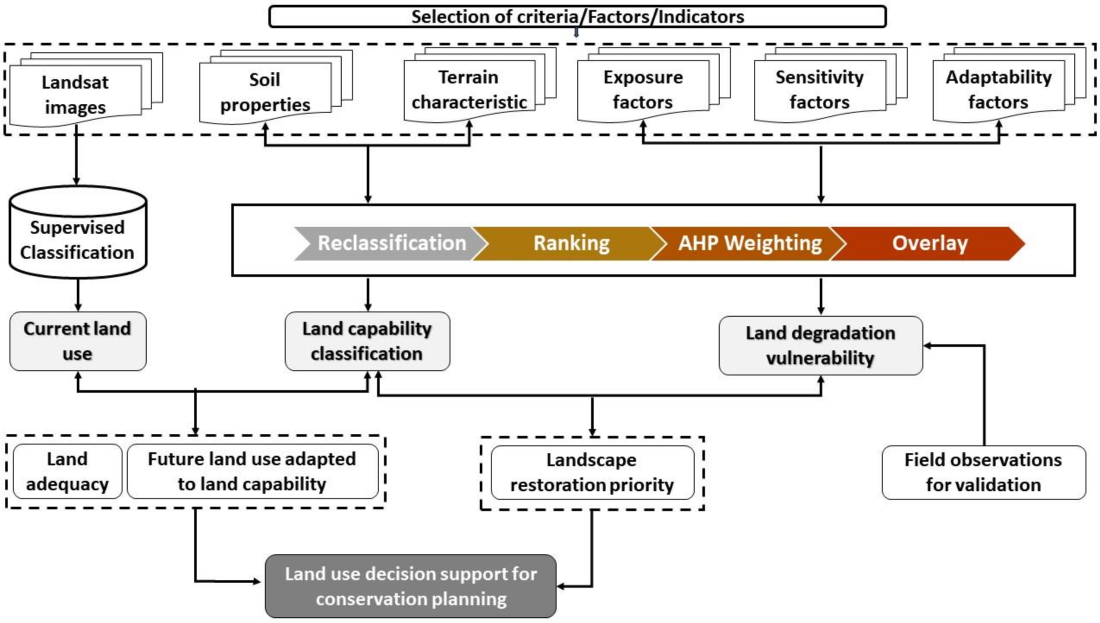


Figure 3.11 Methodological framework of the GIS-based AHP approach for land use and conservation planning decision support in response to land degradation.

3.7.7.1. Overview of the MCDA model

The Multi-criteria Decision Analysis (MCDA) is a decision-making tool that involves the selection of criteria, the weighting of criteria, and the combination of criteria to find solutions that satisfy decision-makers rather than an illusory optimum solution (Berliner, 2009). In the context of this study, the purpose is to make informed decisions about the prioritization area for the implementation of landscape restoration initiatives based on the land degradation vulnerability, the land capability, and the current LULC. The selection of land degradation criteria or proxies of land degradation was made through an extensive analysis of literature, field observations, and results from spatial analysis in the previous sections of this study and knowledge about the drivers of land degradation in the study area as perceived by the land user (results of the community consultation through questionnaire survey). Once the criteria were selected, their modalities which have different units were standardized at a common unit ranging from 0 to 5 and classified (ranked) according to their influence on the land degradation vulnerability (1=very low, 2= low, 3=moderate, 4=high, 5=very high). After the harmonization of the unit of criteria, the criteria were compared two by two (pairwise comparison) through the application of the Analytical Hierarchy Process (AHP) by using the EasyAHP plugin of QGIS 2.18. The AHP approach was proposed by Saaty (1980) and is performed through a pair-wise comparison of factors each other based on their relative importance (equal, moderate, strong, very strong, and extremely strong). This comparison is done on the 1-9 point scale proposed by Saaty (1980, 2008) (Table 3.7).

Table 3.7: A fundamental Verbal and numeric scale for the pairwise comparison of criterion according to the Analytical Hierarchy Process.

Numerical scale	Response Alternatives of Experts
1	Criteria i is equally important as Criterion j
3	Criterion i is slightly more important than Criterion j
5	Criterion i is more important than Criterion j
7	Criterion i is strongly more important than Criterion j
9	Criterion i is extremely more important than Criterion j
1/3	Criterion i is slightly less important than Criterion j
1/5	Criterion i is less important than Criterion j
1/7	Criterion i is strongly less important than Criterion j
1/9	Criterion i is extremely less important than Criterion j

Source: Saaty (1980), Saaty (2008), Herzberg *et al*. (2019)

Using this pair-wise comparison method, two criteria were compared at a time based on expert knowledge, field observation, and literature review to obtain a comparison matrix. The results of the pairwise comparison was presented in a matrix which compares the priorities of all criteria against each other matrix where C_{ij} represents the level of importance accorded to criterion i as compared to criterion j (Table 3.8).

Table 3.8: General form of a pairwise comparison matrix (A)

1	C_{12}	C_{1i}	C_{1j}	C_{1n}
C_{21}	1	C_{2i}	C_{2j}	C_{2n}
C_{i1}	C_{i2}	1	C_{ij}	C_{in}
C_{j1}	C_{j2}	C_{ji}	1	C_{jn}
C_{n1}	C_{n1}	C_{ni}	C_{nj}	1

Source: Adapted from Herzberg *et al*. (2019)

After the computation of the pairwise matrix, the next step was the normalization of the matrix by dividing each element C_{ij} of the pairwise comparison matrix by the value of the sum of numbers in each column of the matrix. Therefore, the normalized value of the numerical scale of comparison was calculated as follows according to Herzberg *et al*. (2019):

$$\overline{C_{ij}} = \frac{c_{ij}}{\sum_{i=1}^{n} c_{ij}} \quad \text{(Equation 3-28)}$$

where $\overline{C_{ij}}$, the normalized value of C_{ij}, n the number of compared criteria and $\sum_{i=1}^{n} C_{ij}$ is the sum of C_{ij} by column j from matrix A. The result was used to elaborate a normalized pairwise comparison matrix (Table 3.9).

Table 3.9: General form of a Normalized Matrix

$\overline{C_{11}}$	$\overline{C_{12}}$	$\overline{C_{1i}}$	$\overline{C_{1j}}$	$\overline{C_{1n}}$	$\boldsymbol{w_1}$
$\overline{C_{21}}$	$\overline{C_{22}}$	$\overline{C_{2i}}$	$\overline{C_{2j}}$	$\overline{C_{2n}}$	$\boldsymbol{w_2}$
$\overline{C_{i1}}$	$\overline{C_{i2}}$	$\overline{C_{ii}}$	$\overline{C_{ij}}$	$\overline{C_{in}}$	$\boldsymbol{w_i}$
$\overline{C_{j1}}$	$\overline{C_{j2}}$	$\overline{C_{ji}}$	$\overline{C_{jj}}$	$\overline{C_{jn}}$	$\boldsymbol{w_j}$
$\overline{C_{n1}}$	$\overline{C_{n2}}$	$\overline{C_{ni}}$	$\overline{C_{nj}}$	$\overline{C_{nn}}$	$\boldsymbol{w_n}$

Source: Adapted from Herzberg *et al*. (2019)

After obtaining the normalized matrix, the final step was the determination of the weight of each criterion by averaging the value of each row in the normalized matrix (Saaty 1980, 2008). Thus, from the above matrix (Table 3.9), the standard weight of each criterion was derived by dividing the sum of the normalized row of the matrix by the number of criteria (parameters) as follows:

$$\boldsymbol{w_i} = \frac{\sum_{j=1}^{n} \overline{C_{ij}}}{\boldsymbol{n}} \text{ (Equation 3-29),}$$

where $\boldsymbol{w_i}$ is the weight of criterion i and $\sum_{j=1}^{n} \overline{C_{ij}}$ is the sum of $\overline{C_{ij}}$ by row j from the standardized pairwise comparison matrix.

In the perspective to validate the results of the consistency of judgment in making the decision and to have some indications of the compatibility and rationality between compared criteria, the consistency index (CI) and consistency ratio (CR) was used. The Consistency Index (CI) is calculated as follows:

$$CI = \frac{\lambda_{max-n}}{n-1} \text{ (Equation 3-30) where n is the number of criteria and}$$

$$\lambda_{max} = \frac{\sum_{j=1}^{n} \frac{w_i * C_{ij}}{w_i}}{n} \text{ (Equation 3-31)}$$

with C_{ij}, the important level of criterion i as compared to criterion j and w_i is the weight of criterion i.

The Constancy ratio was calculated based on the following relation:

$$CR = \frac{CI}{RI} \text{ (Equation 3-32)}$$

where CR is the Consistency Ratio and RI is Random Index. The value of the random index (Table 3.10) has been already provided by Saaty (1980). An inconsistency of 10% is considered acceptable according to Saaty (1980), therefore if the CR ≤ 0.1, the pairwise comparison can be considered valid, otherwise a review and adjustment of the comparison is done.

Table 3.10: Values of RI

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

n= number of criteria used and RI is the Random inconsistency.

Source: Saaty (1980).

3.7.7.2. Methodological framework for land degradation vulnerability assessment based on the AHP approach and IPCC vulnerability framework

For a good assessment of land degradation vulnerability, this study considers both the natural (biophysical) and anthropogenic (socio-economic) indicators of vulnerability. This study is based on the IPCC framework for vulnerability assessment. In that framework, three components of vulnerability that should be considered are exposure, sensitivity, and adaptability. The application of this framework in the assessment of the vulnerability at the landscape level in the study area was done in three steps: firstly, the determination of the indicators of exposure, adaptative capacity, and sensitivity. After that, the different indicators were weighted using the Analytical Hierarchy process. Lastly, an overall indicator of vulnerability was obtained by summing the score of each vulnerability component. A set of indicators of these three components was identified based on the assessment of drivers of land degradation in the study area (Figure 3.12).

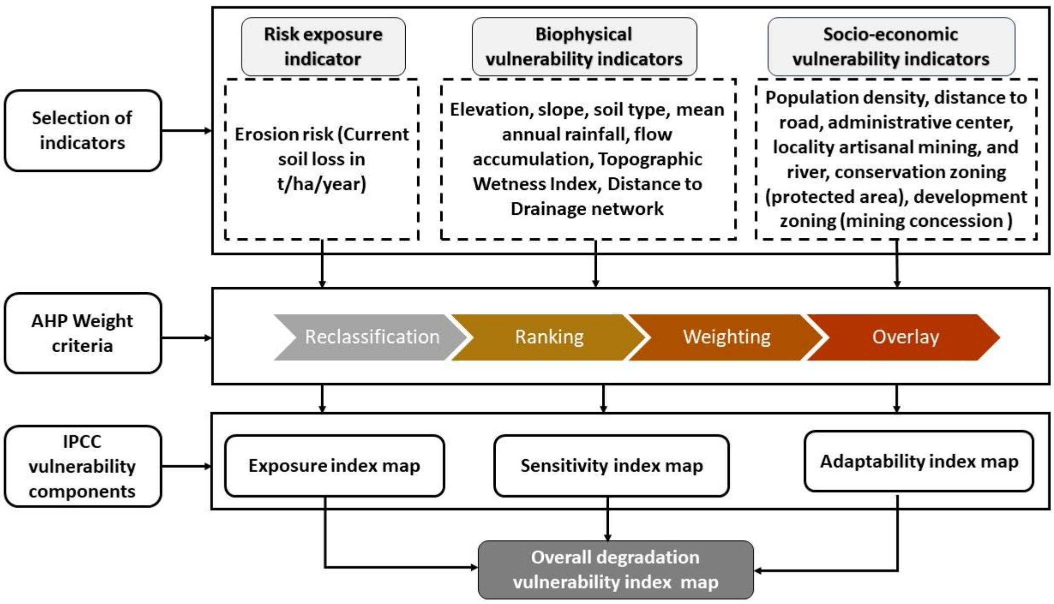


Figure 3.12: Methodological framework of the AHP-GIS-based approach for modeling the land degradation vulnerability.

For the exposure of the land to water erosion risk, the current rate of soil loss by erosion (erosion risk) calculated through the RUSLE model was considered an indicator of physical land degradation in the study area. The sensitivity which represents the response of the land system when it is experiencing the exposure was determined as a function of topography, soil type, and hydroclimatic factors. Adaptability which refers to the adaptative capacity in response to the land degradation process was estimated based on socio-economic characteristics such as population density, accessibility factors, and land use management as these factors are related to adaptability (Zhao *et al*., 2020). Thus, an Exposure index (EI), sensitivity index (SI), and adaptability index (AI) were computed through the application of the weighted linear combination of criteria (Malczewski, 1999). For this, the weight of each criterion obtained by using a pairwise comparison of criteria through AHP was multiplied by their standardized score (standardized ranking value of parameters) and then the results were summed to obtain the index. The spatial zoning map of each index was obtained by applying the following formula:

$$Index_x = \sum_{i=1}^{n} R_i W_i \text{ (Equation 3-33)}$$

Where W_i is the weight of the criteria I and R_i is the score value (rank) of the feature in the thematic layer and n is the.

3.7.7.3. Characterization of the exposure of the land to erosion risk

The current soil erosion rate was used as a proxy of the risk exposure to the physical land degradation process. Area with high erosion potential is more vulnerable to loss of land productivity due to the loss of topsoil. Furthermore, the sediment loading and siltation of rivers associated with soil loss have an impact on the water ecosystem and can contribute to flooding. Thus it was important to integrate this process into the land vulnerability model of the study area. The soil loss intensity was classified into five levels of vulnerability: very low (< 5 t/ha/year), low (5-10 t/ha/year), moderate (10-50 t/ha/year), high (50-100 t/ha/year), and very high (> 100 t/ha/year).

3.7.7.4. Characterization of the biophysical vulnerability

a) Classification and ranking of the biophysical vulnerability indicator

It is well known that the topographic factors (slope gradient, altitude, topographic wetness index), hydroclimatological factors (vertical distance to drainage network, flow accumulation, and rainfall intensity), and edaphic factors (soil type) affect the susceptibility to land degradation. Thus this range of indicators identified in the literature was standardized and ranked using a scale of 1 to 5 depicting the level of land degradation vulnerability (1 corresponding to very low vulnerability and 5 to very high vulnerability) based on the expert assessment as presented (Table 3.11).

Table 3.11: Justification of classification and ranking of selected biophysical factors of land degradation vulnerability

Factor	**High rank**	**Low rank**	**Justification**
Slope gradient	Steeps	Flat	An increase in the slope gradient induces an increase of erosion and shallow landslide susceptibility (Sharma & Singh, 2017).
Altitude gradient	High altitude	Low altitude	Altitude is a factor controlling the humidity in the region, and the occurrence of landmass in the region is associated with high altitude (Maki *et al*. 2021).
TWI	High wetness	Low wetness	The distribution of wetness conditions and influences the surface water runoff. Floods, erosion and landslides are more likely to occur in areas where the wetness conditions are high.
Soil type	High erodibility	Low erodibilit y	The soil with fine texture such as those rich in clay have a low infiltration potential, thus contributing to the runoff and soil erosion
Rainfall	High intensity	Low intensity	High rainfall intensity contributes to the occurrence of erosion, landslides, and flooding.
Distance to the drainage network	Low distance	High distance	The occurrence of erosion and landslides through river incision, and flooding are high on the river bank.
Flow accumulation	High accumulation	Low accumula tion	The area where there is an accumulation of surface water after rainfall events are likely to be affected by flooding, erosion, and landslide incidence

The topographic factor which was considered in this study is the slope gradient (percent), the altitude gradient, and the Topographic Wetness Index. These factors were derived from an SRTM-DEM of 30 m of spatial resolution. The slope gradient is a major factor that determines the terrain stability and controls the velocity of water runoff as well as the water infiltration potential (Sharma & Singh, 2017). An increase in the slope gradient induces an increase in the velocity of surface water runoff and a reduction of the infiltration, thus increasing erosion and shallow landslide susceptibility. Since steep slopes are more susceptible to erosion and landslides, they have been given the highest weight of 5. The physical land degradation vulnerability potential for the flat area is 1, indicating that they are the least susceptible to landmass movement. In addition, altitude is a factor controlling the humidity in the region, and the occurrence of landmass in the region is associated with high altitude (Maki *et al*., 2021). Furthermore, the gradient of altitude determines the ecological zones of species in this region and it's recognized that the ecosystem in high altitude is most vulnerable to environmental changes. For instance, there is a stratification of vegetation according to altitude in the Kahuzi-Biega National Park. Thus the very high altitude gradient (> 2050m) has been given the highest rank of 5 while the area whit the very low altitude gradient (< 1250) was given the lowest rank of 1 as they are least susceptible to land mass movement. The topographic wetness index (TWI) indicates the distribution of wetness condition and influence the surface water runoff. This index depends on the upstream contributing area per width orthogonal to the flow direction and slope gradient (Sharma1 & Singh, 2017) and it is estimated using the following formula:

$$TWI = ln\left(\frac{a}{tang\ (\beta)}\right) \text{ (Equation 3-34)}$$

with a, the specific catchment area obtained by dividing the catchment area A by the catchment contour length L, and β the slope gradient. Floods and landslides are more likely to occur in areas where the wetness conditions are high. The greatest rank of land degradation vulnerability was given to the area with TWI>19 while the lowest TWI (<7) was given the lowest rank.

To take into account the influence of the edaphic factor, the soil type of the study area derived from the SOTERCAF database was classified according to their erodibility. The texture of the soil influences the soil erodibility as it controls the infiltration potential of the soil. The soil with fine texture such as those rich in clay have a low infiltration potential, thus contributing to runoff and soil erosion. The soil types were classified according to their resistance to soil erosion The Acrisols have been given the maximum weightage of 5 due to their high erosivity and low infiltration capacity suggesting that they have the most contributing factors to the occurrence of erosion, landslide, and flooding in the area.

Rainfall intensity is one of the biophysical drivers of soil erosion and shallow landslide through its abrasive capacity (rainfall erodibility). The rainfall intensity also influences the occurrence of flooding as this process occurs mostly when the rainfall depth is high in the study area. The long-term annual rainfall derived from the Wordclim database was used to discrete the space into a different zone of rainfall intensity. The area characterized by an annual rainfall less than 1500 mm/year was given the lowest weight of 1 while the highest rank of 5 was given to the areas with annual rainfall higher than 1800 mm/year. During the rainfall event, water flows from the convex area and accumulates in the concave area of the landscape. This flow accumulation process was considered in the land degradation vulnerability model of the study area because the area where there is an accumulation of surface water after rainfall events is likely to be affected by flooding, erosion, and landslides incidence. The flow accumulation was estimated based on the SRTM-DEM of the study area using the hydrological analysis module of SAGA-GIS 7.8.2. In this context, flow accumulation is defined as the number of pixels where flow is accumulated in a particular area. The study area was categorized into 5 levels of vulnerability to land degradation, with high flow accumulation ($>10^6$ upstream cells number) indicating a high level of vulnerability.

The vertical distance to the drainage network which gives an insight on the depth of the water table compared to the topographic surface was also considered as an indicator of the land degradation vulnerability in the study area. The distance to the drainage network indicates the influence of the drainage density on the stability of soil cover. There is an association between the drainage density, the potential of dissection of the terrain through erosion, and the flood occurrence in the study area. It is evident that the flooding occurrence is high on the river bank and diminishes when the distance from the river increases. It can also be noted that the chance of flooding is high in the areas where the drainage density is high as the surface water runoff is high in these areas. Therefore, the lowest rank of 1 was given to the locations with the highest vertical distance to the drainage network (>100m). Nevertheless, areas with the lowest distance (<25m) were given the highest rank of 5.

b) Development of the sensitivity index

The computation of the sensitivity index was done by considering the biophysical factor of land degradation vulnerability. All these factors were compared through the AHP approach and their respective weights were determined. The Sensibility index (SI) was defined as:

$$SI = w_1 * R + w_2 * DN + w_3 * FA + w_3 * SG + w_4 * AG + w_5 * TWI + w_6 * ST$$
(Equation 3-35)

With R the annual rainfall, DN the distance to the drainage network, FA the flow accumulation, SG the slop gradient, AG the altitude gradient, and TWI the topographic wetness index, w1, …, w5 their respective weights.

3.7.7.5. Characterization of the socio-economic vulnerability indicator

a) Classification and ranking of the socio-economic vulnerability indicators

The socio-economic factors of land degradation vulnerability that are considered in this study are land use management factors (zoning policy), population density, and accessibility factors (distance to roads, distance to major rivers, distance to artisanal mining sites, distance to locality, and distance to center). For ranking and standardization, these criteria were classified into five classes based on the degree of vulnerability with 1 representing the lowest vulnerability and 5 the highest vulnerability as depicted (Table 3.12).

Table 3.12: Justification of classification and ranking of selected socio-economics factors of land degradation vulnerability

Factor	High rank	Low rank	Justification
Population density	High density	Low density	The vulnerability to land degradation increases when the population density is high.
Distance to road	Near	Far	The land degradation vulnerability would increase when the distance from the road network decrease
Distance to the administrative center	Near	Far	The access to markets which are concentrated in the major administrative group center contribute to the land degradation vulnerability.
Distance to locality	Near	Far	The impact of land degradation is expected to be high in the villages where people depend mostly on natural resources for their livelihood.
Distance to rivers	Near	Far	Riparian vegetations are more vulnerable to environmental changes.
Distance to artisanal mining sites	Near	Far	The intensification of mining activities is responsible for adverse environmental changes such as deforestation, slope instability, and loss of biodiversity.
Protected area	Absence	Presence	The land degradation vulnerability is expected to be low in the protected area compared to its surroundings due to the restriction of certain activities.
Mining concession	Presence	Absence	The intensification of anthropogenic activities inside the mining concession increases the vulnerability to land degradation.

For the socio-economic vulnerability, the population dynamics (population density) were considered as an indicator of social vulnerability, and the accessibility criteria (distance to roads, distance to major administrative center, distance to village, and distance to artisanal mining), were considered as indicators of economic vulnerability while the zoning for conservation (protected area) and development purpose (mining concession) were considered as indicators of land use management. The population density data was derived from the WorldPop Open Population Repository (WOPR). The vulnerability to land degradation increases when the population density is high as more people are exposed to this risk and a high density of population implies a high pressure on natural resources to satisfy their needs. In consequence, the greatest rank of the vulnerability of 5 was assigned to the area with a population density higher than

700 inhabitants/km^2 while the lowest rank of vulnerability was given to the area with a population density of less than 100 inhabitants/km^2. In the study area, most of the economic activities, as well as important infrastructures such as schools, hospitals, and markets, are concentrated in the major administrative group center, thus it is important to take into account the distance from this economic pool to highlight the vulnerability associated with these economic activities. In addition, the impact of land degradation is expected to be high in the villages where people depend mostly on natural resources for their livelihood. Thus, we consider that the vulnerability to land degradation should be high when the distance to the village and administrative center decreases. Another factor of land degradation vulnerability in the study area is the distance from roads. This is related to the fact that most human settlements are located along the road network. In addition, the permeabilities of the soil along the road network associated with the compaction of soil slow down the infiltration and increase the runoff potential thus contributing to soil erosion. In consequence, the land degradation vulnerability would increase when the distance from the road network decreases. Furthermore, the distance to the river network was considered an indicator of ecological vulnerability as riparian vegetation is more vulnerable to environmental changes. Artisanal mining is responsible for adverse environmental changes in Eastern DR Congo. The Euclidian distance from administrative centers, villages (locality), artisanal mining sites, rivers, and roads was obtained by using the *proximity* tool of QGIS. Using the natural break interval, the proximity variables were standardized and reclassified into 5 levels of vulnerability with the highest value of 5 assigned to the nearest distance (<3000m) and the lowest value of 1 assigned to the highest distance (>12000 m)

Land use management is an important factor to consider in the assessment of land degradation vulnerability. There is also an implementation of land conservation mechanisms through the designation of protected areas (park and forest reserve) and development policy through the establishment of the mining concession in D.R. Congo. The land degradation vulnerability may depend on these land management policies. For instance, the designated protected areas are expected to be less vulnerable due to the prohibition of certain activities while the mining concession is more vulnerable to land degradation due to the intensification of anthropogenic activities.

b) Development of the adaptability index

The adaptability index was computed by considering the socio-economics factors of vulnerability. The pairwise comparison of the socio-economic factor of land degradation vulnerability was done through the AHP approach to obtain the weight of each factor (W_i) and the adaptability index (AI) was computed using the equation 3.36:

$$AI = w_1 * MC + w_2 * PA + w_3 * PD + w_4 * DL + w_5 * DAc + w_6 * DRo + w_7 * DRi + w_8 * DAm \quad \text{(Equation 3-36)}$$

With MC the mining concession, PA the protected area, PD the population density, DL the distance to the locality, DAc the distance to the administrative center, DRo distance to the road, DRi is the distance to the river, Dam the distance to artisanal mining and with their respective weight.

3.7.7.6. Computation of the overall vulnerability index

The model to establish the zoning of prone-area to land degradation was defined by integrating the exposure (EI), the sensitivity (SI), and the adaptability index (AI). The three indexes were compared through the AHP approach and the final land degradation vulnerability index (LDVI) was computed using the equation 3.37

$$LDVI = w_1 * EI + w_2 * SI + w_3 * AI \quad \text{(Equation 3-37)}$$

This model (Equation 3.37) was applied to determine the land degradation-prone area where landscape restoration action should be prioritized. Based on the developed model, the land degradation vulnerability map of the study area was produced. This map was classified into five classes of vulnerability (very low, low, moderate, high, and very high) based on the natural break interval. The area with very low vulnerability is those that don't necessitate any restoration measures. The area with low vulnerability was given a low priority for restoration, the area with moderate vulnerability was given a medium priority and the area with high and very high vulnerability was given a high priority for implementation of restoration measures based on the level of degradation. Furthermore, the zonal statistics were computed to determine the mean value of the vulnerability index at the watershed level. Based on this approach the watershed was prioritized according to their vulnerability.

3.7.7.7. Performance of the model

The validation of the developed models was done by considering the soil erosion and shallow landslide occurrence data as a proxy of physical land degradation. These data were used to validate the developed model to predict land degradation vulnerability. To assess the reliability of the Analytical Hierarchy Process (AHP) model to predict the hotspot of land degradation in the study area, we assessed the relationship between the occurrences data of landmass features observed on the field and through Google Earth images with the class of land degradation vulnerability by using the frequency ratio approach. The probabilistic frequency ratio (FR) approach as proposed by Pradhan *et al*. (2012) was used to assess the relationship between the occurrence data of erosion features and the class of land degradation vulnerability determined by applying the AHP model. The frequency ratio approach provides a valuable ranking to identify the closeness of the relationship between the occurrence of land degradation features and the class of land degradation vulnerability. In this approach, the frequency ratio was defined as the ratio of the proportion of occurring land degradation features (erosion and shallow landslides) in each land degradation vulnerability class to the proportion of the land degradation vulnerability class to the total area considered. The value of FR equal to one was used as a threshold (Tehrany *et al*., 2017, Gayen *et al*., 2020): a value that is higher than 1 indicates a high correlation while a value less than 1 shows a low correlation between the classes of vulnerability and the land degradation features occurrence. The overall accuracy was obtained by dividing the sum of land degradation features observed in the high and very high vulnerability zones by the total number of erosion features observed in the study area.

3.7.7.8. Land capability analysis

The land capability represents the ability of the land for agriculture and non-agricultural land use based on a set of combinations of soil characteristics and slope (Romshoo *et al*., 2020). The assessment of land suitability for land use was done through the land capability analysis. The land capability depends on different physical factors including the nature of the soil and the topography (Al Saya *et al*. 2022, Nguyen *et al*., 2023). In the context of this study, the USDA land capability classification of the soil resources was adapted to the study area context. The USDA land capability consists of 8 levels ranging from I to VIII in descending order of land productivity. In the context of this study, we considered the four classes suitable for agricultural productivity (I to IV) but stricter soil and water conservation are required as the class order increase, and the class of non-arable land of USDA's classification (classes V-VIII) was grouped into a single class V characterized by a poor land capability for agricultural purpose but suitable for forestry purpose following the approach suggested by Al Saya *et al*. (2021) and Nguyen *et al*. (2023). The main factors used in this study for land capability assessment are soil texture, soil depth, and slope. The soil factors were derived from the Afsis database while the slope was derived from a DEM. Since these factors don't have the same influence on the land capability, different weight was allocated based on the weights provided in the literature (Al Saya *et al*. 2022), and pairwise comparison was done to avoid bias in the allocation of weight. These factors were paired and compared using the AHP approach to produce the land capability index of the study area as can be seen in Table 3.13.

Table 3.13: Factor for land capability classification for the study area

Capability	**I (High)**	**II(Moderate)**	**III(Low)**	**IV(Very low)**	**V(Non-arable)**
Texture (**T**)	Medium	Sandy	Fine	Very fine	Very fine
Soil depth (**SD**)	very deep	Deep	Moderate	Shallow	Very shallow
(in Cm)	(>150)	(150-100)	(100-50)	(25-50)	(< 25)
Slope (**S**)	Flat	Gentle	Moderate	Steep	Very steep

The land capability index (LCI) was defined as

$$LCI = w_1 * T + w_2 * SD + w_3 * S \text{ (Equation 3-38)}$$

The land capability was used as a basis for adaptative land use planning to reduce the land degradation vulnerability in the study area (Figure 3.13). The flowing stages were followed: (1) the current land use map was obtained by doing a supervision classification of Landsat images, (2) the land capability maps were obtained by combining soil data (soil texture and soil depth) and terrain characteristics (slope gradient) derived from a digital elevation model based on the land capability classification of USDA, (3) the land capability maps and the land use maps were combined to obtain the land adequacy map, (4) the land adequacy map was used to adjust the land use maps to its capability, (5) the frequency ratio of the occurrence of landslides and soil erosion within the land capability classes was calculated to assess the correlation between the land capability and the degradation.

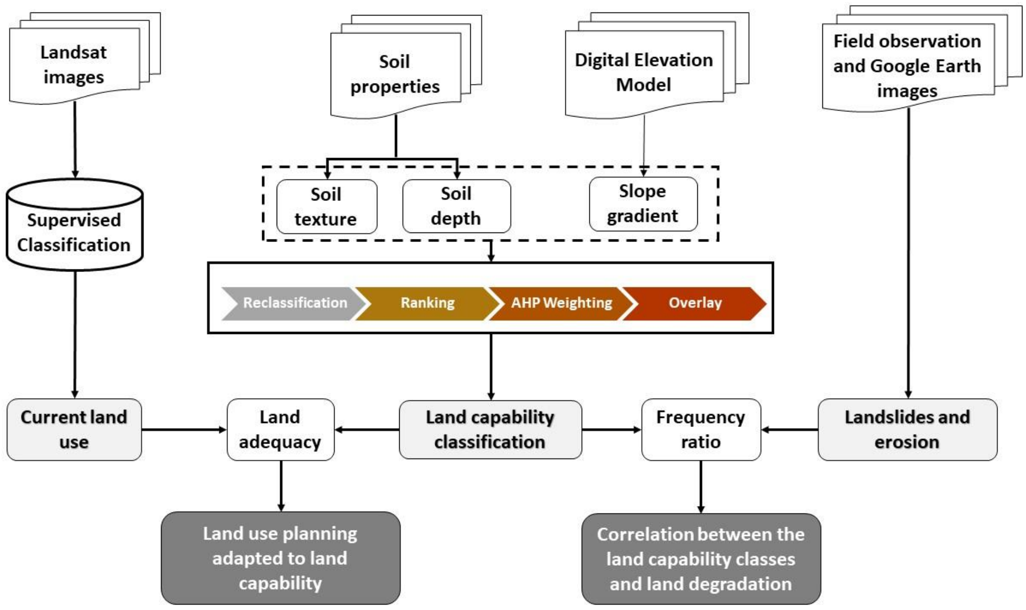


Figure 3.13: Methodological framework for land capability assessment and its integration in the land use plan.

3.7.7.9. Integration of the land capability in the land use plan

To assess if the current land use is sustainable and done following the land use capability, the current LULC (2020) was intersected with the land use capability maps to obtain the land use adequacy maps. The land adequacy maps discriminate the area where the land is used according to its capability or not (Taveira *et al*. 2021). Following the criteria proposed by Al Saya *et al*. (2021, 2022), the lands were classified into 3 categories to assess the adequacy of the current land use management:

(1) Land being underutilized: grassland and shrubland covering the most productive land capability classes (I, III, III) and unproductive land (bare land) over prime lands (I, II, III, IV)

(2) Land managed within its capability: agricultural area found in the prime land (I, II, III, and IV), shrublands and grassland over lands capability classes IV and V, unproductive land (bare land) over lands capability class V, forest and wetland over any land capability class, built-up land over land capability IV and V

(3) Land being overutilized: land being used over its capability includes agricultural land over the land capability class V, built-up areas over prime lands (I, II, III)

The results of this reclassification helped to identify the area where the land is misused (underutilization and overutilization) which reflects the unsustainable utilization of land. This land utilization potential map was used to identify the area where the land use adjustments are necessary for an optimal allocation of land use based on the land capability. The comparison of the current LULC types with the corresponding land capability classes was necessary to perform this adjustment. This approach is used in land use planning to suggest different land use scenarios to optimize land utilization and the conservation of the environment (Gashaw *et al*., 2018, Nguyen *et al*. 2023). Considering that the built-up land and wetland (waterbody) are not practical options for land use conversion (Al Saya *et al*. 2022, Nguyen *et al*., 2023), the LULC scenario was focused on the conversion among agricultural land, bare land, forest land, shrubland and grassland (pasture land). The suggested LULC alternative aims to optimize the current LULC according to its capability and ensure the preservation and protection of the land against degradation processes. This implies that any allocation of other LULC types to agriculture use must align with its associated capability class. The correlation between the land capability class and land degradation was evaluated by using the frequency ratio of occurrence of degradation features (landslides and erosion) observed in the field and through Google Earth images following the approach preconized by Nguyen *et al*. (2023). When the frequency ratio is higher than 1, it implies a high predisposition of the capability class to landslides or erosion while when the value of frequency ratio is less than 1, it indicates a lower likelihood of this occurrence.

3.7.9. Analysis of perception on land degradation

A questionnaire was administrated to the people living in Kalehe territory to assess their perception of land degradation and to identify the conservation practices that they have adopted to cope with this problem. The quantitative and qualitative data collected through the household questionnaire was encoded in the SPSS 16.0 and Excel 2013 software where basic descriptive statistics, chi-square test, and binary logistic regression model were performed accordingly to the 6 sections of the questionnaire covering the socio-economic characteristics of the household, the perception on land degradation, the drivers of change of flow of ecosystem service and the ecosystem service value of land use type as perceived by local communities. The analysis includes tabulations, cross-tabulation, and descriptive statistics such as frequencies and presentation of data in the form of tables, charts, and graphics. The Chi-test of independence was used to assess the dependence among the qualitative variables. Furthermore, the logistic regression models were used to identify the determinant factors of the adoption of conservation measures. The logistic regression model (Equation 3.39) is described as

$$\ln\left(\frac{P_i}{1-P_i}\right)= \beta 0+ \beta 1X1 + \beta 2X2 + \cdots \beta iXi + e \quad \text{(Equation 3-39)}$$

Where $\ln(Pi/(1 - Pi\,))$ is the log of odds, Pi the probability of outcomes, β_0 the intercepts or constant of the model $\beta_1, \beta_2, \beta_3, \ldots, \beta_i$ are the correlation coefficient associated with each dependent variable $X_1, X_2, X_3, \ldots X_i$ and e the error term. These coefficients reflect the effects of explanatory variables on its log of odds and not the direct effect of the change in explanatory variables on the probability of outcomes Pi. However, these coefficients can be used to interpret the probability or odds of outcomes as a positive coefficient indicating an increase in the odds or probability of outcomes when there is an increase in the value of the corresponding explanatory variable (Asfew *et al*., 2023).

To establish the model of community adoption of conservation measures to cope with the problem of land degradation, a value of 1 was assigned to all households that adopted at least one conservation measure ("adopters”) while a value of 0 was assigned to those that did not adopt any conservation measures ("non-adopters”). These binary variables were used as dependent variables while the social factors (age, sex, marital status, household size, education, residency or stayed period), institutional factors (land ownership, access to training and extension services, farming experience or seniority), physical factors (farmland size, distance to farmland, slope of the farmland), economic factors (main activity), attitudinal factor (perception on farmland productivity).

CHAPTER FOUR

RESULTS

4.1. Introduction

This chapter presents the findings based on the objectives of the study and includes the results on (i) land use dynamics in Kalehe territory during the 1987-2020 period and forecast the future situation for the 2030-2070 period under the business as usual scenario, (ii) the modeling of the land use susceptibility and identification of the underlying drivers of LULC change based on the logistic regression modeling approach (iii) the land productivity dynamics from remote sensing perspectives (iv) the perceived ecosystem service value variation over LULC changes (v) the model of soil erosion dynamics under different land use and adoption of conservation practices scenarios, (vi) the spatial pattern of the land degradation vulnerability and land evaluation for prioritization of area for restoration based on an MCDA approach, and (vii) the land user perspectives on land degradation and adoption of conservation practices to cope with this problem. The results were obtained through the analysis of Landsat images, GIS mapping, field surveys, and secondary sources of information.

4.2. Lulc Dynamic And Its Implication To Land Degradation

4.2.1. Accuracy assessment of images classification

Findings revealed that the overall accuracy of the LULC classification for the years 1987, 2002, and 2020 the overall accuracy is greater than 80% and the overall Kappa statistics vary between 0.8 and 0.83 indicating a high level of agreement and satisfactory accuracy of LULC classification which are acceptable for the classification and detection of LULC types (Table 4.1).

Table 4.1: Accuracy assessment of the LULC classification.

LULC	**1987**		**2002**		**2020**	
	UA (%)	**PA(%)**	**UA(%)**	**PA(%)**	**UA(%)**	**PA(%)**
Forest	83.16	88.76	85.71	85.71	96.88	100.00
Cropland	68.42	98.48	85.71	100.00	78.13	78.13
Wetland	87.37	91.21	85.71	75.00	93.75	83.33
Settlement	86.32	75.23	71.43	83.33	78.13	67.57
Grassland	64.21	62.89	100.00	77.78	78.13	96.15
Shrub	90.53	74.78	85.71	85.71	84.38	84.38
Bare land	96.84	93.88	71.43	83.33	90.63	96.67
Overall accuracy (%)	82.41		83.67		85.71	
Kappa index	0.80		0.81		0.83	

UA= User's Accuracy, PA=Producer's Accuracy

4.2.2. Study area's LULC characteristics for 1987, 2002 and 2020

The maps presented in Figure 4.1 show the LULC pattern based on the results from Landsat images classification for the years 1987, 2002, and 2020. They present the spatial distribution of 7 LULC types identified in the Kalehe territory.

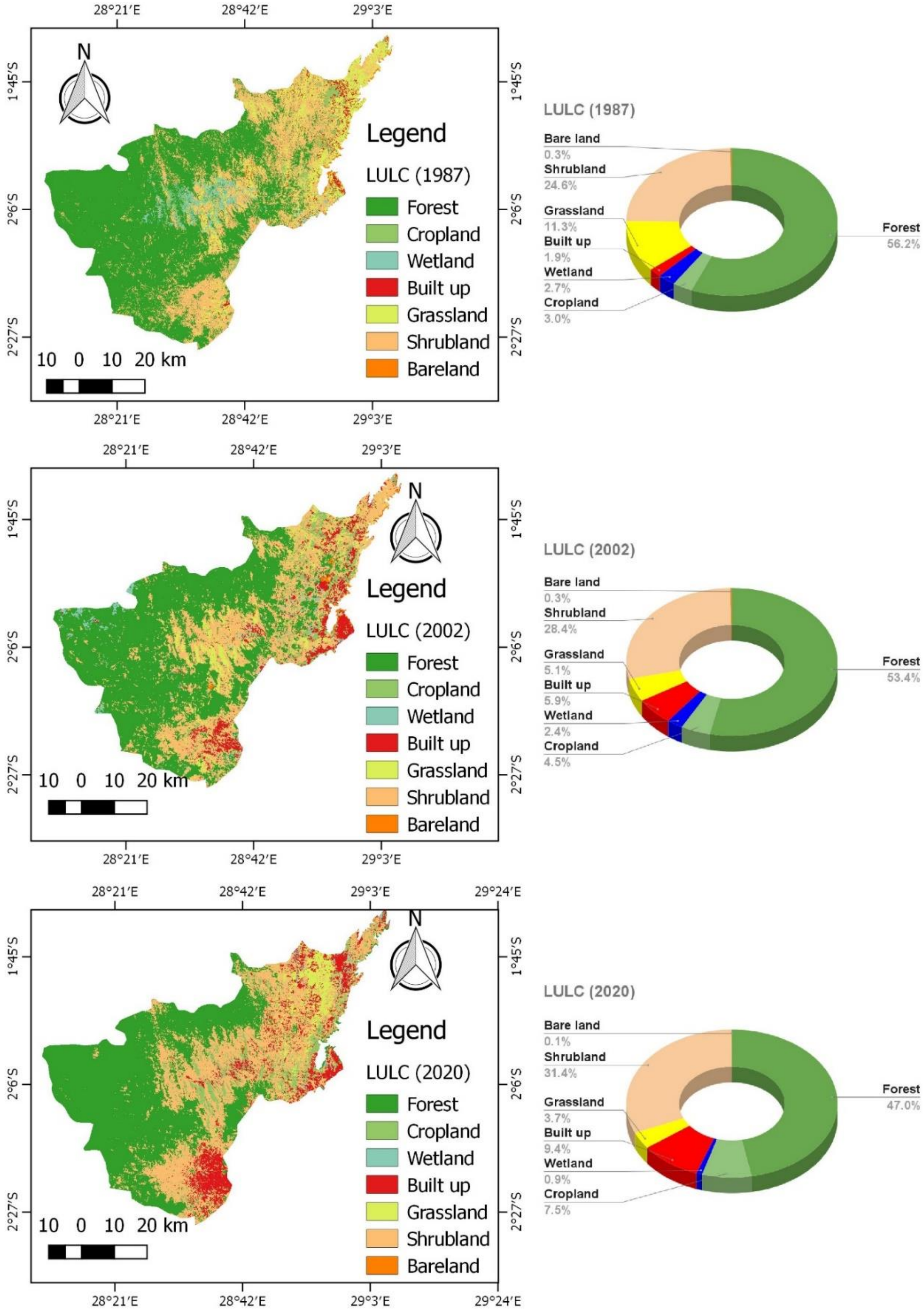


Figure 4.1: LULC types derived from Landsat TM of 1987, 2002, and 2020 in Kalehe territory, Eastern DR Congo.

The spatio-temporal distribution of each LULC type was quantified in terms of proportions and total area for each study periods. The proportion of LULC type for 1987, 2002, and 2020 are presented in Table 4.2. It is observed that the forest cover is the dominant LULC type during the three period of analysis but its surface is shrinking over time.

Table 4.2: LULC area for 1987, 2002 and 2020 in Kalehe territory.

LULC	**1987**		**2002**		**2020**	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Forest	2335.65	56.25	2216.36	53.38	1952.48	47.02
Cropland	125.40	3.02	186.11	4.48	312.96	7.54
Wetland	112.80	2.72	101.27	2.44	36.99	0.89
Built up	78.54	1.89	245.08	5.90	388.59	9.36
Grassland	468.50	11.28	211.81	5.10	153.22	3.69
Shrubland	1019.82	24.56	1179.78	28.41	1305.09	31.43
Bare land	11.61	0.28	11.92	0.29	3.00	0.07

The largest proportion of LULC type during the year 1987 are forest land, shrub land, and grassland which occupy 56.25%, 24.56%, and 11.28% of the total surface area of the Kalehe territory respectively. The cropland represents only 3% of the territory. The bare land, built-up area, and wetland are the least represented and occupy 0.28%, 1.89%, and 2.72%, respectively (Table 4.2).

It is evident from Table 4.3 that during the year 2002, the landscape was subjected to transformation represented by the regression of forestland (- 2.87%), grassland (-6.10%), and wetland (-0.28%). In contrast, the cropland (+1.46%), shrubland (+3.84%), and built-up area (+3.85%) have been expanded. The forest land (53.37%) was the most dominant LULC during this year. It is followed by shrubland (28.41%), grassland (5.10%), built-up area (5.90%), and cropland (4.48%). The bare land (0.29%) and wetland (2.44%) were the least represented.

Table 4.3: LULC change for 1987-2002, 2002-2020, and 1987-2020.

LULC	1987-2002		2002-2020		1987-2020	
	Area (km^2)	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Forest	-119.29	-2.87	-263.88	-6.36	-383.17	-9.23
Cropland	60.71	1.46	126.85	3.06	187.56	4.52
Wetland	-11.53	-0.28	-64.28	-1.55	-75.81	-1.83
Built up	166.54	4.01	143.51	3.46	310.05	7.47
Grassland	-256.69	-6.18	-58.59	-1.41	-315.28	-7.59
Shrubland	159.96	3.85	125.31	3.02	285.27	6.87
Bare land	0.31	0.01	-8.92	-0.22	-8.61	-0.21

In 2020, forestland (47.02%), shrubland (31.43%), built-up area (9.36%), and cropland (7.54%) remained the most dominant land use type in the territory. The bare land (0.07%), wetland (0.89%), and grassland (3.69%) are the least represented. The results show that there is an expansion of the cropland (+3.05%), built-up area (+3.45%), and shrubland (+3.02%) while the forestland (-6.35%), wetland (-1.54%) and grassland (-1.41%) are decreasing.

4.2.3. LULC dynamics during the 1987-2020 period

The dynamics of the LULC change over the three periods (1987-2002 representing the first period, 2002-2020 representing the second period, and 1987-2020 representing the whole period) were analyzed based on the temporal and annual rate of change to make the comparison of LULC types over time. In the entire period of analysis (1987-2020), the forestland, grassland, wetland, and bare land decreased by -16.41%, -67.0%, -67.20%, and -74.19% at a rate of 11.61km^2/year, -9.55km^2/year, -2.30km^2/year and -0.26km^2/year respectively (Table 4.3). In contrast, the built-up area, cropland, and shrub increased by 394.75%, 149.57%, and 27.97%. Thus the bare land and grassland display the highest negative rate of change whereas the built-up area and cropland display the highest positive rate of change (Table 4.4).

Table 4.4: LULC trends in 1987-2002, 2002-2020, and 1987-2020.

LULC	1987-2002			2002-2020			1987-2020		
	RC	**TC**	**AC**	**RC**	**TC**	**AC**	**RC**	**TC**	**AC**
Forest	-7.95	-5.11	-0.15	-14.66	-11.91	-0.36	-11.61	-16.41	-0.50
Cropland	4.05	48.41	1.47	7.05	68.16	2.07	5.68	149.57	4.53
Wetland	-0.77	-10.22	-0.31	-3.57	-63.47	-1.92	-2.30	-67.20	-2.04
Built up	11.10	212.03	6.43	7.97	58.56	1.77	9.40	394.75	11.96
Grassland	-17.11	-54.79	-1.66	-3.26	-27.66	-0.84	-9.55	-67.30	-2.04
Shrubland	10.66	15.69	0.48	6.96	10.62	0.32	8.64	27.97	0.85
Bare land	0.02	2.67	0.08	-0.50	-74.86	-2.27	-0.26	-74.19	-2.25

RC=Rate of change (km^2/Year), TC=Temporal change (%) and AC=Annual rate of change (%/Year.

In 1987, there was 2335.65km^2 of forest cover (56.25%), this surface decreased to 2216km^2 (53.38%) in 2002, and to 1952.48km^2 (47.02%) in 2020 (Table 4.2). This implies that there is a temporal decrease of 5.11% for 15 years, from 1987 to 2002, and a decrease of -11.61% was observed during a period of 18 years, from 2002 to 2020 (Table 4.3). Considering the two periods of analysis, the annual rate of deforestation increased from 0.15%/Year during the 1987-2002 period to 0.66%/Year during the 2002-2020 period. From 1987 to 2020, 16.41% of forests have been converted to other lands. During this period the annual rate of deforestation is 0.47%/year (Table 4.4).

The wetland coverage decreased from 112.8km^2 (2.72%) to 101.27km^2 (2.44%) in 2002 and 36.96km^2 in 2020 (Table 4.2). These results suggest that the wetland area decreased by 10.22% from 1987-2002 and by 63.47% between 2002 and 2020. The rate of decrease of wetlands during these two periods is 0.31%/year and 2.30%/year, respectively. The overall rate of wetland loss over the entire period of analysis (1987-2020) is 67.20%, accounting for a loss of 2.04 %/year (Table 4.4).

The bare land presents the highest pic of surface area loss during the entire study period. In 1987, there was 11.61km^2 (0.28%) of bare land (Table 4.2). This surface increased to 11.92km^2 (0.29%) in 2002. However, it drastically decreased to 3km^2 (0.07%) in 2020. The overall decrease in bare land during the 1987-2020 period is 74.19%. The annual change regarding the bare land area is 0.05%/year, -4.16%/year, and -2.25%/year over the 1987-2002, 2002-2020, and 1987-2020 periods (Table 4.4).

The grassland also shows a decreasing pattern during the study period. In 1987, the coverage area of grassland was 468.5km^2 (11.28%), but this surface decreased to 211.81km^2 (5.10%) in 2002 and 153.22km^2 (5.10%) in 2020 (Table 4.2). Therefore, about 67.30% of the grassland cover was changed to other land during the 1987-2020 period. This represents a loss of -1.66 %/year, -1.54 %/year, and -2.04 %/year during the 1987-2002, 2002-2020, and 1987-2020 periods, respectively (Table 4.4).

The cropland increased from 125.4km^2 (3.02%) in 1987 to 186.11km^2 (4.48%) in 2002 and 312.96km^2 (7.55%) in 2020 (Table 4.2). Thus the cropland has a temporal growth of 48.41%, 68.16%, and 149.57% during the 1987-2002, 2002-2020, and 1987-2020, respectively. This indicates that the cropland expansion rate increased from 1.47%/year during the 1987-2020 period to 3.79%/year for the 2002-2020 period. The overall expansion rate of the cropland over the entire period (1987-2020) is 4.53%/year (Table 4.4).

The surface coverage of the built-up area was 78.54km^2 (1.89%) in 1987. This surface raised to 245.08km^2 (5.90%) in 2002 and 388.59km^2 (9.36%) in 2020 (Table 4.2). This indicated that between 1987 and 2002, a temporal change of 212.03% was observed over 15 years while a change of 58.56% was observed between 2002 and 2020, over 18 years. Thus, during the 33 years (1987-2020), an overall expansion of the built-up area of 394.75% was observed. According to this, the built-up expansion rate in the study area was 6.43 %/year during the 1987-2020 period and 3.25% between 2002 and 2020. The overall expansion rate of the built-up area between 1987 and 2020 is 11.96 %/year (Table 4.4).

The coverage area of shrubland was 1019.82km^2 (24.56%) in 1987 but it increased to 1179.78km^2 (28.417%) in 2002 and 1305.9km^2 (31.43%) in 2020 (Table 4.2). Thus, there is a temporal increase of 15.69% from 1987 to 2002 and 10.62% from 2002 to 2020. For a period of 33 years, ranging from 1987 to 2020, the increasing rate of shrubland in the territory is 27.97%. This shows that the annual rate of shrubland expansion was 0.48%/year, and 0.59%/year for the 1987-2002 and 2002-2020 periods, respectively. In addition, the overall rate of increase of the shrubland for the 33 periods of study is 0.85 %/year (Table 4.4).

4.2.4. LULC change between 1987-2020

The inter-transition of LULC types to changing phenomena from 1987 to 2020 is presented in Table 4.5. This table show that, in term of area (inkm^2) three major LULC transitions involved the conversion of forest land to shrub (466.58km^2), shrub to built-up area (165.98km^2), and grassland to shrub (151.37km^2).

Table 4.5: LULC change transition matrix between 1987 and 2020.

		Change to LULC of 2020 (area in km^2)							
		Forest	**Crop-land**	**Wet-land**	**Built-up**	**Grass-land**	**Shrub**	**Bare-land**	**Total 1987**
Change from LULC in 1987	Forest	**1793.41**	34.18	4.54	31.88	4.97	**466.58**	0.10	2335.65
	Cropland	4.94	**19.40**	4.37	15.10	20.66	60.87	0.07	125.40
	Wetland	13.44	11.37	**2.60**	10.31	0.05	75.02	0.00	112.80
	Built up	0.41	15.40	1.19	**38.77**	10.71	11.77	0.29	78.54
	Grassland	6.45	132.16	8.50	123.14	**46.63**	**151.37**	0.25	468.50
	Shrub	132.28	99.92	14.37	**166.98**	69.00	**537.09**	0.18	1019.82
	Bare land	1.55	0.53	1.42	2.41	1.20	2.40	**2.10**	11.61
	Total 2020	1952.48	312.96	36.99	388.59	153.21	1305.09	3.00	4152.32

Results presented in the above table show that during the period from 1987 to 2020, 76.78% (1793.41km^2) of forestland, 52.66% (537.09km^2) of shrub land, 49.36% (38.77km^2) of built-up land, 15.47% (19.40km^2) of cropland, 9.95% (46.63km^2) of grassland, 18.11% (2.10km^2) of bare land, and 2.31% (2.6km^2) of wetland remained unchanged. Thus, from the 7 LULC types, the wetland was the most vulnerable while the forestland was the least vulnerable to LULC change. Regarding the observed trend of LULC changes, there is a considerable decrease in forestland due to its conversion to shrubland (466.58km^2), cropland (34.18km^2), and built-up area (31.88km^2) as can be seen in Table 4.5. In addition, the decline in grassland is predomitaely attributed its transformation to shrubland (151.37km^2) and cropland (132.16km^2), despite an increase in area from shrubland (69.00km^2) and cropland (20.06km^2). Furthermore, the shrinking of wetland was evident as it has been converted to shrubland (75.02km^2), forestland (13.44km^2), and cropland (11.37km^2). The aforementioned pattern was observed in bare land which has been converted to forest land (1.55km^2), built-up area (2.41km^2), and shrubs (2.40km^2). In contrast, there was an expansion of cropland, built-up area, and shrubland. The area dedicated to agriculture use exhibited an expansion from 125.40km^2 in 1987 to 312.86km^2 in 2020 although a specific portion of its surface was converted to shrub (60.87km^2), grassland (20.66km^2) and built-up area (15.10km^2). The primary factor contributing to the augmentation of cropland is the reduction in grassland (132.16km^2), shrub (99.82km^2), forest land (34.18km^2), built-up area (15.40km^2), and wetland (11.37km^2). Concurrently, the built-up area underwent substantial expansion by increasing from 78.54km^2 in 1987 to 388.59km^2 in 2020. The shrubland (166.98km^2), grassland (123.14km^2), and forestland (31.88km^2) constitute the main contributor to this expansion. With respect to the conversion of shrubland, its surface rose from 1019.82km^2 in 1987 to 1305.09km^2 in 2020 although its area was simultaneously changed to forest land (132.28km^2), built-up area (166.98km^2) and cropland (99.92km^2). Forest (466.58km^2), grassland (151.37km^2), wetland (75.02km^2), and cropland (60.87km^2) are the major contributors to the expansion of shrubland in the study area (Table 4.5).

To better understand these changes, a quantitative assessment of the change analysis of the gain, loss, and net change has been done for each LULC type (Table 4.6). The gain, loss, and net change in terms of area (in km^2) were derived from the results presented in the transition matrix (Table 4.6).

Table 4.6: Total area of gains and losses of LULC types between 1987 and 2020.

LULC	1987	2020	No change		Gain		Loss		Net change	
	Area (km^2)	Area (km^2)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Forest	2335.6	1952.48	1793.41	47.02	159.07	3.83	542.24	13.06	-383.17	-9.23
Cropland	125.40	312.96	19.40	7.54	293.56	7.07	106	2.55	187.56	4.52
Wetland	112.80	36.99	2.6	0.89	34.39	0.83	110.2	2.65	-75.81	-1.83
Built up	78.54	388.59	38.77	9.36	349.82	8.42	39.77	0.96	310.05	7.47
Grassland	468.50	153.22	46.63	3.69	106.58	2.57	421.87	10.16	-315.28	-7.59
Shrubland	1019.82	1305.09	537.09	31.43	768	18.50	482.73	11.63	285.27	6.87
Bare land	11.61	3.00	2.10	0.07	0.89	0.02	9.51	0.23	-8.61	-0.21

Among the 7 LULC categories, cropland, built-up area, and shrubland show sizeable gross grains but forestland, wetland, grassland, and bare land present losses of their surface indicating that some LULC types are experiencing an increasing pattern while others are decreasing (Table 4.6). Furthermore, the built-up area displayed the highest positive net change (349.82km^2) and shrubland had the second-highest net change (285.27km^2) while cropland and are displaying a very slight net change (187.56km^2). In contrast, wetland, forest land, grassland, and bare land presented a negative net change with a total surface change of -75.18km^2, -383.17km^2, -315.29km^2, and -8.61km^2 respectively (Table 4.6).

Figure 4.2 presents the spatial pattern of the major LULC transitions that occurred in the Kalehe territory over the last 33 years. It can be observed through this map that during the 1987-2020 period, the study area was dominated by stable land cover which represented 58.35% (2433.03 km^2) of the territory.

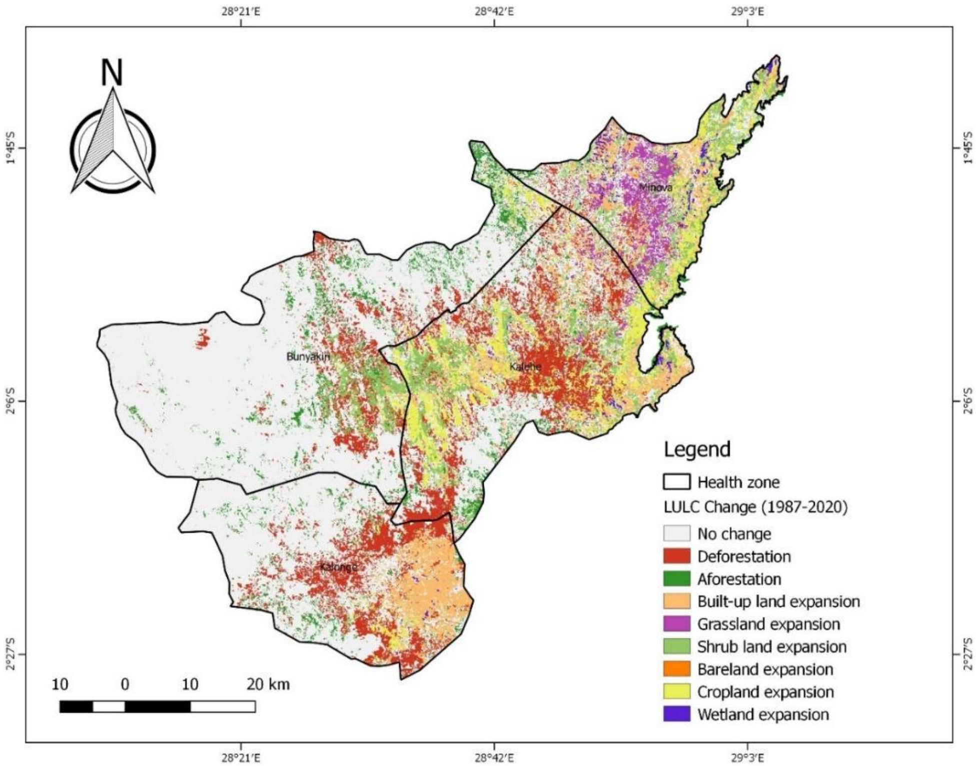


Figure 4.2: Majors LULC transition during the 1987-2020 period.

The deforestation was identified as the most prominent proximate driver of LULC change in the study area between 1987 and 2020 (Table 4.6). During this period, deforestation occurred in 13.06% (542.24km^2) while afforestation occurred in only 3.83% (159.07km^2) of the study area. This deforestation was mainly associated with built-up land expansion, shrubland expansion, cropland expansion, and grassland expansion which occurred in 8.42% (349.82km^2), 18.50% (768.00km^2), 7.07% (293.56km^2), and 2.57% (106.48km^2) of the territory, respectively. During this period, the bare land has expanded to 0.02% (0.88km^2) while the wetland expanded to 0.74% of the territory as a result of inundation.

4.2.5. Landscape characteristics

The measurable units of landscape characteristics are landscape metrics (landscape structure and composition). These metrics constitutes the surrogate for change in landscape and they are used for the quantification and description of spatial pattern and ecological process. It is in this perspective that the landscape composition and structure metrics derived from the analysis of LULC maps from 1987-2020 period were described.

4.2.5.1. Landscape composition

Table 4.7 presents the descriptive statistics of landscape composition metrics in terms of LULC types in Kalehe territory during the 1987-2020 period.

Table 4.7: Descriptive statistics of the landscape composition metrics

LULC types	1987			2002			2020		
	Mean	**Sd**	**CV**	**Mean**	**Sd**	**CV**	**Mean**	**Sd**	**CV**
FL	31.88	29.7	93.06	32.28	27.41	84.91	26.31	30.39	115.53
CL	5.00	5.98	119.66	8.09	8.68	107.21	11.78	11.18	94.90
WL	0.55	0.96	173.9	2.91	3.09	106.09	2.54	3.48	137.05
BA	5.06	6.09	120.3	10.43	10.41	99.87	12.53	11.60	92.58
GL	20.00	18.0	90.06	6.14	6.31	102.79	5.73	7.94	138.46
SL	20.40	16.6	81.44	23.27	17.16	73.76	24.47	18.13	74.10
BL	0.57	0.72	126.12	0.34	0.54	162.36	0.09	0.16	176.04

Key: Sd= Standard deviation, CV= Coefficient of variation, FL=Proportion of forestland, CL=Proportion of cropland, WL=Proportion of wetland, BA=Proportion of built-up area, GL=Proportion of grassland, SL=Proportion of shrub land, BL=proportion of bare land.

Throughout the entire analysis period (1987-2020), forestland and shrubland dominated the landscape in each watershed while wetlands and bare land were the least represented. In 1987, grassland was the third most dominant land cover, but it was surpassed by the expansion of built-up areas and croplands in 2002 and 2020. Forestland, followed by grassland, displayed the largest area decrease from 1987 to 2020. During this period, the highest increase in area was observed in the shrubland, followed by the built-up area and cropland. The value of the coefficient of variation of the proportion of the land cover categories within the 59 watershed shows that the highest variability in term of landscape composition was observed for wetland and bare land in 1987, cropland and bare land in 2002, and grassland and built-up areas in 2020 (Table 4.7).

4.2.5.2. Landscape structure

The Table 4.8 presents the mean of the 15 landscapes metrics selected for this study and their variability at the watershed level in the study area. The landscape metrics that present a high variability across the 1987-2020 timeframe include the patch density

(PD), edge density (ED), Landscape shape index (LSI), Mean patch size (AREA_MIN), and Shannon's diversity index (SHDI). In contrast, metrics such as the Patch cohesion index (COHESION), AI, Perimeter-area fractal dimension (PAFRAC), Mean perimeter-area (PARA_MN), and Mean shape index (SHAPE_MN) exhibit the lowest variation during this period.

Table 4.8: Descriptive statistics of the selected landscape structure metrics.

Landscape	1987			2002			2020		
Metrics	Mean	Sd	CV	Mean	Sd	CV	Mean	Sd	CV
Fragmentation metrics									
PD	8.8	5.46	62.1	4.35	2.66	61.1	5.13	3.59	69.9
LPI	46.96	22.8	48.6	42.76	21.8	50.9	45.67	21.24	46.5
ED	53.14	31.9	59.9	31.61	18.57	58.7	34.15	22.89	67.0
Aggregation and contagion metrics									
AI	90.47	4.29	4.74	94.55	2.34	2.47	94.08	2.98	3.17
CONTAG	60.12	15.2	25.3	62.58	15.1	24.1	48.4	18.15	37.5
COHESION	97.86	1.51	1.54	97.92	1.4	1.43	97.89	1.6	1.63
Shape complexity metrics									
AREA_MN	46.31	59.9	129.5	53.31	53.41	100	172.7	234.3	136
SHAPE_MN	1.34	0.06	4.1	1.36	0.06	4.65	1.41	0.11	7.99
PARA_MN	570.36	66.7	11.7	439.6	77.27	17.6	382.9	131.6	34.4
PAFRAC	1.35	0.04	2.77	1.24	0.03	2.37	1.25	0.03	2.59
LSI	8.28	5.97	72.1	5.65	3.6	63.7	5.58	3.48	62.4
Configuration metrics									
IJI	49.14	15.4	31.3	61.5	16.33	26.5	65.98	10.44	15.8
ENN_MN	189.38	67.4	35.6	358.7	167.8	46.8	224.1	102.5	45.7
Diversity metrics									
SHDI	0.82	0.41	50.4	0.94	0.47	50.6	0.84	0.46	54.4
SIDI	0.44	0.22	49.5	0.48	0.24	49.3	0.45	0.25	54.5

Key: Sd= Standard deviation, CV= Coefficient of variation, PD=Patch density, LPI= Largest Patch Index, ED=Edge density, LSI=Landscape shape index, IJI=Interspersion and juxtaposition index, AI=Aggregated index, COHESION= Patch cohesion index, CONTAG.= Contagion, AREA_MN= Mean patch size, SHAPE_MN=Mean shape index, PARA_MN=Mean perimeter-area ratio, ENN_MN=Mean Euclidian nearest neighbor distance, PAFRAC= Perimeter-area fractal dimension, SHDI=Shannon's diversity index, SIDI= Simpson's diversity index

The results demonstrate that there is a temporal variation in the value of the considered index (Table 4.8). Both the patch density (PD), edge density (ED), and Landscape shape index (LSI) which are fragmentation indexes decreased from 1987 to 2002 but increased from 2002 to 2020. The AREA_MIN presents a similar pattern indicating that the fragmentation levels increased in the second period (2002-2020) compared to the first period (1987-2020). In contrast, the aggregation index (AI), the cohesion index (COHESION), and the contagion index (CONTAG) increased during the first period but decreased in the second period. The large shape index (LSI) shows an increasing trend during the two periods but the mean shape index (SHAPE_MN), the Perimeter-area fractal dimension (PAFRAC), and the Mean perimeter-area ratio (PARA_MN) present a decreasing pattern suggesting a decreased in shape complexity over time. The Interspersion and juxtaposition index (IJI) exhibited a consistent increase from 1987 to 2020. However, the Mean Euclidian nearest neighbor distance (ENN_MN) between patches reveals a shift in trend over time. Specifically, there was an increase in ENN_MN during the 1987-2002 period, followed by a decrease during the 2002-2020 period. This result suggests that the isolation between patches was higher in the first period compared to the second period. Considering the whole period of analysis (1987-2020), it is observed that the isolation between patches has increased as the ENN_MN increased from 189.38±67.39m in 1987 to 224.14±102.46m in 2020. There is an increase in diversity index (Shannon's diversity index SHDI and Simpson's diversity index, SIDI) value between 1987 and 2002 while it is observed that the value of these indexes decreased between 2002 and 2020. This indicates that the patch heterogeneity was high in the first period compared to the second period. However, the diversity index shows that the actual (2020) landscape heterogeneity is high compared to the observation from 1987.

4.2.5. Exploration of potential underlying drivers of LULC change

The potential underlying drivers of LULC changes included in this study are:

4.2.5.1. Biophysical variable

Topographic variables such as altitude, slope gradient, slope aspect, and soil type were considered potential drivers of LULC change in the study area. As can be seen in Figure 4.3, the altitude of the territory varies between 801m and 3030 m with a mean value of 1684 m±468 m showing that the territory is dominated by hilly. Furthermore, the territory is dominated by steep slopes which constitutes a constraint for built-up and agricultural expansion. The slope gradient varies between 0 and 186.76% with a mean of 26.37± 17.62% indicating that the steep slope is the most dominant in the study area. The territory has also a diversity of slope orientations which influence the insolation and this could affect the LULC in the study area as the seed’s crops depend on the amount of solar radiation. The slope aspect varies between 0 and 360 degrees with a mean of 181.77± 104.08 degrees indicating that most of the slopes are oriented to the south. The edaphic factors play also a great role in the allocation of land use. In the study area, 3 types of soil can be distinguished: acrisols, ferrasols, and cambisols. The humic cambisols are the predominant soil in the territory covering about 48.8% (2047.93km^2) of the surface, followed by the haplic acrisols account for 39.1% (1642.55km^2) of the territory while the humic ferrasols are the least dominant representing only 12.1% (509.72km^2) of the area (Figure 4.3). These soils have different fertility levels and constitute a constraint for agriculture development and thus influence the expansion of cropland.

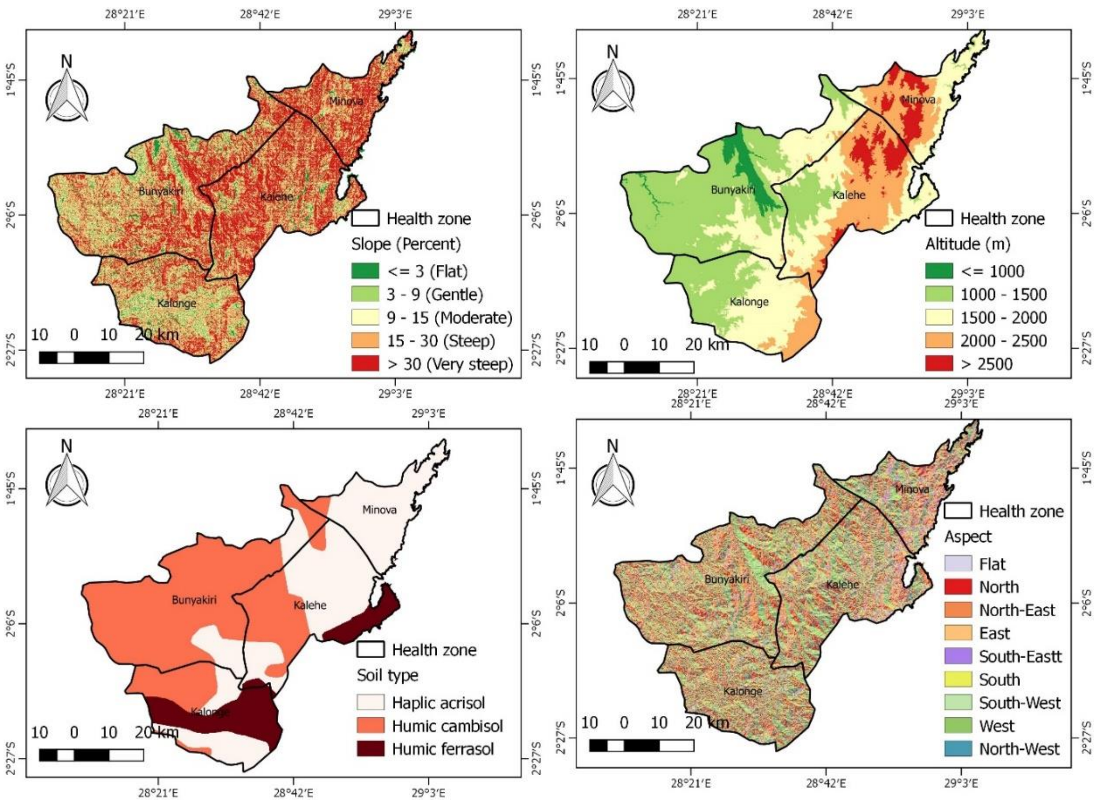


Figure 4.3: Spatial variability of biophysical variables in Kalehe territory.

4.2.5.2. Socio-economic and population dynamics variables

The population dynamics constitute a potential driver of LULC change due to their dependency on natural resources. There is a spatial heterogeneity in the spatial distribution of population density in the Kalehe territory. For instance, for the year 2020, the Kalehe territory has a population density varying between 5 inhabitants/km^2 and 1097 inhabitants/km^2 with a mean of 223 inhabitants/km^2 but its spatial distribution is heterogeneous (Figure 4.4).

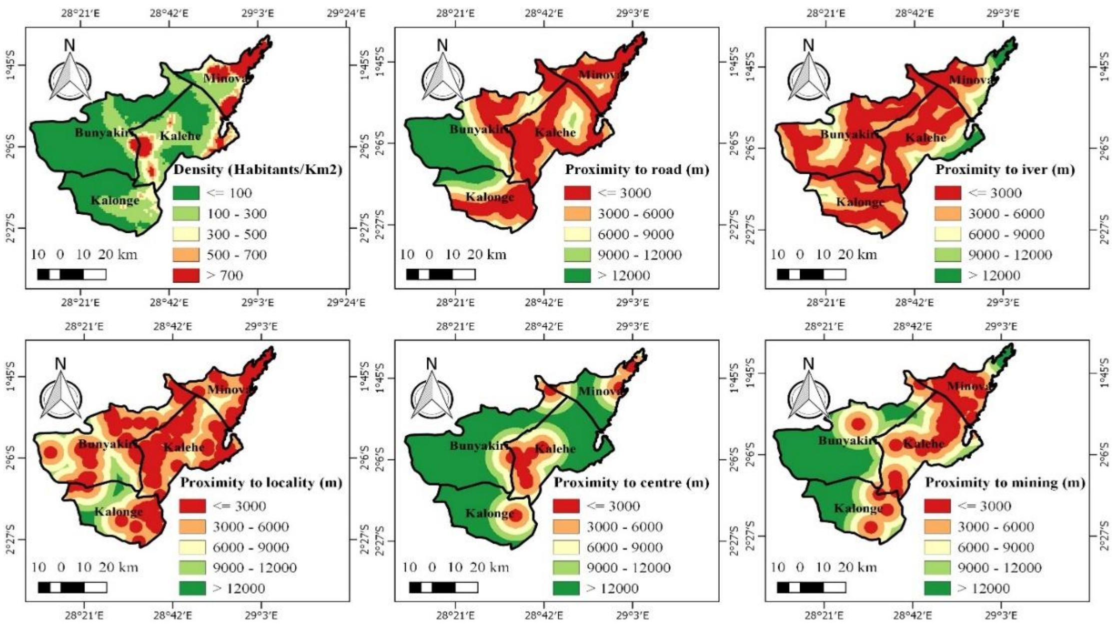


Figure 4.4: Population density, and proximity factors in the Kalehe territory.

It can be observed from Figure 4.4 above that the high density of the population is in the eastern part and central part of the territory. However, the low density of the population is observed in the western part of the territory. It is expected that the human pressure on natural vegetation and the development of anthropogenic activity will be more prominent in the areas where the population density is high. This population is unequally distributed in the major administrative center (administrative groups) and the locality (village). A total of 14 administrative groups' centers and 161 localities (villages) are inventoried in the territory. Hence the proximity to administrative group center and locality were considered as potential underlying drivers of LULC (Figure 4.4). The administrative groups' center has a high population density which implies a high demand for natural resources but also a high accessibility to the market as most of the commercial activities are focused in this area. Thus, the proximity to the locality and center constitutes an important factor that can influence the LULC type in the study area. The settlements are mostly concentrated in the vicinity of roads which constitute an asset for the flow of resources and development of economic activities. The anthropogenic influence on the natural resource may be influenced by the distance to the road. In this perspective, the proximity to the road network, both national and secondary roads crossing the study area, has the potential to be used as a predictive variable in the LULC model. Furthermore, access to water resources constitutes a constraint in the implementation of settlement for domestic usage, livestock consumption as well and the need for water for the development of agricultural activities. As water access constitutes a major constraint in any human development, the proximity to water resources has the potential to influence the LULC in this territory. Therefore, the Euclidian distance in meters to the major rivers in the study area was mapped. Furthermore, the artisanal mining activity plays a great role in the economic development of the study area. A total of 261 artisanal mining sites were inventoried in this area. This mining activity influences the configuration of the landscape and can influence the LULC to change over time. In this context, the proximity to artisanal mining sites (Figure 4.4) is considered a potential driver of LULC change in the study area.

4.2.5.3. Development and conservation policy variable (Zoning)

Conservation policy and development policy have been implemented in the territory of Kalehe through the delineation (zoning) of protected areas and mining concession. The Figure 4.5 illustrates the conservation zoning and mining concession zoning in the Kalehe territory.

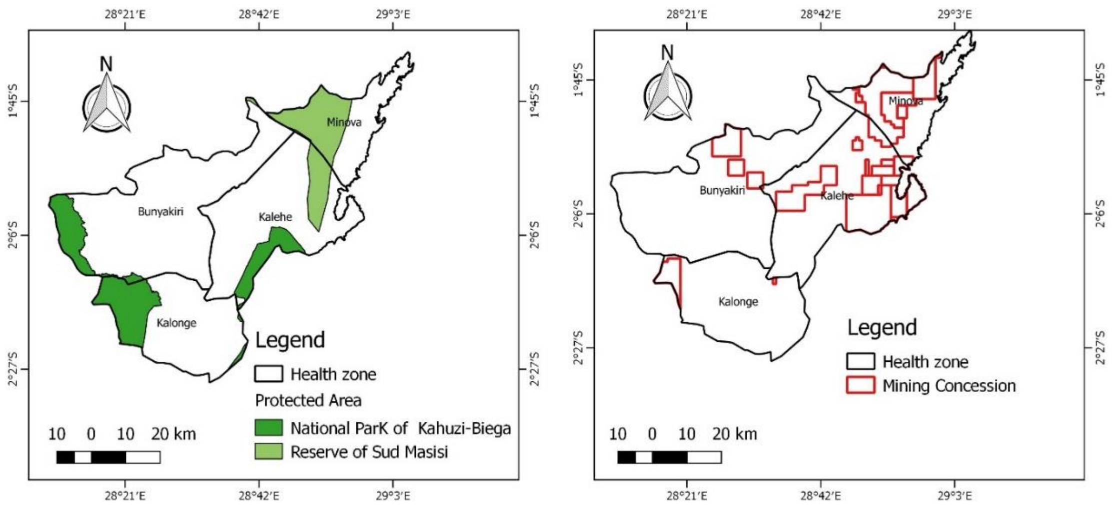


Figure 4.5: Protected area and mining concession in Kalehe territory.

From a conservation perspective, it can be observed in Figure 4.5 that an extent of the Kahuzi-Biega National Park and the Reserve of Sud-Masisi are located in the territory of Kalehe. Thus a total of 878.75km^2, representing 21.07% of the study area are being designated as protected areas. These protected areas have been delineated to conserve the local biodiversity and the remaining forest. However, anthropogenic activity continues to encroach on the forest in these areas, thus their effectiveness for conservation is questionable. From the perspective of this study, we hypothesized that the area that falls in the protected area has high conservation potential compared to the area which is outside. Thus the conservation policy which was implemented in the study area can contribute to the stability of LULC categories, especially the forest land. In addition to that, mining concessions have been attributed to mining companies as a strategy for economic development in the area. A total of 867.01km^2 or 20.79 percent of the territory is covered by mining concession. The presence of mining activity can influence the dynamic of the population in the area as well as the development of other economic activity and the demand for natural resources thus influencing the LULC change in the study area

4.2.5.4. Multicollinearity analysis of the potential drivers of LULC change

The multi-collinearity analysis among the potential underlying drivers of LULC changes was tested using the Variance Inflation Factor (VIF) and the findings are presented in Table 4.9.

Table 4.9: Collinearity Statistics of the independent variables.

Variables	Tolerance	VIF
Slope	0.972	1.028
Altitude	0.4	2.5
Distance to the administrative center	0.28	3.568
Mining concession	0.619	1.616
Distance to locality	0.707	1.414
Distance to river	0.64	1.562
Conservation	0.601	1.665
Aspect	0.986	1.014
Distance to road	0.237	4.213
Distance to artisanal mining	**0.171**	5.856
Population	0.565	1.771
Soil	0.658	1.519

It can be observed from the above table that the minimum tolerance of the 12 driving factors is 0.171 which is higher than the critical value of 0.1. Furthermore, the analysis of the multicollinearity among the predictors through the VIF, indicated that most of the predictor's variables have a moderate value of VIF (less than 10), indicating that there is no multicollinearity in the independent variables (Table 4.9).

4.2.6. LULC change susceptibility modelling

The main LULC conversions which occurred in the study area between 1987 and 2020 are deforestation, built-up area expansion, shrub expansion, and cropland expansion (Figure 4.2). The influence of potential biophysical and socio-economic drivers of LULC change on the five most LULC changes occurring in the study area was determined using a logistic regression approach (Table 4.10 and Table 4.11).

Table 4.10: Overall models of major LULC changes in Kalehe Territory.

Variables	**Deforestation model**		**Built-up land expansion model**		**Cropland expansion model**		**Shrub land expansion model**	
	β	**p-value**	**β**	**p-value**	**β**	**p-value**	**β**	**p-value**
Slope	0.00171	0.77	-0.00493	0.42	0.01643	0.04**	0.00461	0.32
Altitude	0.00023	0.45	0.00226	<0.001***	-0.00044	0.38	-0.00085	<0.001***
Distance to center	-0.00002	0.36	-0.00001	0.46	-0.00002	0.43	-0.00003	0.13
Mining concession	-0.229	0.45	0.31012	0.24	-0.48466	0.27	0.32558	0.14
Distance to locality	-0.00003	0.61	-0.00008	0.22	-0.00019	0.09*	-0.00007	0.14
Distance to river	-0.00002	0.60	0.00003	0.34	0.00012	0.03**	0.00007	0.01***
Conservation	-0.7294	0.02**	-0.7002	0.03**	-0.88744	0.13	-0.35685	0.19
Aspect	0.00082	0.39	-0.00018	0.85	-0.00647	<0.001***	0.00171	0.03**
Distance to road	-0.00011	0.01**	-0.00011	0.07*	0.000002	0.98	-0.00007	0.06*
Distance to mining sites	-0.00007	0.04**	-0.00007	0.09*	-0.0002	<0.001***	-0.00009	0.001***
Population	-0.00277	<0.001**	0.00084	<0.001***	-0.00057	0.19	-0.00035	0.11
Soil	-0.42364	0.02**	0.77475	<0.001***	-0.35532	0.19	-0.36735	0.01**
Constant	0.29481	0.73	-6.52897	<0.001***	0.92416	0.46	1.53848	0.02**
Model chi-square ($\chi2$)	100.3		174.125		73.372		122.694	
Model Nagelkerke R^2	0.183		0.29		0,219		0.182	
Correct prediction (%)	87.8		86.2		95.1		80.1	
AUC	0.753±0.020		0.82±0.16		0.809±0.030		0.710±0.030	

*β: Estimated coefficient; SE: Standard error; R^2: Coefficient of determination; *, ** , *** significant at 10%, 5% and 1% level of significance, respectively.*

The findings from both the overall (Table 4.10) and best-fit developed models (Table 4.11) indicated that the conservation zoning, distance to roads, and distance to artisanal mining sites, population density, and soil types are the most important factors that significantly influence the occurrence of deforestation in the study area. It was also observed that the built-up area expansion is positively influenced by the altitude, the distance to roads, the soil type and the population density but negatively influenced by the conservation zoning. The soil type constitutes the most influential factor on built-up expansion with an odds ratio of 2.29. On the other hand, the cropland expansion model indicated that the most influential factors influencing this expansion are the slope gradient and aspect, the proximity to locality, and the proximity to the artisanal mining area. It was observed that the slope gradient has the most positive influence while the occurrence of the conservation zoning has the most negative influence on the expansion of cropland. Regarding the expansion of shrubland, the results show that this expansion is significantly influenced by topographic factors such as altitude and slope, edaphic factor (soil type), and proximity factors (distance to river, artisanal mining sites, and roads). The Table 4-11 presents the coefficients (β) and significance of the Walid test (p-value) of the best-fit models of the majors LULC changes based on the step-wise logistic regression.

Table 4.11: Best-fit models of major LULC changes in Kalehe Territory.

Variables	Deforestation model		Built-up land expansion model		Cropland expansion model		Shrubland expansion model	
	β	**p-value**	**β**	**p-value**	**β**	**p-value**	**β**	**p-value**
Slope					0.01503	0.04*		
Altitude			0.00228	<0.001***			-0.00105	<0.001***
Distance to center								
Mining concession								
Distance to locality					-0.00019	0.03**		
Distance to river							0.00007	<0.001***
Conservation	-0.88122	<0.001***	-0.67636	0.01**	-1.43444	0.01***		
Aspect					-0.00649	<0.001***	0.00171	0.03**
Distance to road	-0.00013	<0.001***	-0.00014	0.01**			-0.00009	<0.001***
Distance to mining sites	-0.00009	<0.001***	-0.00006	0.07*	-0.00017	<0.001***	-0.00011	<0.001***
Population	-0.00288	<0.001***	0.00109	<0.001***				
Soil	-0.41602	0.01**	0.82899	<0.001***			-0.29583	0.03**
Constant	0.69558	0.06*	-7.06811	<0.001***	-0.57931	0.23	1.50991	0.01***
Model chi-square ($\chi 2$)	95.778		169.176		64.605		111.905	
Model Nagelkerke R^2	0.175		0.282		0.193		0.167	
Correct prediction (%)	87.9		86.2		95.1		79.8	
AUC	0.746±0.020		0.817±0.16		0.813±0.030		0.685±0.032	

*β: Estimated coefficient; SE: Standard error; R^2: Coefficient of determination; *,**, *** significant at at 10%, 5% and 1% level of significance, respectively.*

Considering the coefficient of the best-fit model (Table 4.11), the probability of deforestation (P_{Def}), built-up expansion (P_{Bexp}), cropland expansion (P_{Cexp}), and Shrubland expansion (P_{Sexp}) within the study area can be defined by:

$$P_{Def} = \frac{exp(0.69558-0.88122*CZ-0.00013*DRo-0.00009*\mathrm{DAm}-0.00288*\mathrm{Pd}-0.41602*\mathrm{ST})}{1+exp(0.69558-0.88122*CZ-0.00013*DRo-0.00009*\mathrm{DAm}-0.00288*\mathrm{Pd}-0.41602*\mathrm{ST})} \quad \text{(Equation 4-1)}$$

$$P_{Bexp} = \frac{exp(-7.06811+0.00228*\mathrm{Alt}-0.67636*\mathrm{CZ}-0.00014*\mathrm{DRo}-0.00006*\mathrm{DAm}+0.00109*\mathrm{Pd}+0.82899*\mathrm{ST})}{1+exp(-7.06811+0.00228*\mathrm{Alt}-0.67636*\mathrm{CZ}-0.00014*\mathrm{DRo}-0.00006*\mathrm{DAm}+0.00109*\mathrm{Pd}+0.82899*\mathrm{ST})} \quad \text{(Equation 4-2)}$$

$$P_{Cexp} = \frac{exp(-0.57931+0.01503*\mathrm{Sl}-0.00019*\mathrm{Dlo}-1.43444*\mathrm{CZ}-0.00649*\mathrm{Sa}-0.00017*\mathrm{DAm})}{1+exp(-0.57931+0.01503*\mathrm{Sl}-0.00019*\mathrm{Dlo}-1.43444*\mathrm{CZ}-0.00649*\mathrm{Sa}-0.00017*\mathrm{DAm})} \quad \text{(Equation 4-3)}$$

$$P_{Sexp} = \frac{exp(1.50991-0.00105*\mathrm{Alt}+0.00007*\mathrm{DRi}+0.00171*\mathrm{As}-0.00009*\mathrm{DRo}-0.00011*\mathrm{DAm}-0.29583*\mathrm{ST})}{1+exp(1.50991-0.00105*\mathrm{Alt}+0.00007*\mathrm{DRi}+0.00171*\mathrm{As}-0.00009*\mathrm{DRo}-0.00011*\mathrm{DAm}-0.29583*\mathrm{ST})} \quad \text{(Equation 4-4)}$$

With DRi=distance to the river, Sl= slope. DLo= distance to the locality, As= Aspect, Alt= Altitude, CZ= Conservation zoning, DRo= Distance to roads, DAm= Distance to artisanal mining sites, Pd= Population density, ST= Soil type.

To determine the area with a high suceptibility of deforestation, cropland expansion, built-up land expansion, and shrubland expamsion in the study area, the above equations (4-1 to 4-4) were applied along with the spatial data of the determinant drivers of LULC changes. Figure 4.6 presents the susceptibility maps of these majors LULC changes within the study area.

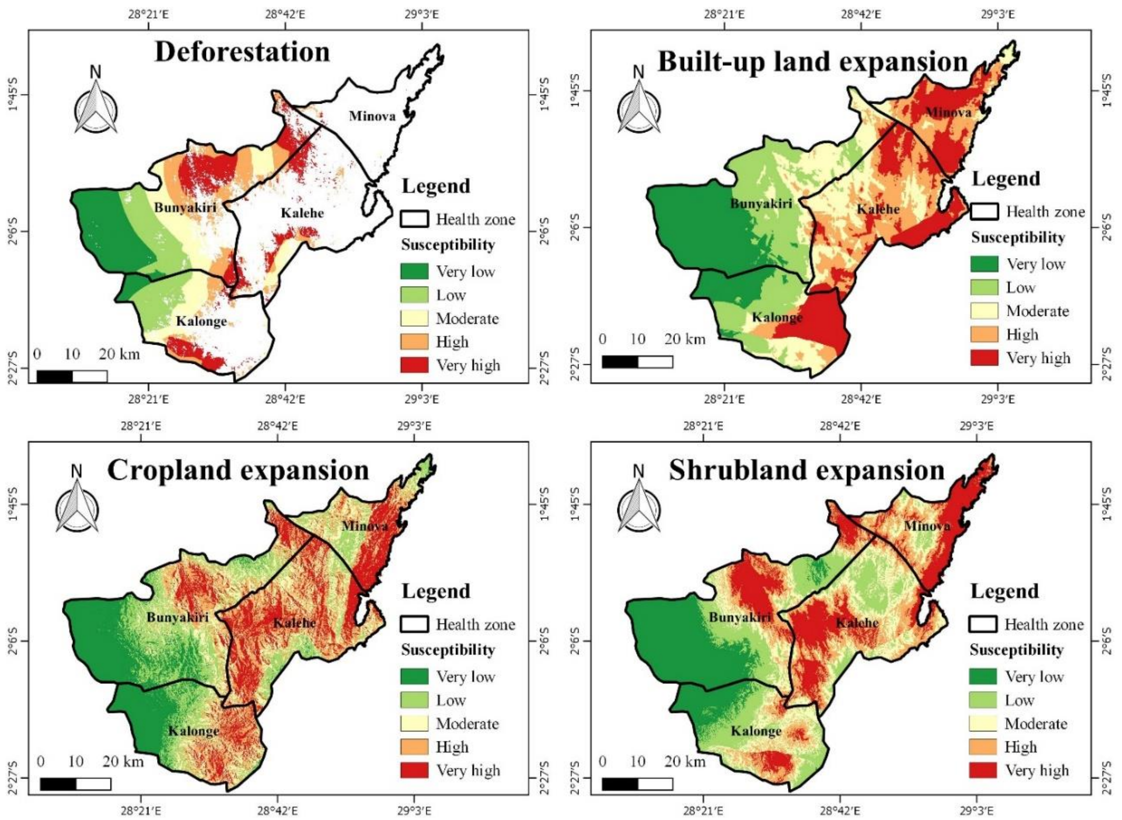


Figure 4.6: Susceptibility maps of the major LULC changes in Kalehe Territory.

The best-fit model of deforestation obtained through a backward step-wise regression as can be seen in Table 4.11, is characterized by low Nagelkerke R^2 (R^2=17.5%) but the significant Chi-square value ($\chi 2$=97.778, df=5, p-value<0.001) of the Omnibus test and the overall accuracy (correct prediction value) which is above 75% show that the model is appropriate in explaining the relationship between the deforestation and the dependent variables. The pseudo-R-square (measured with the Nagelkerke R^2) indicated that the deforestation model explained between 17.5% and 18.3% of variability indicating that the model performance of the deforestation was generally low. The comparison of the predicted and true values through the area under the curve ROC (Receiver Operating Characteristic) curve (AUC) allows for the evaluation of the accuracy of the model. The AUC values vary between 0.706 and 0.785 at a confidence level of 95% with an overall value of 0.746. The AUC value is above 0.7 for this model indicating that it has a good discrimination ability to classify the deforested area and no deforested area significantly better than by chance. Thus the model is appropriate to discriminate the false positive and true positive prediction.

Considering the most influential variables of the built-up expansion, the Omnibus chi-square of the model as shown in Table 4.11 shows that the best-fit model of built-up expansion is significant ($\chi 2=169.176$, df=6, p-value<0.001). The Nagelkerke R^2 indicates that 28.2% ($R^2=0.282$) of the variability of built-up land expansion is explained by the selected factors. The overall accuracy of the prediction is 86.2%. Thus the developed model is appropriate to predict the area where there is the expansion of built-up land compared to those where this change is not occurring. Based on the pseudo-R-square (measured with the Nagelkerke R^2), it can be seen that the models explained between 28.2% and 29.0% of the variability of built-up land expansion. The validation of the predictive capacity of the model through the AUC shows that its value varies from 0.789 and 0.851. The area under the ROC curve is 0.82 at a confident level of 95%. Furthermore, the AUC is significantly different by 0.5 (p-value<0.001) meaning that the best model classifies the group (built-up expansion area and no built-up expansion area) better than by chance.

The accuracy of the cropland expansion models is presented in the table 4.11. The best-fit model of cropland expansion as seen above was statistically significant ($\chi 2=36.9$, Df= 5 at $P < 0.001$). The significant drivers of cropland expansion explained 19.3% (Nagelkerke $R^2=0.129$) of variance. However, the model has a correct prediction value of 96% by using the six determinant explanatory variables. Thus, the developed model can be used to predict the probability of cropland expansion. The Nagelkerke R^2 of the models shows that between 19.3% and 21.9% of the variability in cropland expansion have been explained. The AUC indicated also that the shrubland expansion model is accurate as it values are ranging from 0.751 to 0.867 at a confidence level of 95%. The overall value of AUC is 0.813±0.030 which is significantly different from 0.5 at p-value<0.001, indicating that the cropland expansion model, classifies areas that changed and that did not change better than by chance.

The best-fit model of shrub land expansion obtained through a backward step-wise regression as is seen in Table 4-11 is characterized by low Nagelkerke R^2 (R^2=16.7%). However, the Omnibus chi-square test shows that the model is significant ($\chi2$=111.905, df=6, p-value<0.001). Furthermore, the overall accuracy (correct prediction value) is above 75%. Thus the developed model is appropriate in explaining the relationship between the shrub land expansion and the dependent variables. The value of the Nagelkerke R^2 shows that between 16.7% and 18.2% of the variability of the shrubland, expansion have been explained by the model. Furthermore, the AUC of the ROC ranges from 0.623 to 0.747 with an overall value of 0.685 at a confidence level of 95%. This value is significantly different from 0.5 (p-value<0.001). Thus the model performs better than the chance to discriminate the area with shrub land expansion from the area where this change does not occur.

4.2.7. LULC prediction for 2030, 2050 and 2070

In this section, the transition potential, the validation of the LULC prediction, and the projected dynamics during the 2020-2070 period are presented.

4.2.7.1. LULC transition potential analysis

The transfer of direction of LULC categories is shown by the transition probability matrix (Table 4.12). It can be seen that from 1987-2002, forestland, shrubland, and built-up area were the most stable LULC type with probabilities of no change of 0.81, 0.50, and 0.39 respectively.

Table 4.12: Transition probability matrix of LULC change between 1987 and 2002.

		Change to LULC of 2002						
		Forest	Crop-land	Wet-land	Built-up	Grass-land	Shrub land	Bare land
Change from 1987	Forest	**0.81**	0.00	0.02	0.00	0.01	0.15	0.00
	Cropland	0.15	**0.09**	0.05	0.14	0.17	0.38	0.02
	Wetland	0.15	0.03	**0.03**	0.05	0.06	**0.68**	0.00
	Built up	0.02	0.20	0.02	**0.39**	0.18	0.19	0.00
	Grassland	0.04	0.17	0.02	0.19	**0.18**	0.41	0.00
	Shrubland	0.25	0.06	0.03	0.09	0.07	**0.50**	0.00
	Bareland	0.17	0.05	**0.10**	**0.36**	0.02	0.14	**0.16**

The forest land has a high probability to be transformed into shrub land whereas the shrub land was likely to be transformed into a forest. The built-up area has a high probability of being transformed into cropland. The most dynamics classes are wetland, cropland, bare land, and grassland with stability probability of 0.003, 0.09, 0.16, and 0.18 respectively. In these classes, the wetland was primarily transformed into shrub land, cropland to shrub land, bare land to build up area, and grassland to shrub land. On the other hand, there is a consistency in the transition pattern of LULC classes with the previous period from 2002 to 2020 as can be seen in Table 4.13. The most stable LULC type are forest, shrub land, and built-up area with 0.78, 0.59, and 0.52 probabilities respectively.

Table 4.13:Transition probability matrix of LULC change between 2002 and 2020

		Change to LULC of 2020						
		Forest	Crop-land	Wet-land	Built-up	Grass-land	Shrub-land	Bare-land
Change from LULC from 2002	Forest	**0.78**	0.01	0.00	0.01	0.00	0.19	0.00
	Cropland	0.01	**0.24**	0.02	0.21	0.20	0.32	0.00
	Wetland	0.44	0.03	**0.06**	0.19	0.01	0.27	0.00
	Built up	0.02	0.12	0.03	**0.52**	0.08	0.23	0.01
	Grassland	0.01	0.48	0.00	0.16	**0.11**	0.23	0.00
	Shrubland	0.14	0.10	0.01	0.12	0.05	**0.59**	0.00
	Bareland	0.31	0.03	0.01	0.13	0.28	0.18	**0.06**

The forest land and built-up area were mostly transformed into shrubland. In contrast, shrub-land has a high probability of being transformed into a forest. The most dynamic LULC types are still bare land, wetland, grassland, and cropland with the probability of stability of 0.06, 0.06, 0.11, and 0.24 respectively. In these classes, the bare land was primarily transformed into forest land, wetland into forestland, grassland into cropland, and cropland into shrub land.

From 1987 to 2020, forest land, shrub land, and built-up land are the most stable LULC classes in the study area with a respective probability of stability of 0.77, 0.53, and 0.49 as is evident in Table 4.14.

Table 4.14: Transition probability matrix of LULC change between 1987 and 2020

		Change to LULC of 2020						
		Forest	Crop -land	Wet -land	Built-up	Grass -land	Shrub -land	Bare -land
Change from LULC of 1987	Forest	**0.77**	0.01	0.00	0.01	0.00	0.20	0.00
	Cropland	0.04	**0.15**	0.03	0.12	0.16	0.49	0.00
	Wetland	0.12	0.10	**0.02**	0.09	0.00	0.67	0.00
	Built up	0.01	0.20	0.02	**0.49**	0.14	0.15	0.00
	Grassland	0.01	0.28	0.02	0.26	**0.10**	0.32	0.00
	Shrubland	0.13	0.10	0.01	0.16	0.07	**0.53**	0.00
	Bareland	0.13	0.05	0.12	0.21	0.10	0.21	**0.18**

During this period, the forest has a high probability of being transformed into shrub land whereas the shrubland has a high probability of being transformed into the built-up area and the built-up area is likely to be transformed into cropland. However, the wetland, grassland, cropland, and bare land were the most affected by the changes with 0.02, 0.10, 0.15, and 0.18 probabilities of stabilities. The wetland was primarily transformed into shrub land, the grassland to shrub land and cropland, the cropland into shrub land, and bare land to shrub land.

The transition probability matrix based on the 1987-2020 trends for prediction of LULC of 2030 is shown in Table 4.15. This probability matrix shows the probability of each land cover in 2020 changing to other land covers in 2030. From the results presented in table 4.15, it can be noted that the forest has a high probability of being transformed into shrubland (0.2) compared to other LULC types. The cropland is likely to be transformed into shrubland (0.49) while its expansion is likely to occur at the expanse of grassland. Similarly, the grassland (0.26) and bare land (0.22) showed a high probability of transformation to built-up land. The regression of wetland is likely to occur due to its transformation in shrubland (0.67).

Table 4.15: Transition probability matrix of LULC change between 2020 and 2050

Change from LULC of 2020	Change to LULC of 2030							
		Forest	Crop-land	Wet-land	Built-up	Grass-land	Shrub-land	Bare-land
	Forest	0.78	0.01	0.00	0.01	0.00	0.20	0.00
	Cropland	0.04	0.16	0.03	0.12	0.16	0.49	0.00
	Wetland	0.12	0.10	0.02	0.09	0.00	0.67	0.00
	Built up	0.01	0.20	0.02	0.48	0.14	0.15	0.00
	Grassland	0.01	0.28	0.02	0.26	0.11	0.32	0.00
	Shrubland	0.13	0.10	0.01	0.16	0.07	0.53	0.00
	Bareland	0.14	0.04	0.12	0.22	0.10	0.21	**0.18**

During the next three decades, there is a high probability of expansion of shrubland to wetland (0.64), cropland (0.46), grassland (0.30), and forestland (0.19) as can be observed in Table 4.16. The cropland (0.27) and built-up area (0.25) are expected to expand mostly on grassland. In the other hand, bare land is more likely to be transformed into the built-up area (0.21).

Table 4.16: Transition probability matrix of LULC change between 2020 and 2050

Change from LULC of 2020	Change to LULC of 2050							
		Forest	Crop-land	Wet-land	Built-up	Grass-land	Shrub-land	Bare-land
	Forest	0.79	0.01	0.00	0.01	0.00	0.19	0.00
	Cropland	0.03	0.20	0.03	0.11	0.16	0.46	0.00
	Wetland	0.11	0.10	0.07	0.08	0.00	0.64	0.00
	Built up	0.00	0.19	0.01	0.52	0.13	0.14	0.00
	Grassland	0.01	0.27	0.02	0.25	0.14	0.30	0.00
	Shrubland	0.12	0.09	0.01	0.15	0.06	0.55	0.00
	Bareland	0.13	0.03	0.12	0.21	0.10	0.18	0.24

The transition probability matrix of each LULC observed in 2020 changing to other LULC types in 2070 (Table 4.17) shows that the forestland, built-up area, and shrubland are expected to be the most stable LULC categories with the probability of persistence of 0.68, 0.40 and 0.24 respectively. In contrast, the most dynamic LULC types are bare land, wetland, grassland, and cropland with the probability of stability of 0.09, 0.02, 0.11, and 0.15 respectively. In these classes, there is a high probability of transformation of bare land to the built-up area (0.23), wetland to shrubland (0.54), grassland to shrubland (0.37), and cropland to shrub land (0.46). Both cropland (0.20) and built-up land (0.25) are more likely to expand to grassland.

Table 4.17: Transition probability matrix of LULC change between 2020 and 2070

		Change to LULC of 2070						
		Forest	Crop -land	Wet -land	Built-up	Grass -land	Shrub -land	Bare -land
Change from LULC of 2020	Forest	0.68	0.03	0.00	0.03	0.01	0.24	0.00
	Cropland	0.08	0.15	0.02	0.17	0.12	0.46	0.00
	Wetland	0.16	0.10	0.02	0.14	0.05	0.54	0.00
	Built up	0.02	0.19	0.02	0.40	0.13	0.24	0.00
	Grassland	0.04	0.20	0.02	0.25	0.11	0.37	0.00
	Shrubland	0.16	0.11	0.01	0.19	0.08	0.45	0.00
	Bareland	0.16	0.08	0.07	0.23	0.09	0.29	0.09

4.2.7.2. Validation of the LULC projection

The validation of the LULC projection was done through the evaluation of the difference between the projected and the observed LULC change for the year 2020. Figure 4.7 shows a visual comparison between the classified and the simulated LULC maps for the year 2020.

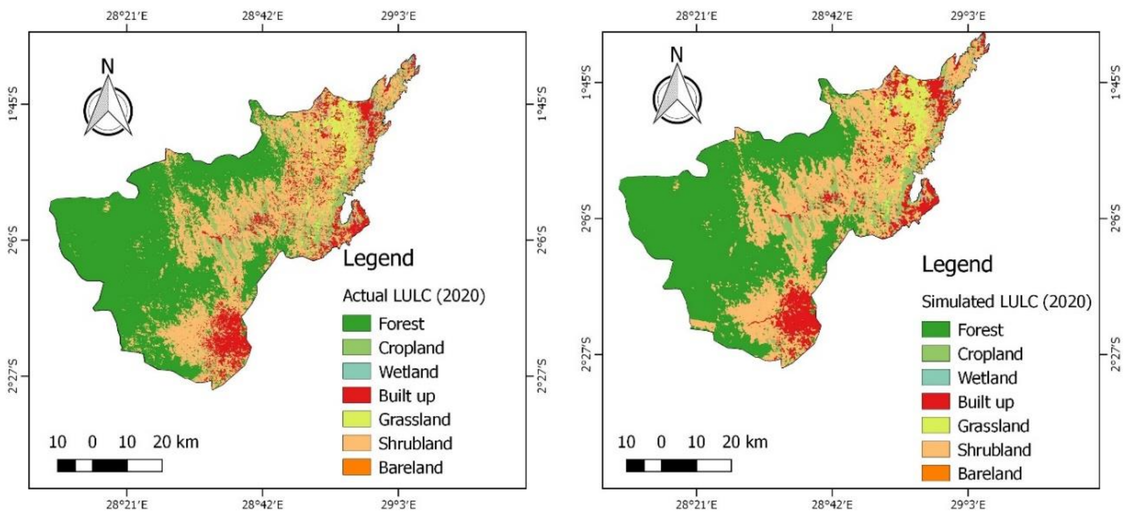


Figure 4.7: Actual and simulated LULC for 2020 in Kalehe territory.

Table 4.18 presents the area statistics of these maps.

Table 4.18: Validation of the predicted LULC based on the actual and simulated LULC for 2020

	Simulated LULC in 2020		Actual LULC in 2020		Change
LULC	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**(%)**
Forest	1950.97	46.98	1952.48	47.02	-0.08
Cropland	270.13	6.51	312.96	7.54	-13.69
Wetland	23.92	0.58	36.99	0.89	-35.34
Built up	391.71	9.43	388.59	9.36	**0.80**
Grassland	161.21	3.88	153.22	3.69	**5.21**
Shrubland	1352.13	32.56	1305.09	31.43	**3.60**
Bareland	2.29	0.06	3.00	0.07	**-23.80**

It can be observed from Table 4.18 that the prediction model has overestimated the surface covered by grassland, built-up area, and shrubland at respective rates of 5.21%, 0.80%, 0.28%, and 3.60% compared to the area observed on the classified map. Other LULC classes have been underestimated at a rate of 0.08% for forestland, 13.69% for cropland, 35.34% for wetland, and 23.80% for bare land. However, the difference in the proportion of LULC between the simulated and the classified maps is not significant. This is confirmed by the result of the Chi-square test under the null hypothesis that there is no significant difference between the surface proportion of the simulated and observed LULC classes in 2020 (X-squared=0.17089, df= 6, p-value=0.99). Additionally, the overall Kappa index is 0.86 indicating that there is a good agreement between the two maps. The overall accuracy of the prediction is 90.98%.

4.2.7.3. LULC characteristics for 2030, 2050 and 2070

The result of the LULC projection for the 2020-2030 period based on past trends as can be seen in Table 4.19 and Figure 4.8 shows that forestland, shrub land, built-up area, and cropland will be the most dominant LULC categories. Table 4.19 shows the proportion of each LULC while Figure 4.8 illustrates the predicted maps for the LULC.

Table 4.19: LULC for the present and projected situation

	2020		2030		2050		2070	
LULC	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Forest	1952.48	47.02	1715.36	41.31	1710.67	41.20	1584.63	38.16
Cropland	312.96	7.54	324.42	7.81	325.59	7.84	353.49	8.51
Wetland	36.99	0.89	34.37	0.83	42.41	1.02	45.16	1.09
Built up	388.59	9.36	496.21	11.95	504.38	12.15	561.80	13.53
Grassland	153.22	3.69	212.99	5.13	208.61	5.02	228.11	5.49
Shrubland	1305.09	31.43	1368.28	32.95	1358.43	32.71	1377.23	33.17
Bareland	3.00	0.07	0.54	0.01	2.40	0.06	2.82	0.07

The results of the simulated LULC in Table 4.19 show that by the year 2030 forestland, shrub, built-up area, and cropland are the most represented and will cover about 41.31%, 32.95%, 11.95%, and 7.81% of the total surface of the territory. The least represented LULC types are bare land (0.01%), wetland (0.83%), and grassland (5.13%). In 2050, the dominant area will be forest (41.19%), followed by shrub land (32.71%), built-up area (12.15%), and cropland (7.84%). The grassland (5.02%), wetland (1.02%), and bare land (0.06%) are the least represented. The most prominent LULC cover in 2070 will be forest land (38.16%), shrub land (33.17%), built-up area (13.53%), and cropland (8.51%). The least represented LULC categories are bare land (0.07%), wetland (1.09%), and grassland (5.49%).

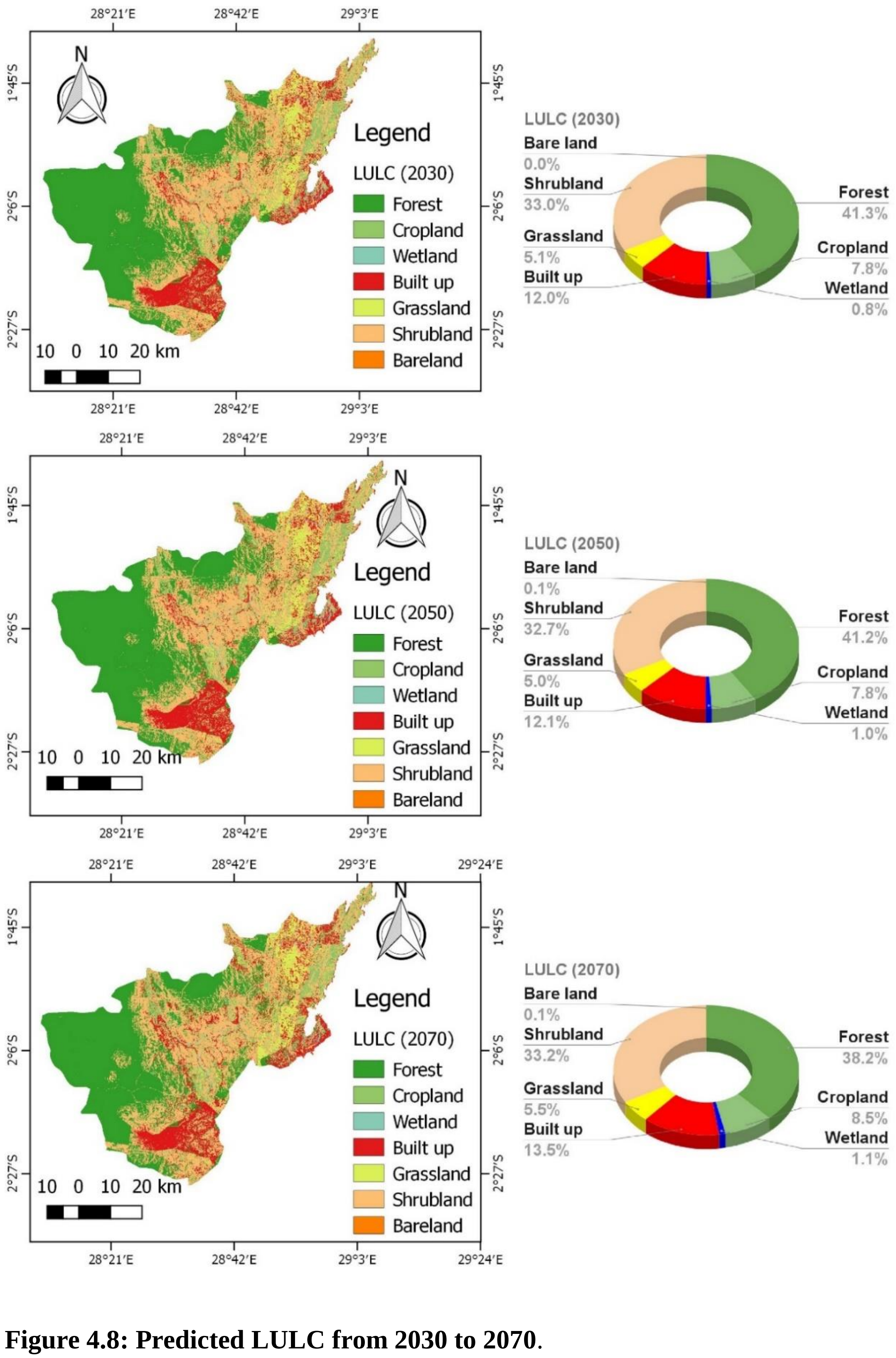


Figure 4.8: Predicted LULC from 2030 to 2070.

Overall, the forest land will continue to decrease in the future while cropland and built-up will increase. As can be seen in the figure below, the wetland will decrease by 2030 but it will increase during the 2030-2070 period.

4.2.7.4. LULC change dynamics during the 2020-2030 period

During the next decade (2030), it is predicted that there will be a general decrease of forestland, wetland, and bare land by 12.37%, 7.07%, and 82.07% respectively compared to the baseline year 2020 as can be seen in Table 4.20. However, the cropland, the built-up area, grassland, and shrubland are predicted to increase by 3.66%, 27.70%, 39.01%, and 4.84% respectively (Table 4.20). It can be noted that the highest positive annual change rate will be observed in grassland and built-up areas which will increase at a rate of 2.17 %/Year (3.32km^2/Year) and 1.54%/Year (5.98km^2/Year), respectively. In contrast, the bare land and wetland will present the highest negative annual change and will decrease at a rate of 4.56%/Year (0.14km^2/Year) and 0.39%/Year (0.15km^2/Year) respectively. The Table 4.20 presents the predicted LULC changes between 2020 and 2030.

Table 4.20: Trend of LULC change between 2020 and 2030.

	LULC (2020)		LULC (2030)		Change (2020-2030)		
	Area (km^2)	**Area (%)**	**Area (km^2)**	**Area (%)**	**TC (%)**	**AC (%/yr)**	**RC (km^2/Yr)**
Forest	1952.48	47.02	1715.36	41.31	**-12.14**	-0.67	-13.17
Cropland	312.96	7.54	324.42	7.81	3.66	0.20	0.64
Wetland	36.99	0.89	30.95	0.83	-7.03	-0.39	-0.15
Built up	388.59	9.36	496.21	11.95	27.70	1.54	5.98
Grassland	153.22	3.69	216.05	5.13	**39.01**	2.17	3.32
Shrubland	1305.09	31.43	1368.28	32.95	4.84	0.27	3.51
Bareland	3.00	0.07	0.54	0.01	**-82.07**	-4.56	-0.14

RC=Rate of change (km^2/Year), TC=Temporal change (%) and AC=Annual rate of change (%/Year)

The major LULC change that will occur in the study area by the year 2030 is the conversion of forest to shrub (390.62km^2), shrub to built-up (208.84km^2), shrub to forest (170.21km^2), cropland to shrub (153.31km^2) and shrub to cropland (131.11km^2) as it is depicted in Table 4.21.

Table 4.21: Projected LULC change transition matrix between 2020 and 2030

		Change to LULC of 2030 (area in km^2)						
		Forest	**Crop-land**	**Wet-land**	**Built-up**	**Grass-land**	**Shrub**	**Bare-land**
Change from LULC from 2020	Forest	1522.71	19.46	0.00	19.68	0.01	**390.62**	0.00
	Cropland	12.42	49.94	9.41	37.44	50.45	**153.31**	0.00
	Wetland	4.39	3.74	0.75	3.29	0.00	24.82	0.00
	Built up	4.00	77.31	7.91	186.18	54.54	58.66	0.00
	Grassland	1.54	42.81	3.11	39.90	17.03	48.83	0.00
	Shrub	**170.21**	**131.11**	13.23	**208.84**	91.45	690.25	0.00
	Bare land	0.41	0.12	0.36	0.65	0.30	0.62	0.54

The Figure 4.9 presents an overview of the major LULC transition which is likely to occur during the 2030 period if the past trend continues in the future.

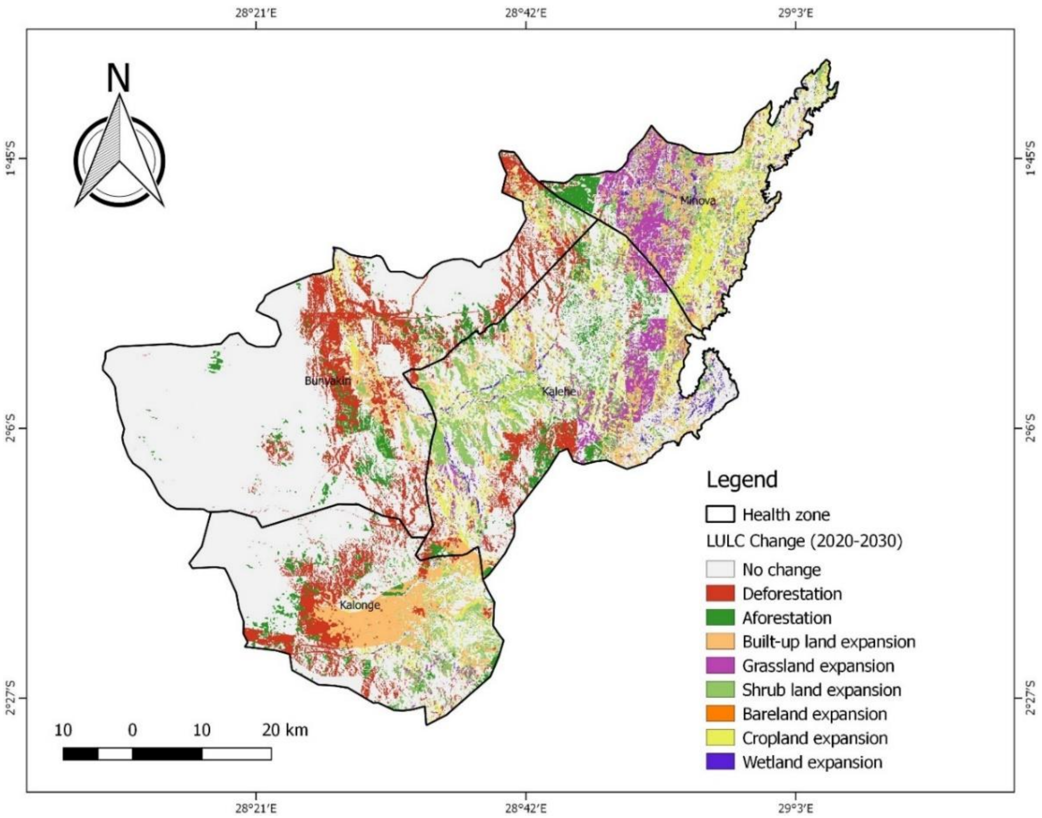


Figure 4.9: Projected majors LULC transition during the 2020-2030 period.

In summary, if the past trend of LULC change continues during the 2020-2030 period, it is projected that the study area will be dominated by stable or persistent land cover which could represent 59.42% (2467.29km^2) of the territory (Figure 4.9). Deforestation would be the most prominent proximate driver of LULC change in the study area. During this period, deforestation would occur in 10.35% (429.77km^2) while afforestation and forest recovery would occur in only 4.65% (192.96km^2) of the study area, inducing net deforestation of 5.69 % (236.81km^2). This deforestation would be mainly associated with built-up land expansion, cropland expansion, shrubland expansion, and grassland expansion which occurred in 7.46% (309.79km^2), 6.61% (274.56km^2), 16.30% (676.85km^2), and 4.74% (196.85km^2) of the territory, respectively. During this period, the bare land is not expected to expand by 0.00% (0.00km^2) while the wetland would expand to 0.82% (34.01km^2) of the territory as a result of inundation (Figure 4.10). The Figure 4.10 presents the proportion of land which are expected to be subjected to the major's land transition during the 2020-2030 period.

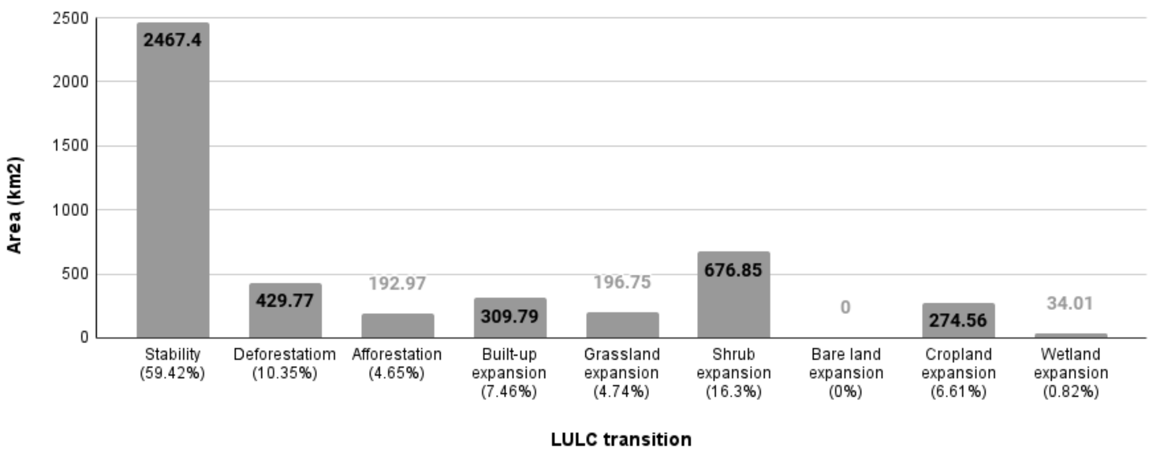


Figure 4.10: Majors LULC transition during the 2020-2030 period.

4.2.7.5. LULC change dynamics during the 2020-2050 period

During the next 30 years, only the forest land and bare land area are expected to decrease at a respective rate of 12.38% and 19.81% respectively compared to their initial area in 2020 as can be seen in Table 4.22. The other LULC categories will increase. It is expected that the grassland and built-up area will present the highest rate of expansion while the cropland and shrub land will experience the lowest rate of annual expansion (Table 4.22).

Table 4.22: Trend of LULC change between 2020 and 2050.

	LULC (2020)		**LULC (2050)**		**Change (2020-2050)**		
	Area (km^2)	**Area (%)**	**Area (km^2)**	**Area (%)**	**TC (%)**	**AC (%/yr)**	**RC (km^2/Yr)**
Forest	1952.48	47.02	1710.67	41.20	-12.38	-0.34	-6.72
Cropland	312.96	7.54	325.59	7.84	4.04	0.11	0.35
Wetland	36.99	0.89	42.41	1.02	14.65	0.41	0.15
Built up	388.59	9.36	504.38	12.15	29.80	0.83	3.22
Grassland	153.22	3.69	208.61	5.02	36.15	1.00	1.54
Shrubland	1305.09	31.43	1358.43	32.71	4.09	0.11	1.48
Bareland	3.00	0.07	2.41	0.06	-19.81	-0.55	-0.02

RC=Rate of change (km^2/Year), TC=Temporal change (%) and AC=Annual rate of change (%/Year)

Based on the results of the transition matrix presented in Table 4.23, the major LULC change (more than 100km^2) that will occur in the study area by the year 2050 is the transformation of forest to shrub land (365.01Km^2), shrub to the built-up area (201.19km^2), shrub to forest (159.00km^2), cropland to shrub (145.01km^2) and shrub to cropland (120.78km^2).

Table 4.23: Projected LULC change transition matrix between 2020 and 2050

		Change to LULC of 2050 (area in km^2)						
		Forest	**Crop-land**	**Wet-land**	**Built-up**	**Grass-land**	**Shrub**	**Bare-land**
Change from LULC from 2020	Forest	1533.75	25.32	3.36	22.42	2.53	**365.10**	0.00
	Cropland	10.82	61.46	10.59	34.60	50.32	**145.01**	0.16
	Wetland	4.02	3.56	2.64	3.06	0.00	23.71	0.00
	Built up	1.43	72.28	5.63	203.93	50.69	53.29	1.34
	Grassland	1.65	41.77	2.64	38.47	22.11	46.52	0.08
	Shrub	**159.00**	**120.78**	17.54	**201.19**	83.31	723.13	0.14
	Bare land	0.38	0.09	0.35	0.62	0.29	0.54	0.72

The Figure 4.11 presents an overview of the major LULC transition which is likely to occur during the 2030 period if the past trend continues in the future.

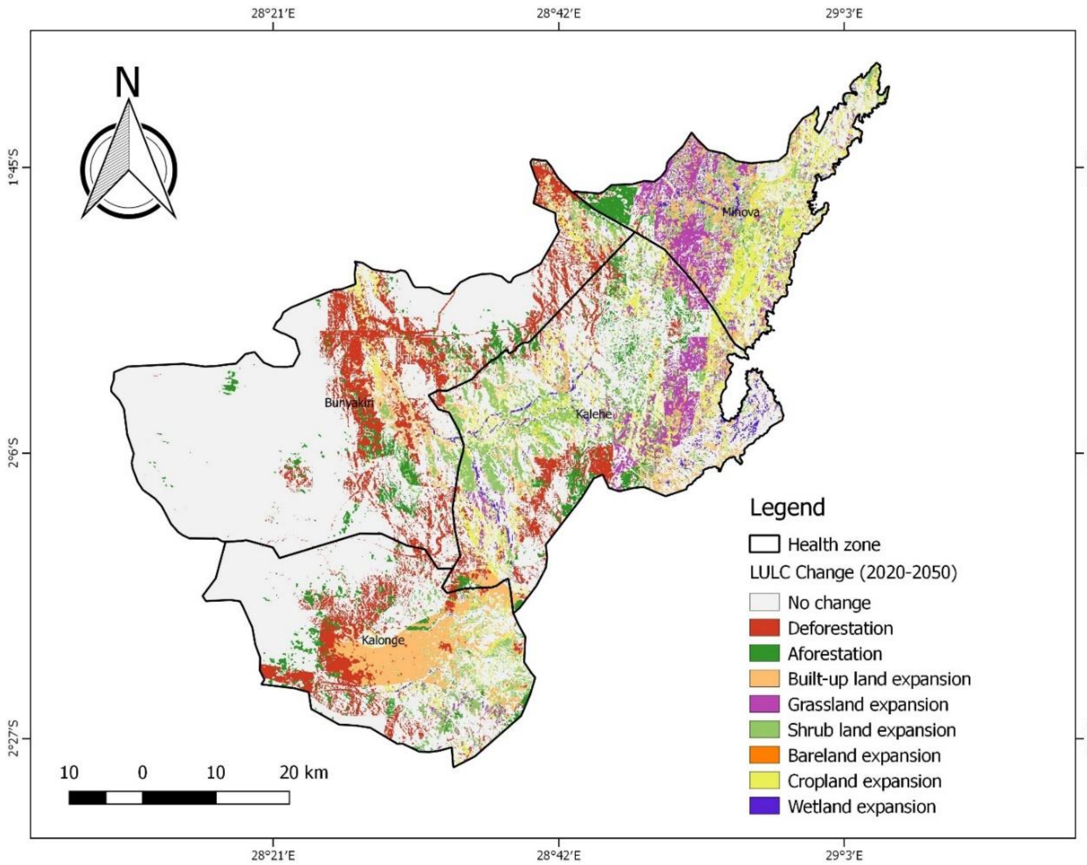


Figure 4.11: Projected majors LULC transition during the 2020-2050 period.

In summary, during the 2020-2050 period, if the past trend of LULC change continues in the future, it is projected that the study area will be dominated by the stable land cover which could represent 61.36% (2547.74km^2) of the territory (Figure 4.11). Deforestation would be the most prominent proximate driver of LULC change in the study area. During this period, deforestation would occur in 10.08% (418.73km^2) while afforestation and forest recovery would occur in only 4.27% (177.31km^2) of the study area, indicating that net deforestation of 5.81% (241.42km^2). This deforestation would be mainly associated with shrubland expansion, built-up land expansion, cropland expansion, and grassland expansion which occurred in 15.27% (634.17km^2), 7.23% (300.35km^2), 6.35% (263.79km^2), and 4.51% (187.13km^2) of the territory, respectively. During this period, the bare land is expected to expand by 0.04% (1.62km^2) while the wetland would expand to 0.97% (40.11km^2) of the territory as a result of inundation (Figure 4.12).

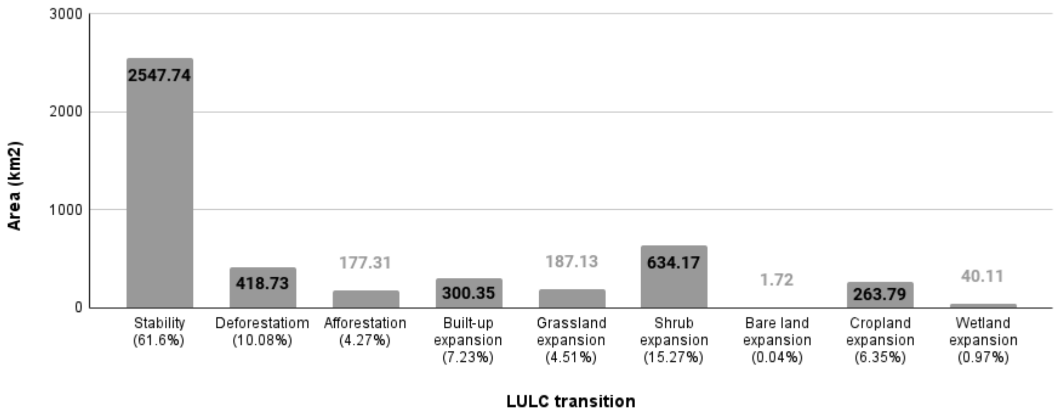


Figure 4.12: Majors LULC transition during the 2020-2050 period.

4.2.7.6. LULC change dynamics during the 2020-2070 period

By the year 2070, it is expected that only the forest land and grassland will decrease compared to their situation of 2020 while the other LULC categories will increase in terms of area (Table 4.24). The forest land is expected to decrease by 18.84% compared to the base line period, indicating an annual forest loss of 0.35% per year or 6.81km^2 per year. During the next five decades, the grassland built-up area, wetland, cropland,

and shrubland are expected to decrease by 49.86%, 44.57%, 17.89%, 12.95%, and 5.53% compared to their surface in 2020 as presented in Table 4.34.

Table 4.24: Trend of LULC changes in 2020 and 2070.

	LULC (2020)		LULC (2070)		Change (2020-2070)		
	Area (km^2)	**Area (%)**	**Area (km^2)**	**Area (%)**	**TC (%)**	**AC (%/yr)**	**RC (km^2/Yr)**
Forest	1952.48	47.02	1584.63	38.16	-18.84	-0.35	-6.81
Cropland	312.96	7.54	353.49	8.51	12.95	0.24	0.75
Wetland	36.99	0.89	45.16	1.09	22.09	0.41	0.12
Built up	388.59	9.36	561.80	13.53	44.57	0.83	3.21
Grassland	153.22	3.69	228.11	5.49	48.88	0.91	1.39
Shrubland	1305.09	31.43	1377.23	33.17	5.53	0.10	1.34
Bareland	3.00	0.07	2.82	0.07	-5.86	-0.11	-0.003

RC=Rate of change (km^2/Year), TC=Temporal change (%) and AC=Annual rate of change (%/Year)

The major LULC changes (more than 100km^2) that will occur in the study area by the year 2070 (Table 4.25) are the conversion of forest to shrub (470.44km^2), shrub to built-up (242.71km^2), shrub to forest (204.25km^2), shrub to cropland (147.26km^2) and cropland to a shrub (143.09km^2).

Table 4.25: Projected LULC change transition matrix between 2020 and 2070

		Change to LULC of 2070 (area in km^2)						
		Forest	**Crop-land**	**Wet-land**	**Built-up**	**Grass-land**	**Shrub**	**Bare-land**
Change from LULC from 2020	Forest	1334.74	50.87	7.17	66.88	22.17	**470.44**	0.21
	Cropland	23.86	47.34	7.61	53.72	37.12	**143.09**	0.22
	Wetland	5.75	3.73	0.69	5.12	1.76	19.93	0.00
	Built up	8.25	73.33	7.22	154.18	50.71	93.73	1.18
	Grassland	6.64	31.18	3.13	38.68	16.97	56.47	0.14
	Shrub	**204.25**	**147.26**	19.52	**242.71**	99.21	591.34	0.81
	Bare land	0.49	0.25	0.20	0.68	0.27	0.86	0.26

The Figure 4.13 presents an overview of the major LULC transition which is likely to occur during the 2030 period if the past trend continues in the future.

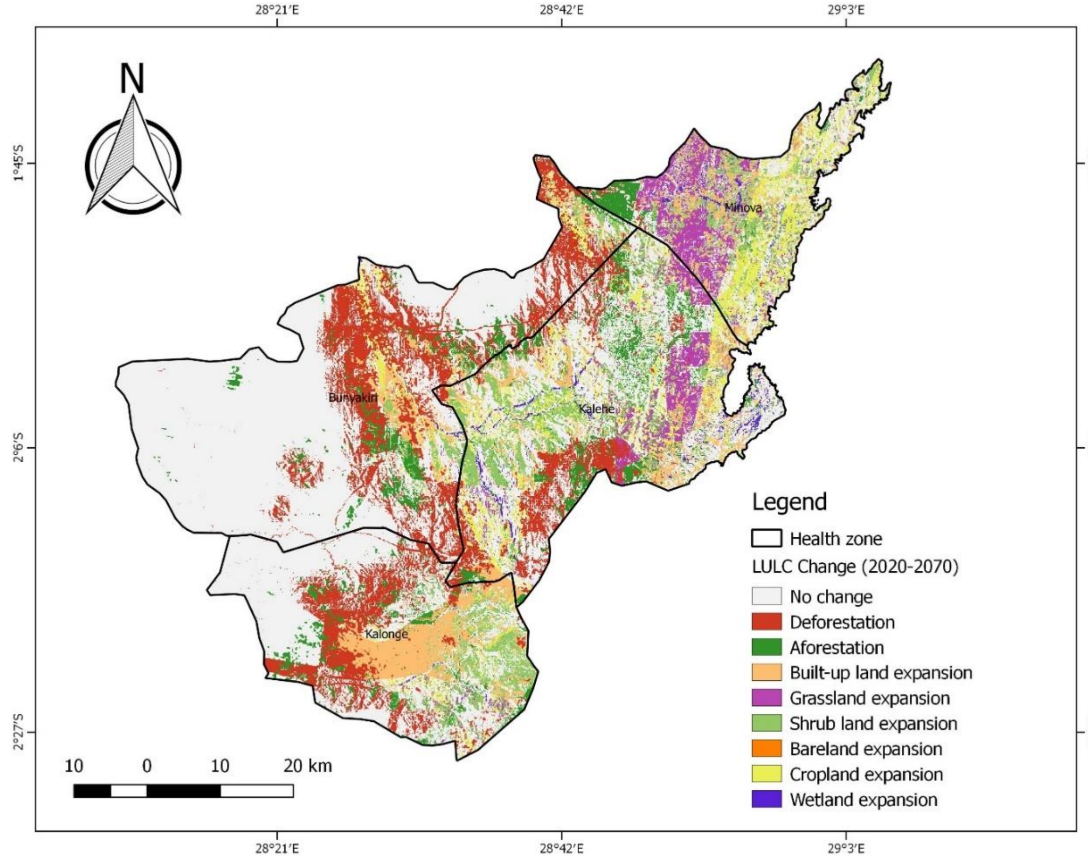


Figure 4.13: Projected majors LULC transition during the 2020-2070 period.

In summary, during the 2020-2070 period, if the past trend of LULC change continues in the future, it is projected that the study area will be dominated by the stable land cover (no change of LULC) which could represent 51.67% (2145.52km^2) of the territory (Figure 4.14). Deforestation would be the most prominent proximate driver of LULC change in the study area. During this period, deforestation would occur in 14.88% (617.74km^2) while afforestation and forest recovery would occur in only 6.00% (249.23Km^2) of the study area, indicating a net deforestation of 8.88 % (368.51km^2). This deforestation would be mainly associated with shrubland expansion, built-up land expansion, cropland expansion, and grassland expansion which occurred in 18.89% (784.52km^2) 9.82% (407.79), 7.38% (306.63km^2), and 5.09% (211.23km^2) of the territory, respectively. During this period, the bare land is expected to expand by 0.06%

($2.30km^2$) while the wetland would expand to 1.08% ($44.85km^2$) of the territory as a result of inundation (Figure 4.14). The Figure 4.14 presents the proportion of land that is expected to be affected by the major LULC transition during the 2020-2070 period in term of gain or loss of their surfaces.

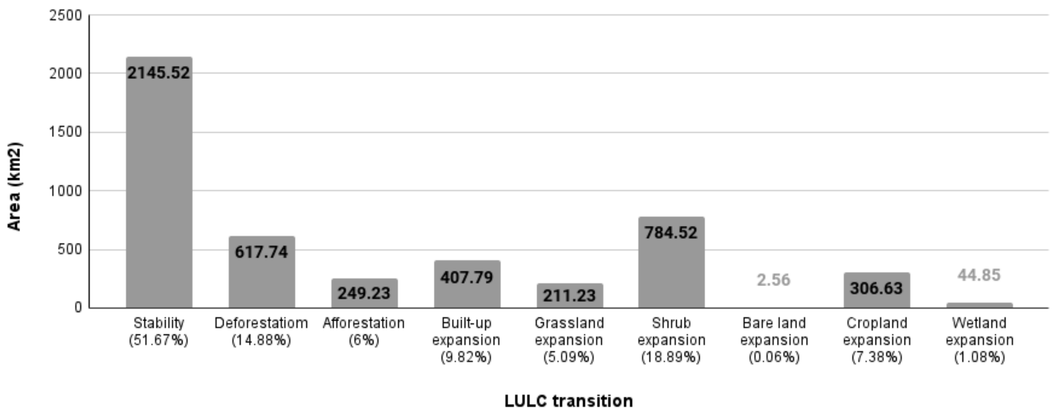


Figure 4.14: Majors LULC transition during the 2020-2070 period.

4.2.8. Implication of LULC dynamics on land cover degradation

4.2.8.1. Status of land cover degradation

The identification of the negative, positive, and stable LULC transition was done based on the transition matrix of each period to determine the land cover status. Based on field observation the following decision matrix (Table 4.26) was produced to discriminate areas with land cover improvement (positive land cover transition), land cover degradation (negative transition), and land cover stability (no change).

Table 4.26: Decision matrix for land cover degradation assessment.

		LULC of the final year						
LULC in the initial year		FL	CL	WL	B	GL	SL	BL
	Forest land (FL)	**0**	-	-	-	-	-	-
	Cropland (CL)	+	**0**	-	-	-	+	-
	Wetland (WL)	-	-	**0**	-	-	-	-
	Built up (B)	+	+	-	**0**	+	+	-
	Grassland (GL)	+	-	-	-	**0**	+	-
	Shrubland (SL)	+	-	-	-	-	**0**	-
	Bareland (BL)	+	+	+	+	+	+	**0**
	0	Stability	-	Degradation		+	Improvement	

The negative change implies deforestation, the vegetation loss due to the transition from grassland and shrubland to other LULC categories. The transformation of cropland to forestland is considered an improvement of land associated with afforestation. However, the transformation of cropland to grassland indicates land degradation resulting from the withdrawal of agricultural activities due to the decrease in land productivity. In contrast, the transformation of agricultural land to shrub land is classified as a land improvement. Old fallows were classified as shrubland and they are recognized to be productive land for agricultural activities by land users. The conversion of cropland to build-up area, grassland, and bareland is also considered as negative transition. On the other hand, the expansion of cropland to the built-up area and bare land is considered a positive change. The barre land expansion to other types of land constitutes a negative transition as well as the encroachment of wetlands. The decrease of wetlands in the study area is mostly associated with their drainages for cropland activities or built-up area expansion. The expansion of wetland to cropland and built-up area, vegetation cover (forest, shrub, and grassland) resulting from inundation constitutes a negative transition in the study area but its expansion to bare land depicts a wetland establishment which constitutes a positive change.

The analysis of the land cover status during the 1987-2020 period indicated that about 34.17% (1424.79km^2) of the study area is subjected to land degradation, 58.72% (2448.25km^2) is stable and there is an improvement in 7.11 % (286.44km^2) as can be seen in Table 4.27. By comparing the two periods of analysis it can be seen that 28.87% (1203.72km^2) of the territory was degraded during the 1987-2002 period but the situation changed during the second period where 26.93% (1122.74km^2) of the territory is showing a degradation.

Table 4.27: Land cover status from 1987 to 2020.

Period	**1987-2002**		**2002-2020**		**1987-2020**	
Land cover status	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Degradation	1203.72	28.87	1122.74	26.93	1424.79	34.17
Stability	2546.93	61.08	2647.70	63.50	2448.25	58.72
Improvement	418.84	10.05	399.04	9.57	296.44	7.11

The maps presented in Figure 4.15 show the spatial pattern of land cover degradation associated with land use changes during the 1987-2020 period.

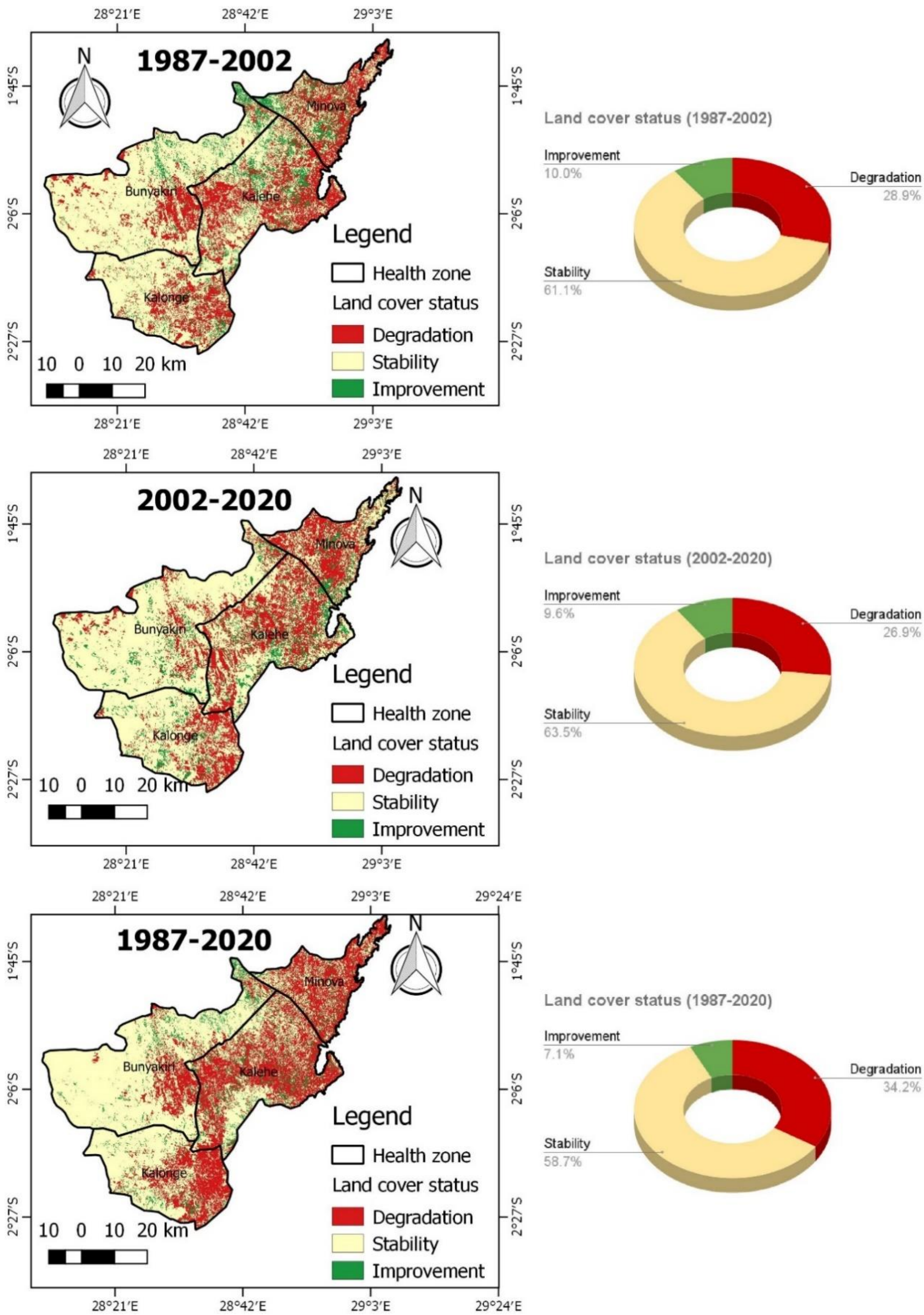


Figure 4.15: Land cover status during the 1987-2002, 2002-2020, and 1987-2020 periods.

Based on the result of the projected LULC, it is projected that 28.28% of the land will be degraded in 2030, 27.28% in 2050, and 33.65% in 2050 if the past trend of land use changes continues in the future as presented in Table 4.28. These results imply that land degradation neutrality should not be attended to in the future if the past trend of LULC continues.

Table 4.28: Projected land cover status from 2020-2070

Period	**2020-2030**		**2020-2050**		**2020-2070**	
Land cover status	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Degradation	1174.07	28.28	1133.22	27.29	1397.08	33.65
Stability	2467.72	59.43	2548.50	61.38	2147.04	51.71
Improvement	510.24	12.29	470.30	11.33	607.89	14.64

The maps presented in Figure 4.16 show the projected spatial pattern of land cover degradation associated with land use changes for the 2030-2070 period compared to the current situation (2020).

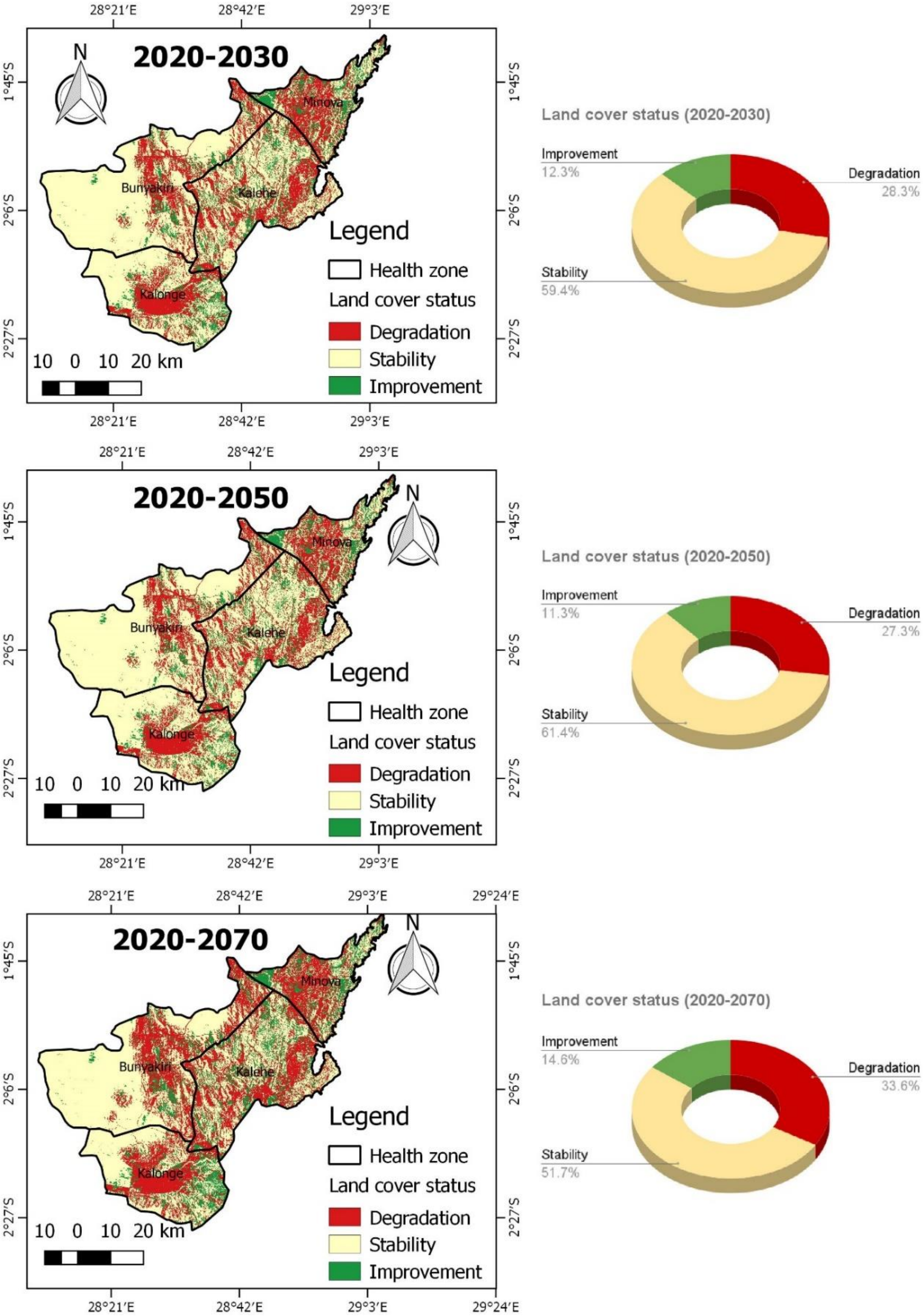


Figure 4.16: Projected land cover status for the 2020-2030, 2020-2050, and 2020-2070 period.

4.2.8.2. Land cover degradation modeling and susceptibility mapping

The identification of the drivers of negative land use transition which induces land cover degradation was done through a logistic regression analysis by considering the occurrence of negative LULC transition as the dependent variable and the drivers of LULC as the independent variables. The results of the stepwise Walid backward logistic regressions which was performed are presented in Table 4.29.

Table 4.29: Best-fit model of land cover degradation.

Variables	β	S.E.	Wald	p-value	EXP(β)
Altitude	0.0008334	0.0002309	13.0203	0.000308**	1.0008
Mining concession	0.5724909	0.1987815	8.29440	0.003977**	1.7726
Distance to locality	-0.000101	4.133E-05	5.98177	0.014454*	0.9998
Distance to river	5.348E-05	2.527E-05	4.47803	0.034333*	1.00005
Conservation	-0.684615	0.2418960	8.01006	0.004652**	0.50428
Distance to road	-9.733E-05	3.249E-05	8.96935	0.002745**	0.9999
Distance to mining site	-9.411E-05	2.545E-05	13.6784	0.000217**	0.9999
Population	0.000656	0.0002385	7.56301	0.005958**	1.00065
Constant	-0.804297	0.4841585	2.75967	0.096668	
Model chi-square (χ2)	389.724				
Model Nagelkerke R^2	0.415				
Model correct prediction	74.40%				

*β: Estimated coefficient; SE: Standard error; R^2: Coefficient of determination; Exp(B): odds ratio. *, ** significant at 5% and 1% level of significance, respectively.*

The results in Table 4.29 indicate that land cover degradation is significantly influenced by topographic factors, conservation and development zoning, population density, and proximity drivers. It was found that altitude is positively associated with the occurrence of land cover degradation, indicating that land cover degradation is likely to occur at higher altitudes than at lower altitudes. The occurrence of mining concession has the most influential power on the occurrence of land cover degradation. However, the presence of conservation zoning (national park and forest reserve) is negatively associated with the occurrence of land cover degradation. This implies that these conservation measures are effective and appropriate and should be considered by the mining concession owner to reduce their impact on the land resource. Among the proximity drivers of accessibility, only the distance to the river is positively associated with the occurrence of land cover degradation indicating that the land cover degradation is likely to occur in areas that are far from the rivers. In contrast, there is a negative association between the distance to locality (village), distance to roads, and distance to artisanal mining sites with the occurrence of land cover degradation. These results imply that land cover degradation is likely to occur in the proximity of villages, roads, and artisanal mining sites. Furthermore, land cover degradation is positively associated with the population density. This depicts the impact of human pressure on natural resources in the study area.

The Omnibus Test of the Model coefficient shows that model was statistically significant ($\chi 2$=389.724,df=7, p-values<0.001), explained 41.50% (Nagelkerke R square=0.415) of the variability of land cover degradation and has a correct prediction of 74.40%. This model has been used to establish the susceptibility map of land cover degradation and it is formulated as follows:

$$P_i = \frac{\exp(-0.8043+0.00083*X1+0.57249*X2-0.0001*X3+0.00005*X4 -0.68462*X5-0.0001*X6-0.00009*X7+0.00066*X8)}{1+\exp(-0.8043+0.00083*X1+0.57249*X2-0.0001*X3+0.00005*X4 -0.68462*X5-0.0001*X6-0.00009*X7+0.00066*X8)} \quad \text{(Equation 4-5)}$$

With pi= probability of land cover degradation, X1= altitude, X2= mining concession, X3= distance to the locality, X4= distance to the river, X5=protected area, X6=distance to the road, X7= Distance to artisanal mining, X8= population density. This equation was used to establish the susceptibility map of land cover degradation in the study area.

Based on this model (Equation 4-5), the map of land cover degradation susceptibility has been produced (Figure 4.17) to indicate the area where this degradation is likely to occur.

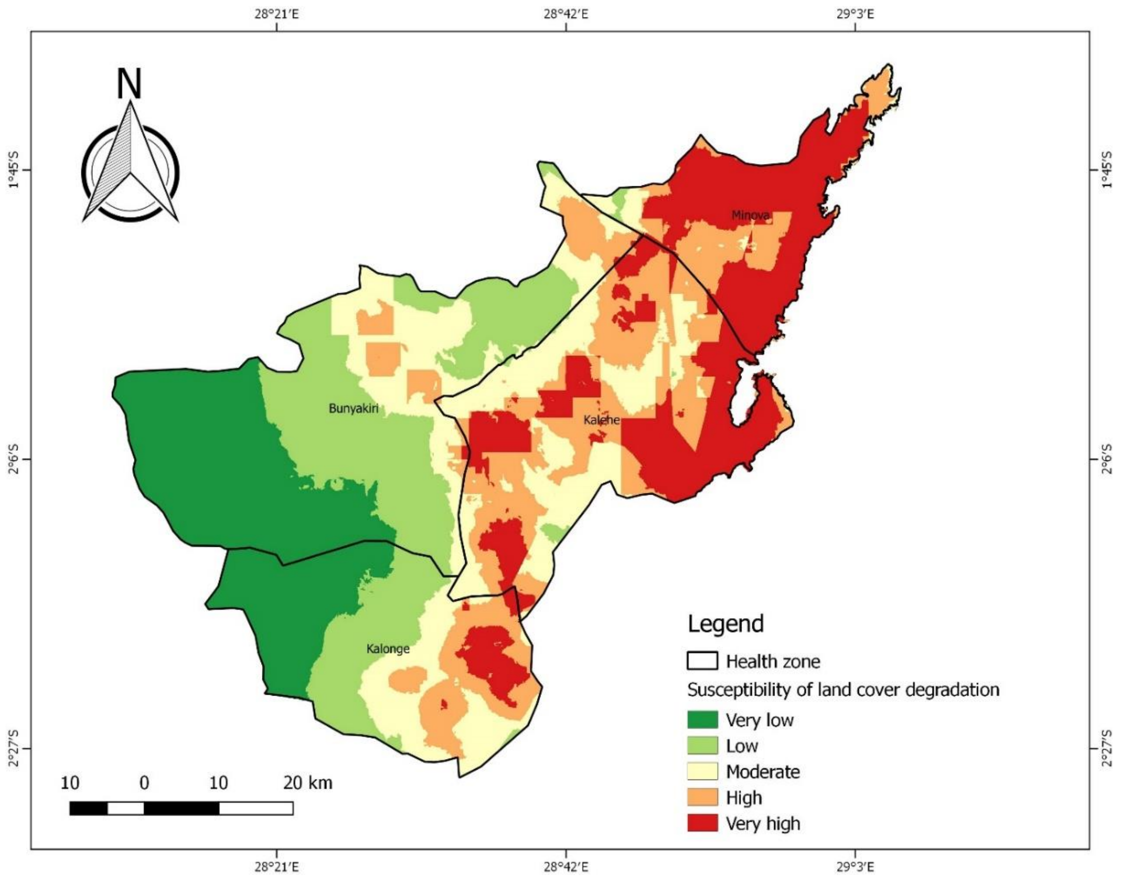


Figure 4.17: Susceptibility map of land cover degradation in Kalehe territory.

This map (Figure 4.17) shows that there is a spatial variability in the susceptibility to land cover degradation among the four health zones in Kalehe territory. For instance, the Minova and Kalehe zones are dominated by high to very-high susceptible zones while the Bunyakiri and Kalonge are dominated by low to very low susceptible zones. It can also be observed that the very high susceptible zones to land cover degradation dominate at the shoreline of Lake Kivu in the eastern part of the territory while the very low susceptible zones are dominating in the western part of the territory. The ROC test indicated that this model (Equation 4-5) has an AUC varying between 0.780 and 0.833

with a mean value of 0.807±0.013 at a confidence level of 95%. This suggests that this model has good predictive power, exceeding a random assignment by 30.7%.

4.2.9. Land productivity dynamics over LULC changes

This section presents the dynamics of land productivity by using the trend of Landsat-based NDVI during the 1987-2020 period as a proxy to determine the areas that are characterized by an improvement of the vegetation productivity (restoration), decrease of land productivity (degradation) and no change in land productivity (stability). The land productivity dynamics are analyzed at the territorial level and per LULC category to assess the vulnerability of each LULC category to degradation. After identifying the area characterized by a decrease in land productivity, the logistic regression model was used to assess the impact of biophysical and socio-economic factor on the persistent decrease of land productivity.

4.2.9.1. Land productivity status and trend during the 1987-2020 period

The trend in NDVI during the 1987-2020 period was used as a proxy of land productivity dynamics. The map presented in Figure 4.18 demonstrates that there is a spatial and temporal variation of the annual NDVI in the Kalehe territory which reflects the change in land productivity and greenness of vegetation (biomass) over time for the 1987-2020 period.

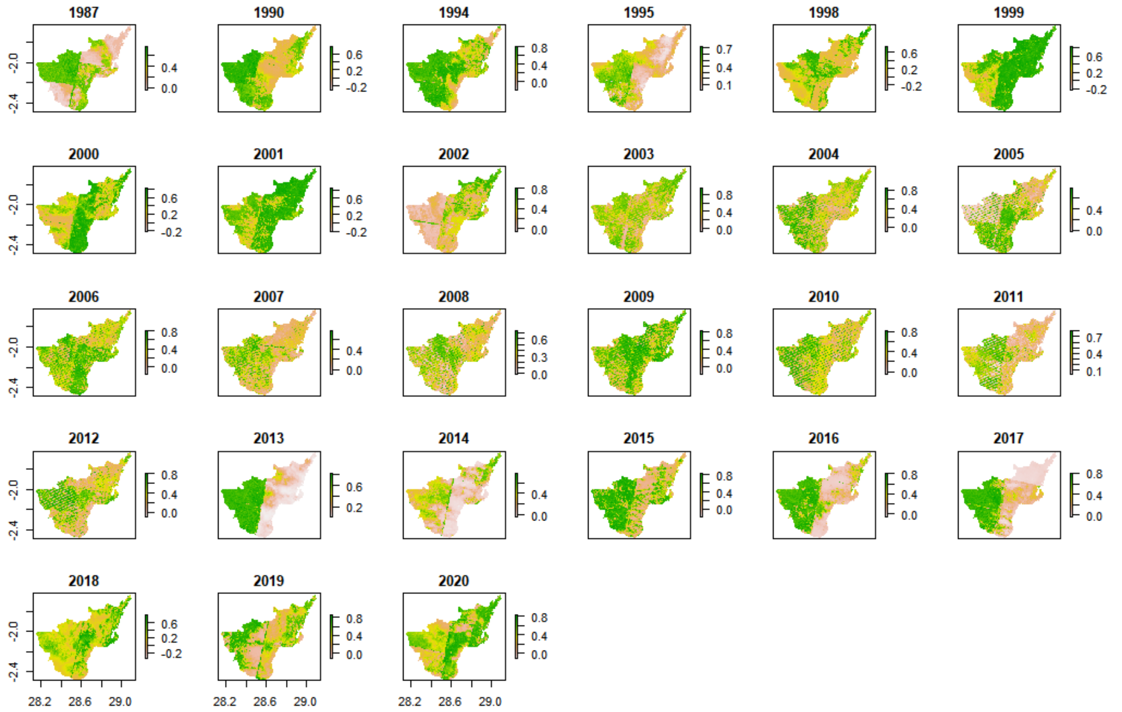


Figure 4.18: Spatio-temporal variation of mean annual NDVI from 1987 to 2020 in Kalehe territory.

The spatial aggregated annual NDVI mean range between 0.22 for the year 2014 and 0.59 for the year 1999 with a mean value of 0.39±0.07. Despite that, there is an annual fluctuation of annual NDVI, the temporal variation of the annual average NDVI at the territorial level shows that there is a general decrease in mean annual NDVI over the 1987-2020 period and the trend equation is y=2.26-0.0009x (Figure 4.19). The decrease rate of the mean NDVI is -0.000932 per year and R= -0.09.

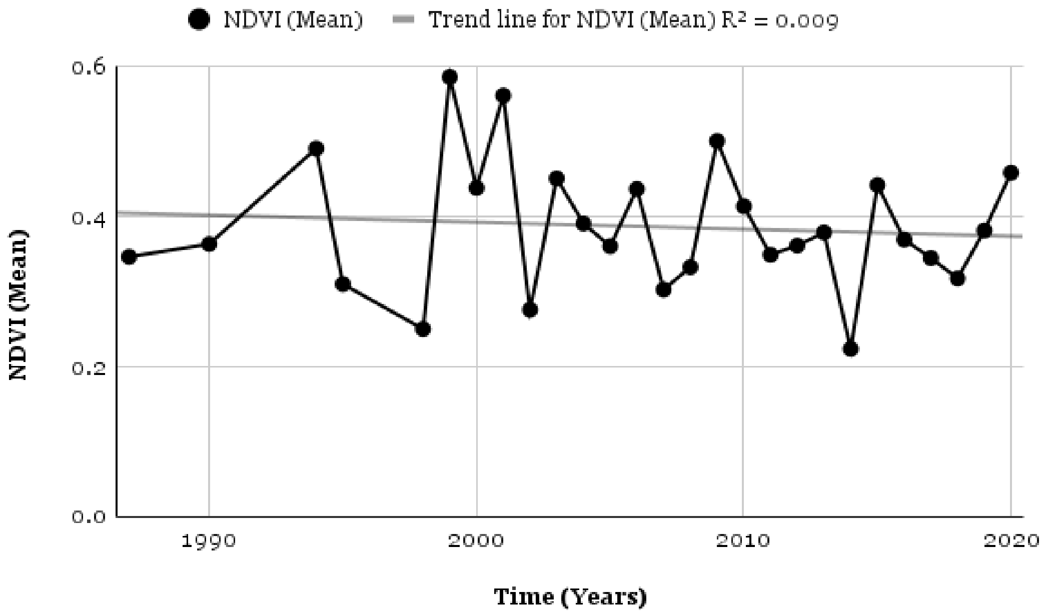


Figure 4.19: Temporal variation of the mean annual NDVI over the 1987-2020 period in Kalehe territory.

From 1987 to 1994 (Figure 4.20), there was a relative increase of NDVI which is observed in the western part of the territory. After the year 1994, the trends show a general decrease until the year 1998. From 1999 to 2001, there was a fluctuation of NDVI value but the values were higher compared to that from the previous period of observation. After this period, relatively reduced biomass trends were observed between 2002 and 2014. From 2015 to 2018, a decrease in the productivity of biomass was also observed but after this year an increase in land productivity was observed compared to the previous years. The results of the NDVI trends analysis show the evolution of land productivity and the development of vegetation during the 1987-2020 period (Figure 4.20).

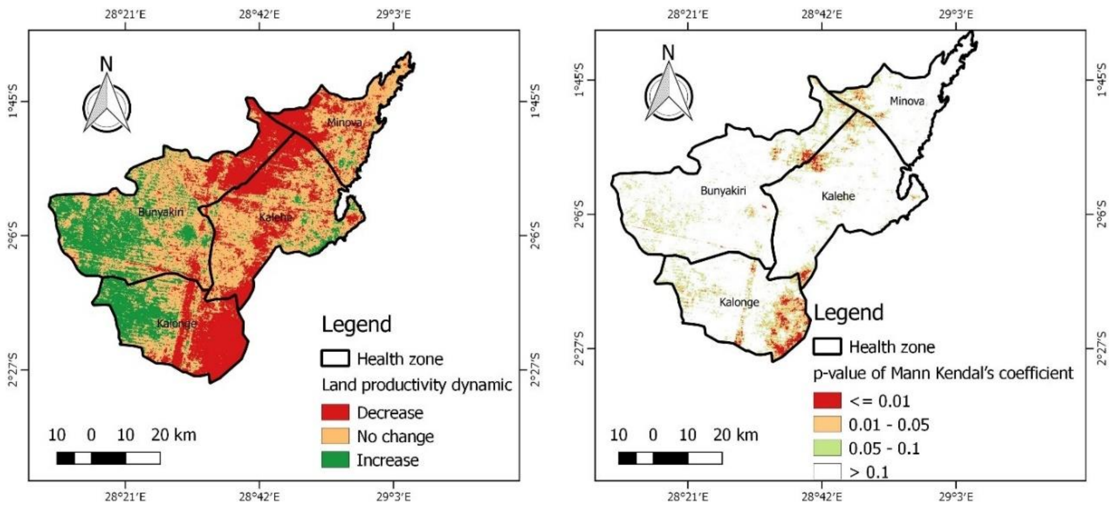


Figure 4.20: Maps showing the spatial distribution of the Mann Kendal's coefficient (τ) and p-value of the trend of land productivity (NDVI) in Kalehe territory over the 1987-2020 period.

The τ correlation coefficient of the Mann-Kendall trend analysis test show that 31.25% (1303.175km^2) of the territory presents a negative trend indicating a decrease in land productivity whereas 47.90% (1997.365km^2) shows stability in the trend of NDVI indicating stability in land productivity and 20.84% (869.1312km^2) is characterized by a positive trend of NDVI indicating an increase in land productivity (Figure 4.20 and Figure 4.21). The negative trend of NDVI which reflects the degradation of vegetation or the decrease of vegetation activities is mostly observed in the North-East and South-East of the territory (Figure 4.20). The positive values of τ coefficient which indicate the vegetation greening are mostly observed in the western part of the territory.

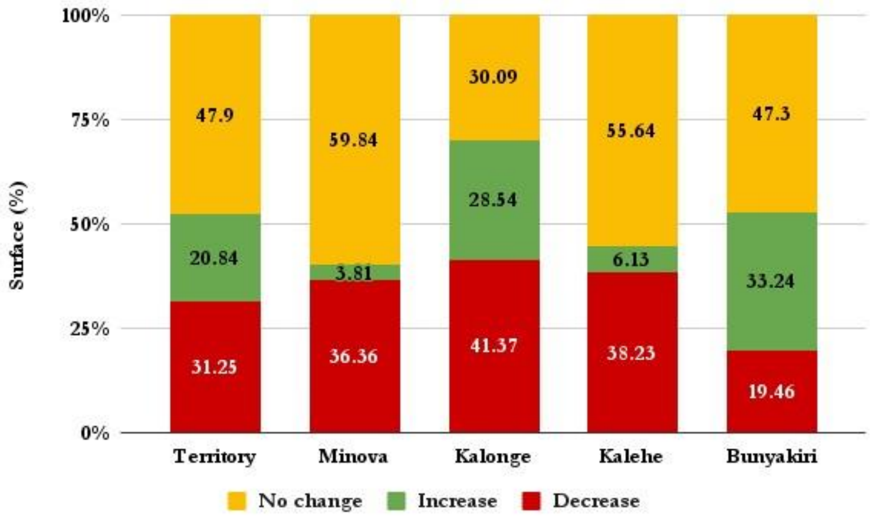


Figure 4.21: Barplot showing the variation of land productivity per health zone and at territorial level according to the trend of NDVI.

Considering the proportion of area with an increasing, decreasing, and stability of NDVI per health zone (Table 4.30), the chi-square test of independence (X-squared = 57.553, df = 6, p-value = 1.412e-10) shows that there is a dependency between the trend of NDVI and the health zone in the Kalehe territory. Thus the land productivity dynamics is location specific.

Table 4.30: Land productivity dynamics per health zone

Land productivity	Decrease		Increase		No change	
Health zone	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Bunyakiri	309.00	19.46	527.73	33.24	751.12	47.30
Kalehe	458.28	38.23	73.52	6.13	667.05	55.64
Kalonge	370.02	41.37	255.28	28.54	269.14	30.09
Minova	197.34	36.36	20.66	3.81	324.78	59.84

The high proportion of surface affected by a decrease in land productivity is observed in the Kalonge zone where 41.37% (370.02km^2) of its surface is characterized by a negative trend of NDVI over the last 33 years. It is followed by the Kalehe zone and Minova, with respectively 38.23% (458.28km^2) and 36.36% (197.34km^2) of surface affected by the decrease in land productivity (Table 4-30). The Bunyakiri zone is the least affected as only 19.46% (527.73km^2) of the area present a decrease of NDVI while there is an improvement of biomass productivity in the western part of this zone (Table 4.30) adjacent to the low altitude zone of Kahuzi-Biega National Park.

The spatial distribution of p-value derived from the Mann-Kendall trend analysis shows that 86.06% (3615.32km^2) of the Kalehe territory is characterized by no significant change of NDVI at a confident level of 90% during the study period (Figure 4.21). Thus, the decrease of NDVI is significant in 10.8% (453.83km^2) of the total surface area whilst only 3.13% (131.36km^2) shows a significant increase or positive trend of land productivity. The area with a significant increasing of NDVI is located mostly in the western part of Kalehe territory in the zone adjacent to the lowland region of the Kahuzi-Biega National Park. However, the area with a significant decrease of NDVI is located in the southern part of the territory, even in the area covered by the highland part of the National Park of Kahuzi-Biega and in the North-Eastern part of the region, including the area covered by the Natural Reserve of Nord Masisi (Figure 4.22).

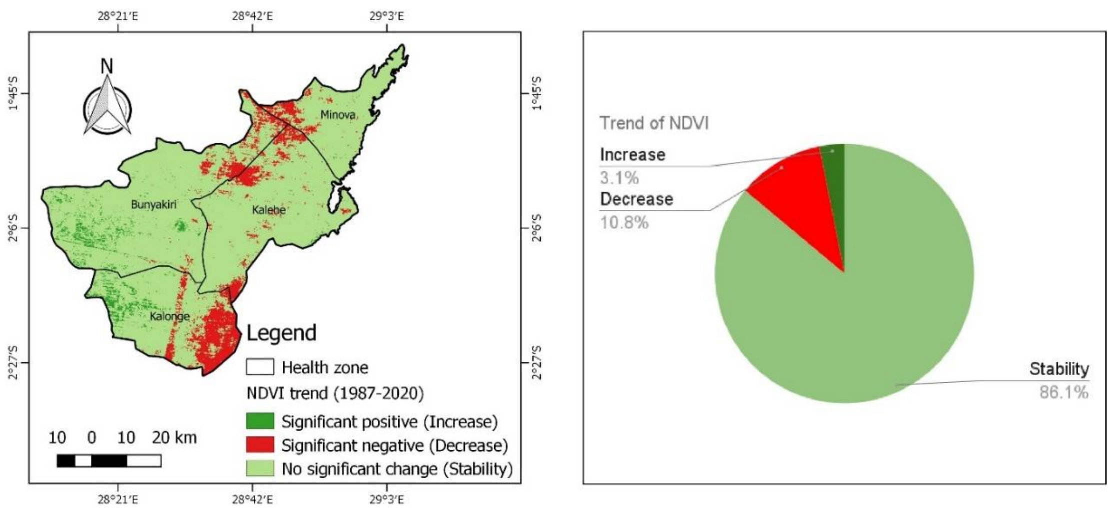


Figure 4.22: Map showing the spatial pattern of significant and no significant trend of NDVI for the 1987–2020 period in Kalehe territory.

4.2.9.2. Land productivity status per LULC categories

The analysis of the association between the land productivity status of different LULC categories has been done through the intersection of the land condition maps obtained based on the NDVI trend from the 1987-2020 period and the LULC maps from the year 2020 and is presented in Figure 4.23. This map shows the area where the productive capacity of the land has decreased and where restoration action is necessary.

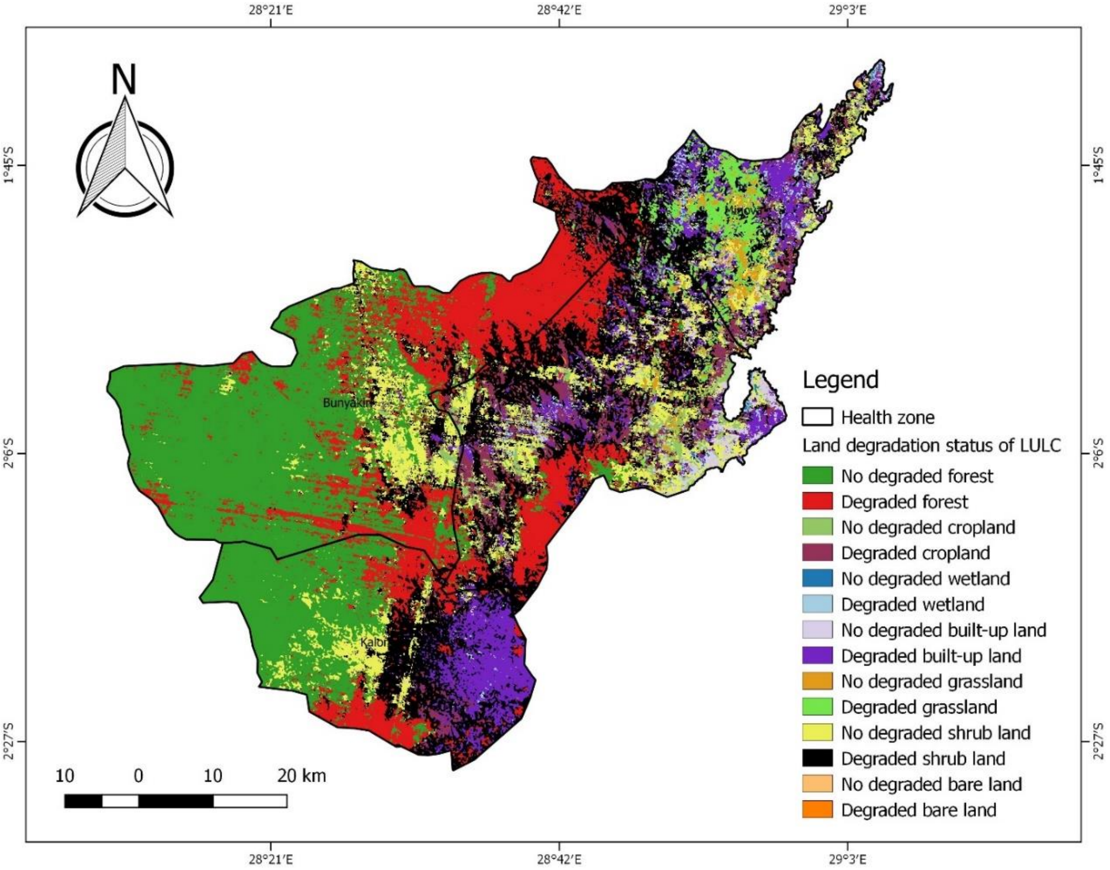


Figure 4.23: Intersection of the LULC map of 2020 and the land condition map for the 1987-2020 period based on the NDVI trend analysis.

The land productivity dynamics as shown in Table 4.31 vary according to the LULC types (X-squared = 93.667, df = 12, p-value = 9.593e-10). The proportion of each LULC type that is being degraded at the territorial level (Table 4.31) shows that built-up area, shrub land, wetland, cropland, and grassland are the most affected by land degradation at 54.27%, 40.01%, 36.27%, 31.58% and 30.36% of their surfaces experience a decrease in land productivity. Only 20.89% of the total surface of forest cover and 27.33% of bare land are characterized by a decrease in productivity.

Table 4.31: Proportion of LULC types that are being degraded at the territorial level.

Land productivity	**Decrease**		**Increase**		**No change**	
LULC (2020)	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Bare land	0.82	27.33	0.53	17.67	1.65	55.00
Built up	213.01	54.27	19.59	4.99	159.91	40.74
Cropland	100.34	31.58	22.08	6.95	195.36	61.48
Forest	415.19	20.89	699.62	35.21	872.23	43.90
Grassland	46.82	30.36	7.03	4.56	100.38	65.08
Shrub land	548.55	40.01	121.80	8.88	700.55	51.10
Wetland	13.51	36.27	1.73	4.64	22.01	59.09

As can be seen in Figure 4.24, the magnitude of productivity declination for the different LULC could be arranged as follows: Built-up land > Shrubland>Wetland > Cropland > Grassland > Bare land > Forest land. However, it can be noted that the highest extent in terms of decrease in land productivity is found in shrub land (548.55km^2), followed by forest land (415.19km^2), built-up area (213.01km^2) and cropland (100.34km^2).

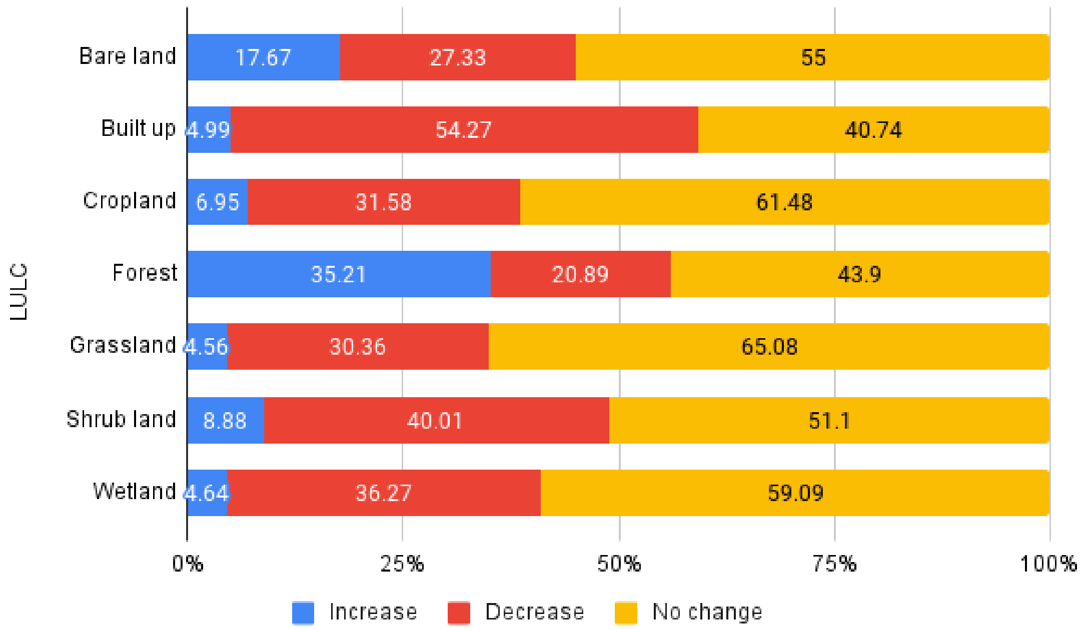


Figure 4.24: Barplot showing the land productivity dynamics per LULC category in Kalehe Territory.

4.2.9.3. Modelling of land productivity degradation and susceptibility mapping

The model of land productivity degradation obtained through the application of the backward stepwise regression (Table 4.32) shows that the degradation of land productivity is significantly influenced by the altitude, the distance to the major centers, the distance to the river, and the distance to artisanal mining sites.

Table 4.32: Best-fit model of land productivity degradation between 1987 and 2020.

Variables	β	S.E.	Wald	p-value	Exp (β)
Altitude	0.00150	0.00022	43.4401	4.3713E-11**	1.002
Distance to the administrative center	-0.00011	0.00001	55.0913	1.1506E-13**	1.000
Mining concession	-0.40603	0.21923	3.4301	0.06401784	0.666
Distance to river	-0.00006	0.00002	8.2624	0.00404747**	1.000
Distance to artisanal mining	-0.00006	0.00002	7.8722	0.00502016**	1.000
Constant	0.02128	0.47010	0.0020	0.96389997	
Model chi-square (χ2)	418.468				
Model Nagelkerke R^2	0.461				
Model correct prediction	80.30%				
AUC	0.833±0.014				

*β: Estimated coefficient; SE: Standard error; R^2: Coefficient of determination; Exp(B): odds ratio. *, ** significant at 5% and 1% level of significance, respectively.*

The results of the omnibus test show that the model was significant with a chi-square of 418.468, a degree of freedom of 5, and a p-value< 0.001. This model explained 46.10% (Nagelkerke R square=0.461) of the variability of land productivity degradation and has a correct prediction of 80.30%. This model has been uded to establish the susceptibility map of land productivity degradation and it is formulated as follows:

$$P_i = \frac{exp(\ 0.02128+0.00150*X1-0.00011*X2-0.40603*X3-0.00006*X4-0.00006*X5)}{1+exp(\ 0.02128+0.00150*X1-0.00011*X2-0.40603*X3-0.00006*X4-0.00006*X5)}$$ (Equation 4-6)

With pi= probability of land productivity degradation, X1= altitude, X2= distance to the administrative center, X3= mining concession, X4= distance to the river, X5=Distance to artisanal mining. This equation was used to establish the susceptibility map of the land productivity degradation in the study area.

Based on this model (Equation 4-6), the map of land productivity degradation susceptibility has been produced (Figure 4.25) to indicate the area where this degradation is likely to occur. The validation of the developed model through the ROC test indicated that this model has an AUC varying between 0.806 and 0.860 with a mean value of 0.833±0.014 at a confidence level of 95% (Table 4.33).

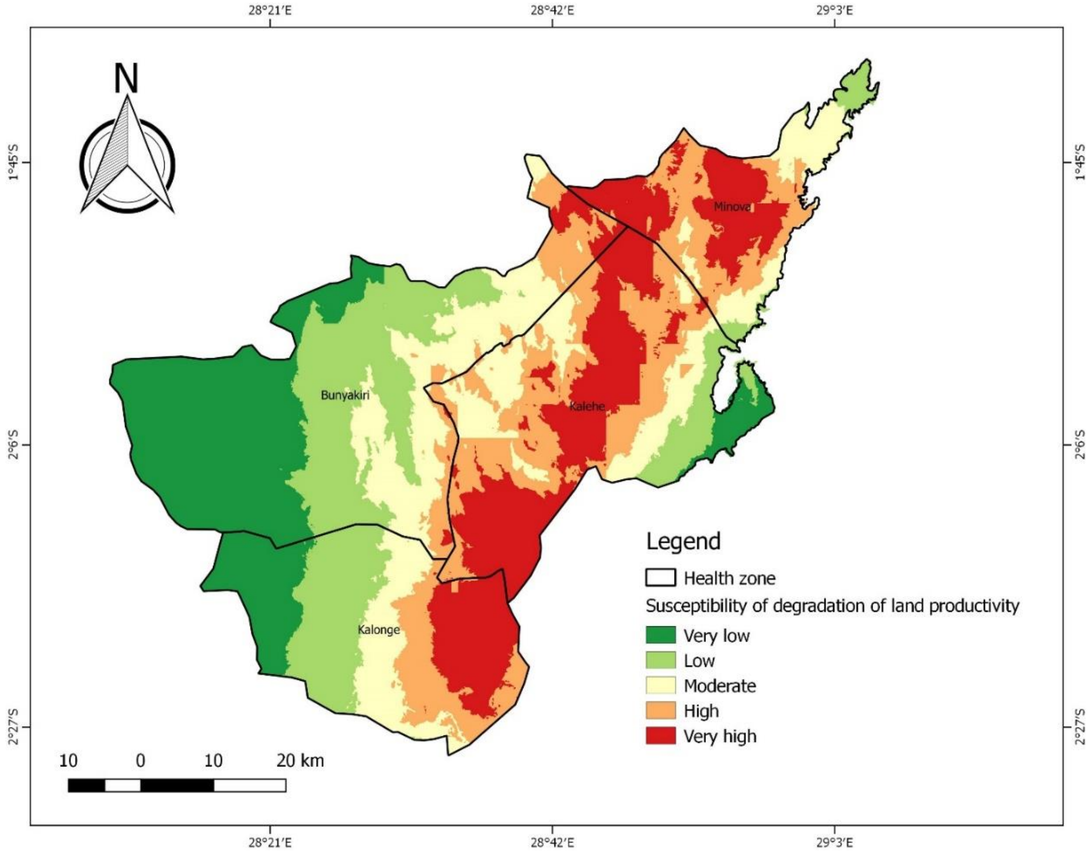


Figure 4.25: Susceptibility map of land productivity degradation in Kalehe territory.

4.2.10. Ecosystem services value variation over LULC changes

The dynamics of ecosystem service supply constitute an indicator of land degradation. In this section, an attempt to associate the community perception of ecosystem service value with the land degradation assessment was made. To elaborate on this GIS-based community participation in land degradation assessment, the ecosystem service matrix model was used during the stakeholder consultation through a questionnaire survey to provide the perceived ecosystem service value of each ecosystem (LULC) as perceived by the local community in Eastern DR Congo. After that, the ecosystem service value provided by the local communities was associated with the LULC maps derived from the classification of the Landsat images in a GIS environment to obtain the ecosystem service potential maps. A trend analysis of the ecosystem service value at different periods allowed us to determine the area showing an increase, decreasing, and stability in providing the ecosystem service. Finally, a multiple linear regression model was used to assess the relation between the perceived ecosystem service potential and the landscape characteristics.

4.2.10.1. Ecosystem service and their ranking

The respondents confirmed their dependence on 30 ecosystem services categorized into 15 provisioning services, 6 regulating services, 3 supporting services, and 6 cultural services in the Kalehe territory as shown in Table 4.33.

Table 4.33: Assessment matrix of ES value assigned to different LULC types.

ES/LULC	For.	Crop.	Gr.&S	Wet.	Set.	Bar.	Total
Provisioning service							
Bushmeat	3.0	0.0	0.9	0.0	0.0	0.0	3.9
Firewood	3.0	1.0	1.9	0.0	0.0	0.0	5.9
Timber	3.0	0.1	0.1	0.0	0.0	0.0	3.2
Bamboo	2.8	0.0	0.0	0.1	0.0	0.0	2.9
Grass for livestock	1.8	2.0	2.9	1.2	0.2	0.0	8.1
Grass for house construction	0.5	0.0	2.8	1.9	0.0	0.0	5.2
Fishes	0.0	0.0	0.0	3.0	0.0	0.0	3.0
Edibles plants	2.9	3.0	0.0	1.4	0.0	0.0	7.3
Mushroom	2.9	0.7	0.8	0.0	0.0	0.0	4.4
Edibles fruits	2.8	2.8	0.1	0.0	0.1	0.0	5.8
Medicinal plant	2.8	1.9	1.0	1.0	0.0	0.0	6.7
Drinking water	1.0	0.0	0.3	2.5	0.1	0.0	3.9
Water for bathing	1.3	0.0	0.0	2.8	0.0	0.0	4.1
Water for livestock	1.6	0.0	0.2	2.9	0.0	0.0	4.7
Honey	2.9	0.0	0.7	0.0	0.0	0.0	3.6
Total value	**32.3**	**11.5**	**11.7**	**16.8**	**0.4**	**0.0**	**72.7**
Regulating service							
Erosion control	2.8	0.1	2.4	0.4	0.0	0.0	5.7
Flood control	2.7	0.0	1.6	2.7	0.0	0.0	7.0
Fresh air (clean air)	2.7	0.2	0.9	1.0	0.0	0.0	4.8
Water purification	2.8	0.0	2.4	2.7	0.0	0.0	7.9
Disease control	1.1	0.0	0.0	0.0	0.0	0.0	1.1
Pollination	2.4	2.7	0.2	0.5	0.1	0.0	5.9
Total value	**14.5**	**3.0**	**7.5**	**7.3**	**0.1**	**0.0**	**32.4**
Supporting services							
Biodiversity conservation	2.9	2.9	1.9	1.0	1.8	0.0	10.5
Conservation of water quality	2.7	2.7	0.0	2.2	2.1	0.0	9.7
Conservation of soil fertility (Fertile soil)	2.6	2.6	0.8	1.5	1.6	0.0	9.1
Total value	**8.2**	**8.2**	**2.7**	**4.7**	**5.5**	**0.0**	**29.3**
Cultural service							
Spiritual belief	1.1	0.0	0.2	0.2	0.5	0.0	2.0
Historical importance	2.2	1.1	0.2	0.7	2.7	0.0	6.9
Aesthetic values	2.4	2.2	1.2	1.2	2.4	0.0	9.4
Recreation	1.1	0.5	1.7	0.1	2.8	0.0	6.2
Social relations	1.3	2.6	0.8	0.6	2.9	0.0	8.2
Educational values	2.0	2.3	0.6	0.0	2.4	0.0	7.3
Total value	**10.1**	**8.7**	**4.7**	**2.8**	**13.7**	**0.0**	**40.0**
Total general	**65.1**	**31.4**	**26.6**	**31.6**	**19.7**	**0.0**	**174.4**

Key: For=Forest land, Crop.=Cropland, Gr.&S= Grassland and shrubland, Wet.=Wetland, Set.=Settlement, Bar= Bare land.

As can be seen in Table 4.33 above, the respondents gave different values to these ecosystem services with the provisioning service scoring highly, followed by the cultural service and the regulating service while the supporting service scored low. Based on the total score assigned by the respondents to each LULC regarding their importance in providing the ecosystem services (Table 4.33), the forestland is perceived as the most important in providing the ecosystem service, followed by wetlands, grassland and shrubs, cropland, and settlements. Forest was considered very important for the provisioning services such as bushmeat, firewood, timber, bamboo, gathering of mushrooms, wild plants, wild edible fruits, medicinal plants, and honey, regulating service of erosion control, flood control, air quality control, and water purification, as well as supporting services of biodiversity, water quality, and soil fertility conservation. The cropland is considered to be very important for provisioning services of edible fruits and vegetables, regulating services such as the control of pollination by providing habitats for pollinating insects, and cultural service by enhancing the social relations among people. Grasslands and shrubs are perceived to have a high value for providing grass for livestock and house construction. The wetland was high ranked for the supply of water for multiple usage (bathing, livestock, drinking) and fish production, for regulating services related to flood control and water purification. The settlements are considered to have a high value in providing cultural services through their historical importance, the opportunity for recreation, and enhancing the social relations among the inhabitants. The barren land is considered as no important in proving the ecosystem service by all the land users (Table 4.33).

4.2.10.2. Perceived ecosystem service value of each LULC

There is a significant difference between the mean score and the perceived ecosystem value in the study area for the different LULC types as attested by the result of the

ANOVA test (Df=4, F value=12.45, p-value=$9.76*10^{-9}$) and perceived ecosystem service value presented in Table 4.34 and Figure 4.26.

Table 4.34: Mean ecosystem service value per LULC and ecosystem service.

ES category /LULC	Forest land	Cropland	Grassland and shrub	Wetland	Settlements	Barren land
Cultural service	1.68	1.45	0.78	0.47	2.28	0
Provisioning service	2.15	0.77	0.78	1.12	0.03	0
Regulating service	2.42	0.5	1.25	1.22	0.02	0
Supporting services	2.73	0.9	1.57	1.83	0	0

Overall, the forest is perceived to have a high ecosystem service value (Mean score=2.17), followed by the wetland (Mean score=1.08), grassland and shrubs (Mean score=0.95), and cropland (Mean score=0.86). However, the settlement (Mean score=0.47) has a low ecosystem service value, and no value is perceived for the barren land (Figure 4.26).

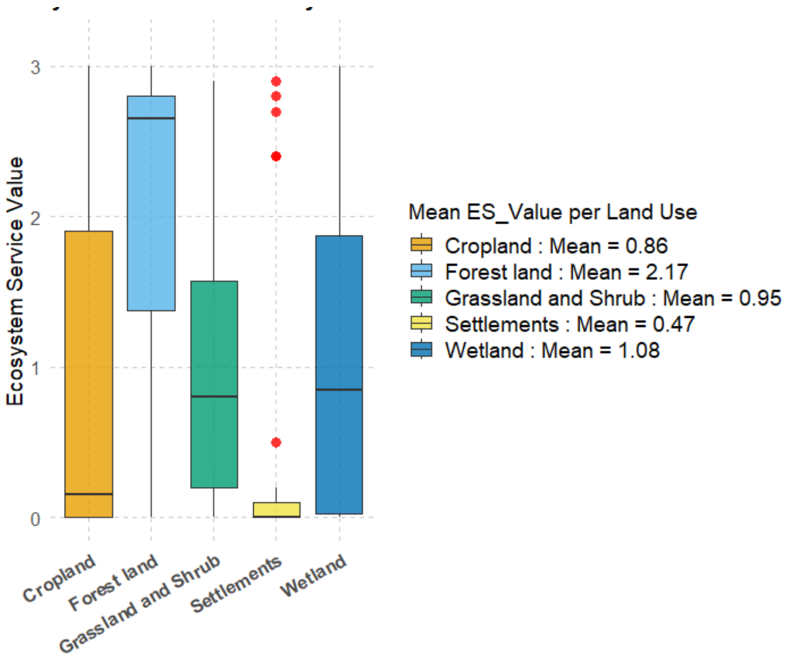


Figure 4.26: Boxplot of the perceived value of ecosystem service per LULC type in Kalehe territory.

The results of the Wilcox pairwise comparison test of the mean score of the perceived ecosystem service value per LULC as presented in Figure 4.26 show that the perceived value of the forest is significantly different from those of the cropland (p-value<0.0001), grassland, and shrub (p-value<0.0001), settlements (p-value<0.0001) and wetland (p-value<0.0001). The perceived ecosystem value for settlements is significantly different from those of the wetland (p-value=0.01) and grassland and shrub (p-value<0.0001) but there is no significant difference between the perceived value of settlements with cropland (p-value=0.31). Furthermore, the perceived value of the cropland is not significantly different from those of the grassland and shrub (p-value=0.75) and wetland (p-value=0.75). Also, there is no significant difference between the perceived value of grassland and shrubs compared to the wetland (p-value=0.89). The variation of the mean values across the ecosystem service categories and LULC types in the Kalehe territory are presented in the Figure 4.27.

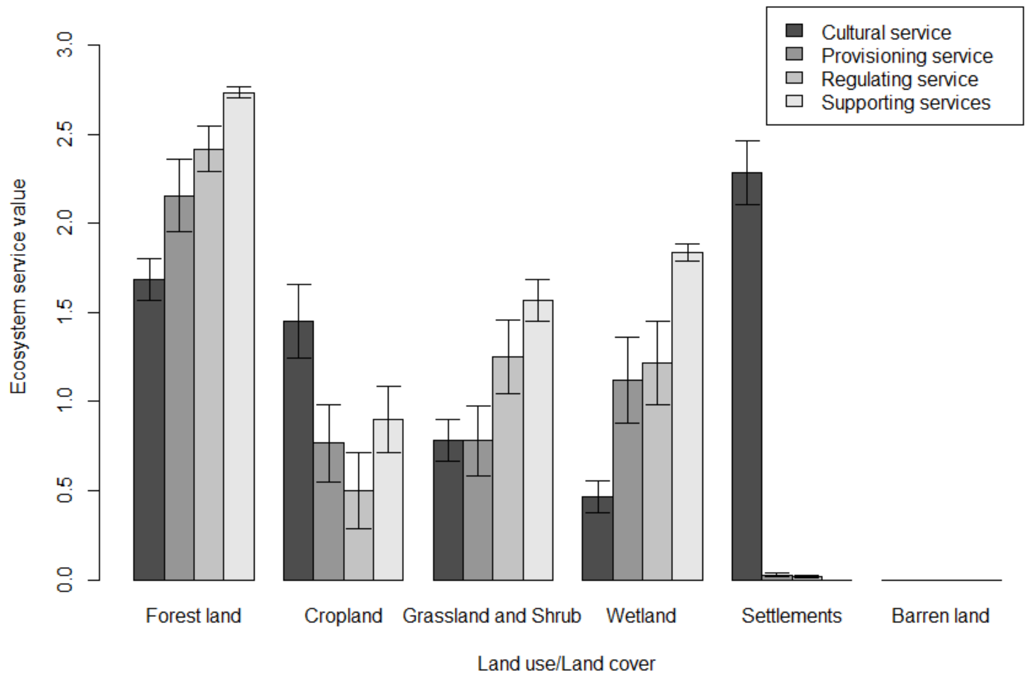


Figure 4.27: Mean ecosystem service value per LULC and ecosystem service category in Kalehe territory.

It can be further seen from Figure 4.27 that for the cultural service, there was a significant difference between the perceived value of different LULC types (F=5.51, Df=4, p-value=0.002). The high value is observed for the settlements (mean score=2.28), forestland, and cropland (mean score=1.45) due to the perceived benefits of these ecosystems for historical importance, esthetic inspiration, recreation opportunities, education value, and opportunity for social relation. The grassland and shrubs (mean value=0.78) are recognized to be important for recreation opportunities. The lowest value is perceived for the wetland (mean score=0.47) as people perceived that this ecosystem has the least historical, esthetic, and educational importance. No importance for cultural perspective was recognized for the barren land.

The comparison of the mean value of the LULC type in supplying the provisioning service show in Figure 4.27 that this LULC provides different provisioning service (F-value=9.41, Df=4, p-value<0.0001). The forest land (mean score=2.15) is characterized by a high potential for provisioning services followed by the wetland (mean score=1.12), the grassland (mean value=0.78), and cropland (mean score=0.77). The lowest value is observed for the settlement (mean score=0.03). This high value allocated to the forest by the inhabitants is related to the high number of provisioning services which are important for the livelihood of the inhabitants.

The respondent perceived that the LULC type has different values for the regulating services (F-value=5.98, Df=4, p-value=0.002). Forest (Mean score=2.42), grassland (Mean score= 1.25), and wetland (Mean score= 1.22) are recognized to be important in regulating flood, erosion, and maintaining soil fertility. Cropland (Mean score= 0.50) and settlement (Mean score= 0.02) are considered as least important for regulating service (Figure 4.27). The mean LULC value for supplying the supporting service is significantly different from one land use to another (F-value=11.58, Df=4, p-value=0.0009). The supporting services are mainly provided by the forest land (Mean score = 2.73), wetland (Mean score = 1.83), grassland (Mean score=1.57), and cropland (Mean score = 0.9). However, the respondent considers that the settlements and barren land are not important for the supplying of supporting services.

4.2.10.3. Status of ecosystem supply potential for 1987, 2002, and 2020

The mean ecosystem service values shown in Table 4.34 resulting from the evaluation matrix were combined with the LULC maps from the different years to produce the ecosystem services potential maps. The spatial distribution of the four ecosystem service supply potentials from the different LULC classes in 1987, 2002, and 2020 are presented in Figure 4.28.

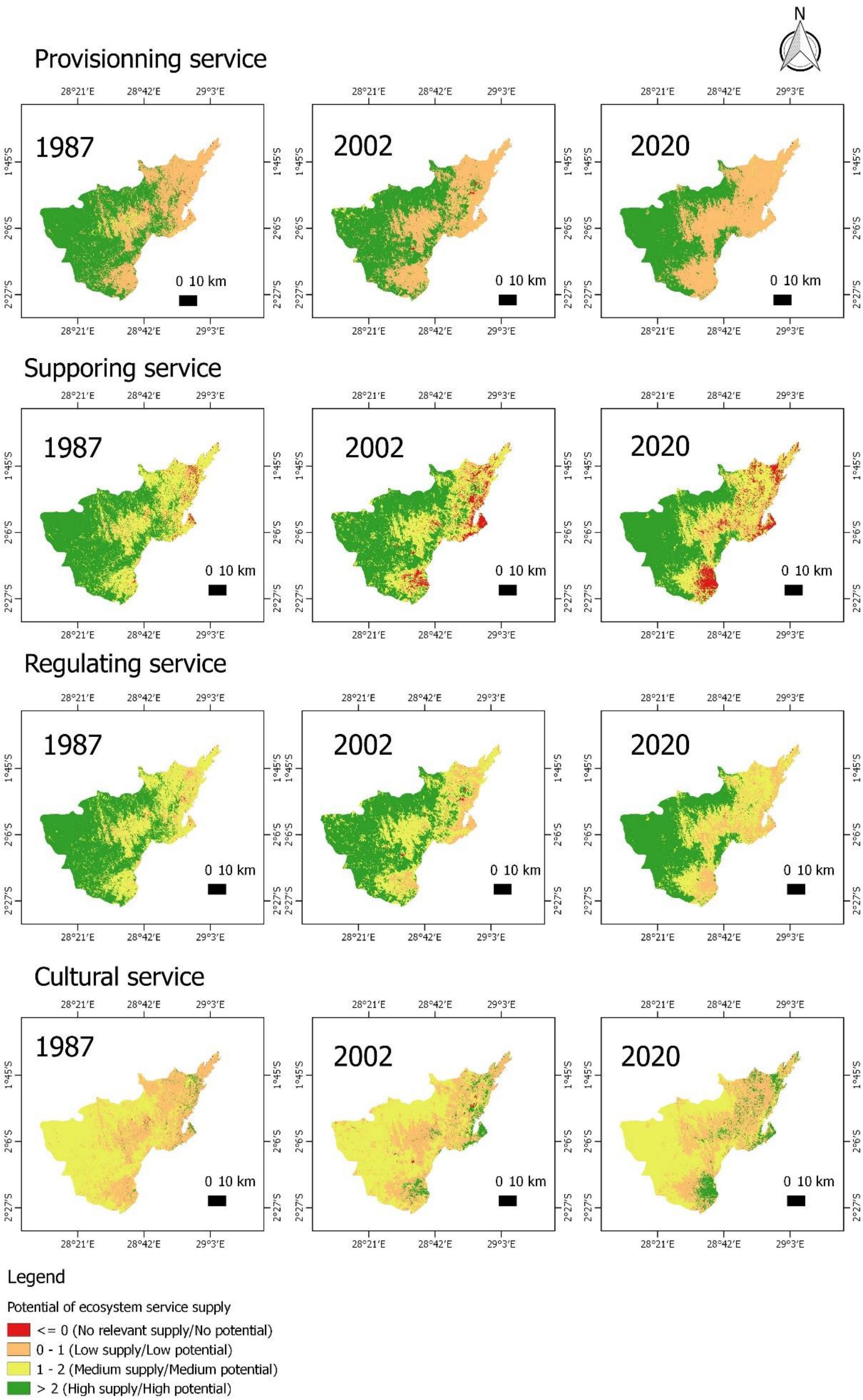


Figure 4.28: Maps of ES supply potential for the 1987-2020 period based on the perceived value from the evaluation matrix.

The overall ecosystem service supply potential maps obtained by summing the results from the four categories of ecosystem service and rescaling the results for the years 1987, 2002, and 2020 are presented in Figure 4.29.

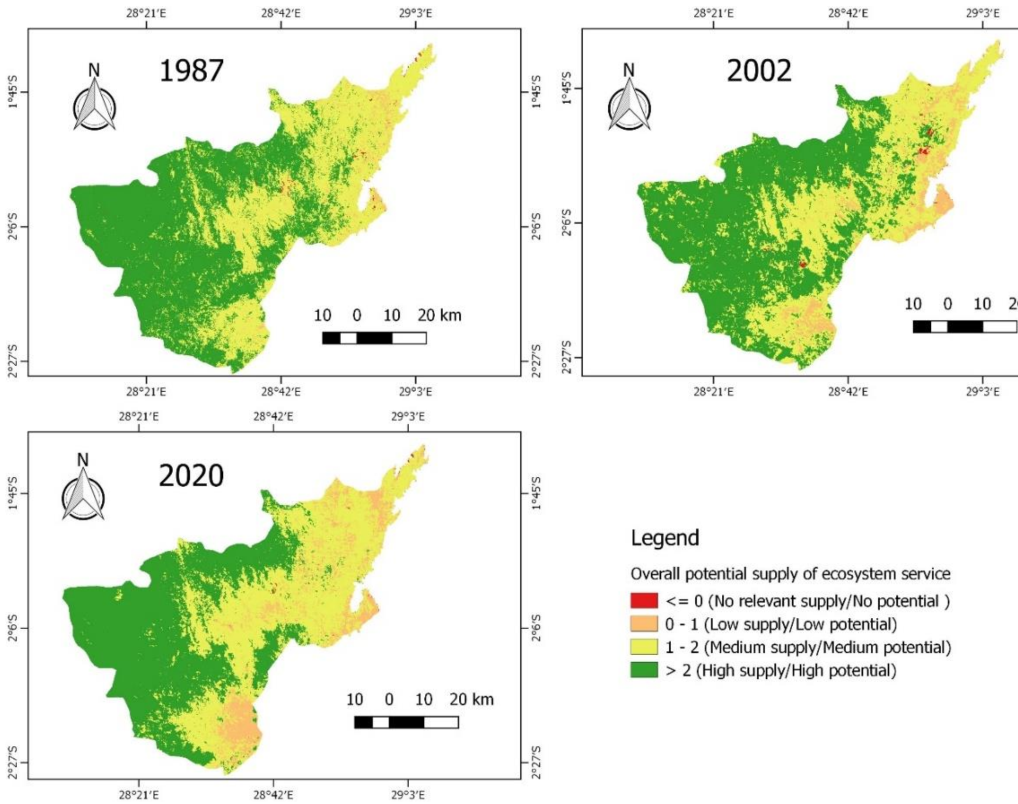


Figure 4.29: Maps of overall ES supply potential for the 1987-2020 period based on the perceived value from the evaluation matrix.

The Table 4.35 presents the mean aggregated value per united area and their change over the 1987-2002, 2002-2020, and 1987-2020 periods.

Table 4.35: Average ecosystem supply potential at the territorial level and its changes between 1987 and 2020

Ecosystem service category	Average of ES value			Change (%)		
	1987	2002	2020	1987-2002	2002-2020	1987-2020
Provisioning service	1.55	1.47	1.35	-5.16	-8.16	-12.9
Regulating service	1.86	1.77	1.63	-4.84	-7.91	-12.37
Supporting services	2.18	2.07	1.92	-5.05	-7.25	-11.93
Cultural service	1.32	1.37	1.39	3.79	1.46	5.3
Overall	**2.31**	**2.23**	**2.1**	**-3.46**	**-5.83**	**-9.09**

Overall, there is a decreasing pattern in the supply of ES (9.09%) in the study area with an overall score of 2.31 in 1987 and 2.1 in 2020 (Table 4.35). The service with the highest value per unit area is supporting services with a score varying from 2.18 in 1987 to 2.07 in 2020. It is followed by the regulating (score ranging from 1.86 in 1987 to 1.63 in 2020) services and provisioning services (score ranging from 1.55 in 1987 to 1.35 in 2020). Only the potential supply of cultural services increased in the area but the value of this service per unit area is the lowest with the value ranging from 1.32 in 1987 to 1.39 in 2020. Other services show a decreasing pattern. The provisioning services, followed by the supporting services and regulating services showed the highest decreasing pattern during the 1987-2002, 2002-2020, and 1987-2020 period.

4.2.10.4. Spatial trend of ecosystem service value over the 1987-2020 period

The analysis of the trend of ecosystem service based on the overall ecosystem service supply potential map for the 1987-2020 period is presented in Figure 4.30. This map shows the area with the increasing, decreasing, and persistent trend of ecosystem supply over the study period. About 28.44% (1177.62km^2) of the study area is characterized by a decreasing pattern of ecosystem service potential, 7.38% (305.39km^2) by an increasing pattern, and 64.18% (2657.72km^2) do not experience any change.

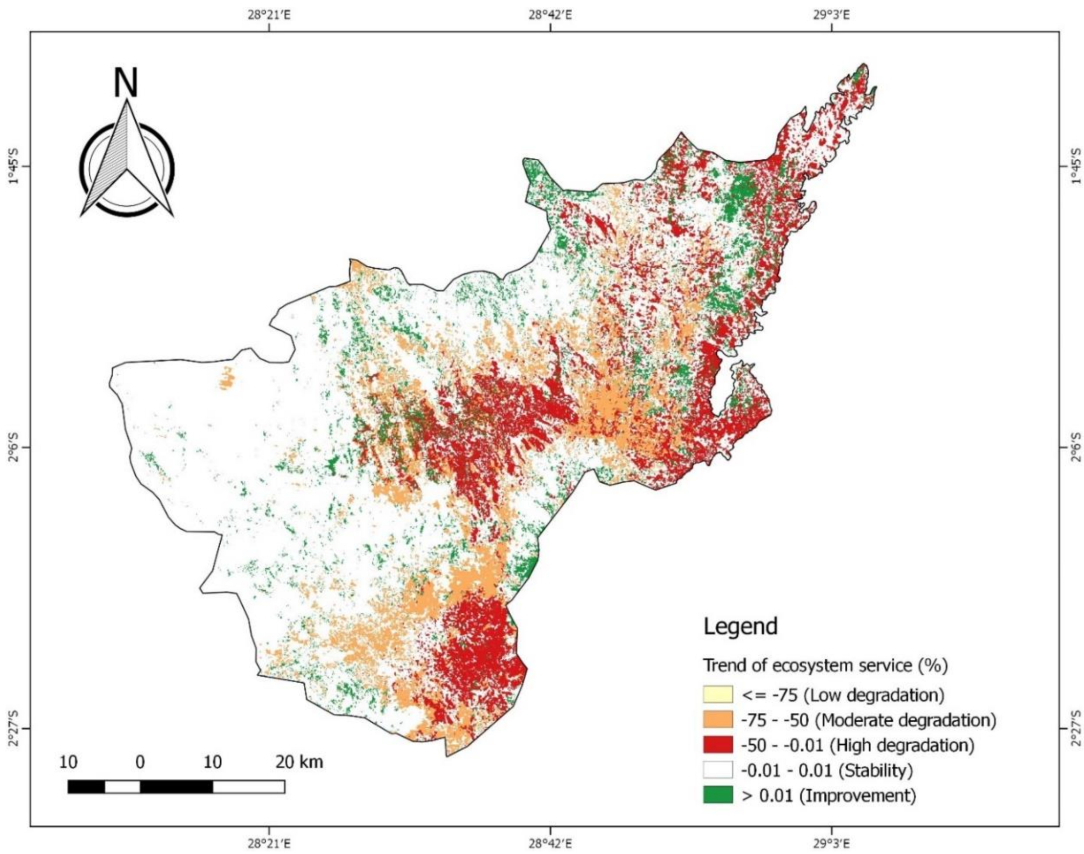


Figure 4.30: Trend of ecosystem service supply potential from 1987 to 2020.

The Figure 4.31 presents the spatial trend of ecosystem service supply potential per health zone within the study area.

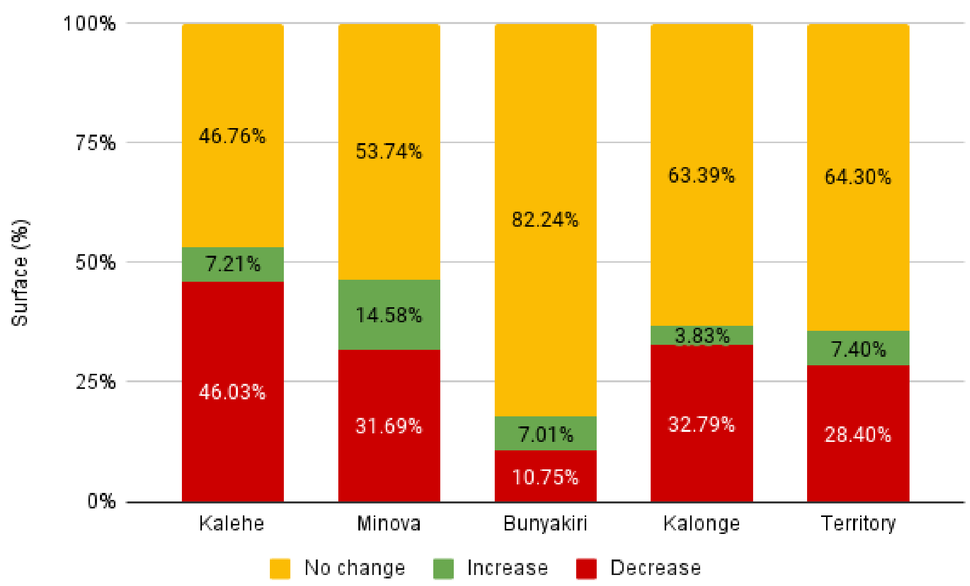


Figure 4.31: Spatial trend of ecosystem service supply potential per health zone.

It can be seen from Figure 4.31 above that there is a spatial variability in the extent of the degradation of ecosystem service supply in the study area. The trend of ecosystem service supply varies according to the health zone (X-squared = 40.208, df = 6, p-value = 4.146e-07). The highest level of decreasing pattern in the supply of ecosystem service is observed in the Kalehe health zone where 46.03% (556.59km^2) of its surface experienced a decrease in the ES supply. It is followed by the Kalonge and Minova with 32.78% (291.66km^2) and 31.68% (172.65km^2) of degraded ES respectively. The Bunyakiri health zone has the lowest degradation of ecosystem service as only 10.75% (169.41km^2) of its surface is degraded (Figure 4.31).

4.2.10.5. Impact of landscape characteristics on ecosystem service value

In this section, the impact of landscape structure and composition are analyzed and modeled based on the PCA and multiple linear regression model to determine the optimal landscape pattern which should be considered during the land use planning process to enhance the provisioning of ecosystem services.

A. Principal Componnent Analysis (PCA) of perceived ecosystem service value and landscape metrics

The scree plot obtained from the PCA of the perceived ecosystem services value (ES_Value) and the landscapes metrics indiated that there is ten principal componnents which explain the landscape characteristics variability and ecosystem service dynamics within the study area as shown on Figure 4.32.

In total, the PC1 (Dim1) and PC2 (Dim2) explained 51.4% of this variability. The PC1 and PC2 explained 38.2% and 13.2% of the total variance of ecosystem service value and landscape characteristics. The highest contributers for the PC1 which shows the variability in the ecosystems services value are the SIDI, SHDI,AI, ED, FL, PD, COHESION, LPI and AREA_MN. Among these landscape metrics, only the FL, LPI, COHESION, and AI show a positive association with the ES value indicating that the increase of these landscape metrics contributes to the increase of the ecosystem service supply potential while the ED, SDI, SHDI, and PD present a negative association with the ES value. In contrast, the highest crontributors to the PC2 are CONTAG, PARA_MN, SHAPE_MN, IJI, AREA_MN, ENN_MN. Among these metrics, the CONTAG, SHAPE_MN, AREA_MN, and ENN_MN show a positive association with the ES value while the PARA_MN and IJI present a negative association with the ES value. These landscapes metrics which have a contribution to the the PC1 and PC2 higher than the expected average contribution, indicated by a red dash line on the graph (Figure 4.32), are variables that are correlated with the PC1 and PC2. Therefore, they are the most important in explaining the variability of the landscape metrics and the perceived ecosystem service value.

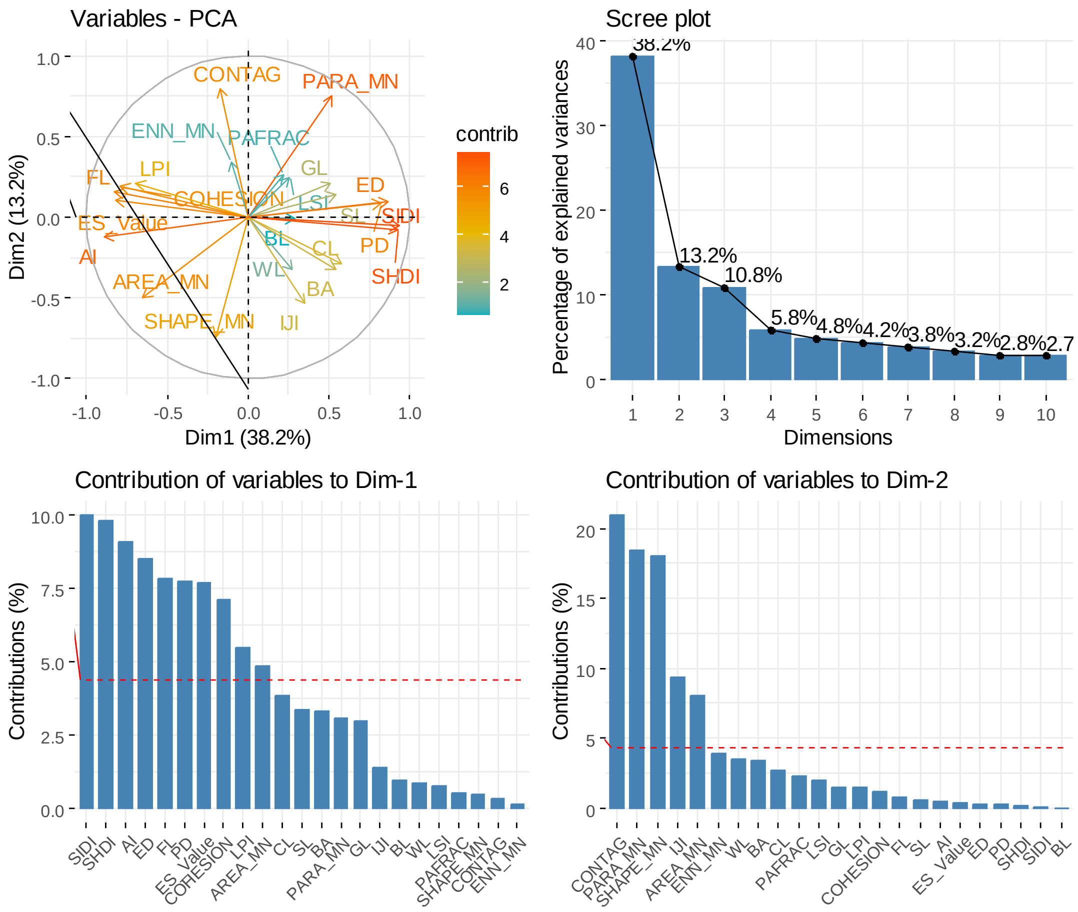


Figure 4.32: PCA of ecosystem service value and landscape metrics.

Key: Sd= Standard deviation, CV= Coefficient of variation, PD=Patch density, LPI= Largest Patch Index, ED=Edge density, LSI=Landscape shape index, IJI=Interspersion and juxtaposition index, AI=Aggregated index, COHESION= Patch cohesion index, CONTAG.= Contagion, AREA_MN= Mean patch size, SHAPE_MN=Mean shape index, PARA_MN=Mean perimeter-area ratio, ENN_MN=Mean Euclidian nearest neighbor distance, PAFRAC= Perimeter-area fractal dimension, SHDI=Shannon's diversity index, SIDI= Simpson's diversity index.

B. Impact of landscape composition on the supply of ES

The results of the linear regression test between the landscape composition (proportion of each LULC type) and the ES supply potential value as can be seen in Table 4.36

reveal that there is a significant correlation between the two parameters. The best-fit linear regression model resulting from the step-wise regression model of the ES value as a function of the proportion of the LULC categories in the landscape (Table 4.36) indicates that the proportion of forest land has the highest significant positive influence on the provision of ES whereas the proportion of bare land, wetland, and built-up area have the most negative influence on the overall ES supply potential.

Table 4.36: Best-fit linear regression model of ES value as a function of landscape structure metrics.

	Coefficient	Std. Error	t value	Pr(>|t|)
(Intercept)	2.127	0.090	23.541	< 2e-16 ***
FL	0.009	0.001	8.009	3.16e-13 ***
CL	-0.008	0.003	-2.930	0.003 **
WL	-0.019	0.007	-2.552	0.012 *
BA	-0.013	0.003	-4.434	1.79e-05 ***
GL	-0.007	0.002	-3.478	0.0006 ***
SL	-0.008	0.001	-5.475	1.83e-07 ***
BL	-0.082	0.027	-3.059	0.003 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Key: FL=Proportion of forest, CL=Proportion of cropland, WL=Proportion of Wetland, BA=Proportion of Built-up area, GL=Proportion of Grassland, SL=Proportion of shrub land, BL=proportion of Bare land.

Among the 7 LULC types namely: grassland, shrubland, and cropland have the lowest negative influence on the ES supply potential. The model is significant (F-statistic: 90.25 on 7 and 148 DF, p-value: < 0.0001) and explains 80.12% of the variability of ES supply potential. The equation of the model which describes the effect of landscape composition on the ES supply potential, therefore, is:

$$ES = 2.127 + 0.009 * FL - 0.008 * CL - 0.0018 * WL - 0.013 * BA - 0.007 * GL - 0.008 * SL - 0.082 * BL \text{ (Equation 4-7)}$$

C. Impact of landscape structure on the supply of ES

The results of the step-wise linear regression model of the ES value as a function of the landscape structure metrics show that the selected landscape metrics can explain 70.39% (adjusted R^2=0.7039) of the variability of ecosystem service supply potential as shown in Table 4.37.

Table 4.37: Best-fit linear regression model of ES value as a function of landscape structure metrics.

	Coefficients	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.896	3.851	-0.492	0.623
LSI	0.0104	0.006	1.811	0.073 .
AREA_MN	0.007	0.002	2.771	0.006 **
SHAPE_MN	-2.195	0.745	-2.946	0.004 **
PARA_MN	-0.001	0.001	-1.848	0.067 .
PAFRAC	5.517	0.917	6.019	2.41e-08 ***
CONTAG	-0.015	0.009	-1.609	0.110
COHESION	-0.068	0.044	-1.537	0.127
SIDI	-2.095	0.535	-3.914	0.0001 ***
AI	0.093	0.026	3.547	0.0006 ***

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

The model as evident above is statistically significant at 95% of confidence (F-statistic: 32.17 on 9 and 109 DF, p-value: < 2.2e-16). Based on the coefficients of the model, the Simpson diversity index (SIDI) and Shape index (SHAPE_MN) have the highest negative influential power on the potential supply of ES while the Perimeter-area fractal dimension (PAFRAC), Aggregation index (AI), and Mean patch size have the most influential positive power on the ES. The multiple regression model that best describes the relationship between the potential of ES supply (ranging from 0 to 3) and the spatial organization of the land units (landscape structure) is

$$ES = -1.896 + 0.01 * LSI + 0.007 * AREA\_MN - 2.195 * SHAPE\_MN - 0.001 * PARA\_MN + 5.517 * PAFRAC - 0.015 * CONTAG - 0.068 * COHESION - 2.095 * SIDI + 0.093 * AI \quad \text{(Equation 4-8)}$$

4.3. Soil Erosion Dynamics

The erosion process contributes to the degradation of soil. Therefore, the monitoring of soil erosion is important for soil and water conservation planning. In this section, the soil erosion dynamics are assessed at the territorial level in Eastern DR Congo by using the Kalehe territory as a case study. Two perspectives were adopted in the monitoring of soil erosion: a spatial modeling of erosion using the RUSLE equation and a local community monitoring of erosion based on a questionnaire survey. The RUSLE model was integrated into the GIS along with Geospatial data related to climate, soil, LULC, and topography. The spatial variability of different parameters of the RUSLE model is first presented. Secondly, the dynamics of soil erosion due to LULC change are assessed. Then a scenario analysis of soil erosion under the adoption of soil and water conservation is presented to determine the most effective conservation practice adopted in the study area. For conservation purposes, the association of the landscape pattern and the dynamic of soil erosion is assessed to determine the optimal landscape structure and composition which should be adopted during the land use planning process to reduce the problem of erosion. This section presents also the local community's perception of the states, causes, consequences, and adopted measures to cope with the problem of erosion. Furthermore, the determinants of this perception and the constraints for the adoption of soil and water conservation measures are outlined.

4.3.1. Spatial and temporal distribution of RUSLE parameters

The RUSLE parameters include the rainfall erosivity (R), the soil erodibility (K), the slop length and steepness factors (LS), the land cover management factor (C), and the conservation practices factor (P). These factors are essential to estimate the annual soil loss by erosion. Hence their spatial and temporal distribution within the study area were determined.

4.3.1.1. Rainfall erosivity (R factor)

The spatial variation of the influence of rainfall energy on the erosion dynamics is illustrated by the value of the R (see Figure 4.33).

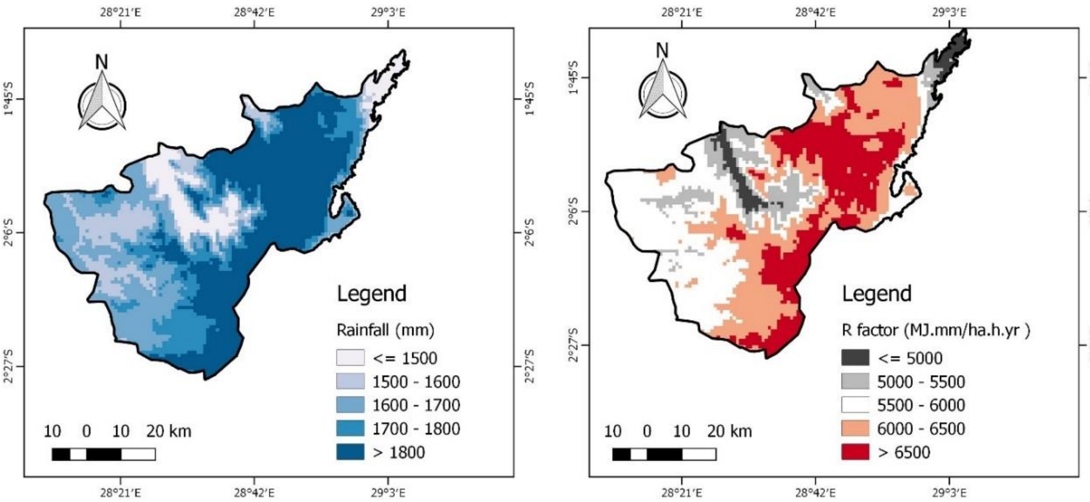


Figure 4.33: Spatial variability of the annual rainfall and R factor.

Under the current pattern of rainfall based on the long-term observation from Wordclim data, the R varies between 4430.22 MJ.mm/ha.h.yr and 6894.06 MJ.mm/ha.h.yr with a mean value of 6025±506.25 MJ.mm/ha.h.yr. The intensity of the R factors increases with the increase in altitude (elevation). Thus it is observed that the highest capacity of rainfall to induce erosion occurs in the high plateau (altitude >2000m) whereas the lowest value of R factor is observed at the lowland in the western part of the territory and low plateau (altitude <1000m) in the North-western part of the study area.

4.3.1.2. Soil erodibility (K factor)

The soil erodibility (K) in the Kalehe territory varies between 0.016 t.ha.h/ha.MJ.mm and 0.020 t.ha.h/ha.MJ.mm with a mean value of 0.018±0.0005 t.ha.h/ha.MJ.mm (Figure 4.34) indicating that the soils of this area are more susceptible to erosion.

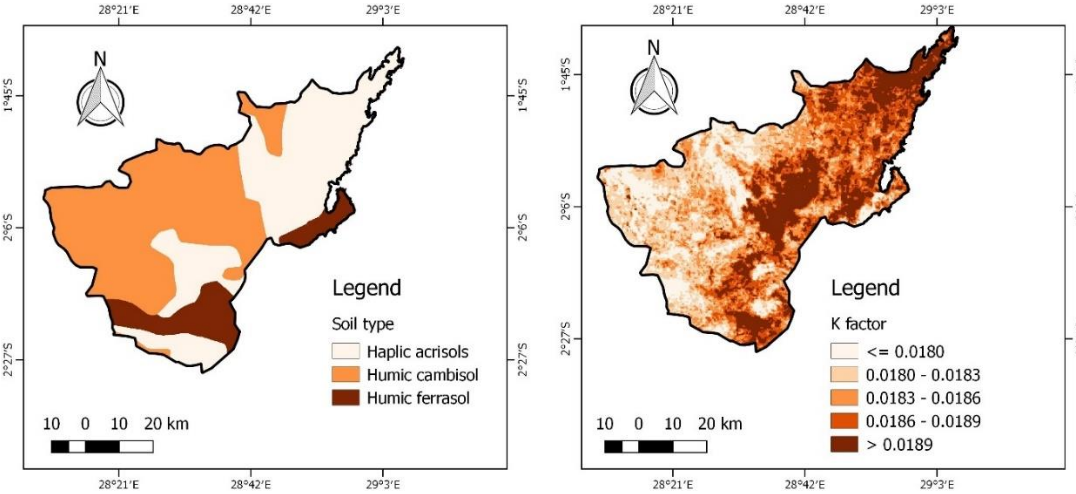


Figure 4.34: Spatial variability of the soil types and K factor.

The erodibility shown in Figure 4.34 above varies according to the sand, silt, clay, and organic matter content of soil types that are identified in the study area (Table 4.38).

Table 4.38: Soil characteristics (Mean and Standard deviation, SD) and variability of K factors in Kalehe territory

Soil type	CLAY (%)		SAND (%)		SILT (%)		CARBON (g/Kg)		K factor	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
Acrisols	40.29	3.1	34.53	3.6	25.17	2.4	65.09	14.76	0.019	0.0004
Cambisols	45.48	5.9	30.66	5.9	23.85	2.0	50.77	8.97	0.018	0.0005
Ferrasols	43.51	3.2	32.29	3.1	24.19	2.4	57.14	11.94	0.018	0.0005

As illustrated in the Table 4.38, the haplic acrisols (K=0.0188±0.0004 t.ha.h/ha.MJ.mm) followed by the humic ferrasols (K=0.0184±0.0005 t.ha.h/ha.MJ.mm) present the highest susceptibility to erosion whereas the lowest susceptibility is attributed to the humic cambisols (K=0.0183±0.0005 t.ha.h/ha.MJ.mm). It can be observed that the lowest level of soil erodibility is observed in the western part of the territory where there is a dominance of humic cambisols (Figure 4.34).

4.3.1.3. Topographic factors (LS factor)

Figure 4.35 presents findings of the slope gradient and LS factor variations in the study area.

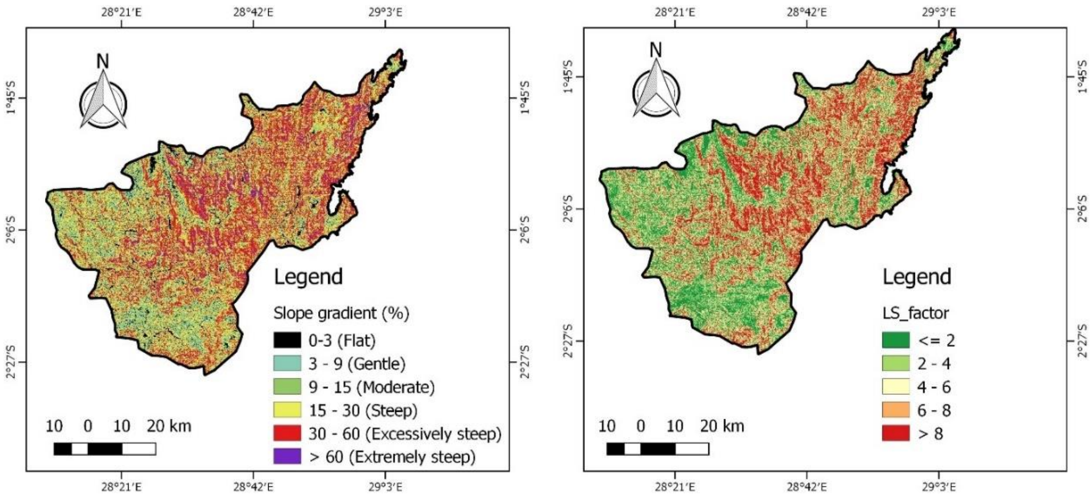


Figure 4.35: Spatial variation of the slope gradient and LS factor.

The influence of the slope length (L) and the slope gradient (S) on the occurrence of erosion is expressed by the LS factor derived from a void-filled DEM. This factor varies between 0.03 and 129.00 with a mean value of 5.67±5.21. The high value of LS factors is associated with the high gradient of slope in the study area where the slope gradient has a mean value of 26.37± 17.62% indicating that the steep slope is the most dominant.

4.3.1.4. Cover and management factor (factor C)

The effect of LULC change on erosion is illustrated by the C factor as presented in Figure 4.36.

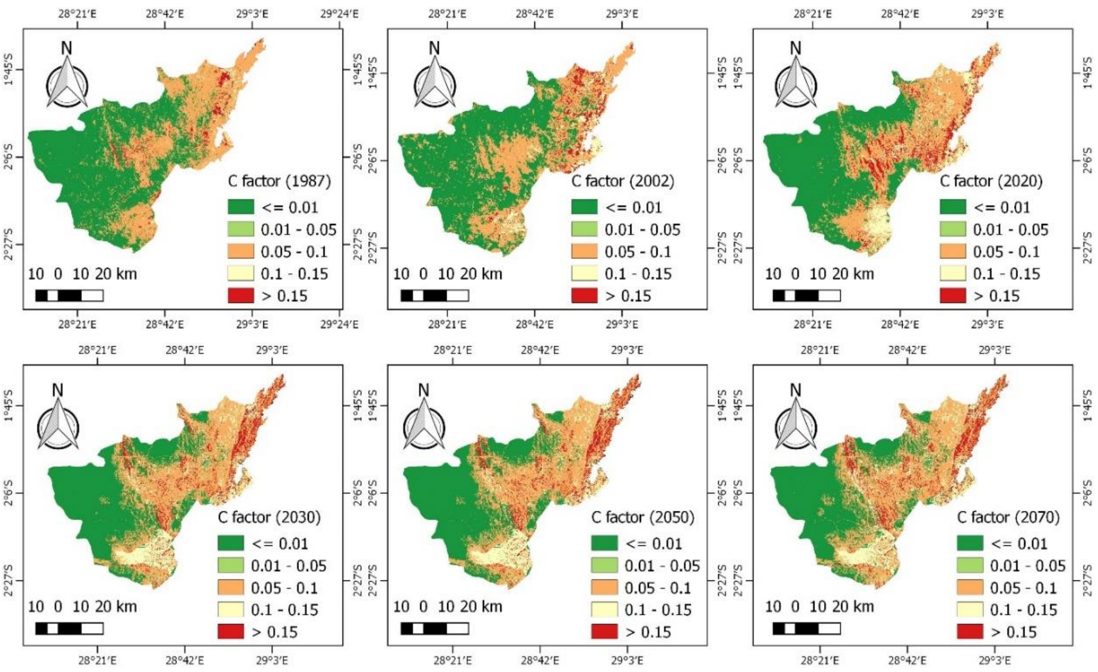


Figure 4.36: Spatial and temporal variability of C factor.

The C factor which shows the vulnerability of soil to erosion due to LULC change presents a wide spatial variation over the considered period (Figure 4.36). Indeed, the mean C factors have increased from 0.041±0.056 in 1987 to 0.046±0.060 in 2002 and 0.058±0.068 in 2020 due to the decrease in forest cover and increase of built-up area over time. The same trend is expected to continue in the future as the value of C will increase from 0.062±0.068 in 2030 to 0.063±0.068 in 2050 and 0.066±0.068 in 2070. This implies that the soil is becoming more and more vulnerable to erosion due to the anthropogenic pressure on the natural vegetation. This can be correlated with the extension of deforestation, cropland land, and urban expansion in the study area.

4.3.1.5. Conservation practice (Factor P)

The spatial variation of the P factor for different conservation planning practices, including strip cropping, contouring, broad-based terracing, and bench terracing is presented in Figure 4.37.

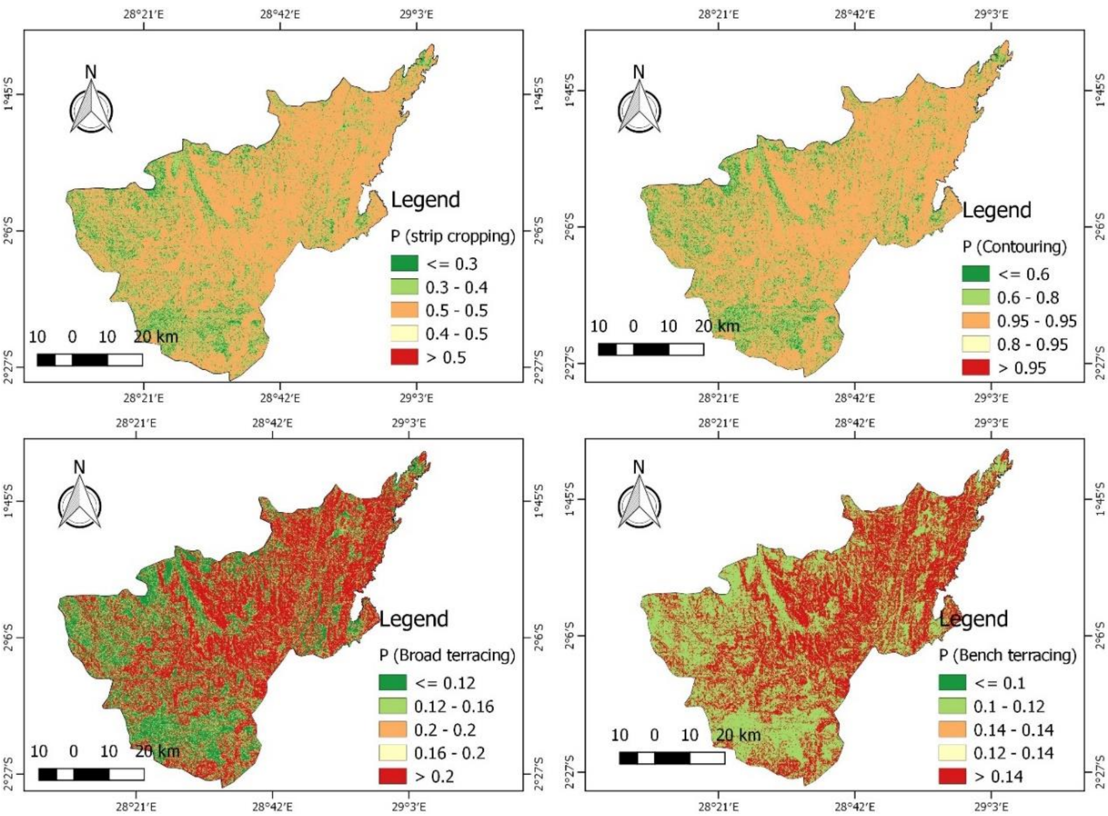


Figure 4.37: Variation of the P factors for differents conservation options.

Considering four soil conservation practices that can reduce the erosion in the study area when adopted, the results presented on the above Figure 4.37 above show that the P value for the strip cropping option varies between 0.15 and 0.5 with a mean value of 0.41±0.11, the contouring has a P value ranging from 0.5 to 0.95 with a mean value of 0.81±0.16. The broad-based terracing has a P value which varies between 0.10 and 0.20 with a mean value of 0.17±0.04 and the bench terracing has a P factor varying between 0.10 and 0.14 with a mean value of 0.12±0.02.

4.3.2. Soil erosion dynamics during the 1987-2020 period

The soil loss derived from the RUSLE model presented in Figure 4.38 and Table 4.39 shows that there is a spatial and temporal variability of erosion following the LULC change in the study area. The maps presented in Figure 4.38 show the pattern of erosion for the 1987, 2002, and 2020 years. They were categorized into three classes: low (<10 t/ha/yr), moderate (10-50 t/ha/yr), and high (>50 t/ha/yr).

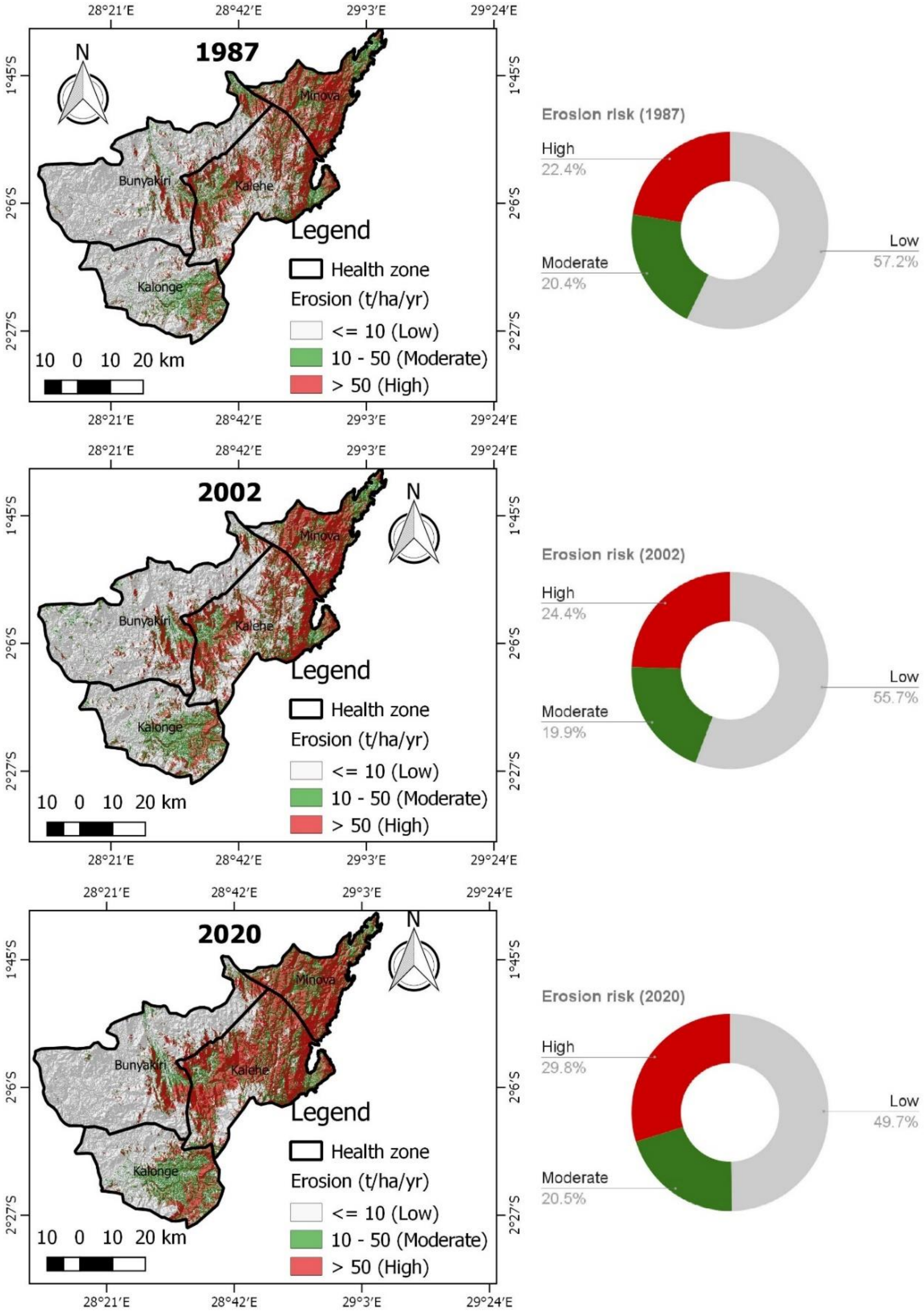


Figure 4.38: Soil erosion map of 1987, 2002, and 2020 in Kalehe territory.

The proportion of each class of soil erosion severity and their surface extension are presented in Table 4.39. The area characterized by an acceptable soil loss of less than 10 t/ha/year decreased over time from 57.5% in 1987 to 55.72% in 2002 and 49.67% in 2020. At the same time, there is a substantive increase in the high-risk erosion zone from 22.37% in 1987 to 24.41% in 2002 and 29.81% of the territory in 2020 (Table 4.39).

Table 4.39: Area of each erosion risk class in the study area for 1987, 2002, and 2020

Erosion risk	**Soil loss (t/ha/year)**	**1987**		**2002**		**2020**	
		Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Low	0-10	2366.20	57.21	2304.62	55.72	2054.44	49.67
Moderate	10-50	844.44	20.42	821.81	19.87	848.51	20.52
High	>50	925.35	22.37	1009.56	24.41	1233.04	29.81

It can be seen from Table 4.40 that the mean annual soil loss in 1987 was 32.08 t/ha/year which increases to 36.01 t/ha/year and 44.35 t/ha/year in the years 2002 and 2020 respectively as result of LULC. As can be seen in this Table 4.40, the overall increase in soil loss intensity during the 1987-2020 period is 1.15 %/Year. The highest rate of change of erosion intensity was observed in the second period 2002-2020 where the mean annual soil loss increased by 1.29 %/Year but it was 0.82 %/Year during the first period as a result of conservation efforts in the study area.

Table 4.40: Change of mean annual soil loss between 1987 and 2020.

Year	**Mean annual soil loss (t/ha/Year)**	**Period**	**PC (%)**	**RC (%/Year)**
1987	32.08	1987-2002	12.25	0.82
2002	36.01	2002-2020	23.16	1.29
2020	44.35	1987-2020	38.25	1.16

PC= Percentage of change, RC= Annual rate of change.

4.3.3. Scenarios analysis of erosion dynamics

The soil erosion dynamics were assessed under two distinct scenarios for planning soil conservation measures: the business as usual scenarios which assess the potential future pattern of soil erosion if the past trend of LULC change observed during the 1987-2020 period continues in the future and the conservation scenario which assess the pattern of soil erosion under different adoption of conservations measures to defines the best soil and water conservation options that should be accepted in the study area to reduce the problem of erosion. For comparison purposes, the current situation (2020) is considered as the baseline situation.

4.3.3.1. Scenario 1: Baseline

The erosion risk for the year 2020 is considered as the actual situation of the erosion. Based on the severity of soil erosion risk (Figure 4.39), the territory was classified into three severity classes for planning and implementing appropriate priority-based conservation measures: the low severity class which does not require the implementation of conservation measures as the erosion is low than the tolerable soil loss (< 10t/ha/year), the moderate severity (10-50 t/ha/year), and the high severity class (>50 t/ha/year) which necessitate urgent implementation of conservation measures.

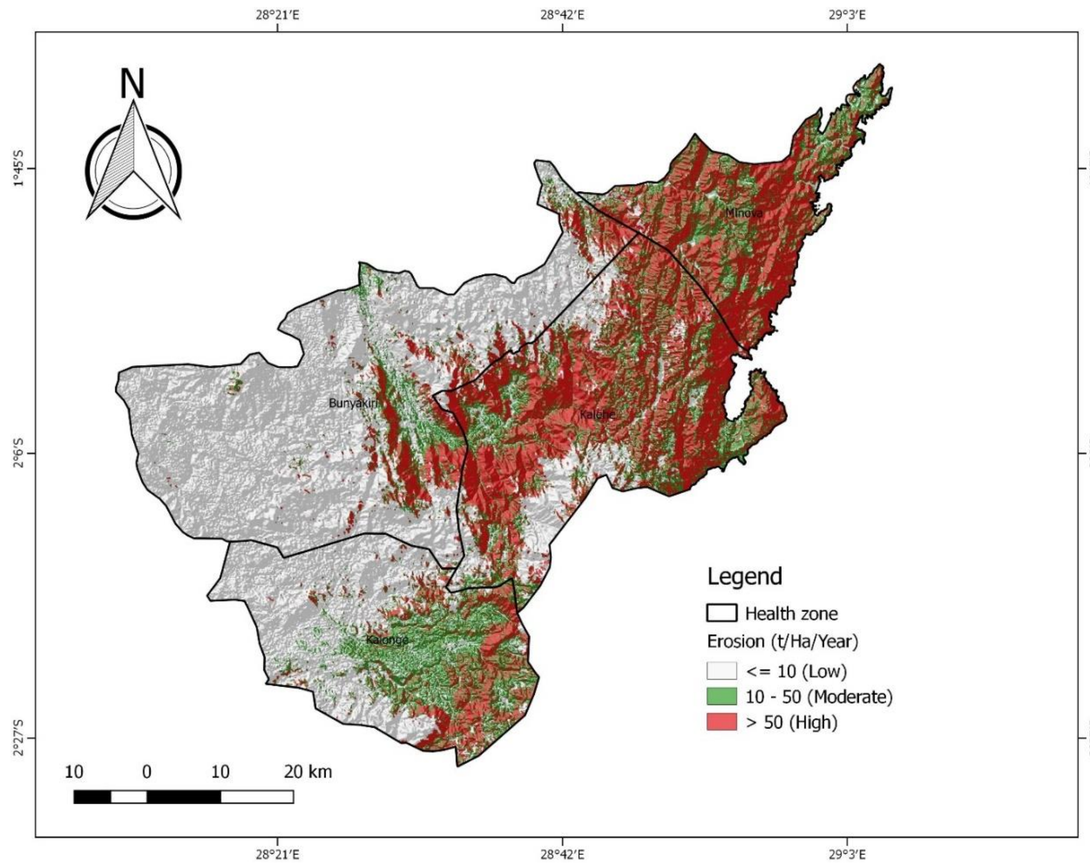


Figure 4.39: Baseline situation of erosion risk in Kalehe territory.

Considering the actual LULC the mean annual soil loss is 44.35 t/ha/year at territorial level, 1.10 t/ha/year for the low severity class, 30.82 t/ha/year for the moderate severity class and 122.14 t/ha/year for the high severity class (Table 4.41). The high severity class represents only 29.81% of the territory but it contributes to 84.12% of the total soil loss while the low severity class which have a high surface coverage (49.67%) contributes to only 1.26% of the total soil loss. The moderate severity class of erosion represents 20.52% of the territory but it contributes to only 14.60% of the total soil loss at territorial level (Table 4.41). The results presented in Table 4.41 shows that substantial soil losses in the study area are generated by small surfaces area from the high severity class of erosion.

Table 4.41: Area coverage and statistics of soil erosion risk under the baseline scenario

Erosion risk	Soil loss	Area coverage		Mean soil loss	Total soil loss	
Class	(t/ha/Year)	(km^2)	(%)	(t/ha/Year)	(t/Year)	(%)
Low	0-10	2054.44	49.67	1.10	226267.9	1.26
Moderate	10-50	848.51	20.52	30.82	2615351	14.60
High	>50	1233.04	29.81	122.14	15060470	84.12

The current situation of erosion in the study area is influenced by the site's characteristics such as the LULC types, the slope classes, altitude gradient, and the soil types (Figure 4.40). The Figure 4.40 presents the area proportion of different categories of LULC types, the slope gradient classes, the soil type and the altitude gradient classes as well as their contribution to the total annual soil loss at territorial level during the year 2020.

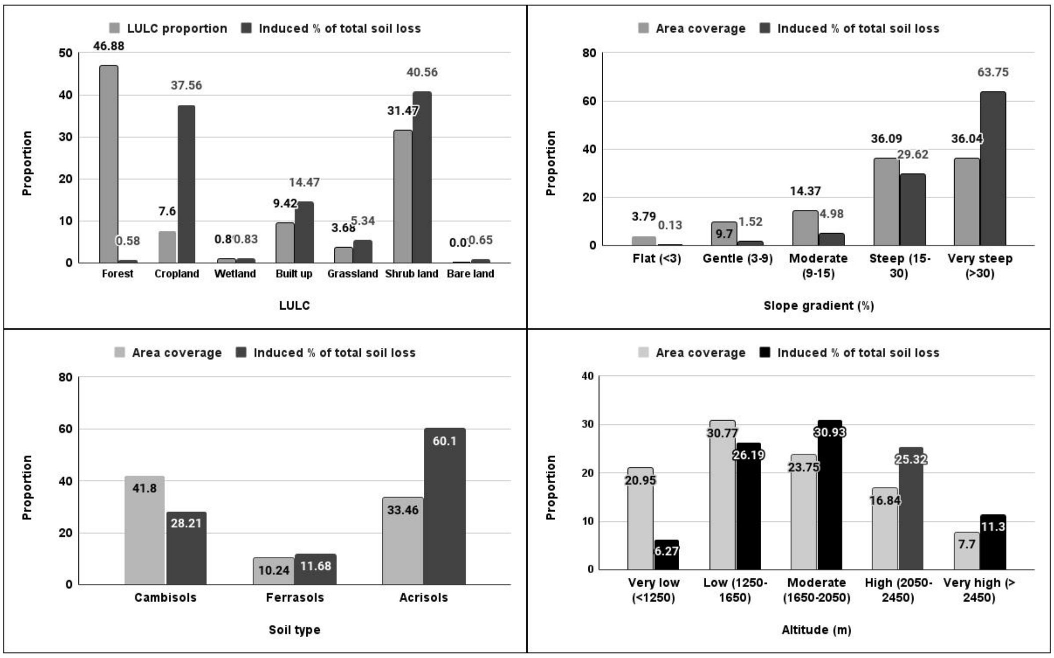


Figure 4.40: Area coverage of LULC types, slope classes, altitude gradient, soil types, and induced proportion of soil loss by erosion.

a) Soil losses under various LULC types

The spatial dynamics of erosion are currently influenced by the LULC (Table 4.42). The highest mean annual soil loss is found on bare land (389.14 t/ha/year), cropland (215.19 t/ha/year), built-up area (66.87 t/ha/year), grassland (63.26 t/ha/year) and shrubland (56.11 t/ha/year). The lowest soil loss is found on forest land (0.54 t/ha/year). In this regard, the forestland is the least vulnerable to erosion while the bare land and cropland are the most vulnerable. Although the forestland covers 46.88% of the territory, it contributes to only 0.58% of the total soil loss. It constitutes with grassland the lowest contributor to erosion in the study area. However, the shrubland, cropland, and built-up area constitute the highest contributor to erosion in the study area.

Table 4.42: Mean and total soil loss per LULC category

LULC	**Area coverage**		**Mean soil loss**	**Total soil loss**	
classes	**(km^2)**	**(%)**	**(t/ha/year)**	**(t/Year)**	**(%)**
Forest	1968.78	46.88	0.54	106556.96	0.58
Cropland	319.06	7.60	215.19	6865779.15	37.56
Wetland	37.26	0.89	40.70	151647.98	0.83
Built up	395.61	9.42	66.87	2645671.96	14.47
Grassland	154.38	3.68	63.26	976563.82	5.34
Shrub land	1321.55	31.47	56.11	7414650.28	40.56
Bare land	3.05	0.07	389.14	118618.58	0.65

b) Soil losses under various slopes classes

The rate of soil loss within the Kalehe territory increase with the increase slope of the slope gradient (Table 4.43), indication a positive relation between the occurrence of erosion and the slope gradient. The minimum soil erosion rate of 1.44 t/ha/year and 6.72 t/ha/year are observed on flat and gentle slope while the maximum erosion rate of 35.21 t/ha/year and 75.88 t/ha/year are observed on steep and very steep slopes. The territory is dominated by steep and very steep which contribute to the total annual soil loss by 29.62% and 63.75% respectively.

Table 4.43: Rate of soil erosion per slope category

Slope gradient (%)	Area coverage		Mean soil loss	Total soil loss	
Class name	**(km²)**	**(%)**	**(t/ha/Year)**	**(t/Year)**	**(%)**
Flat (<3)	159.90	3.79	1.44	23037.89	0.13
Gentle (3-9)	409.41	9.70	6.72	275010.38	1.52
Moderate (9-15)	606.41	14.37	14.87	902014.66	4.98
Steep (15-30)	1522.85	36.09	35.21	5361351.78	29.62
Very steep (>30)	1520.74	36.04	75.88	11538614.76	63.75

c) Soil losses under various soil types

The erosion rate is influenced by the soil erodibility in the Kalehe territory. The erosion rate is higher under the acrisols (66.47 t/ha/year) and lower under the cambisols (24.98 t/ha/year) (Table 4.44). The acrisols represents only 33.46% of the territory, but it contributes to 60.10% of the total soil loss at the territory level. Although the rate of soil erosion under the ferrasols is higher (42.23 t/ha/year) compared to those on the cambisols (24.98 t/ha/year), it is the least contributor to the total annual soil loss (11.68%) as it covers only 10.24% of the territory. The cambisols is the most represented soil in the territory as it covers 41.80% of the territory but it contributed to only 28.21% of the total soil loss.

Table 4.44: Effects of soil type on rate of soil loss

Soil	Area coverage		Mean soil loss	Total soil loss	
type	**(km²)**	**(%)**	**(t/ha/Year)**	**(t/Year)**	**(%)**
Cambisols	2030.41	41.80	24.98	5072241.58	28.21
Ferrasols	497.37	10.24	42.23	2100307.38	11.68
Acrisols	1625.67	33.46	66.47	10805789.65	60.10

d) Soil losses under various altitude gradient

The rate of erosion increases with the elevation gradient (Table 4.45). According to the elevation (altitude) classification, the highest mean soil erosion rate from the high-altitude zone (2050-2450m) and very high-altitude zone (>2450m) was found to be 65.05 t/ha/year and 63.51 t/ha/year, followed by 56.34 t/ha/year under moderate altitude (1650-2050m). However, the low erosion rate of 12.95 t/ha/year and 36.83 t/ha/year is observed at the very low elevation zone (<1250m) and low elevation zone (1250-1650m) respectively.

Table 4.45: Effects of elevation gradient on rate of soil loss

Altitude (m)	**Area coverage**		**Mean soil loss**	**Total soil loss**	
Class name	**(km^2)**	**(%)**	**(t/ha/Year)**	**(t/Year)**	**(%)**
Very low (<1250)	870.02	20.95	12.95	1126568	6.27
Low (1250-1650)	1277.84	30.77	36.83	4706521	26.19
Moderate (1650-2050)	986.40	23.75	56.34	5557621	30.93
High (2050-2450)	699.39	16.84	65.05	4549569	25.32
Very high (> 2450)	319.70	7.70	63.51	2030567	11.30

4.3.3.2. Scenario 2: LULC change scenario

The map in Figure 4.41 presents the projected spatial pattern of erosion in the study area for the years 2030, 2050, and 2070 under the business-as-usual scenarios by considering that the past trend of LULC and climate changes will continue in the future. In this scenario, it is considered that both the LULC and the climate will change simultaneously.

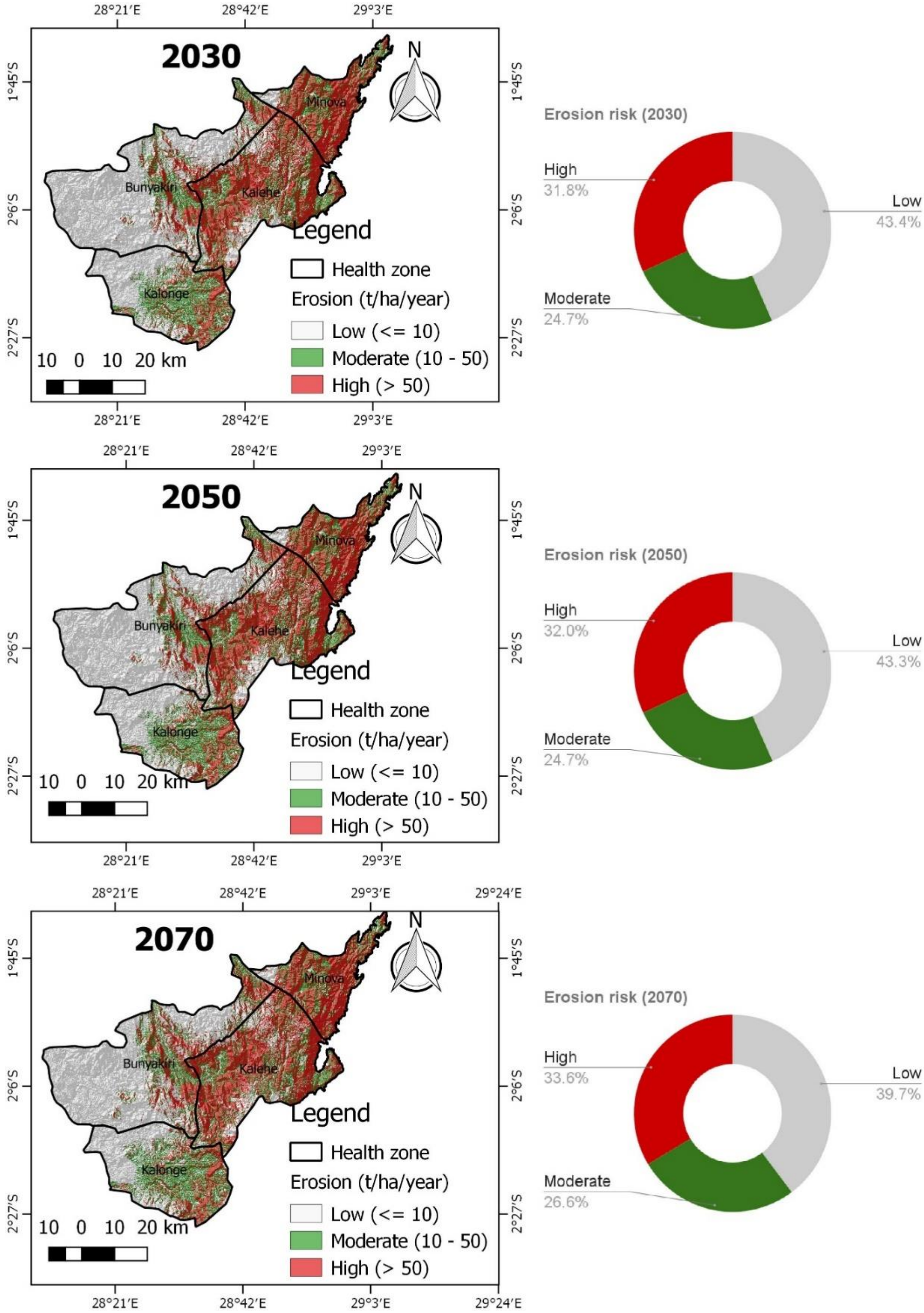


Figure 4.41: Soil erosion map of 2030, 2050, and 2070 in Kalehe territory.

As can be seen from Table 4.46**,** it is expected that the average soil erosion will increase in the study area due to the effect of LULC change if the actual trend continues in the future during the 2020-2030, 2020-2050, and 2020-2070 period. The average soil erosion in 2020 is 44.35 t/ha/year but it is projected to increase to 46.42 t/ha/year in 2030, 46.79 t/ha/year in 2050, and 48.38 t/ha/year in 2070. This represents an annual increase of soil erosion by 0.47 %/year for the 2020-2030 period, 0.18 %/year for the 2020-2050 period, and 0.18 %/year for the 2020-2070 period (Table 4.46).

Table 4.46: Change of mean annual soil loss between 2020 and 2070.

Year	Mean annual soil loss (t/ha/Year)	Period	PC (%)	RC (%/Year)
2030	46.42	1987-2002	4.67	0.47
2050	46.79	2002-2020	5.50	0.18
2070	48.38	1987-2020	9.09	0.18

PC= Percentage of change, RC= Annual rate of change

Like in 2020, the territory will still be dominated by areas with a low risk of erosion that will cover 43.45% of the territory in 2030. However, in the years 2050 and 2070, the area characterized by the low risk of erosion will still be decreasing while the area of high risk of erosion will increase as can be seen in Table 4.47. It is projected that the area characterized by a soil loss higher than the tolerable limit of 10 t/ha/year will represent 56.55% in 2030, 56.57% in 2050, and 60.25% in 2070.

Table 4.47: Erosion risk class in the study area for 2030, 2050 and 2070

Erosion risk	Soil loss (t/ha/yr)	2030		2050		2070	
		Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Low	0-10	1796.85	43.45	1792.11	43.33	1643.99	39.75
Moderate	10-50	1021.89	24.71	1021.08	24.69	1101.27	26.63
High	>50	1317.13	31.85	1322.68	31.98	1390.61	33.62

4.3.3.3. Scenario 3: Adoption of water and soil conservation measures

The effectiveness of the implementation of the best soil and water conservation practices to combat erosion in the study area was tested. Five management practices including strip cropping, contouring, bench-based terracing, broad-based terracing, and agroforestry are considered and the findings are presented in Figure 4.42.

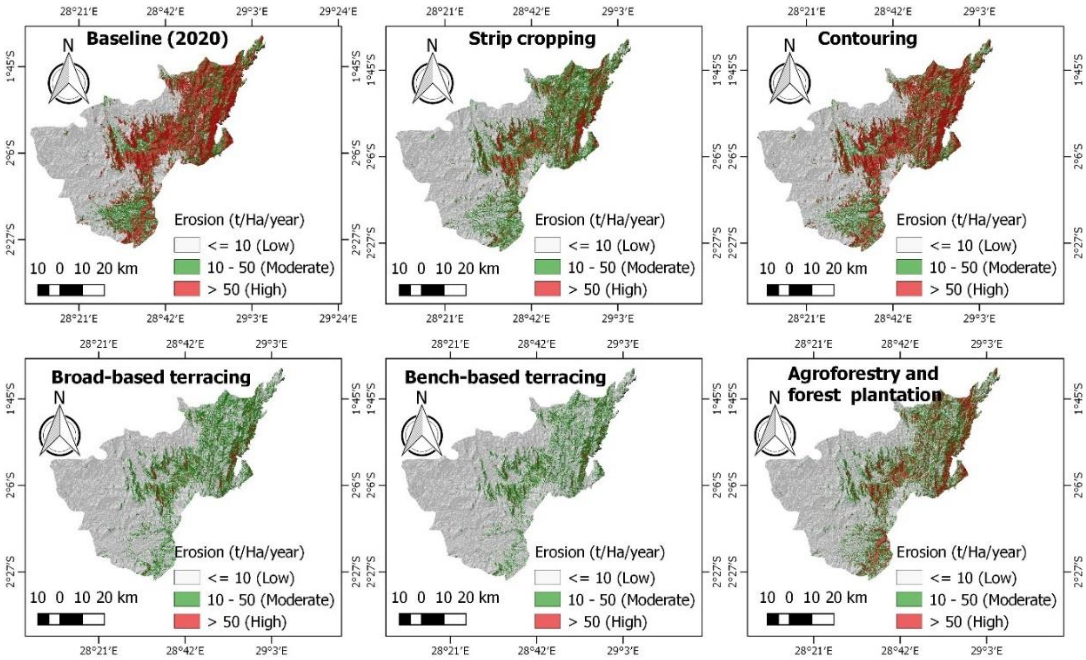


Figure 4.42: Soil erosion dynamics under conservation scenarios.

It can be deduced from the findings presented in Table 4.48 that the actual soil erosion would be reduced from 44.35 t/ha/year (actual situation) to 20.38 t/ha/year through the application of strip cropping, 39.20 t/ha/year for contouring, 8.17t/ha/year for broad terracing, 5.92 t/ha/year for bench-based terrace, and 16.73 t/ha/year for agroforestry and forest plantation. This implies that the rate of soil loss due to erosion would decrease by more than 80% due to the application of terracing, 64.83% for agroforestry, 54.05% for strip cropping, 11.61% for contouring.

Table 4.48: Erosion dynamic under different soil and water conservation scenarios

Conservation practice	Mean annual soil loss (t/ha/Year)	Change (%)
Contouring	39.2	-11.61
Strip cropping	20.38	-54.05
Brod based terracing	8.17	-81.58
Bench based terracing	5.92	-86.65
Agroforestry and forest planting	16.73	-62.28
Baseline	44.35	0.00

The analysis of the effectiveness of conservation options to reduce soil erosion in the study area as shown in Table 4.49 shows that terracing is the best option to reduce erosion risk in the study area. This technic consists of the implementation of a series of level strips along the slope at a vertical interval to reduce the land slope and retain water on the land. This technique can be applied through two approaches: broad-base terraces and bench terraces. The application of these techniques in the study area can increase the area with the tolerable soil loss from 49.67% (base line situation) to 80.54% for the bench-based terrace and 71.21% for the broad-based terrace. This is related to the steep slope of the area as the terracing is adapted to hilly lands. It is followed by agroforestry/forest plantation and strip cropping which can increase the low erosion risk zone to 62.07% and 55.60%, respectively, as illustrated in Table 4.49. Strip cropping is a crop rotation system that consists of altering narrow strips of closely sown crops with strips of row crops. These strips serve as a break in the movement of water, thus contributing to erosion reduction. The contouring farming method which consists of the application of farming operations (tilling the soil, planting, and cultivating) following the natural contours of the field slope is the least effective measure for soil conservation in the study area as the situation of erosion risk after the application of this approach is similar to the one from the base line. This is related to the fact that this approach is appropriate for areas with low slope gradients (2-10%) whereas the study area is mostly dominated by steep slopes (mean slope equal to 26%). These methods can be associated with the agroforestry and tree planting to reduce the erosion in the territory. The Table 4.49 shows the variation of erosion risk levels according to the adopted conservation measures.

Table 4.49: Erosion risk level according to the adoption of conservation measures

Erosion risk	**Low (0-10 t/ha/year)**		**Moderate (10-50 t/ha/year)**		**High (> 50 t/ha/year)**	
Scenarios	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**	**Area (km^2)**	**Area (%)**
Baseline	2054.44	49.67	848.51	20.52	1233.04	29.81
Contouring	2026.13	48.99	954.84	23.09	1153.23	27.88
Strip cropping	2299.54	55.6	1368.99	33.1	465.67	11.26
Brod based terracing	2945.06	71.21	1105.92	26.74	83.23	2.01
Bench based terracing	3331.05	80.54	767.54	18.56	37.31	0.9
Agroforestry and forest plantation	2567.81	62.07	1120.62	27.09	448.41	10.84

The Figure 4.43 presents the area coverage of the differents level of erosion risk under the baseline situation and the adoption of conservation practices scenarios.

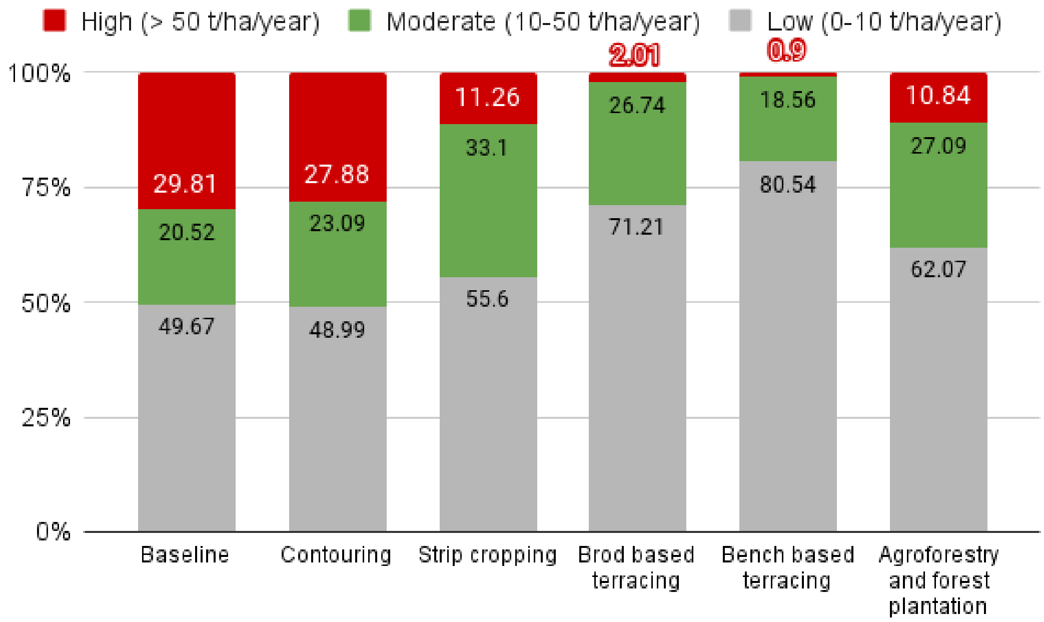


Figure 4.43: Erosion risk's area according to the adopted conservation option.

4.3.4. Soil erosion management plan

The development of a soil erosion management plan is necessary to provides a solution-based approach to the problem of soil erosion in the study area. Therefore, the conservation action suitability map was developed to determine the spatial extent of the suitable area for implementation of soil and water conservation measures to cope with the problem of erosion (Figure 4.44).

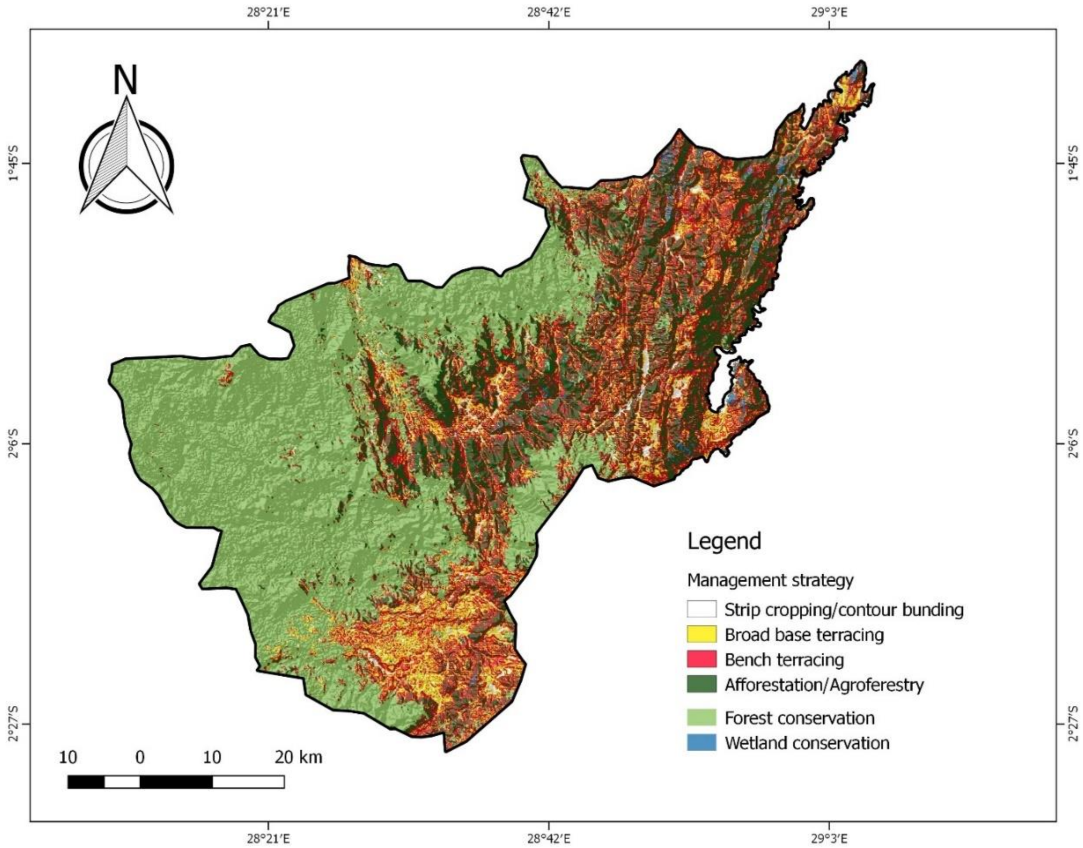


Figure 4.44: Suitability maps for soil and water conservation actions in Kalehe territory.

Based on the soil and water conservation suitability analysis, it can be seen that the bench terracing, afforestation, and broad base terracing are the soil and water conservation measures which are effective in the greatest area coverage of 727.52km^2, 612.33km^2, and 715.55km^2 respectively. Besides, the strip cropping and contour bunding are effective in only 145.42km^2. Since the rate of soil erosion is less than the tolerable limit under the forestland and wetland, the 1952.48km^2 and 36.99km^2 covered by these respective land categories should be conserved (Table 4.50).

Table 4.50: Area coverage of soil and water conservation management strategies

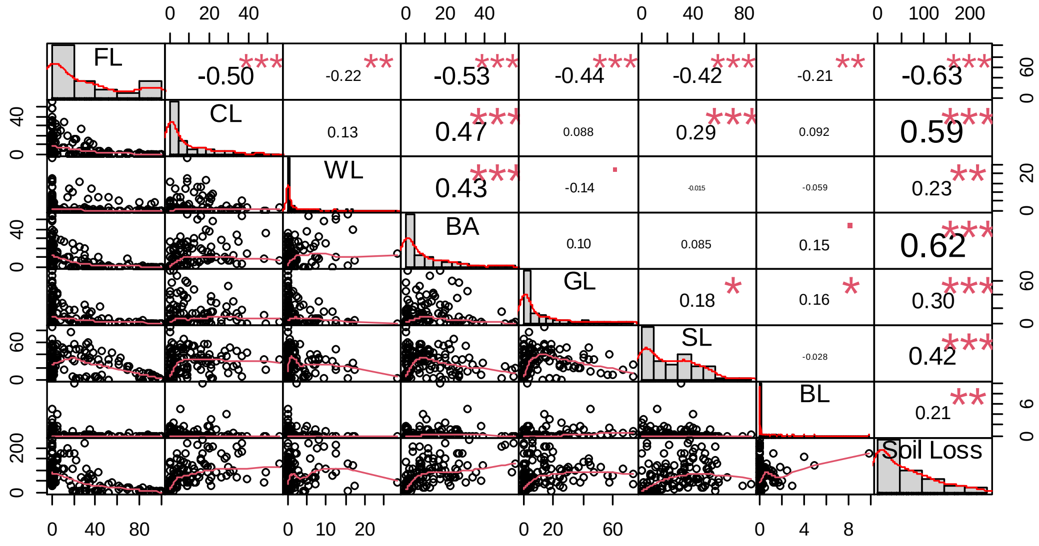
Management strategy	**Slope gradient (%)**	**Erosion rate**	**Area (km^2)**
Strip cropping/Contour bunding	0-5	>10 t/ha/year	145.42
Broad base terracing	5-15	>10 t/ha/year	504.47
Bench terracing	15-30	>10 t/ha/year	727.52
Afforestation	>30	>10 t/ha/year	612.33
Forest conservation	0-150	≤10 t/ha/year	1952.48
Wetland conservation	0-150	≤10 t/ha/year	36.99

4.3.5. Modelling the effect of landscape pattern on soil erosion

An understanding of the impact of landscape patterns on soil erosion dynamics is essential for conservation planning. Using the watershed as the basic environmental unit for conservation planning, the regression model was adopted to quantitatively assess the relationship between the landscape pattern metrics (structure and composition) and the annual soil erosion. This section presents the findings from this analysis.

4.3.5.1. Impact of landscape composition on the erosion dynamics

The results of the Pearson correlation test between the landscape composition (proportion of each LULC type) and the annual soil loss rate as evidenced in Figure 4.45 show that there is a significant correlation between the two parameters.



*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

FL=Proportion of the forest, CL=Proportion of cropland, WL=Proportion of Wetland, BA=Proportion of Built-up area, GL=Proportion of Grassland, SL=Proportion of shrub land, BL=proportion of Bare land

Figure 4.45: Correlation matrix between the annual soil loss by erosion and landcape composition metrix.

Only the proportion of forest land as can be seen in Figure 4.45 is negatively associated with soil loss indicating that the erosion rate decreases when the proportion of forest land increases in the study area. Other LULC proportions in the landscape are positively correlated to soil loss by erosion. Built-up area and cropland are highly correlated to the erosion rate while wetland and shrub land show a slight positive correlation (Figure 4.45). This indicates that the cropland and built-up areas are the most vulnerable land to erosion risk in the study area.

The best-fit linear regression model resulting from the step-wise regression model of the annual soil loss (SL) as a function of the proportion of the LULC categories in the landscape as can be seen in Table 4.51 indicates that the proportion of bare land, built-up area, and cropland have the highest significant positive influence on the erosion whereas the grassland land has the lowest significant influence.

Table 4.51: Best-fit linear regression model of annual soil loss (SL) as a function of landscape composition metrics.

	Coefficient	Std. Error	t value	Pr(>|t|)
(Intercept)	16.7842	10.2438	1.638	0.1034
FL	-0.2093	0.1375	-1.523	0.1299
CL	1.3819	0.3249	4.254	3.70e-05 ***
BA	1.8956	0.3115	6.086	9.36e-09 ***
GL	0.4716	0.2173	2.171	0.0315 *
SL	0.7348	0.1763	4.168	5.19e-05 ***
BL	5.2018	3.0988	1.679	0.0953 .

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

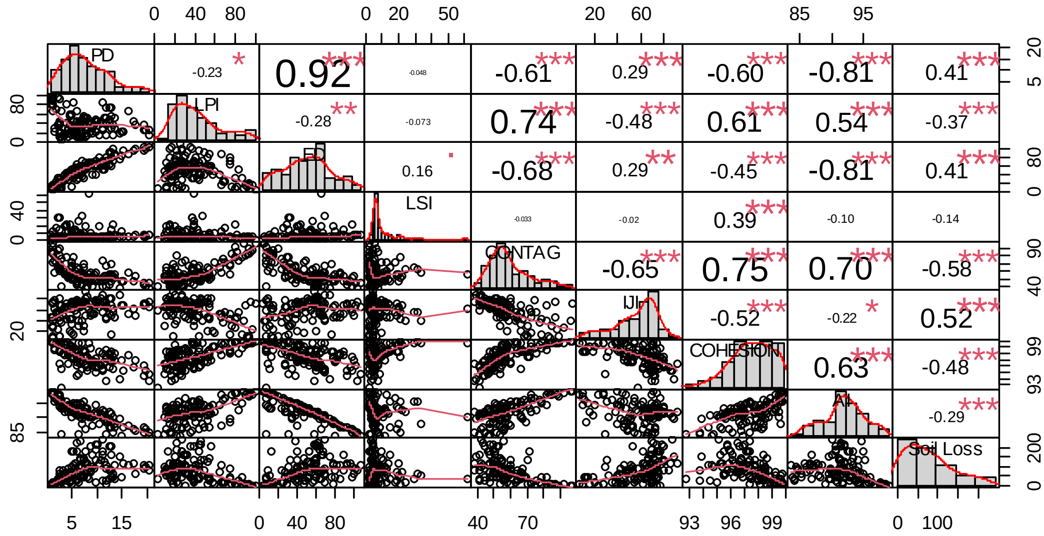
FL=proportion of forestland, CL=Proportion of cropland, WL=Proportion of Wetland, BA= Proportion of Built-up area, SL=Proportion of shrub land, BL=proportion of Bare land.

The model is significant (F-statistic: 41.23 on 6 and 149 DF, p-value: < 2.2e-16) and explains 60.9% (Adjusted R^2=0.609) of the variability of erosion dynamics. The equation of the model which describes the effect of landscape composition on the SL by erosion is:

$$SL = 16.7842 - 0.2093 + 1.3819 * CL + 1.8956 * BA + 0.4716 * GL + 0.7348 * SL + 5.2018 * BL$$ (Equation 4.9)

4.3.5.2. Impact of landscape structure on erosion dynamics

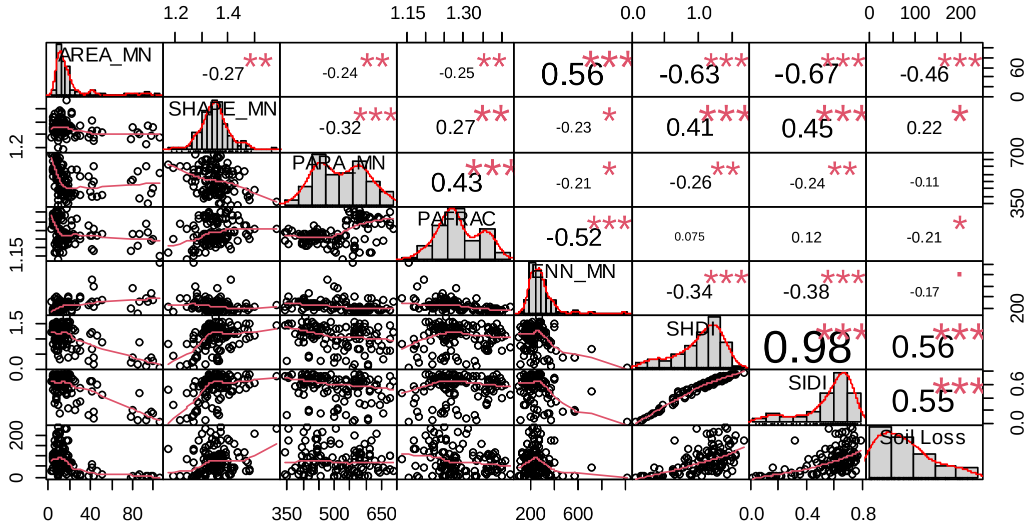
The Pearson correlation analysis whose findings are presented in Figure 4.46 shows that soil erosion is positively influenced by the patch density (PD) and edge density (ED) but negatively influenced by the mean patch area (AREA_MN), largest patch index (LPI), cohesion index (COHESION) and aggregation index (AI) indicating that the fragmentation of the landscape increases the soil erosion whereas the aggregation of patch decreases the annual soil loss.



*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure 4.46: Correlation matrix between the annual soil loss, landscape aggregation and fragmentation index.

In addition, it was found that both the Shannon diversity index (SHDI) and Simpson index (SIDI) are positively associated with annual soil loss indicating that the diversification of class or the heterogeneity of class in the landscape increases the soil erosion. There is also a positive correlation between the Interspersion and juxtaposition index and the annual soil loss (SL) which demonstrates that the isolation of patches increases the erosion risk in the study area (Figure 4.47). However, the contagion (CONTAG) of patches decreases the soil loss by erosion. The results reveal that the shape index (SHAPE_MN) is positively correlated to the annual soil loss (SL) while the Mean perimeter-area ratio (PARA_MN) and Perimeter-area fractal dimension (PAFRAC) are negatively correlated to it (Figure 4.47). This demonstrates that the increase in shape complexity contributes to the decrease of soil erosion.



*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

Figure 4.47: Correlation matrix between the annual soil loss, landscape shape and diversity metrix.

The best-fit linear regression model resulting from the step-wise regression model of the annual soil loss (SL) as a function of the landscape structure metrics was done and findings are presented in Table 4.52.

Table 4.52: Best-fit linear regression model of annual soil loss (SL) as a function of landscape structure metrics.

	Coefficient	Std. Error	t value	Pr(>|t|)
(Intercept)	634.3499	100.2431	6.328	4.73e-09 ***
ED	1.1514	0.2575	4.472	1.80e-05 ***
AREA_MN	-0.4743	0.2426	-1.955	0.0530 .
PAFRAC	-495.0409	77.6258	-6.377	3.73e-09 ***
SHDI	31.3459	15.5570	2.015	0.0462 *

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

ED=Edge density, AREA_MN= Mean patch size, PAFRAC= Perimeter-area fractal d imension, SHDI=Shannon's diversity index.

The findings from the above Table 4.52 above reveal that the Shannon diversity index (SHDI) has a high positive influence on annual soil loss while the PAFRAC has a high negative influence on soil erosion. Furthermore, the edge density (ED) positively influences soil erosion while the Mean patch size (AREA_MN) influences the annual soil loss negatively. These results imply that during land use planning, it should be necessary to reduce the landscape fragmentation and the landscape heterogeneity but increase the size of patches so that the influence of the annual soil loss can be reduced. The model is significant (F-statistic: 29.95 on 4 and 117 DF, p-value: 2.2e-16) and explains 34.89% (Adjusted R^2=0.3489) of the variability of erosion dynamics. The equation of the model which describes the effect of landscape structure on the SL by erosion is:

$$SL = 634.3499 + 1.1514 * ED - 0.4743 * AREA\_MN - 495.0409 * PAFRAC + 31.3459 * SHDI \text{ (Equation 4.10)}$$

4.3.6. Principal Componnent Analysis (PCA) of erosion and landscape metrics

The scree plot obtained from the PCA shows that there is 10 principals componnents (PC) in the variability of the annual soil loss by erosion and the landscape metrics as shown in Figure 4.48. The firsts component PC1 (Dim1) and the second componnent PC2 (Dim2) explained 58% of variability. PC1 and PC2 represents 37.4% and 13.4% of total variance of soil erosion and landscape characteristics. The first component (PC1) is positively associated with the soil loss by erosion. The landscape metrics which constitutes the most contributors to this component are SIDI, SHDI, AI, ED, PD, FL, COHESION, LPI, and AREA_MN. Among these variables, the SIDI, SHDI, AI, ED, and PD are positively associated with the annual soil loss by the erosion. In contrast, the FL, COHESION, LPI, and AREA_MN are negatively associated with the annual soil loss by erosion. In the case of the second component (PC2), its highest contributors are CONTAG, PARA_MN, SHAPE_MN, IJI, and AREA_MN.

Considering this component, the soil loss by erosion is positively associated with the PARA_MIN, and IJI but negatively associated with the CONTAG, SHAPE_MN, and AREA_MN. These landscapes metrics which have a contribution to the the PC1 and PC2 higher than the expected average contribution, indicated by a red dash line on the graph (Figure 4.48), are variables that are correlated with the PC1 and PC2. Therefore, they are the most important in explaining the variability of the landscape metrics and soil loss by erosion. The Figure 4.48 presents the results of the PCA with an emphasisis on the relationship between the variables considering the PC1 and PC2, the scree plots showing the percentage of explained variance for the diferent componnents, and the contribution of differents variables to the PC1 and PC2.

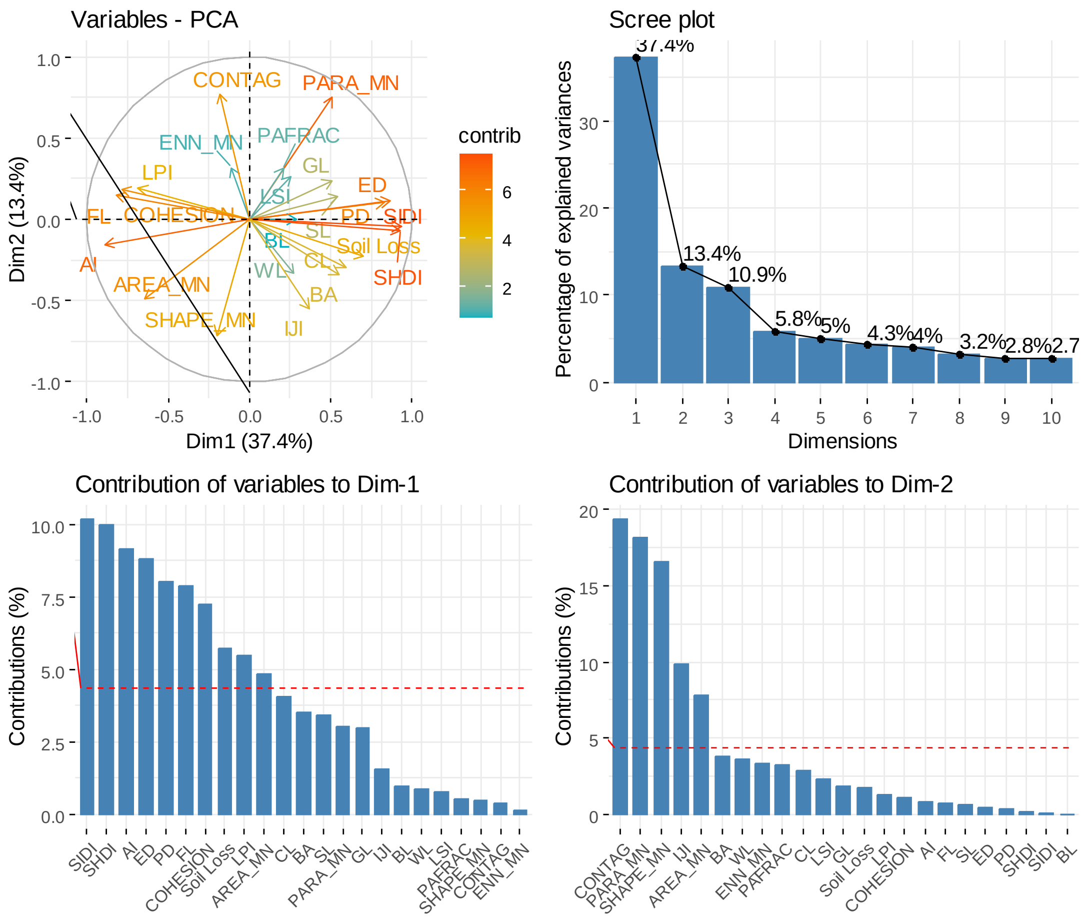


Figure 4.48: PCA of annual soil loss by erosion with landscape metrics.

Key: Sd= Standard deviation, CV= Coefficient of variation, PD=Patch density, LPI= Largest Patch Index, ED=Edge density, LSI=Landscape shape index, IJI=Interspersion and juxtaposition index, AI=Aggregated index, COHESION= Patch cohesion index, CONTAG.= Contagion, AREA_MN= Mean patch size, SHAPE_MN=Mean shape index, PARA_MN=Mean perimeter-area ratio, ENN_MN=Mean Euclidian nearest neighbor distance, PAFRAC= Perimeter-area fractal dimension, SHDI=Shannon's diversity index, SIDI= Simpson's diversity index.

4.4. MCDA MODELING FOR LANDSCAPE RESTORATION PLANNING

4.4.1. Land degradation vulnerability modelling

This study adopted the GIS-based AHP approach and the IPCC vulnerability framework to assess the land degradation vulnerability at the territorial level in Eastern DR Congo using the multicriteria approaches. In the IPCC framework, vulnerability is defined as the resultant of three components: exposure, sensitivity, and adaptability. It is worth noting that, the study employs geospatial analysis of both remotely sensed data, primary data from the field, and secondary data acquired from governmental and no governmental organizations. In this study, the exposure to the ongoing degradation process is defined by the actual rate of erosion quantified through the RUSLE model. The land degradation sensitivity represents the degradation hazard or the susceptibility to degradation associated with natural factors (Biophysical vulnerability) while the land degradation adaptability component represents the degree to which the land will be affected by the degradation due to socio-economics characteristics (anthropogenic vulnerability). The integrated land degradation vulnerability was obtained by summing up these three components. The AHP is used in weighting the biophysical and socio-economics factors of vulnerability to land degradation based on their relative influence. Based on this approach, an integrated land degradation vulnerability model adapted to the context of the study area has been developed. The vulnerability model is validated by using the occurrence data of physical degradation features such as landslides and erosion. Hence the results obtained are presented in this section.

4.4.1.1. Conditioning factors of land degradation vulnerability

In this study, 7 biophysical factors and 8 socio-economic factors influencing the land degradation vulnerability were considered. This section presents the results of the classification and ranking of biophysical and socio-economic vulnerability indicators of the land degradation process in the study area.

A. Biophysical vulnerability indicators

The selected conditioning factors of vulnerability in the study area identified through the field observation and literature review are the topographic factors (the slope gradient, topographic wetness index, altitude), the edaphic factor (soil type), the climatic factor (annual rainfall), and the hydrological factors (distance to drainage network and stream power index). These factors were ranked from 1 to 5 based on their abilities to induce the physical land degradation process (see Table 3.11 for justification). The Figure 4.49 presents the spatial pattern of the biophysical factors of vulnerability in the study area.

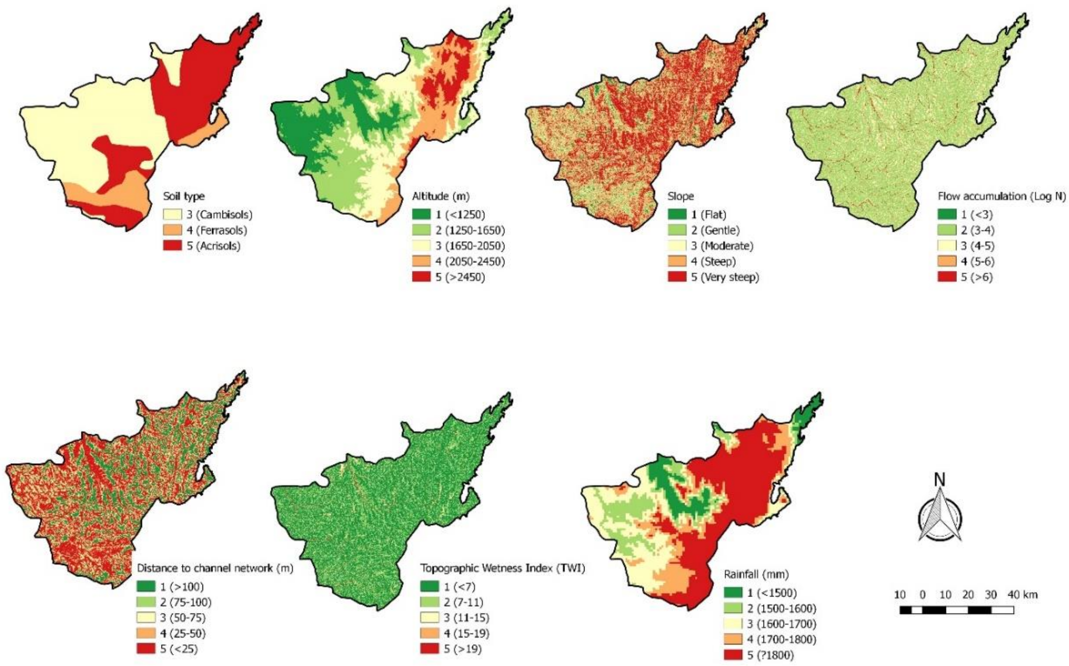


Figure 4.49: Biophysical factors of vulnerability in Kalehe territory.

The aerial extent and the ranking values of the different classes of biophysical factors are presented in Table 4.53.

Table 4.53: Selected factor for characterizing the physical land degradation vulnerability

Factor	Rank	Sub factor	Level of vulnerability	Area (km^2)	Area (%)
Slope gradient (%)	1	Flat <3	Very low	159.9	3.79
	2	Gentle 3-9	Low	409.41	9.7
	3	Moderate 9-15	Moderate	606.41	14.37
	4	Steep 15-30	High	1522.85	36.09
	5	Very steep >30	Very high	1520.74	36.04
Altitude gradient (m)	1	Very low <1250	Very low	870.02	20.95
	2	Low 1250-1650	Low	1277.84	30.77
	3	Moderate 1650-2050	Moderate	986.4	23.75
	4	High 2050-2450	High	699.39	16.84
	5	Very high > 2450	Very high	319.7	7.7
TWI	1	Very low <7	Very low	2584.92	62.2
	2	Low 7-11	Low	1271.42	30.59
	3	Moderate 11-15	Moderate	213.36	5.13
	4	High 15-19	High	72.24	1.74
	5	Very high > 19	Very high	14.12	0.34
Soil type	3	Cambisols	Moderate	2030.41	41.8
	4	Ferrasols	High	497.37	10.24
	5	Acrisols	Very high	1625.67	33.46
Rainfall (mm)	1	Very low <1500	Very low	355.91	8.56
	2	Low 1500-1600	Low	531.53	12.79
	3	Moderate 1600-1700	Moderate	973.81	23.43
	4	High 1700-1800	High	678.74	16.33
	5	Very high >1800	Very high	1615.79	38.88
Vertical distance to drainage network (m)	1	Very high > 100 m	Very low	1675.08	40.04
	2	High 75-100	Low	813.25	19.44
	3	Moderate 50-75	Moderate	540.31	12.91
	4	Low 25-50	High	359.6	8.6
	5	Very low < 25	Very high	795.35	19.01
Flow accumulation (upstream cells number)	1	Very low < 10^3	Very low	449.39	10.87
	2	Low 10^3-10^4	Low	1371.09	33.16
	3	Moderate 10^4-10^5	Moderate	1215.23	29.39
	4	High 10^5-10^6	High	906.93	21.93
	5	Very high > 10^6	Very high	192.42	4.65

The results displayed in Figure 4.50 and Table 4.53 show that there are three types of soils with different resistance to erosion within the study area: the cambisols, the acrisols, and ferrasols. The cambisols are the most dominant soil as they represent 41.80

% of the territory but they are characterized by the lowest erosivisity. As a result, the areas characterized by a very high degradation vulnerability-based on the edaphic characteristics represent 33.46% of the total surface and are dominated by acrisols.

Based on topographic factors, it was found that the slope gradient varies between 0.007% and 159.49% with a mean value of 26.46±17.45%. The territory of Kalehe is dominated by very steep slopes (>30%) which are characterized by a high vulnerability to land mass movement such as soil erosion and landslides. The classes characterized by a high to very high vulnerability based on the slope gradient represent 72.13% and Only 13.49% of the territory is characterized by a very low to low susceptibility based on the slope gradient. Regarding the altitude, it varies between 801 m and 3030 m with a mean value of 1684 m±468 m. Based on this factor, it is evident that about 16.84% and 7.70% of the study area have a high to very high-altitude gradient which depicts a high vulnerability to land degradation. The topographic wetness index constitutes also another factor of vulnerability in the Kalehe territory. This factor which controls the terrain humidity varies between 3.19 and 22.98 with a mean value of 7.19. The results show that the study area is dominated by zone with very low to low TWI which represents 62.20% and 30.59% of the territory. Only 1.37% and 0.34% of the territory presents a high to very high vulnerability to land degradation process induced by this factor.

The hydro-meteorological factors have also an influence on the land degradation vulnerability in the Kalehe territory. As can be seen in Figure 4.50 and Table 4.53, 38.88% of the territory receives an annual precipitation of more than 1800 mm which implies that there is a high potential for rainfall erodibility in the study area. In general, the high rainfall intensity is observed in the high plateau and the eastern part of the study area. After raining, the flow accumulates in the concave areas of the terrain, thus contributing to the landmass movement and flooding. Indeed, the number of cells for flow accumulation range from 899 to 1294226688 cells to which a logarithmic transformation was applied, resulting in value ranging from 2.95 to 8.99. This value was classified into four categories depicting the vulnerability to surface flow accumulation ranging from very low ($<10^3$ cells), low (10^3-10^4 cells), moderate (10^4-10^5), high (10^5-10^6 cells), and very high ($>10^6$ cells). The area with high to very high flow accumulation that is more vulnerable to physical land degradation processes represents 21.93% and 4.65% of the territory. It should be also noted that the study area is covered by a high drainage network density which contributes to its vulnerability to degradation processes such as erosion and landslides due to river incisions of the river bank are common. Due to the high density of the drainage network, about 19.01% of the territory is located at a vertical distance from the drainage network which is less than 25m, and 8.60% is located between 25m to 50m. These areas which are close to the drainage networks have a very high to high vulnerability to river bank erosion, landslides, and flooding.

B. Socio-economic vulnerability indicators

The population dynamics, the accessibility factors, and the land management was used as indicators of the socio-economic vulnerability to land degradation in the study area. The justification of the ranking and the selection of these criteria can be found in Table 3.12 in the methodological section. The Figure 4.50 shows the spatial pattern and results of the ranking of these factors.

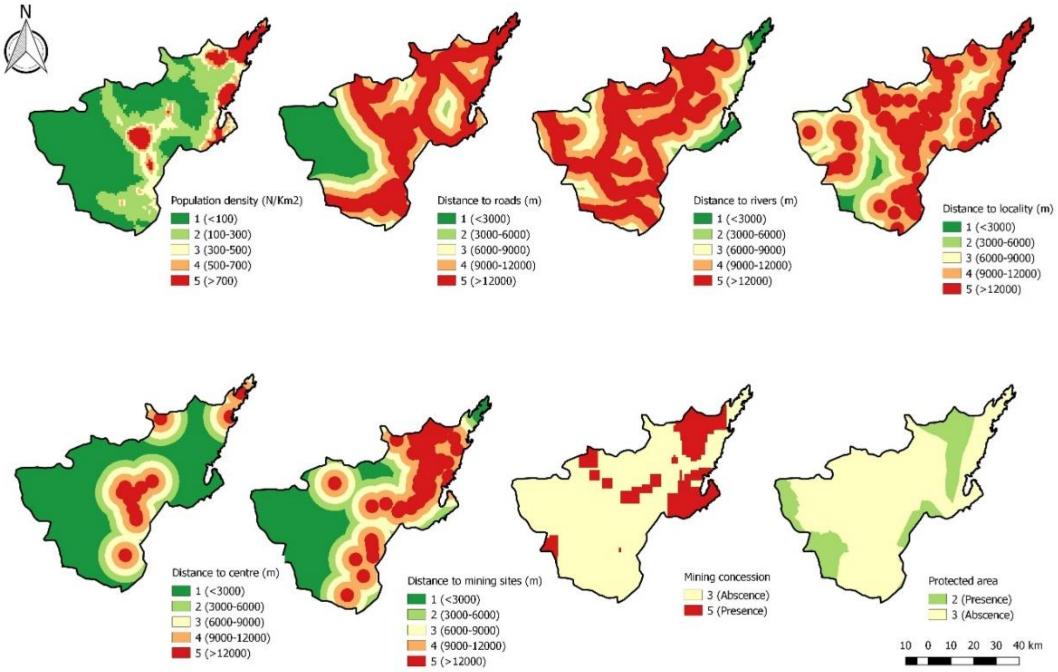


Figure 4.50: Socio-economic factors of vulnerability in Kalehe territory.

The aerial extent and the ranking values of the different classes of socio-economics factors are presented in Table 4.54.

Table 4.54: Selected factor for characterizing the adaptability component of land degradation vulnerability

Factor	Rank	Sub factor	Level of vulnerability	Area (km^2)	Area (%)
Population density (inhabitants/km^2)	1	Very low < 100	Very low	2153.04	51.83
	2	Low 100-300	Low	1124.64	27.08
	3	Moderate 300-500	Moderate	387	9.32
	4	High 500-700	High	173.16	4.17
	5	Very high > 500	Very high	315.86	7.6
Distance to road (m)	1	Very low < 3000	Very high	800.86	19.29
	2	Low 3000-6000	High	213.57	5.14
	3	Moderate 6000-9000	Moderate	441.87	10.64
	4	High 9000-12000	Low	911.89	21.97
	5	Very high > 12000	Very low	1783.07	42.95
Distance to administrative center (m)	1	Very low < 3000	Very high	2339.7	56.36
	2	Low 3000-6000	High	515.97	12.43
	3	Moderate 6000-9000	Moderate	534.1	12.86
	4	High 9000-12000	Low	476.24	11.47
	5	Very high > 12000	Very low	285.59	6.88
Distance to village or locality (m)	1	Very low < 3000	Very high	71.13	1.71
	2	Low 3000-6000	High	247.77	5.97
	3	Moderate 6000-9000	Moderate	664.76	16.01
	4	High 9000-12000	Low	1409.83	33.96
	5	Very high > 12000	Very low	1758.13	42.35
Distance to river (m)	1	Very low < 3000	Very high	145.56	3.51
	2	Low 3000-6000	High	153.22	3.69
	3	Moderate 6000-9000	Moderate	480.35	11.57
	4	High 9000-12000	Low	1157.48	27.88
	5	Very high > 12000	Very low	2214.61	53.35
Distance to artisanal mining (m)	1	Very low < 3000	Very high	1279.75	30.83
	2	Low 3000-6000	High	480.83	11.58
	3	Moderate 6000-9000	Moderate	675.71	16.28
	4	High 9000-12000	Low	841.88	20.28
	5	Very high > 12000	Very low	873.09	21.03
Protected area	1	Presence	Very low	876.61	10.95
	3	Absence	Moderate	3275.17	40.92
Mining concession	3	Absence	Moderate	3292.31	41.13
	5	Presence	Very low	859.47	10.74

The results from Figure 4.50 and Table 4.54 show that the population is unequally distributed with a concentration in the eastern part of the territory at the border of Lake Kivu and the high plateaus area. The low density of the population is found in the western part of the territory which is covered by forest and where there is no high-density road network. Based on the population density, about 7.60% of the territory has a very high density (more than 700 inhabitants/km^2) of the population indicating a high vulnerability to land degradation. Apart from the population dynamics, the vulnerability to land degradation is also influenced by the proximity factor of accessibility including the road distance, distance to rivers, distance to the administrative center, distance to the locality, and distance to artisanal mining sites. These factors have been classified into five buffer zones and rated into five classes of vulnerability to land degradation. Based on this ranking, it was found that areas with a very high socio-economic vulnerability represent 42.95% of the territory due to the proximity to roads, 6.88% associated with the proximity to administrative centers, 42.35% associated with the proximity to locality (village), 53.35% associated to the proximity to rivers and 21.03% associated to the proximity to artisanal mining sites. In addition to that, some land use management policies influence the land degradation vulnerability in the Kalehe territory. Indeed, there is two designated protected area including the National Park of Kahuzi Biega and the Forest Reserve of Sud-Masisi which are dedicated to conservation. These two protected areas cover 10.95% of the total surface of the territory. In the area covered by the designated protected area, the vulnerability to land degradation is expected to be low compared to its surroundings due to resource use restrictions. In contrast, there are also some mining concessions which was allocated in the study area for economic development purpose. They cover a total surface of 10.74% of the territory. In those areas, the vulnerability to land degradation is high due to the intensification of anthropogenic activities related to mining activities (vegetation clearing for mining extraction, soil excavation to access minerals, and construction of mining camps for instance).

4.4.1.2. Land degradation vulnerability assessment

In this study, the land degradation vulnerability is considered as a function of three components: the exposure to erosion risk, the sensitivity depicting the biophysical vulnerability, and the adaptability depicting the socio-economic vulnerability.

A. Characterization of exposure to land degradation

Soil erosion constitutes the main land degradation agent in the Kalehe territory. The Figure 4.51 presents the spatial pattern of the exposure of the land to water erosion within the study area. From this figure, it can be seen that the exposure to high risk of erosion is prominent in the Eastern and central part of the territory while the lowest exposure to erosion risk is observed in the western part. The Minova and Kalehe zones are the most exposed to erosion risk while the Bunyakiri zone is the least exposed.

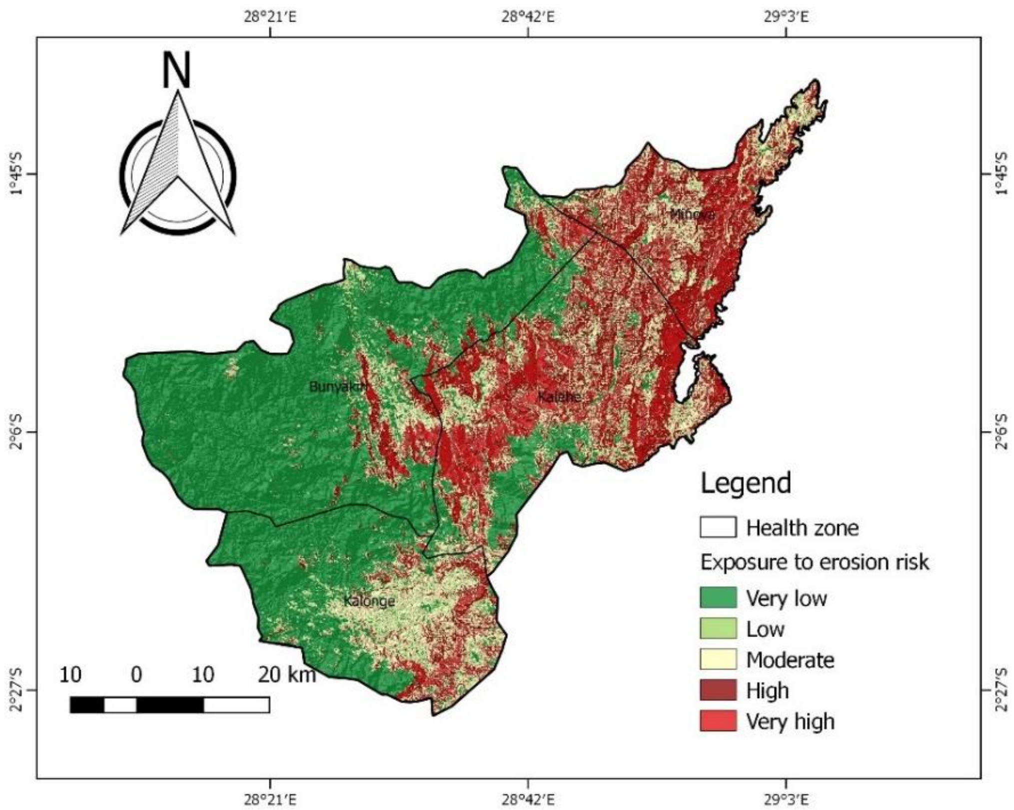


Figure 4.51: Status of vulnerability based on the degree of exposure to erosion in Kalehe territory.

The results from the RUSLE modeling presented in Table 4.55 and Figure 4.52 show that the territory is dominated by an area characterized by very low exposure to erosion risk which represents 47.25%. In contrast, about 20.52%, 17.69%, and 12.13% of the territory are exposed to moderate (30-50 t/ha/year), high (50-100 t/ha/year), and very high (>100 t/ha/year) risk of erosion represents. The area with high erosion risk is more exposed to land degradation related to soil loss compared to the zone characterized by low levels of erosion.

Table 4.55: Selected factor for characterizing the exposure

Factor	Rank	Sub factor	Level of vulnerability	Area (km^2)	Area (%)
Erosion (t/ha/year)	1	Very low 0-5	Very low	1953.96	47.24
	2	Low 5-10	Low	100.48	2.43
	3	Moderate 30-50	Moderate	848.51	20.52
	4	High 50-100	High	731.54	17.69
	5	Very high >100	Very high	501.5	12.13

B. Characterization of sensitivity component of land degradation vulnerability

The development of the sensitivity index was done through a pairwise comparison of the 7 biophysical vulnerability indicators using the AHP process and the findings are presented in Table 4.56.

Table 4.56: Paire-wise comparison matrix and weighting of the factor for the physical land degradation vulnerability index. Lambda=7.556, CI=0.093, CR=0.07

Factors	FA	TWI	ST	R	SG	AG	DN	AHP weight
Flow accumulation (FA)	1	4	0.5	0.333	0.333	0.5	0.5	0.076
TWI	0.25	1	0.143	0.167	0.111	0.167	0.143	0.023
Soil type (ST)	2	7	1	3	1	3	3	0.253
Rainfall (R)	3	6	0.333	1	0.5	1	4	0.163
Slope (SG)	3	9	1	2	1	5	2	0.266
Altitude (AG)	2	6	0.333	1	0.2	1	2	0.118
Drainage network (DN)	2	7	0.333	0.25	0.5	0.5	1	0.101

The weightage of the factor is reliable as the consistency ratio is less than 0.1 (CR=0.07), indicating that there is an internal consistency of the pairwise comparison. This weightage of the parameters allowed for the identification of the most influential factors of physical land degradation vulnerability. Among the 7 factors under consideration, the slope gradient (26.6%) soil type (25.3%), rainfall (16.3%), altitude gradient (11.8%), and distance to the drainage network (10.1%) present the highest influence while the flow accumulation potential (7.6%) and topographic wetness showed (2.3%) showed the least influence. Based on the weightage of the factors above, the equation of the sensitivity index can be defined as follows:

$$SI = 0.163 * R + 0.101 * DN + 0.076 * FA + 0.266 * SG + 0.118 * AG + 0.023 * TWI + 0.253 * ST$$ (Equation 4.11)

With R the annual rainfall, DN the distance to the drainage network, FA the flow accumulation, SG the slop gradient, AG the altitude gradient, and TWI the topographic wetness index, w1, …, w5 their respective weights.

The sensitivity index developed in the previous section was integrated into the GIS along with spatial layers of the biophysical vulnerability indicator of land degradation to produce a sensitivity map of the study area (Figure 4.52). The map was classified into five classes corresponding to five levels of land degradation susceptibility. These classes were determined based on the equal interval classification mode of classification.

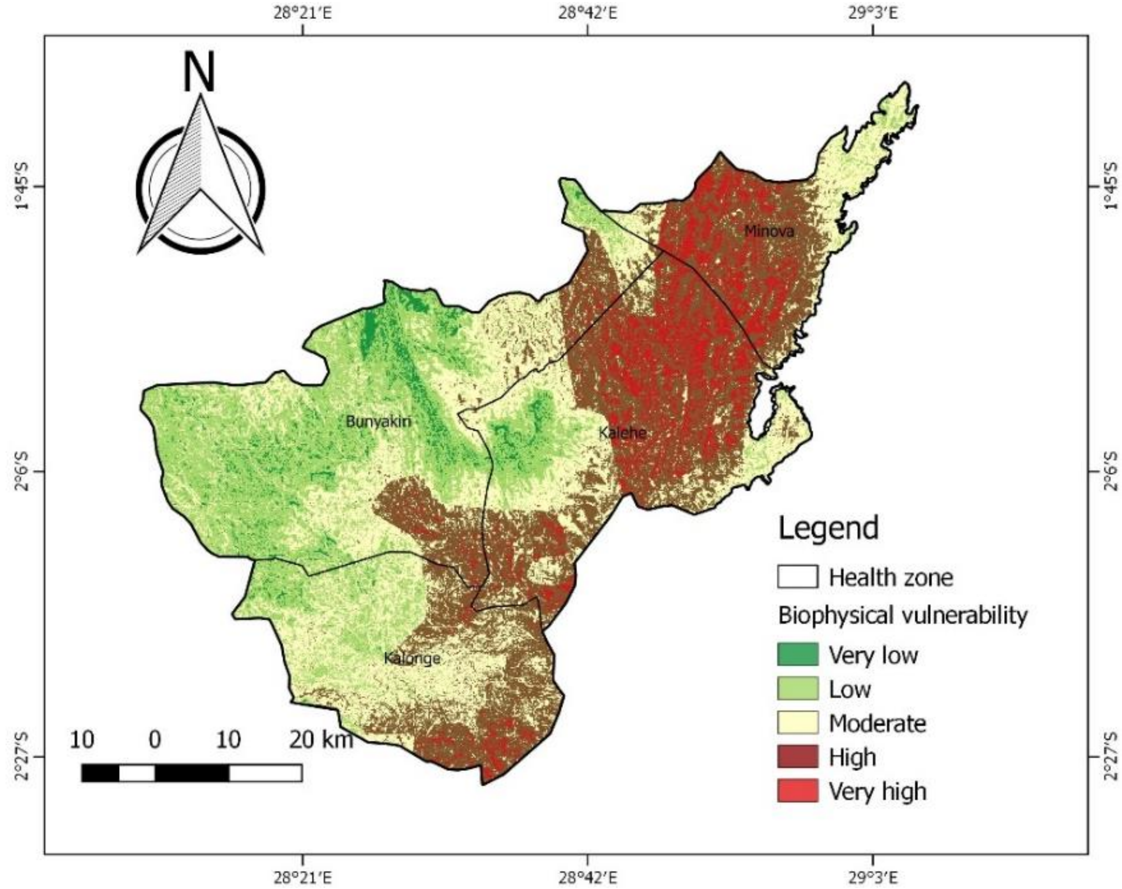


Figure 4.52: Status of vulnerability associated with the sensitivity on land degradation Status in Kalehe territory.

The results presented in Table 4.57 indicate that the zone which has a high to very high vulnerability represents about 39.33% of the territory. This zone is mostly vulnerable to the physical land degradation process and is located in the high plateau in the north part of the territory which is dominated by steep slopes and a high rainfall intensity. The zone characterized by a medium vulnerability to land degradation represents 31.42% of the territory. The area with very low to low susceptibility is dominated in the western part of the study area. The low to very low susceptibility is observed in only 29.67% of the territory (Table 4.57). Those areas are the least susceptible to physical land degradation processes.

Table 4.57: Level of land degradation vulnerability associated with the sensitivity

Level of vulnerability	Very low	Low	Moderate	High	Very high
Area (km^2)	141.69	1083.71	1297.91	1297.90	326.56
Area (%)	3.43	26.24	31.42	31.42	7.91

C. Characterization of adaptability component of land degradation vulnerability

The elaboration of the adaptability index was done by weighting the 8 selected factors of socio-economic vulnerability through the AHP approach. The results of the pairwise comparison of these vulnerability factors and their ranking are in Table 4.58.

Table 4.58: Paire-wise comparison matrix and weighting of the factor for the land degradation vulnerability index. Lambda=8.688, CI=0.098, CR=0.07

Factors	AM	RoD	CD	RiD	LD	MC	PD	PA	AHP weight
Artisanal Mining (DAm)	1	2	1	7	1	1	1	2	0.162
Roads distance (DRo)	0.5	1	3	5	0.5	0.5	0.333	2	0.112
Center distance (DAc)	1	0.333	1	3	0.5	0.333	0.2	2	0.085
River distance (DRi)	0.143	0.2	0.333	1	0.2	0.333	0.25	0.25	0.031
Locality distance (DLo)	1	2	2	5	1	1	1	2	0.162
Mining concession (MC)	1	2	3	3	1	1	2	1	0.173
Population density (PD)	1	3	5	4	1	0.5	1	3	0.191
Protected Area (PA)	0.5	0.5	0.5	4	0.5	1	0.333	1	0.085

The results of this comparison from Table 4.58 above indicate that proximity factors and population dynamics are the most influential drivers of land degradation vulnerability in the study area. The weightage of the land degradation vulnerability factors is reliable as the consistency ratio is less than 0.1 (CR=0.043), indicating that there is an internal consistency of the pairwise comparison. Based on these results, the equation of the adaptability index (AI) is

$$AI = 0.162 * DAm + 0.112 * DRo + 0.085 * DAc + 0.031 * DRi + 0.162 * DLo + 0.173 * MC + 0.191 * PD + 0.085 * PA \quad \text{(Equation 4.12)}$$

With DAm the distance to artisanal mining sites, DRo the distance to roads, DAc the distance to the administrative group center, DRi the distance to rivers, DLo the distance to the locality, MC the presence of mining concession, PD the population density and PA the presence of protected area.

The linear weighted overlay of the 8 factors that contribute to land degradation vulnerability was done to establish zoning of the adaptability component of vulnerability. The classification of the obtained adaptability index per pixel through an equal interval mode was used to define the very low, low, moderate, high, and very high vulnerability zones. The findings are presented in Figure 4.53.

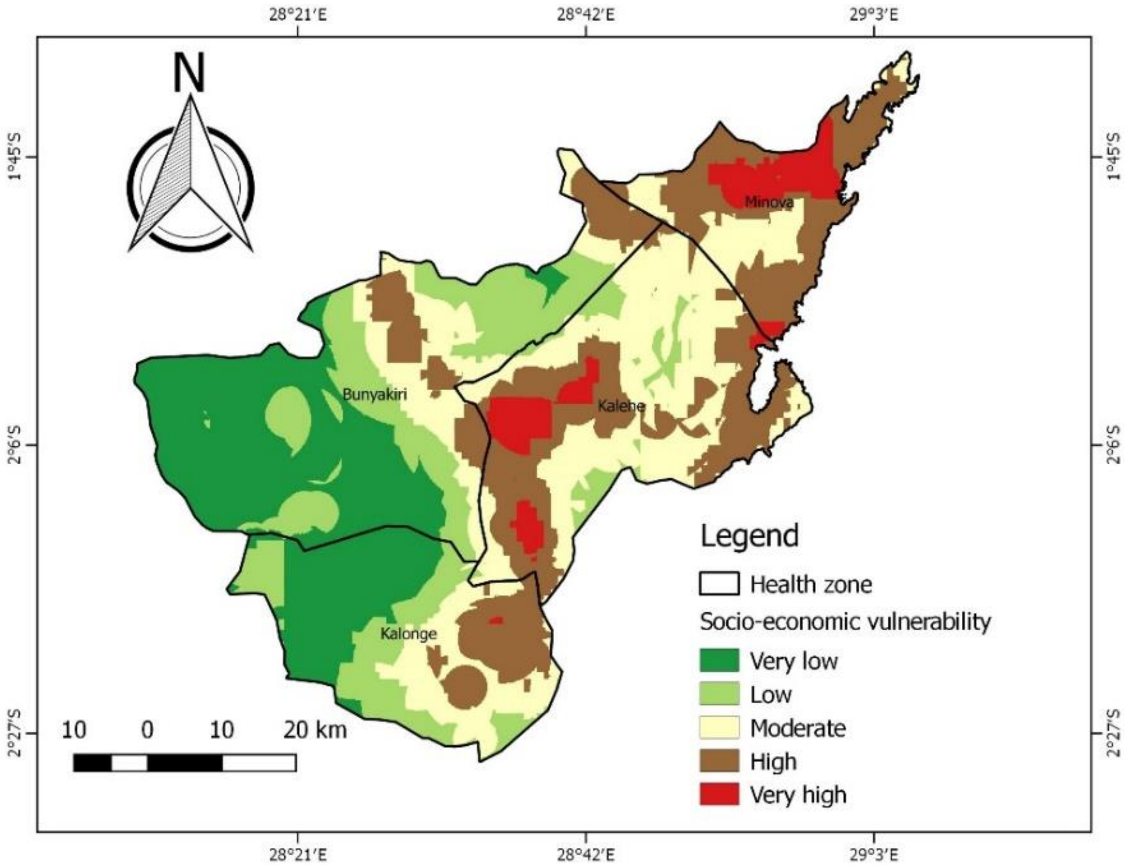


Figure 4.53: Status of the socio-economic vulnerability in Kalehe territory.

The results indicated presented in Table 4.59 that 42.64% of the territory has a very low to low vulnerability to land degradation due to anthropogenic factors while 27.52%

have a moderate vulnerability and 29.84 % presents a very high to high vulnerability to land degradation. As can be seen from the map, the lowest vulnerability is located in the western part of the territory where the density of the population is very low and there are not many road networks. In contrast, there is a high vulnerability in the astern, southern, and central parts of the territory, mostly associated with the proximity to road networks, a high population density, and the abundance of artisanal mining sites.

Table 4.59: Level of socio-economic vulnerability associated with adaptability

Level of vulnerability	Very low	Low	Moderate	High	Very high
Area (km^2)	1003.91	765.11	1141.96	1035.40	202.59
Area (%)	24.20	18.44	27.52	24.96	4.88

C. Integrated land degradation vulnerability

The integrated land degradation vulnerability of the study area was determined by performing a sum of the exposure, sensitivity, and adaptability index. The three sub-components of vulnerability were considered equally important and were given the same weight of 1/3 through the APH pairwise comparison. Thus, the final model of land degradation vulnerability for the study area was defined as:

$$LDVI = SE * 1/3 + [0.163 * R + 0.101 * DN + 0.076 * FA + 0.266 * SG + 0.118 * AG + 0.023 * TWI + 0.253 * ST] * 1/3 + [0.162 * AM + 0.112 * RoD + 0.085 * DAc + 0.031 * DRi + 0.162 * DLo + 0.173 * MC + 0.191 * PD + 0.085 * PA] * 1/3 \quad \text{(Equation 4.13)}$$

With LDVI the land degradation vulnerability index, SE the soil erosion risk, R the rainfall, DN the distance to the drainage network, FA the flow accumulation, SG the slope gradient, AG the altitude gradient, TWI the topographic wetness index, ST the soil type, AM the distance to artisanal mining sites, DRo the road distance, DAc the distance to the administrative center, DRi the distance to rivers, DLo the distance to the locality, MC the occurrence of mining concession, PD the population density and PA the occurrence of the protected area.

This model was applied to assess the land degradation vulnerability of the study area. The resulting map (Figure 4.54) was classified into four vulnerability zones based on an equal interval classification of the vulnerability index. Interestingly there is a zonation of land degradation vulnerability around the forest land. The level of land degradation vulnerability increases with the increase of the distance to forest edges. The no-degraded land with a very low vulnerability is located in the western part of the territory under the forest cover. At the health zones level, it can be seen that the Minova and Kalehe zones are the most vulnerable to land degradation whereas the Bunyakiri is the least vulnerable (Figure 4.54).

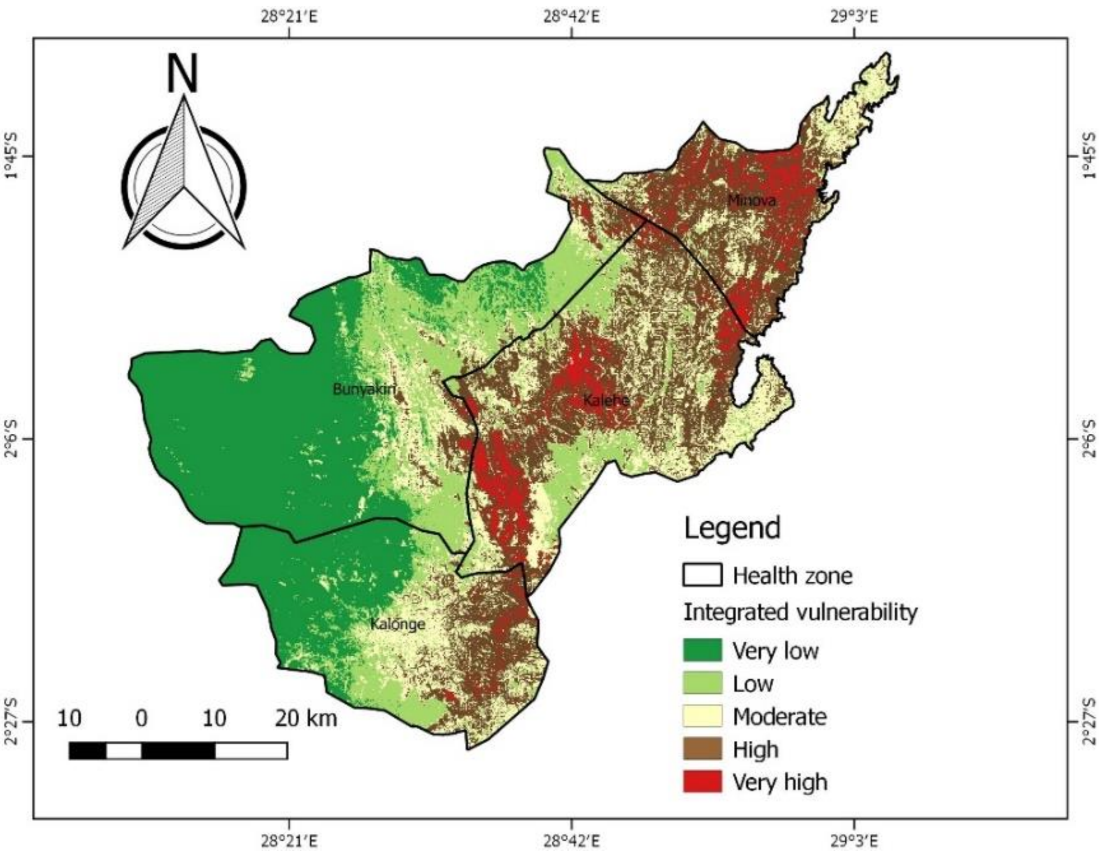


Figure 4.54: Integrated land degradation vulnerability maps of Kalehe territory.

The results reveal that the study area is dominated by areas characterized by very low to low vulnerability of degradation which represents 47.63% of the total surface (Table

4.60). The zone of medium vulnerability covers 20.41% of the territory. The zone characterized by high to very high vulnerability represents 32.01% of the territory.

Table 4.60: Level of land degradation vulnerability in Kalehe territory

Level of vulnerability	Very low	Low	Moderate	High	Very high
Area (km^2)	1209.39	758.10	843.03	1104.23	218.05
Area (%)	29.28	18.35	20.41	26.73	5.28

4.4.1.3. Validation of the land degradation vulnerability model

The frequency ratio (FR) of land degradation features in each land degradation vulnerability zone (very low, low, moderate, high, and very high vulnerability) was calculated to determine their probability of occurrence, and the findings are presented in Table 4.61.

Table 4.61: Frequency ratio of erosion features occurrence and land degradation vulnerability classes

Vulnerability level	Vulnerability zone		Land degradation features		Frequency ratio
	Area (km^2)	A (%)	Number	B (%)	B/A
Very low to low	1967.49	47.63	48.00	4.80	0.23
Moderate	843.03	20.41	174.00	17.38	0.85
High to very high	1322.28	32.01	779.00	77.82	3.91

The results demonstrate that there is a correlation between the occurrence of land degradation features and the level of land vulnerability defined based on the multicriteria decision analysis. The frequency ratio is lower than 1 in the very low to low vulnerability zone (FR=0.23), and the moderate vulnerability zones (FR=0.85) indicating that the probability of occurrence of land degradation features in this zone is very low. In contrast, the frequency ratio is higher than 1 in both the high and very high vulnerability zones (FR=3.91) indicating a high probability of occurrence of land degradation features. This increase in the frequency ratio following the land degradation vulnerability level denotes the agreement between the occurrence of land degradation features and the land degradation vulnerability level defined by the developed model. Overall, the percentage of correct prediction of the occurrence of land degradation features in the high and very high vulnerability zones is 77.82% indicating that the model is reliable for the identification of land degradation vulnerability zones in the study area. The Figure 4.55 shows the distribution of the land degradation features (erosion and landslides) compared to the vulnerability zones within the study area.

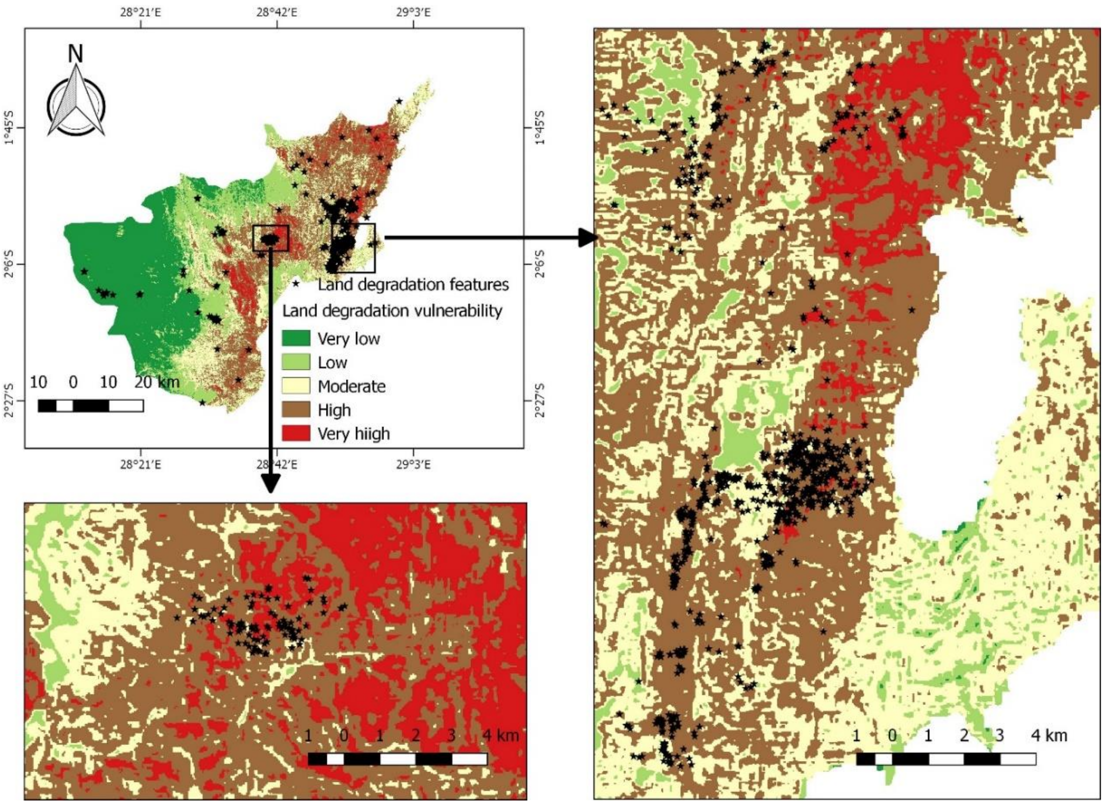


Figure 4.55: Distribution of the land degradation features compared to the vulnerability zones in Kalehe territory.

4.4.2. Land use potential modelling for alternative land use planning

In the Kalehe territory, there is a competition between the use of land for agricultural production and forest conservation purposes. Therefore, a land suitability analysis (land capability or land potential modeling) is necessary to determine which portion of land should be used for agricultural purposes and which should be prioritized for forest landscape restoration. The analysis presented in this section is based on the multicriteria decision approach to undertake the land capability classification for an adaptative land use planning to cope with the problem of land degradation in the Kalehe territory. The aims it to assess if the current land use is done according to its land capability, determine the priority area for implementation of forest landscape restoration initiatives, and then proceed to the adjustment of the land use allocation in areas where the land is misused to reduce the land degradation.

4.4.2.1. Analysis of Land Capability

The land capability was assessed based on three factors: soil texture, soil depth, and slope gradient (Figure 4.56).

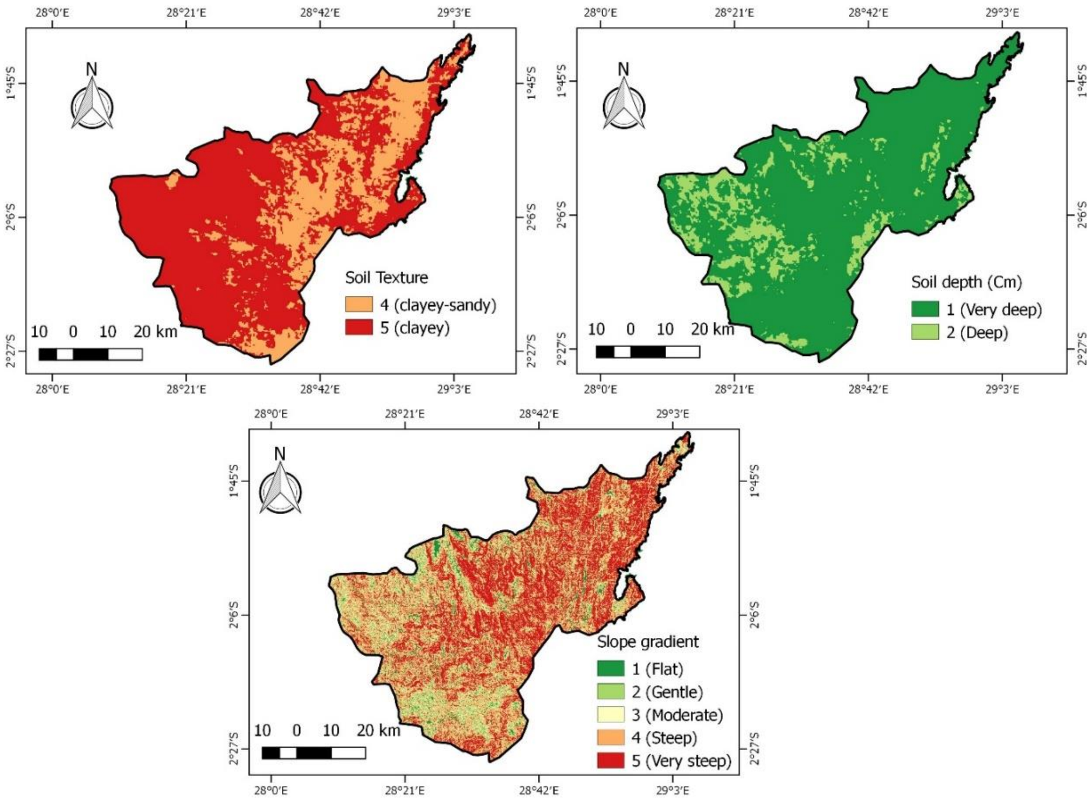


Figure 4.56: Ranking and classification of land capability factors.

The aerial extent and the ranking values of the different classes of factors for land capability classification are presented in Table 4.62.

Table 4.62: Selected factors for Characterizing the Land Capability

Factor	Rank	Sub factor	Capability class	Area (km^2)	Area (%)
Slope gradient (%)	1	Flat <3	I	159.9	3.79
	2	Gentle 3-9	II	409.41	9.7
	3	Moderate 9-15	III	606.41	14.37
	4	Steep 15-30	IV	1522.85	36.09
	5	Very steep >30	V	1520.74	36.04
Soil texture	4	Clayey-sandy	IV	1202.57	28.95
	5	Clayey	V	2950.99	71.05
Soil depth (Cm)	1	Very deep >150	I	3532.81	85.10
	2	Deep 150-100	II	618.38	14.89

Findings from the classification and ranking of land capability factors presented in Figure 4.56 and Table 4.62 revealed that the soil depth varies between 124 cm and 175 cm with a mean value of 165.65 cm. The territory is characterised by a predominance of deep soil with a thickness ranging frm 150 to 100 cm, representing 14.89% (618.38km^2) of the surface area. Additionally, the presence of very deep soils, with a depth exceeding 150 cm, is notable and account for 85.10% of the territory (3532.81km^2).

The texture of the soil in Kalehe has two distinct types: clayey-sandy soil and clay soil. The clayey soil is the most predominant, representing 71.05% (2950.99km^2). In contrast, the sandy clay soil constitutes a comparatively smaller proportion of 28.95% (1202.57km^2). The clayey soil was classified in the capability class V while the sandy clay was assigned to the class IV.

Considering the region’s topography, the area under study is characterised by a predominance of very steep slopes and steep slopes, accounting for 36.09%

(1522.85km^2) and 36.04% (1520.74km^2), respectively. This finding indicates that the land capability classes IV and V are the most prevalent. The moderate slope corresponding to the capability class III encompasses an area of 14.37% (606.41km^2). In contrast, the gentle slope which classified as the land capability class II represents 9.7% (409.41km^2). The flat slope, which corresponds to the land capability class I, is the least represented class. It covers only 3.79% (159.9km^2) of the territory.

The three factors for land capability assessment were compared using the AHP approach to assign weight to each factor (Table 4.63).

Table 4.63: Pairwise comparison of the land capability factors

Factors	SG	ST	SD	AHP weight
Slope gradient (SG)	1	2	2	0.50
Soil texture (ST)	0.5	1	1	0.25
Soil depth (SD)	0.5	1	1	0.25

The two soil characteristics were assigned the same weight of 25% while the slope was assigned a weight of 50% as it constitutes the main constraint for land use in the study area. Thus the equation of the land capability index was defined as

$$LCI = 0.25 * SD + 0.25 * ST + 0.50 * SG \quad \text{(Equation 4.14)}$$

With LCI the land capability index, SD the soil depth, ST the soil texture, and SG the slope gradient.

The land capability map, presented in Figure 4.57, was obtained through a weighted overlay of the three factors and classified into 5 capability classes based on an equal interval.

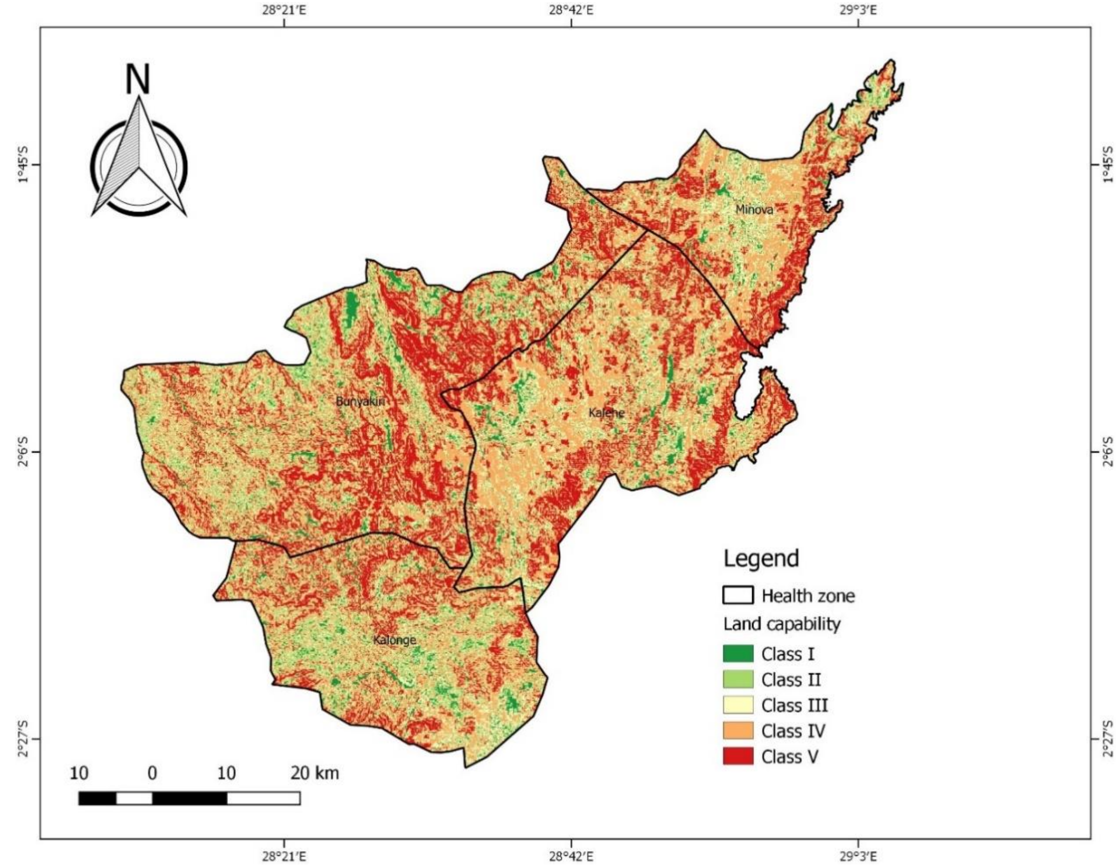


Figure 4.57: Land capability class of the Kalehe territory.

Table 4.64 provides a comprehensive overview of the land capability classification, the suitable land use, and the corresponding soil and water conservation treatments that can be implemented in the study area to avoid the problem of land degradation.

Table 4.64: Land capability class and area coverage in Kalehe territory

Land Capability	**Area (km^2)**	**Area (%)**	**Appropriate land use**	**Soil and water conservation treatments**
Class I	138.19	3.34	Agriculture	Unrestricted agricultural use
Class II	376.54	9.1	Agriculture	Moderate soil and water treatment
Class III	747	18.06	Agriculture	Intensive soil and water treatment
Class IV	1764.17	42.64	Agriculture and pasture	Minimum tillage, agroforestry, implementation of erosion control measures
Class V	1111.21	26.86	Forestry (conservation purpose)	Natural forests should be maintained, or reforested, implementation of erosion control measures and special conservation measures

The land capability classes I to IV which are suitable for agriculture represent 73.14% of the study area. The land capability Class I which is suitable for unrestricted agricultural uses represents 3.14% of the territory. In this zone, the soil is deep and the slope is flat, thus there is no limitation for crop productivity. The land capability class II is found in 9.10% of the territory. In this zone, the soil is deep but the slope is gentle. Thus it requires moderate soil and water conservation practices. The land capability class III covers about 18.06% of the territory. In these zones the slope is moderate and there is a requirement for some special conservation practices to avoid land degradation. The land capability class IV is the most dominant and accounts for 42.64% of the territory. This class is however limited due to the steep slope and any agricultural activity in this area should require the application of soil and water conservation measures. Class V which is not suitable for agriculture but suitable for pasture land, grazing, forest, and urbanization represents 26.86% of the territory. This class is limited for agricultural production due to the very steep slopes which are exposed to land degradation processes and require a strict application of soil and water conservation measures, forest conservation, and afforestation.

4.4.2.2. Integration of the land capability in the land use planning to reduce land degradation vulnerability

Since the territory of Kalehe is already affected by the problem of land degradation, it is essential to assess if the current land use is sustainable and to suggest appropriate land use that aligns with the land capability. Therefore, the correlation between the occurrence of land degradation and land use potential (land capability classes) was assessed to identify the most vulnerable capability classes where conservation action should be prioritized. Furthermore, the land capability map (land use potential map) was intersected with the current land use to identify the area where the land is not used according to its capability and to suggest appropriates land use adjustments for future land use planning to avoid further degradation.

A. Frequency ratio of land degradation and land capability classes

The analysis of the relation between the land capability classes and the occurrence of the land degradation features shows that the degradation is more likely to occur in the capability classes IV and V compared to other classes (Figure 4.58).

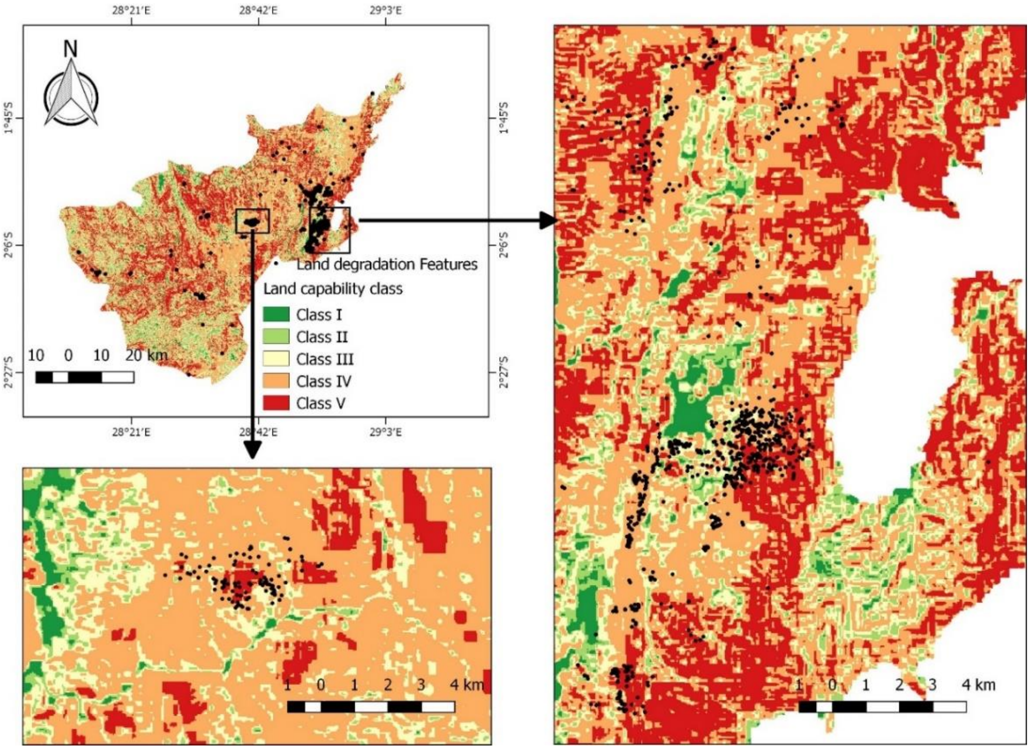


Figure 4.58: Distribution of the land degradation features (erosion and landslides) compared to the land capability classes in Kalehe territory.

The Table 4.65 present the results of the frequency ratio analysis between the land capability classes and the occurrence of land degradation features in the study area.

Table 4.65: Frequency ratio of land degradation features occurrence and land capability classes

Land capability classes	Land capability Zone		Land degradation features		Frequency ratio
	Area (km²)	**A (%)**	**Number**	**B (%)**	**B/A**
Class I	138.19	3.34	1	0.10	0.03
Class II	376.54	9.10	18	1.80	0.20
Class III	747	18.06	102	10.19	0.56
Class IV	1764.17	42.64	576	57.54	1.35
Class V	1111.21	26.86	304	30.37	1.13

From the above Table 4.65, it can be observed that 87.91% of land degradation features observed in the Kalehe territory occurred in the zone with land capabilities IV and V. In addition to that, the frequency ratio is less than 1 in the land capability classes I, II, and III indicating that the probability of occurrence of land degradation features in those areas is low. In contrast, the frequency ratio is higher than 1 in the land capability classes IV and V, indicating a high probability of occurrence of land degradation features. It should be also noted that the frequency ratio of land degradation features increases with the land capability classes, this implies that the high capability classes are the more vulnerable to land degradation processes.

B. Distribution of the current land uses in the capability's classes

Since there is a degradation of natural resources in the Kalehe territory, it is important to identify the area where the land is not used according to its capability and suggest appropriate intervention measures. Table 4.66 presents the distribution of LULC in the different land use capabilities.

Table 4.66: Current LULC types and their distribution in the land capability class

	I (High)	**II (Moderate)**	**III (Low)**	**IV (Very low)**	**V (Non-arable)**	**Total**
LULC	**Area (km^2)**	**Area (km^2)**	**Area (km^2)**	**Area (km^2)**	**Area (km^2)**	**Area (km^2)**
Bare land	0.43	0.27	0.18	0.52	1.21	2.61
Built up	10.62	32.72	73.42	185.27	88.85	390.88
Cropland	6.34	17.44	48.06	163.55	80.13	315.52
Forest	75.31	212.34	356.83	819.46	618.21	2082.15
Grassland	3.79	11.5	40.83	82.05	18.16	156.33
Shrub land	41.75	110.86	247.08	624.2	319.33	1343.22
Wetland	1.51	1.36	3.29	16.98	13.55	36.69
Total	139.75	386.49	769.69	1892.03	1139.44	4327.4

The land use capability classes I to IV are the most productive and represent the arable land that should be allocated to agricultural activity for food production. Class V is the least productive land which should be allocated to other activities such as forest conservation or reforestation and not for agricultural productivity.

The Table 4.67 present the distribution of the current LULC classes in the productive and no productive land capability classes. Based on this classification, 76.67% (3187.96km^2) of the study area is constituted by productive land. Under the current situation, 74.60% of agricultural activities are found on suitable land. It should be noted that 51.83% of agricultural activities are done within class IV which requires special conservation measures before any agricultural activity. However, other land uses are found in the productive land capability class (Class I-IV). It is noted that the baren land

(53.64%), the built-up area (77.26%), the forest land (70.31%), grassland (88.38%), shrubland (63.69%), and wetland (63.07%) are found in the area with a high potential for agricultural activities. This indicates that the land is not managed according to its capability.

Table 4.67: Distribution of LULC classes in the productive and non-productive land capability classes

LULC type	**Area of LULC**		**Productive (Class I-IV)**		**Non-productive (Class V)**	
	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)
Bare land	2.61	0.06	1.40	53.64	1.21	46.36
Built up	390.88	9.03	302.03	77.27	88.85	22.73
Cropland	315.52	7.29	235.39	74.60	80.13	25.40
Forest	2082.15	48.12	1463.94	70.31	618.21	29.69
Grassland	156.33	3.61	138.17	88.38	18.16	11.62
Shrub land	1343.22	31.04	1023.89	76.23	319.33	23.77
Wetland	36.69	0.85	23.14	63.07	13.55	36.93
Total	4327.40	100.0	3187.96	73.67	1139.44	26.33

The distribution of the actual land use that is not following the land capability (overused and underused) is presented in Figure 4.59 and Table 4.68. The comparison of the current LULC (2020) and the land capability maps indicates that 15.88% of the actual land use is not used according to its capability as it is presented in Figure 4.59.

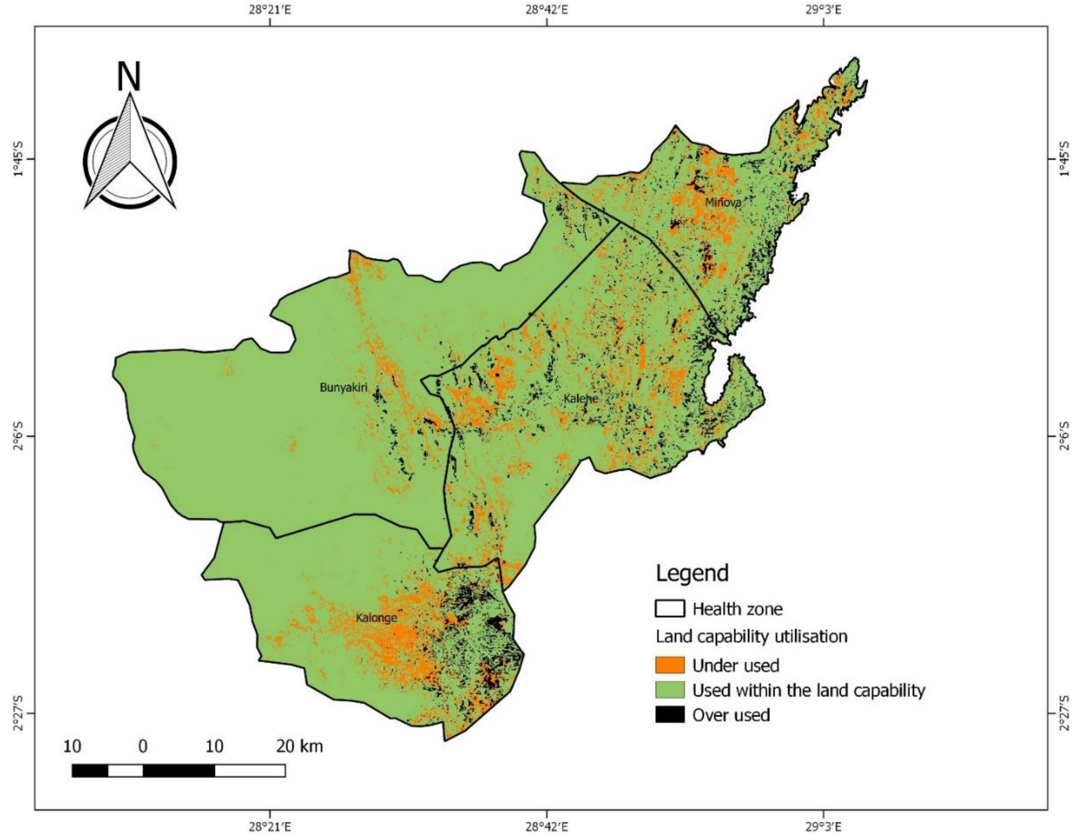


Figure 4.59: Status of land utilization in Kalehe territory.

Under the current situation, 84.88% of land is used within its capability, 10.57% under used, and 4.55% over used. Hence there is a need to plan the land use according to the identified capability classes for the sustainable use and effective conservation of natural resources in the territory.

Table 4.68: Land suitability per LULC type

Land suitability	**Under-used potential**		**Used within capability**		**Over-used potential**		**Total**
LULC	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)
Bare land	1.40	53.64	1.21	46.36	0.00	0.00	2.61
Built up	0.00	0.00	274.12	70.13	116.76	29.87	390.88
Cropland	0.00	0.00	235.39	74.60	80.13	25.40	315.52
Forest	0.00	0.00	2082.15	100.00	0.00	0.00	2082.15
Grassland	56.12	35.90	100.21	64.10	0.00	0.00	156.33
Shrub land	399.69	29.76	943.53	70.24	0.00	0.00	1343.22
Wetland	0.00	0.00	36.69	100.00	0.00	0.00	36.69
Total	457.21	10.57	3673.30	84.88	196.89	4.55	4327.40

C. Land use adjustment based on land capability and suggested conservation measures

The intersection of the land use capability map and the actual LULC serves also as the basis to orient a new land use plan. The land use adjustment was done only in the area where the land is underused and overused to suggest a new land use according to the land capability. In the new land use scenario, the land that was managed within their capability under the current situation was maintained. However, following the recommendations of the USDA, the land capability classes I, II, and III which are more productive were allocated for agriculture to enhance food production when these classes were covered by unproductive land (bare land), shrub, and grassland. The agricultural land over land capabilities III and IV requires the application of soil and water conservation actions to avoid land degradation while the agricultural lands under class I and II don't necessarily require the application of these conservation measures as they are found on flat to gentle slopes. The existing forest and wetland cover were maintained under their current situation regarding the land capability. Class IV was considered to support the built-up expansion and the expansion of natural habitats (forest, grassland, and shrub). In this class, grazing can be done, however, class V which is located on a very steep slope was allocated for afforestation only to support biodiversity conservation, carbon storage, natural water recharge, and other ecosystem services. The spatial patterns of LULC transformation according to this scenario are visually depicted in Figure 4.60.

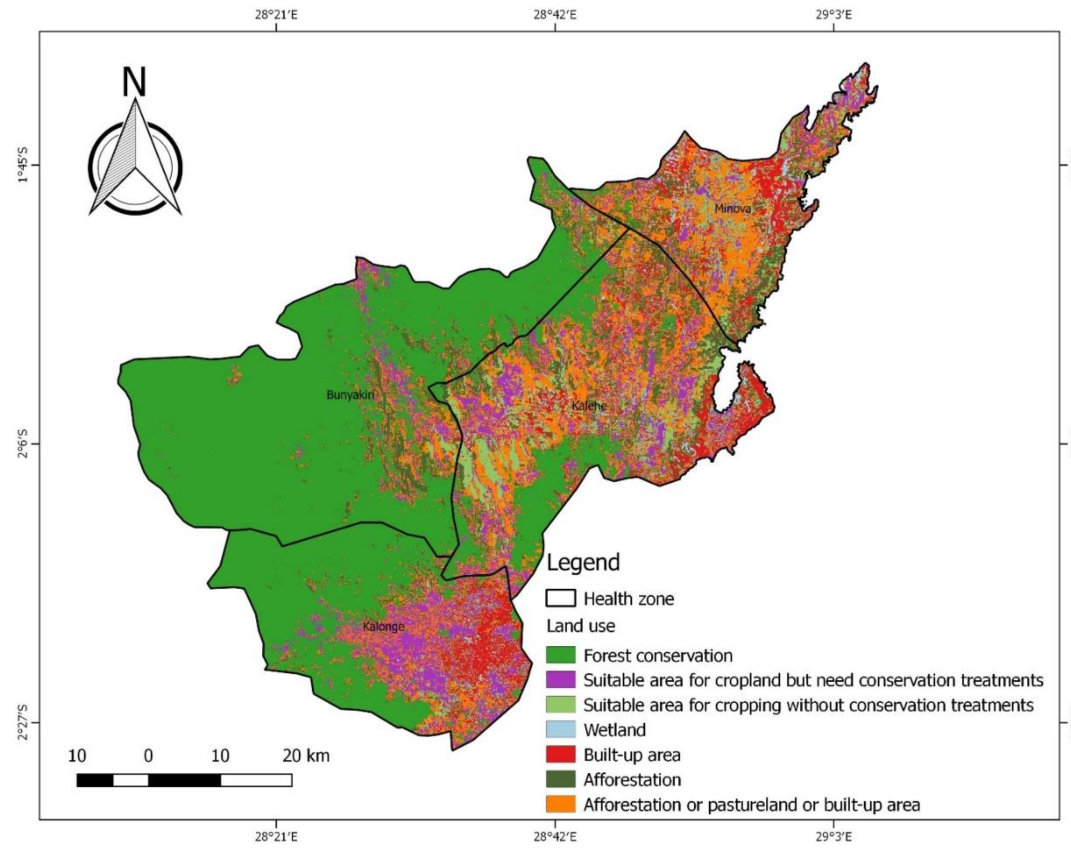


Figure 4.60: Adjustment of the actual land use according to the land capability.

The suggested land use obtained by considering the land capability and the present land use has 7 classes as is shown in Table 4.69.

Table 4.69: Land use adjustments and suggested conservation measures

Land use and land cover	Area (km^2)	Area (%)	Suggested conservation measures
Forest conservation	1943.90	47.02	Forest gape filling, naturally assisted regeneration
Suitable for cropland but needs conservation treatment	474.27	11.47	Terracing, strip cropping, agroforestry, gully plugging
Suitable for cropland without conservation treatment	319.93	7.74	Mulching, contouring
Wetland conservation	36.37	0.88	Avoid wetland encroachment for anthropogenic activities and drainage
Built-up area	269.63	6.52	Increase green space, trenching and drainage ditches, gully plugging, land leveling
Afforestation	412.38	9.97	Tree planting (indigenous and multipurpose trees)
Afforestation or pastureland or built-up	677.74	16.39	Tree planting (indigenous and multipurpose trees), avoid overgrazing

(1) **Forest conservation zone** which represents 47% of the territory. This class contains the actual area covered by forest. In this zone, the conservation action that should be done is the forest gap filling where the forest has been fragmented. This forest gap filling can be done through reforestation with indigenous tree planting or forest protection to allow natural regeneration to occur (natural assisted regeneration). Furthermore, protective measures against forest fire must be considered.

(2) **Suitable area for cropland but needs conservation treatments**: this zone covers 11.47 % of the study area. It contains the area which area suitable for cropland but is located on moderate and steep slopes. This area requires the application of soil conservation measures such as terracing or land leveling, strip cropping, contouring, agroforestry, farmer assisted natural regeneration etc. to reduce soil erosion.

(3) **Suitable area for cropping without conservation treatments**: this zone covers 7.74% of the study area and contains the area that is suitable for agricultural purposes but located on a flat to gentle slope. The cropland on the flat area doesn’t require

particular soil and water conservation measures. However minor soil conservation such as contour bunding and mulching can be applied in these zones

(4) **Wetland conservation**: this includes marshland and areas which are regularly flooded throughout the year which should be avoided for any anthropogenic activity. The encroachment and drainage of the wetland should be avoided. This area covers 0.88% of the study area.

(5) **Built-up area**: this zone includes all the human settlements that are not under the most productive land capability classes I to III. Actual built-up land under the land capability class IV and V are embedded in this category. Built-up areas over the land capability class IV and V are susceptible to erosion due to the steep slopes. Thus it is important to increase the green spaces in those areas to reduce the surface water runoff, control the gully erosion through the application of gully plugging measures, control the surface water runoff through the implementation of trenching, drainage ditches, and land leveling. This area covers about 6.52% of the study area.

(6) **Afforestation zone**: this zone covers about 9.97% of the study area. It represents the unproductive land capability class V which is located on very steep slopes. This area is more vulnerable to erosion and landslides. To reduce this problem, it is necessary to cover the soil with vegetation and one way to do that is through afforestation. An emphasis should be placed on the indigenous tree species for the preservation of local biodiversity and multi-purpose trees to meet the needs of people in wood energy, food, medicine, and wood for construction, for instance. Other conservation measures such as trenching can be applied in this zone to control the surface water runoff.

(7) **Afforestation or pastureland or built-up expansion**: this zone covers about 16.39% of the study area. It includes the area which is covered by grassland and

shrub land but located in the least productive land capability class IV. Since this zone is least productive, agricultural activities should be minimized. In this zone, afforestation can be done through the plantation of fruit trees to allow both the protection of soil and carbon storage and contribute to food security. Pastureland can also be extended in this area for grazing. The expansion of the built-up area can also be done in this zone. However, the area around the rivers in a buffer zone of 50 m should be avoided as this zone is prone to erosion.

4.5. Perception On Land Degradation And Adoption Of Conservation Measures

During the conservation planning process, it is important to assess the spatio-temporal dynamics of environmental changes, the causes of these dynamics, the pressure put on the environment through human activities, consequences, and the response to environmental changes in a given community. In the previous section, the GIS and remote sensing approaches were used to assess these factors for conservation planning purposes. However, it is important to take into account the local knowledge of the community during the assessment of the drivers, pressure, state, impact, and response (DPSIR) to the land degradation dynamics resulting from diverse land utilization in the study area. Therefore, this section presents the perception of the local community on forest degradation, farmland degradation, and soil water erosion with an emphasizes on the state, the cause, the consequence, and the adopted strategy to cope with these environmental problems in their community. Furthermore, the socio-economic determinants of adoption of conservation measures to cope with the problem of land degradation are assessed.

4.5.1. Socio-economic and structural characteristics of respondents

The people's perception of land degradation and the adoption of conservation depends on their socio-economic characteristics, structural characteristics of their farmlands, and institutional factors such as access to extension services. The socio-economic characteristics of the respondents are presented in Table 4.70.

Table 4.70: Socio-economic characteristics of respondents and structural characteristics of farmland in Kalehe territory. N=384

Variables	N (%)	Chi-Square test			Variables	N (%)	Chi-Square test		
		χ^2	df	p-value			χ^2	df	p-value
Age		59.2	2	<0.001	**Farmland size**		85.7	2	<0.001
20-30 years	36.7				*<1 ha*	53.1			
30-50 years	47.4				*1-2 ha*	32.3			
> 50 years	15.9				*>2 ha*	14.6			
Sex		3.4	1	0.0662	**Distance to farmland**		28.2	2	<0.001
Male	45.3				*< 30 min.*	26.6			
Female	54.7				*30-60 min.*	27.3			
Marital status		312.5	2	<0.001	*> 60 min.*	46.1			
Single	14.3				**Farming seniority**		21.0	3	<0.001
Married	75.8				*0-10 years*	21.9			
Separated	9.9				*10-20 years*	34.4			
Size of the household		12.7	2	0.0017	*20-30 years*	25.0			
<5	26.0				*> 30 years*	18.8			
5-10	40.9				**Slope of the farmland**		68.1	2	<0.001
> 10	33.1				*Flat*	15.9			
Source of livelihood		650.0	3	<0.001	*Gentle*	33.9			
Cropping	81.2				*Steep*	50.3			
State agent	5.5				**Farmland productivity**		219.8	2	<0.001
Small business	9.1				*Decreased*	68.8			
Others∗	4.2				*Increased*	12.0			
Level of education		192.3	4	<0.001	*No change*	19.3			
None	27.3				**Erosion occurrence**		42.7	1	<0.001
Primary	34.1				*No*	38.8			
Secondary	32.6				*Yes*	61.2			
Tertiary	5.5				**Extension service**∗∗		126.0	1	<0.001
Others	0.5				*No*	78.6			
Stayed period		15.8	2	<0.001	*Yes*	21.4			
10-20	35.4				**Land ownership**		6.9	2	0.032
20-30	40.4				*Inherited*	33.3			
>30	24.2				*Bought*	27.9			
					Rented	38.8			

∗*Artisanal miners, carpenters, motorcyclists, sawyers, charcoal maker*

∗∗*Participation in training or campaigns on soil and water conservation*

Table 4.70 shows that most of the respondents involved in this study were women (54.7%). It was also found that the sampled household heads are an adult as 47.4% of respondents have an age between 30 years and 50 years old. In terms of the level of education, it was found that only 27.3% of them did not attend school, thus most of the respondents are literate. However, most of them only attended primary school (34.1%) or secondary school (32.6%). The majority of the respondents were married (75.8%) and 74 % of households had more than 5 people. This is explained by the fact that people get married at a very young age (less than 30 years old) and according to their customs, children are seen as a richness. Table 4.70 further shows that most of the respondents have lived in the area for more than 20 years (64.6%), thus they have a good knowledge of the environmental change that occurred in their locality. In addition, 81.2% of the land users depend on subsistence agriculture and livestock keeping for their livelihood. Only 27.8% are engaged in off-farm activities. It was found that only 61.2% of the respondents own the land (inherited or bought). Therefore, land use tenure constitutes an issue in the area because 38.8% depend on rented land to exercise their farming activities.

The respondents have a farming experience of more than 10 years (78.1%). This implies that they have a long experience, have used the land for a long period and there is a potential that they have adapted their land management to the changes that occurred in their environment. However, access to extension services in the area is very low as only 21.4% have participated in a training or campaign related to conservation practices. This implies that the knowledge about conservation practices is low in these areas. It was also found as can be seen in Table 4.70 that smallholder farmers are predominant with farmland size less than 1 ha (53.1%). This farmland is far from the house as 73.4% of the respondent reported that they walk more than 30 minutes from their homeland to the farmland. Fifty-point-three percent (50.3%) of respondents reported that their farmland is located on a steep slope and 33.9% reported that the status of their farmland is a gentle or moderate slope. This shows that the farmland is located in inadequate or marginal land where erosion is prominent as 66.7% of the respondent reported that they are currently experiencing the problem of erosion in their farmland. This influences crop productivity which has decreased over the last 10 years as reported by 68.5% of respondents.

4.5.2. Respondent's perception of farmland degradation

4.5.2.1. Farmland degradation status

Answering the question about the productivity of the land over the last 10 years, the land users perceived farmland degradation as a problem in their localities as 68.8% of farmers observed that the productivity of their land has decreased over the last 10 years in their locality as can be seen in Figure 4.61.

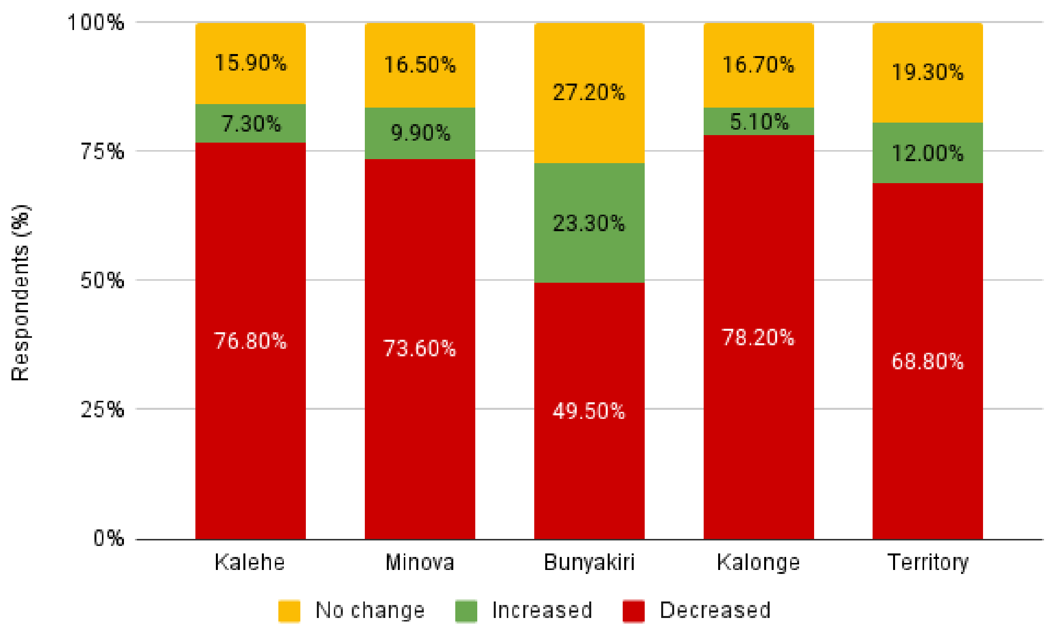


Figure 4.61: Barplot showing the land user perception of farmland productivity per health zone in Kalehe territory.

It was found that the land user perception of farmland degradation in the study area varies spatially from one health zone to another as can be seen in Figure 4.61. The chi-square test (X-squared = 28.328, df = 6, p-value = 8.15e-05) shows that there is a dependence or association between the perception of farmland productivity and the health zone. The highest perception of farmland degradation is perceived in Kalonge, Kalehe, and Minova where 78.2%, 76.8%, and 73.5%, respectively, of land users have observed a decrease in cropland production. However, the lowest perception of land users on farmland degradation is observed in Bunyakiri where only 49.5% of people have observed a decrease in cropland productivity and it is where the highest productivity was observed (Figure 4.61).

4.5.2.2. Respondent's perception of the cause of farmland degradation

The farmers perceived various causes of farmland degradation in their locality. Table 4.71 presents the perceived reasons for the decrease in farmland productivity in their entity.

Table 4.71: The main reason for decreased crop production in Kalehe territory.

Perceived cause of decreased crop production	**Health zones**				**Territory**
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Soil erosion	12.2%	11.6%	14.6%	10.3%	**12.2%**
Loss of firtility	26.8%	45.5%	21.4%	52.6%	**36.5%**
Unreliable rainfall	12.2%	4.1%	12.6%	3.8%	8.1%
Crop diseases	6.1%	4.1%	4.9%	5.1%	4.9%
Limited or inadequate land	3.7%	5.0%	10.7%	1.3%	5.5%
Lack of agricultural input/High cost of agricultural input	3.7%	1.7%	1.0%	5.1%	2.6%
Inadequate labour	3.7%	0.8%	1.9%	1.3%	1.8%
Poor access to subdiary program	0.0%	2.5%	2.9%	0.0%	1.6%
Continuous cultivation without fallowing	30.5%	24.0%	27.2%	19.2%	**25.3%**
Not aware	1.2%	0.8%	2.9%	1.3%	1.6%
Chi-square test	X-squared = 48.839, df = 27, p-value = 0.006				

From Table 4.71, it can be seen that the majority of respondents (36.5%) perceived loss of soil fertility due to continuous cultivation without fallow (25.3%) as the main cause of farmland degradation. About 12.2% of respondents associated the cause of farmland degradation with soil erosion which affects their land. Other main causes of degradation of farmland that have been perceived by the land users are unreliable rainfall (8.1%) which is not consistent along all the cultural seasons, crop diseases (4.9%), and cultivation on limited or inadequate land (5.5%) such as hill slopes where the problem of erosion is more recurrent. The perception of the cause of farmland degradation depends on the health zone (X-squared = 48.839, df = 27, p-value = 0.006178).

4.5.2.3. Adopted option due to decrease in crop production

The respondents had adopted different strategies to cope with this problem of farmland degradation as is shown in Table 4.72.

Table 4.72: Adopted option due to decrease of crop production in Kalehe territory.

Adopted option due to decrease of crop production	**Health zones**				**Territory**
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Looked for additional land	36.6%	33.1%	25.2%	23.1%	29.7%
Improve the fertility of the land	7.3%	2.5%	2.9%	5.1%	4.2%
Fallow	39.0%	21.5%	29.1%	35.9%	30.2%
Crop succession rotation	11.0%	27.3%	19.4%	17.9%	19.8%
Intercroping	4.9%	14.0%	13.6%	9.0%	10.9%
Agroforestry	1.2%	1.7%	1.0%	1.3%	1.3%
None	0.0%	0.0%	8.7%	7.7%	3.9%
Chi-square test	X-squared = 41.683, df = 18, p-value = 0.001				

Due to scarcity of land, only 30.2% of respondents do the fallows to improve the fertility of the land. Other adopted strategies are crop succession or rotation (19.8%) and intercropping (10.9%). The improvement of soil fertility through manure or household waste application is done by only 4.2% of land users.

Due to farmland degradation, about 29.7% of respondents reported that they looked for additional land when productivity decreased (Table 4.72). Respondents as can be seen in Table 4.73 noted that their preference for additional land was old fallow land or shrub land (40.6%) and forest (35.7%). They justify their choice by the fact that old fallow (shrubland) is considered to recover soil fertility after a few years (2 to 4 years) and require less labor compared to forest land.

Table 4.73: Land user's preference for additional land in Kalehe territory.

LULC type preference for additional land	**Health zones**				**Territory**
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Forest land	13.4%	35.5%	46.6%	44.9%	35.7%
Fallow	43.9%	38.0%	35.0%	48.7%	40.6%
Grassland	4.9%	8.3%	16.5%	3.8%	8.9%
Others (wetlamd, barren land)	0.0%	1.7%	1.9%	2.6%	0.8%
No preference	37.8%	16.5%	0.0%	0.0%	13.3%
Chi-square test	X-squared = 93.724, df = 12, p-value< 0.0001				

As can be seen in Table 4.73, the adopted strategy when the farmland productivity decrease depends on the health zone (X-squared = 41.683, df = 18, p-value = 0.001224).

4.5.3. Respondent's perception on forest degradation

4.5.3.1. Forest degradation status

The people of the Kalehe territory associate forest degradation with the loss or scarcity of timber and no forest timber products, the scarcity of wildlife animals, and the reduction of amenities (beauty) of the forest landscape in their environment. Based on these indicators, they rated the level of forest degradation as high and this was explained using estimates of forest products that were said to have become scarce or non-existent; moderate if they obtained forest products but in diminished quantities and hence must walk longer distance to access them, and low when the availability of forest resource has not changed significantly over the last decade. The respondents have varied views on forest land degradation status in Kalehe territory. Most of them (58.1%) perceived that forest degradation is high and constitutes a serious problem in their territory (Figure 4.62). Only 18.2% of respondents declared that forest degradation is low while 23.7% of them consider that it is moderate. It was further established that respondent's perception of forest degradation depended on their location in the health zone (X-squared = 30.871, df = 6, p-value = 2.683e-05) of the Kalehe territory as can be seen in Figure 4.62.

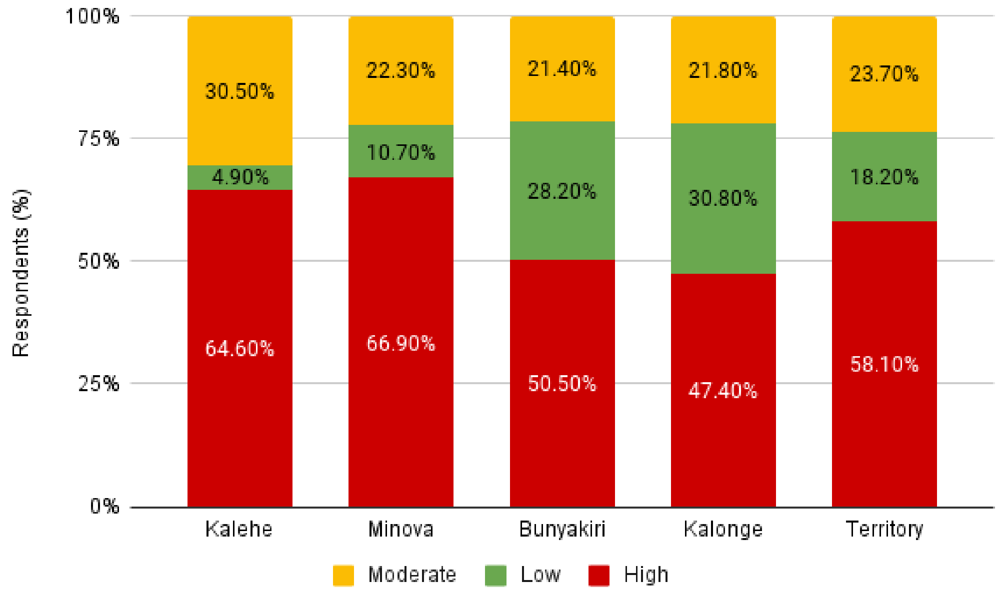


Figure 4.62: Barplot showing the perception of the status of forest degradation during the last decay in the Kalehe territory.

For instance, the high level of forest degradation is perceived by 66.9% of respondents in Minova, 64.6% in Kalehe, 50.5% in Bunyakiri, and 47.4% in Kalonge as is evident in Figure 4.62. The moderate level of forest degradation is perceived by 30.5% of respondents in Kalehe, 21.4% in Bunyakiri, 22.3% in Minova, and 21.8% in Kalonge. The low level of forest degradation is perceived by 30.8% of respondents in Kalonge, 28.2% in Bunyakiri, 10.7% in Minova, and 4.9% in Kalehe health zones (Figure 4.62).

4.5.3.2. Respondent's perception of the causes of forest degradation

Findings showed that people perceived different causes of forest degradation in their territory. As can be seen in Table 4.74, the main direct causes of forest degradation in this territory are charcoal and firewood production (72.4%) which constitute the main source of energy and high demand to supply the major towns (Bukavu and Goma) around the territory, agriculture expansion through shifting cultivation on slash and burn (65.1%) which constitute the main source of livelihood in this territory, and timber harvesting or forest logging (54.9%), overgrazing and expansion of pastureland (52.9%).

Table 4.74: Land user's perception of the direct causes of forest degradation.

Perceived direct causes of forest degradation	Percentage of repondents		Chi-Square test		
	No (N%)	Yes (N%)	$\chi 2$	df	p-value
Charcoal and firewood production	27.60%	72.40%	77.04	1	<0.001
Agriculture expansion/shifting cultivation	34.90%	65.10%	35.04	1	<0.001
Settlements expansion	68.80%	31.20%	54	1	<0.001
Expansion of mining activities in forest land	91.10%	8.90%	260.04	1	<0.001
Bush and forest fire in forest land	79.70%	20.30%	135.38	1	<0.001
Overgrazing and expansion of pastureland	47.10%	52.90%	1.26	1	0.262
Land colonization by refugees since 1994	73.70%	26.30%	86.26	1	<0.001
Timber harvesting /Forest logging	45.10%	54.90%	3.76	1	0.052
Hunting due to the need for bushmeat	91.40%	8.60%	263.34	1	<0.001
Development of infrastructures (roads)	91.10%	8.90%	260.04	1	<0.001

As is evident in the results above, the number of people who identified settlement expansion, expansion of mining activities in forest land, unplanned bush and forest fire in forest land, land colonization by refugees since 1994, hunting due to the need for bush meat, and development of infrastructures (roads) as the direct cause of forest degradation were low compared to those who did not. These are perceived as the lowest drivers of forest degradation in this area. Figure 4.63 shows images of direct drivers of forest degradation observed during fieldwork.

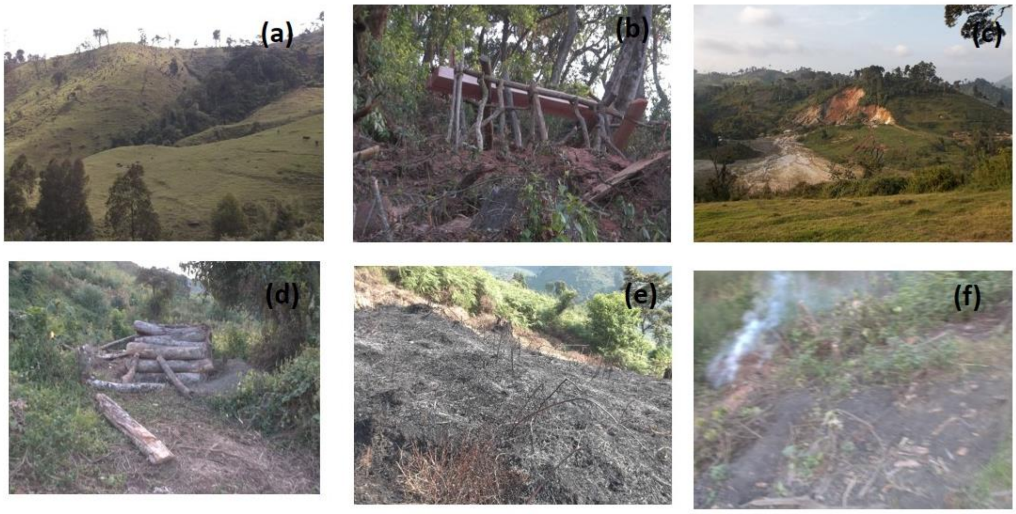


Figure 4.63: Direct drivers of forest degradation in Kalehe territory.

A. Pasture land expansion B. Timber logging C. Mining activities D. Fuel wood E. Slush and burn agriculture F. Charcoal production.

Field findings from the study area as shown in Table 4.75 indicated that population growth (64.3%) due to immigrants, followed by poverty (57.8%), the increased demand for wood for charcoal production and firewood which constitute the main source of energy in Kalehe (55.7%), the lack of off-farm activities (53.6%) which led to the expansion of agricultural land through the slash and burning practices are perceived as the main indirect drivers of forest degradation. Table 4.75 shows the indirect causes of forest degradation as established from the field.

Table 4.75: Land user's perception of the indirect cause of forest degradation.

Perceived indirect causes of forest degradation	Percentage of repondents		Chi-Square test		
	No (N%)	Yes (N%)	χ2	df	p-value
Lack of off-farm activity	53.60%	46.40%	2.04	1	0.153
Poverty	42.20%	57.80%	9.38	1	0.002
Population growth	35.70%	64.30%	31.51	1	<0.001
Poor access to alternative sources of energy	76.30%	23.70%	106.26	1	<0.001
Increased demand for wood	44.30%	55.70%	5.04	1	0.025
Conflict, Rebellion, and political instability	87.50%	12.50%	216.00	1	<0.001

4.5.3.3. Consequences or indicators of forest degradation

Respondents identified some consequences that occur in their territory and which constitute the indicators of forest degradation as can be seen in Table 4.76. Among them is the lack of firewood which has become far from the settlement (46.9%), the scarcity of non-timber products (16.7%) such as bush meat, mushrooms, honey, wild fruits, and wild vegetables, the lack of wood for construction, the loss of soil fertility (9.6%) leading to the decline in crop yield and the problem of erosion and landslide. It was determined that the indicators of forest degradation vary according to health zones (X-squared = 45.296, df = 30, p-value = 0.03622) as illustrated in Table 4.76.

Table 4.76: Indicators of forest degradation in Kalehe territory.

Indicators of forest degradation	Health zones				Territory
	Kalehe (N=82)	Minova (N=121)	Bunyakiri (N=103)	Kalonge (N=78)	Total (N=384)
Scarcity of no forest timber prodduct	26.8%	12.4%	12.6%	17.9%	16.7%
Lack of firewood	36.6%	50.4%	50.5%	47.4%	46.9%
Lack of wood for construction	2.4%	12.4%	4.9%	7.7%	7.3%
Floods	2.4%	3.3%	2.9%	2.6%	2.9%
Depletion of water resources	1.2%	0.8%	1.9%	3.8%	1.8%
Soil erosion and landslide	3.7%	6.6%	9.7%	3.8%	6.2%
Change in rainfall pattern	6.1%	0.8%	1.0%	0.0%	1.8%
Loss of soil fertility	13.4%	9.1%	9.7%	6.4%	9.6%
Wild animals have been scarce	3.7%	1.7%	4.9%	5.1%	3.6%
Siltation of rivers	1.2%	2.5%	1.9%	3.8%	2.3%
Deterioration of air quality	2.4%	0.0%	0.0%	1.3%	0.8%
Chi-square test	X-squared = 45.29, df = 30, p-value = 0.03622				

4.5.3.4. Perceived solution to reduce forest degradation

To cope with the problem of forest degradation in Kalehe territory, the respondents proposed that priority should be focused on the improvement of agriculture productivity to limit the expansion of the slash and burn agriculture into forest land (24.0%), the promotion of tree planting through environmental education service (19.8%), the promotion and capacity building on alternative sources of livelihood to limit the expansion of agricultural activities into farmlands and to limit the pressure on forest ecosystem (14.6%), the sustainable use of forest resource through collaboration with local communities (14.1%), poverty eradication through the enabling access to financial resources to develop off farm activities (6.5%), law enforcement through their strict application to reduce corruption in forestry sector (6.2%), improvement of land ownership to avoid the land grabbing by immigrant and “man with power”, promote the accessibility to alternative source of energy and utilization of energy saving stove to reduce the use of charcoal and firewood (2.9%), control the unwanted forest fire due to slush and burn agriculture (2.6%) and protection of wildlife habitat (1.3%). This is properly illustrated by Table 4.77 which shows that the priority action for reduction of forest degradation depends on health zones (X-squared = 72.790, df = 30, p-value<0.0001). For instance, in Kalehe zones, the most recommended actions are the tree planting and improvement of agricultural productivity while in Minova zone it is the tree planting, sustainable use of forest resource and improvement of sustainable use of forest resource. In Bunyakiri, the most recommended actions are the improvement of agricultural activities, the sustainable use of forest resource and the promotion of alternatives livelihoods activities. In Kalonge zones the improvement of agricultural activities and promotion of alternatives livelihoods activities are the most prominents options to reduce the forest degradation.

Table 4.77: Perceived solution to reduce forest degradation in Kalehe territory.

Prefered actions to reduce forest degradation	**Health zones**				**Territory**
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Improve agriculture productivity	19.5%	18.2%	22.3%	39.7%	24.0%
Law enforcement	1.2%	5.8%	12.6%	3.8%	6.2%
Promote tree planting	35.4%	25.6%	10.7%	6.4%	19.8%
Sustainable use of forest ressource	8.5%	19.0%	18.4%	6.4%	14.1%
Use alternative source of energy	3.7%	3.3%	3.9%	0.0%	2.9%
Control forest fire	0.0%	3.3%	2.9%	3.8%	2.6%
Improve ownership of the land	2.4%	2.5%	4.9%	5.1%	3.6%
Promote alternative livelibhood activities	14.6%	10.7%	17.5%	16.7%	14.6%
Poverty eradication	11.0%	6.6%	1.9%	7.7%	6.5%
Protect the wildlife habitat	1.2%	0.8%	1.0%	2.6%	1.3%
No response	2.4%	4.1%	3.9%	7.7%	4.4%
Chi-square test	X-squared = 72.790, df = 30, p-value<0.0001				

4.5.4. Respondent's perception of soil erosion

4.5.4.1. Perceived trend of soil erosion

Erosion is perceived as a problem in Kalehe territory by 61.2% of respondent who has observed that the problem of erosion has increased compared to the last 10 years while it is not considered a problem by 38.8% of respondent who states that there is no change in the trend of erosion (13.0%) or the problem has decreased (25.8%) over the last 10 years. These results are presented in Figure 4.64. The result of the chi-square test of independence as can be seen in Figure 4.64 shows that the perception of the trend of erosion over the last decade depends on the considered health zone in the Kalehe territory (X-squared = 30.448, df = 6, p-value = 3.23e-05).

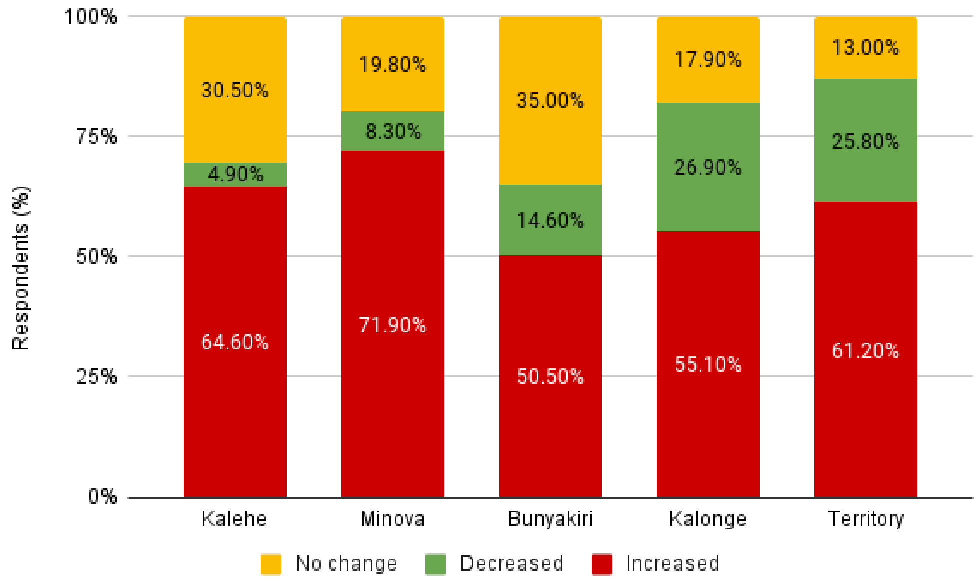


Figure 4.64: Barplot showing the respondent's perception of the trend of erosion per health zone in Kalehe territory.

The high perception of soil erosion is observed in Minova, Kalehe, and Kalonge where 71.9%, 64.6 %, and 55.1% of respondents reported that the erosion problem has increased in their territory over the last decades while the lower perception of soil erosion is observed in Bunyakiri where only 42.9 % perceived that the problem of erosion had increased (Figure 4.64).

4.5.4.2. Indicators of erosion

Different features of erosion were observed by the local communities and these findings are presented in Table 4.78.

Table 4.78: Indicators of soil erosion in Kalehe territory.

Indicators of soil erosion	**Health zones**				**Territory**
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Rills features	19.5%	28.9%	34.0%	16.7%	25.8%
Gullies features	22.0%	28.9%	28.2%	30.8%	27.6%
Landslide features	20.7%	23.1%	2.9%	9.0%	14.3%
Deposits of soil in rivers banks	4.9%	5.0%	7.8%	6.4%	6.0%
Surficial soil loss	11.0%	3.3%	3.9%	2.6%	4.9%
Change of soil coloration	8.5%	7.4%	11.7%	17.9%	10.9%
Stones lines	1.2%	0.0%	2.9%	1.3%	1.3%
Roots pedestral (exposition of roots due to erosion)	1.2%	1.7%	3.9%	2.6%	2.3%
Not aware	11.0%	1.7%	4.9%	12.8%	6.8%
Chi-square test	X-squared = 59.153, df = 24, p-value = 8.405e-05				

As can be seen from the Table 4.78, the gullies (27.6%), rills (25.8%), landslides (14.3%), and changes in soil coloration due to the loss of topsoil (10.9%) are perceived as the predominant indicators of soil erosion in Kalehe territory. Furthermore, 6.0% of the respondent noted that the deposition of soil in river banks which leads to the change of coloration and siltation of rivers constitutes an indicator of soil erosion in their locality. 4.9%% of respondents noted that the slow but continuous surficial soil loss due to erosion which can be referred to as sheet erosion constitutes a slow but serious problem that leads to the degradation of their farmland. In addition, 2.3% of respondents noted that they can identify the erosion in their land when the roots of trees become exposed due to continuous soil loss while 1.3% indicated that the soil becomes stony and the presence of stone lines in their plots is an indicator of soil erosion. Only 6.8% of the respondent was not aware of the sign of erosion. This shows that the community has a good knowledge of the indicators of erosion in their locality and can monitor its trend over time. It was further established that there existed a dependency between the health zone and the observed erosion feature in the Kalehe territory (X-squared = 59.153, df = 24, p-value = 8.405e-05) as can be seen in Table 4.78. Figure 4.65 shows the erosion features observed from the field.

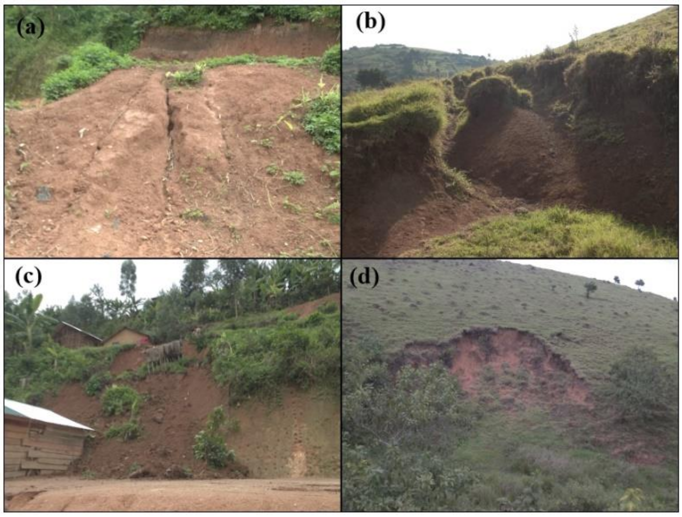


Figure 4.65: Erosion features in Kalehe territory.

A. Rills features B. Gullies C. Landslide in built-up area D. Landslide in pasture land.

Source: Field observation

4.5.4.3. LULC vulnerability to erosion

It is evident from Table 4.79 that land cover types were perceived as not having the same vulnerability to soil erosion.

Table 4.79: Perception on land cover vulnerability to soil erosion.

Most vulnerable LULC type to erosion	Health zones				Territory
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Grazing/Pasture land	3.7%	4.1%	4.9%	2.6%	3.9%
Built up area	22.0%	26.4%	31.1%	32.1%	27.9%
Cropland	45.1%	42.1%	49.5%	52.6%	46.9%
Forest land	0.0%	0.0%	1.9%	1.3%	0.8%
All type of land	29.3%	27.3%	12.6%	11.5%	20.6%
Chi-square test	X-squared = 19.46, df = 12, p-value = 0.07803				

It can be noted from the findings that cropland (46.9%) and built-up area (27.9%) are the most vulnerable while the forestland (0.8%) and grassland and shrub land (3.9%) are least vulnerable to erosion (Table 4.79). However, this perception of the vulnerability of LULC to erosion is independent of the health zone (X-squared = 19.46, df = 12, p-value = 0.07803).

4.5.4.4. Perceived cause of erosion

Soil erosion can be induced by natural factor and anthropogenic factors. Field findings presented in Table 4.80 shows 57% of respondents perceived the natural factors as the main drivers of erosion in the study area.

Table 4.80: Perceived cause of soil erosion in Kalehe territory.

Main cause of erosion	Health zones				Territory
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Nature of soil	8.5%	19.8%	12.6%	10.3%	13.5%
Deforestation	18.3%	21.5%	6.8%	26.9%	18.0%
Heavy rainfall	26.8%	19.0%	19.4%	19.2%	20.8%
Steep slope	20.7%	18.2%	20.4%	15.4%	18.8%
Runoff	0.0%	5.0%	6.8%	2.6%	3.9%
Improper tillage	2.4%	2.5%	2.9%	10.3%	4.2%
Livestock pressure and overgrasing	0.0%	0.8%	7.8%	2.6%	2.9%
Lack of conservation structures	8.5%	7.4%	5.8%	12.8%	8.3%
Improper farming (overcultivation)	1.2%	2.5%	4.9%	0.0%	2.3%
Not aware	1.2%	3.3%	12.6%	0.0%	4.7%
Urbanisation	12.2%	0.0%	0.0%	0.0%	2.6%
Chi-square test	X-squared = 112.2, df = 30, p-value = 2.007e-11				

The finding further shows that physical factors such as heavy rainfall (20.8%), steep slopes (18.8%), and anthropogenic factors such as deforestation (18.0%) are the main causes of soil erosion as perceived by local communities. People are also aware that the lack of conservation infrastructure and improper tillage are factors that exacerbate the problem of erosion in the locality. Only 4.7% of respondents are not aware of the cause of erosion in the Kalehe territory. It was additionally determined that there is a dependence between the perception of the cause of erosion and the health zone in the Kalehe territory (X-squared = 112.2, df = 30, p-value = 2.007e-11) as can be seen in Table 4.80.

4.5.4.5. Main consequences/Effect of erosion

Soil erosion has many consequences which affect the community and the environment. The result of this survey as has been presented in Table 4.81 indicates that respondents perceived erosion as having an adverse impact on farmland. Some of the effects of this as reported include: that soil erosion affects their farmland by decreasing the land productivity (33.3%), contributing to the loss of soil fertility (20.1%), contributing to the soil loss from farmland (14,1%), reduces size of farmland plot (8.3%) and the depth of arable soil (7.3%). All these consequences are interrelated as the loss of topsoil due to erosion lead to a decrease in soil fertility and loss of nutrient in the soil. In consequence, the nutrient is not available to the crop, leading to a decrease in land productivity. The land user perceived that the erosion contributes to the degradation of stream water quality as the sediment load in the river increases, thus contributing to the siltation of the river and change of water color or increasing the turbidity of water in the stream. This has a direct impact on the livelihood of people who use the water river for bathing and livestock consumption. The consequences of erosion are also felt in the settlements where soil erosion contributes to the destruction of infrastructure such as houses. People perceived that the flooding was also a consequence of water erosion in their locality. Findings presented in Table 4.81 further revealed that the perception of consequences in the Kalehe territory depends on the health zone (X-squared = 60.931, df = 27, p-value = 0.0001989).

Table 4.81: Perceived consequences of soil erosion in Kalehe territory.

Main consequences/Effect of erosion	Health zones				Territory
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Soil loss from farmland	15.9%	18.2%	9.7%	11.5%	14.1%
loss of fertility	8.5%	17.4%	16.5%	41.0%	20.1%
Decrease in productivity of the land	36.6%	29.8%	41.7%	24.4%	33.3%
Reduction of soil depth (shallow soil depth)	11.0%	9.9%	4.9%	2.6%	7.3%
Decrease quality of stream water (waterlogging, siltation of rivers)	3.7%	6.6%	9.7%	7.7%	6.2%
Soil become coarser and stony	3.7%	4.1%	1.9%	0.0%	2.6%
Reduction of farm plots size	12.2%	7.4%	9.7%	3.8%	8.3%
flooding	2.4%	3.3%	2.9%	0.0%	2.3%
Destruction of infrastructure and habitation	6.1%	2.5%	1.0%	3.8%	3.9%
Not aware	0.0%	0.8%	1.9%	5.1%	1.8%
Chi-square test	X-squared = 60.931, df = 27, p-value = 0.00019				

4.5.5. Respondent's perception of the adoption of conservation measures

4.5.5.1. Status of adoption of soil and water conservation measures

The adoption of soil and water conservation practices to cope with the problem of erosion in the Kalehe territory is low. Findings presented in Figure 4.66 show that only 43.0% of the respondents have adopted at least one conservation measure to cope with the problem of erosion.

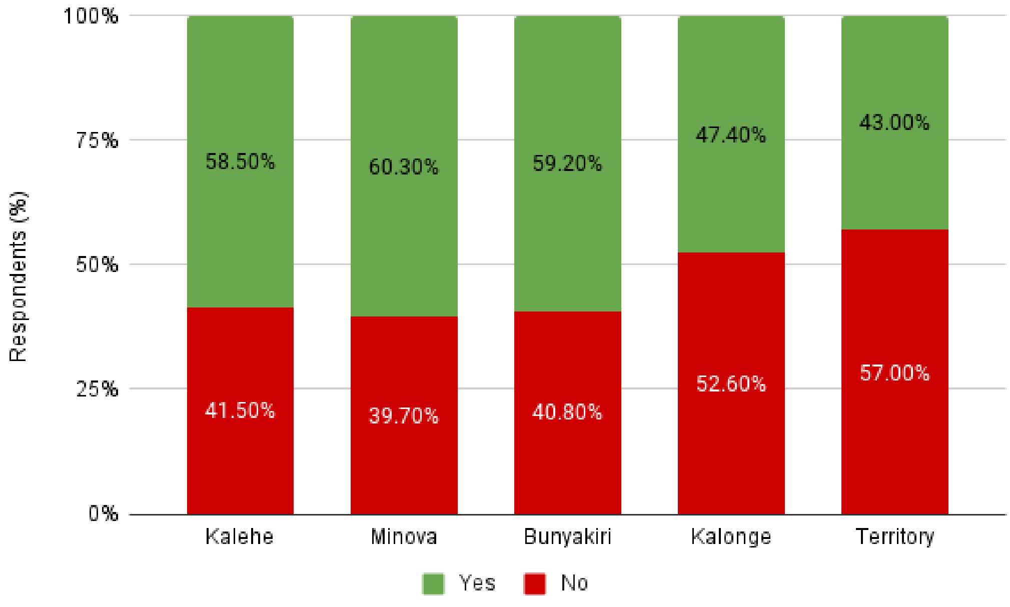


Figure 4.66: Barplot showing the respondent's adoption of soil and water conservation measures to cope with the problem of erosion in Kalehe territory.

At the health zone level, the percentage of adoption of conservation measures is 60.3% in Minova, 59.2% in Bunyakiri, 58.5% in Kalehe, and 47.4% in Kalonge (Figure 4.66), However, the Pearson's Chi-squared test of independence shows that the adoption of conservation practices does not depend on the health zone (X-squared = 3.7458, df = 3, p-value = 0.2902). To cope with the problem of erosion, physical and agronomic conservation practices can be adopted. In the Kalehe territory, only the trenches and drainage ditches are physical conservation measures adopted by 17.2% of the respondents, and other physical measures such as terracing were not adopted as can be seen in Table 4.82.

Table 4.82: Adopted soil and water conservation measures in Kalehe territory.

Conservation measures	Percentage of repondents		Chi-Square test		
	No (N%)	Yes (N%)	χ2	df	p-value
Agroforestry and tree planting	79.90%	20.10%	137.76	1	<0.001
Vegetative cover/mulching	70.30%	29.70%	63.38	1	<0.001
Grassed bounds/ Brushwood fence	89.30%	10.70%	237.51	1	<0.001
Trenches and drainage ditches	82.80%	17.20%	165.38	1	<0.001
Weeding/fallow	65.90%	34.10%	38.76	1	<0.001
Intercropping/Multiple cropping	73.20%	26.80%	82.51	1	<0.001
Crop rotation	87.80%	12.20%	219.01	1	<0.001
At least one conservation	57.00%	43.00%	7.59	1	0.006

In Kalehe territory, people implement drainage ditches at the border of their plots to delineate the limit of their plots and to prevent the livestock from accessing the crop. However, these trenches are also important as they prevent the runoff from reaching the farmland and constitute conservation measures. It is also found that the main agronomic practices that are applied are fallow (34.10% of adoption), mulching (29.70% of adoption), and intercropping (26.80% of adoption). The fallow is mainly applied to recover the soil fertility but people indicated that the fallow land is less vulnerable to soil erosion compared to active cropland. The mulching is mostly applied to conserve the humidity of the soil during the dry season. That is the primary motivation indicated by the community. Intercropping and crop rotation are also used to improve the productivity of the land. Agroforestry and tree planting are implemented by only 20.1% of the respondents. They indicated that their motivation for tree planting is to delineate their land, have a supplement source of fuel wood, and contribute to the reduction of erosion in marginal land. People did not recognize the importance of agroforestry in the improvement of soil fertility rather they planted trees mostly to have firewood or to mark the limit of their farmland plots. The grassland bund is applied by only 10.7% of respondents who consider it as an option to reduce the runoff in their farmland and prevent erosion. Other people noted that their main motivation to implement the grass-bound fence at the border of their plot is to demarcate the limit of their land and to prevent the livestock from consuming their crops. The Figure 4.67 presents the soil and water conservation practices observed from the field.

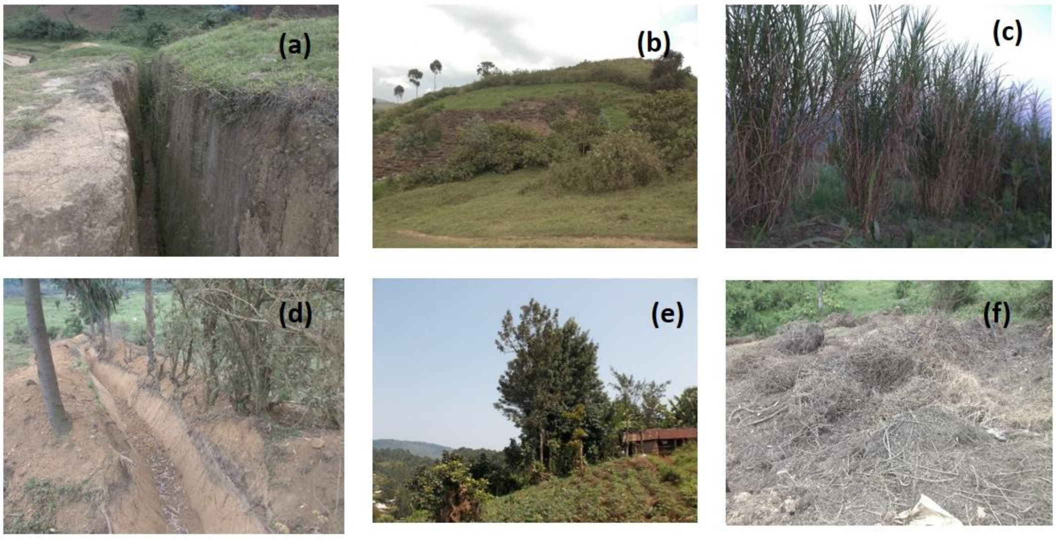


Figure 4.67: Adopted soil and water conservation measures in Kalehe territory.

Key: A and D. Trench and drainage ditches B. Brushwood fence C. Grassed bounds E. Agroforestry.

4.5.5.2. Determinant of adoption of conservation measures

In order to identify the factors that influence the decision of farmers to adopt the soil and water conservation practices, the logistic regression model was used. In this model, the adoption of soil and water conservation was used as the dependent variable (adoption=1, non-adoption=0), and the socio-economic characteristics as independent variables. The result of a logistic regression model, including the regression coefficient (B), the Wald test, the standard error (SE), and the significance levels (p-value) are presented in Table 4.83.

Table 4.83: Logistic regression model estimates for adoption conservation measures to cope with land degradation in Kalehe territory.

Variables	β	S.E.	Wald	Sig.	Exp(β)
Age (AGE)	-0.515	0.225	5.247	0.022*	0.598
Sex (SEX)	0.263	0.255	1.059	0.303	1.300
Marital status (MAR)	-0.151	0.270	0.314	0.575	0.860
Household size (HSIZE)	0.377	0.179	4.429	0.035*	1.457
Main activity (ACTIVITY)	-0.159	0.151	1.107	0.293	.853
Education (EDUC)	0.343	0.143	5.778	0.016*	1.410
Stayed period (RESIDENCY)	-0.419	0.193	4.705	0.030*	0.658
Farmland size (FSIZE)	-0.047	0.172	0.075	0.785	0.954
Distance to farmland (FDIST)	-0.294	0.148	3.938	0.047*	0.746
Land ownership (TENURE)	-0.179	0.143	1.556	0.212	0.836
Farming seniority (FEXPER)	0.475	0.148	10.235	0.001**	1.608
Slope of farmland (SLOPE)	0.432	0.165	6.851	0.009**	1.540
Farmland productivity (FPROD)	-0.014	0.150	0.009	0.926	0.986
Participation in training (TRAINING)	2.307	0.425	29.540	0.000**	10.049
Constant	-0.648	0.529	1.501	0.221	0.523
Model chi-square (χ2)	97.031				
Model Nagelkerke R^2	0.30				
Model correct prediction	70.6%				

*β: Estimated coefficient; SE: Standard error; R^2: Coefficient of determination; Exp(B): odds ratio, R^2: Coefficient of determination. *, ** significant at 5% and 1% level of significance, respectively.*

Regarding the performance of the developed model, the outputs of the Omnibus likelihood ratio test statistic indicated that the chi-square (χ2) exceeds the critical value (97.031) at p-value < 0.001 with 15 degrees of freedom, suggesting a good fitness of the model. The success of the overall prediction indicated that the nine determinant variables have sufficiently explained the land user adoption of conservation practices with a correct prediction value of 70.6%. Correctly predicted adopters and no adopters of the model are 72.1% and 64.8%, respectively. The model explained 30.6% (Nagelkerke R^2=0.306) of the variation in the adoption of conservation practices.

The results from the above Table 4.83 reveal that the size of the household (p=0.035), the education level (p=0.016), participation in training in soil and water conservation (p=0.017), farming seniority (0.001), the slope of farmland (p=0.009) are the factors that positively influence the adoption of conservation measures while the age (p=0.022), stayed period in the territory (p=0.030), distance to farmland (p=0.047), are the factors that negatively affect the adoption of soil and water conservation in the Kalehe territory. These factors and their influence on the decision of farmers to adopt conservation practices are presented in Figure 4.68.

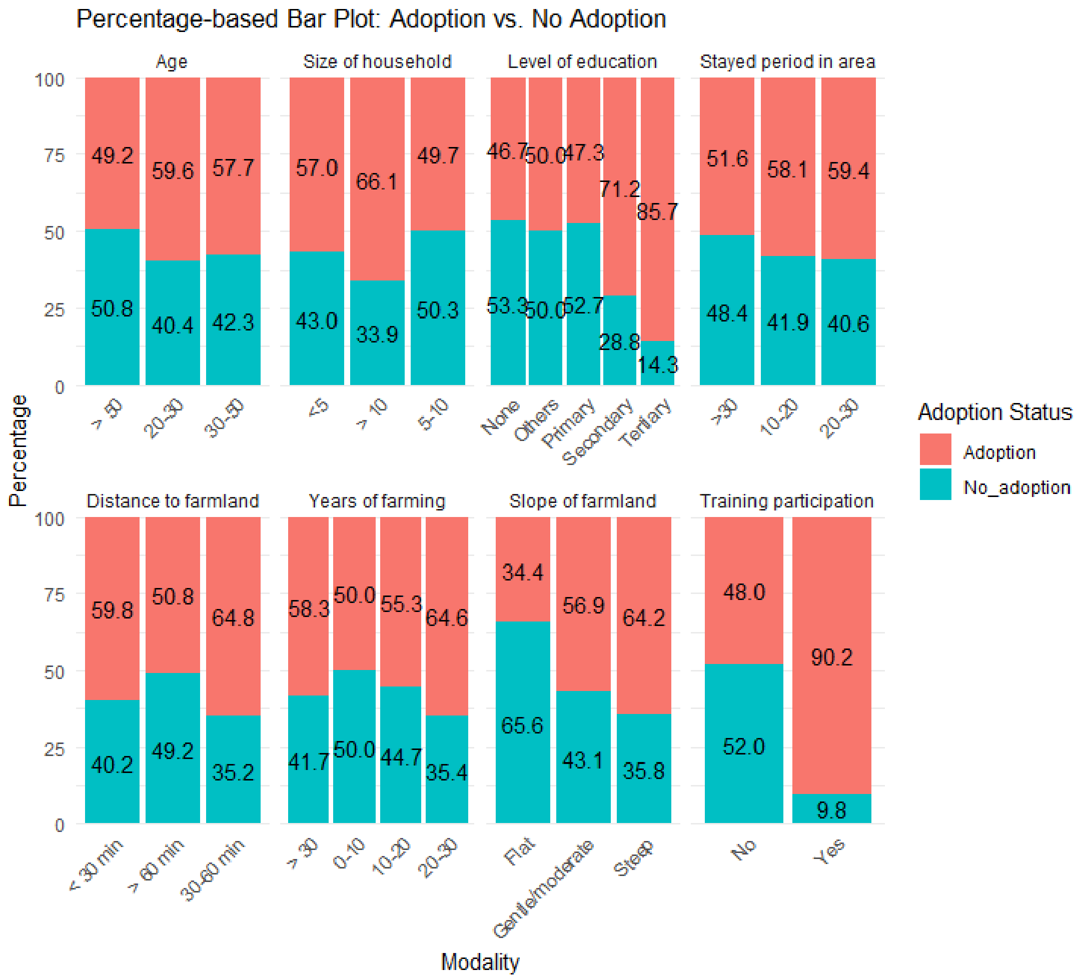


Figure 4.68: Barplot showing the determinant factors of adoption of soils and water conservation (SWC) practices in Kalehe territory.

Age and residency period negatively influence the adoption of conservation practices but the farming seniority positively influences the adoption of conservation practices (Table 4.83). Indeed, field data demonstrated that 59.6%, 57.7%, and 49.2% of people with ages ranging from 20 to 30 years, 30 to 30 years, and more than 30 years adopted the soil and water conservation measures (Figure 4.68). Furthermore, it was found that 58.1% of people who have a residency period between 10 and 20 years, 59.4% of those with a residency period between 20 and 30 years adopted the conservation measures while only 51.6% of those who stayed in the area for more than 30 years adopted the conservation measures (Figure 4.68). However, people with farming seniority of 20 to 30 years (64.6%) and those with more than 30 years (58.3%) of farming experience were the highest adopters of conservation measures while people with farming seniority of less than 10 years (50.0%) were not among the least adopters of conservation measures (Figure 4.68). Then for the same group age, the adoption of conservation practices depends on the years of experience in farming. A senior farmer is more likely to adopt conservation practices by 1.6 times more than junior farmers (Table 4.85). Furthermore, the finding of this study reveals that the adoption of conservation practices increases with the size of the household as 66.1% of households with more than 10 people adopted the conservation measures while only 49.7% of those with 5 to 10 people adopted these measures (Figure 4.68). The value of the odds ratio shows that, if other factors remain constant, the likelihood of the land user adopting the conservation practices increases by 1.5 times when the size of the household increases from less than 5 individuals to more than 10 individuals (Table 4.83). The education level of the household head also increases the likelihood of the adoption of conservation measures. According to the value of the odds ratio, if other factors remain constant, the likelihood of adoption of conservation practices is 1.4 times higher for the literate than the illiterate

(Table 4.83). This is illustrated by the fact that 85.7% of people who have a tertiary level of education, and 75.2% of those with a secondary level of education adopted the conservation measures in their farmlands while only 47.3% and 46.7% of those with a primary level of education and illiterate, respectively adopted the conservation measures (Figure 4.68). Similarly, land user participation in training on conservation practices has a positive impact on the adoption of soil and water conservation practices. Being trained in conservation practice increases the likelihood of adoption of conservation measures by 10 times (Table 4.83). As illustrated in the Figure 4.68 above, 90.2% of people who participated in training about the implementation of conservation measures have adopted them whereas 48.0% of those who did not have access to extension services implemented the soil and water conservation measures in their farmland (Figure 4.68). Moreover, the slope of the land also positively influences this adoption. People with farmland on steep slopes (64.2%) are more likely to adopt the conservation practices compared to those with farmland on gentle slopes (56.9%) and flat areas (34.4%) as illustrated in Figure 4.68. Other factors such as the distance to farmland negatively influence the adoption of conservation measures. People who have a travel time of less than 30 minutes (59.8%) and those with a travel time between 30 and 60 minutes (64.8%) between the home and the farmland were among the highest adopters of conservation measures while those with a travel time of more than 60 minutes (50.8%) were among the least adopters of conservations measures.

4.5.5.3. Challenges for the adoption of soil and water conservation

It was established that different factors can explain the low adoption of conservation practices in the Kalehe territory. Among them, the lack of training (34.4%) and lack of technical support (17.7%) are the most dominant as illustrated in Table 4.84.

Table 4.84: Challenges for the adoption of soil and water conservation.

Challenges for adoption of soil and water conservation	Health zones				Territory
	Kalehe (N=82)	**Minova (N=121)**	**Bunyakiri (N=103)**	**Kalonge (N=78)**	**Total (N=384)**
Requires investment (money, equipment)	11.0%	24.0%	10.7%	6.4%	14.1%
Requires more labour (work)	12.2%	8.3%	10.7%	25.6%	13.3%
Lack of technical support	18.3%	9.9%	25.2%	19.2%	17.7%
Reduced cropland (Small land size)	12.2%	9.9%	5.8%	3.8%	8.1%
Lack of training (Not familiar with the technique)	31.7%	31.4%	36.9%	38.5%	34.4%
Technique not allowed in rented plot	11.0%	11.6%	8.7%	5.1%	9.4%
Large distance from the house to the plot	3.7%	5.0%	1.9%	1.3%	3.1%
Chi-square test	X-squared = 43.245, df = 18, p-value = 0.000739				

Another constraint is financial as 14.1% indicated that they are aware of the techniques but they lack financial support to implement the conservation practices. Another constraint is related to land tenure issues in the area. Some techniques like tree planting and the grass-bound fence were not allowed in the rented plot as reported by 9.4% of respondents. Field findings further (Table 4.84) showed that there existed a dependency between the challenges for the adoption of conservation practices and the health zone in the Kalehe territory (X-squared = 43.245, df = 18, p-value = 0.0007388).

CHAPTER FIVE

DISCUSSION

5.1. Introduction

The chapter discusses the results of the study about both the specific objectives and theoretical background of the study. Thus, it presents the discussion of the findings on the LULC dynamics, the land productivity dynamics, the ecosystem service dynamics, and the soil erosion dynamics as a proxy of land degradation in the study area. It further discusses the application of the GIS-based AHP for land degradation vulnerability modeling, the adaptative land use planning to the land capability in response to land degradation, the determinants of community perception and adoption of conservation practices. Finally, the findings resulting from field observation, remote sensing, spatial modeling, and community perception are integrated into the DPSIR framework to suggest relevant strategies for mitigating land degradation in Eastern DR Congo.

5.2. LULC change dynamic and its implication on land degradation

5.2.1. Uncertainty of the LULC classification

The LULC maps were derived from the classification of annual Landsat image composites which are appropriate for areas characterized by high cloud coverages in Central Africa (Basnet & Vodace, 2015). The overall classification accuracy of classified images which was attained is 82.41%, 83.67%, and 85.71% for the years 1987, 2002, and 2020 respectively. The land use map of the year 2020, exceeds the standard overall classification accuracy level of 85% which is generally used (Anderson, 1976; Foody, 2012). However, the overall accuracy of the LULC maps of the year 1987 and 2002 fall below this threshold. The low overall accuracy of the classified images of 1987 is associated with the low user accuracy of cropland (68.42%,) and grassland (64.21%,) as well as its producer accuracy of 62.89%. The uncertainty in the classification of cropland can be associated with the fact that the study area is dominated by smallholder farmer who practices their activities on less than 1ha of land. Considering the coarse spatial resolution of the Landsat data (30 by 30 meters), a misclassification of some land use classes that are smaller than the pixel size may occur. Furthermore, the grassland and some croplands within the Eastern DR Congo region may have similar reflectance characteristics, which could potentially result in the misclassification of these two classes. The remaining LULC classes, including forestland, built-up land and shrubland have individual user and producer accuracy which exceeds the threshold of 70% (Thomlinson *et al*., 1999; Foody, 2012). These findings signify a good agreement with field observation, thereby substantiating the reliability of the classification system. Despite the uncertainty in the classification, the value of overall accuracy of the LULC maps which exceeds 80% is generally considered acceptable. Furthermore, all the classified Landsat images have a Kappa index values ranging from 0.80 to 0.83. In reference to the classification proposed by Monserud (1990), a Kappa value ranging between 0.70 and 0.85 indicates a very good agreement between the field observation and the classified images. In order to improve the accuracy of classification, future studies on LULC dynamics in Eastern DR Congo should take into consideration the utilisation of high-resolution satellite images such as Sentinel, QuickBird, IKONOS, or SPOT.

5.2.2. Historic trends in LULC changes

The LULC trend analysis shows spatial and temporal changes through the period of analysis. The study reveals that in the 1987-2020 period, forest land, grassland, and wetland have declined in area coverage, while agricultural land and built-up land have been increasing. These observations are consistent with other LULC dynamics studies which was carried out in other parts of the DR Congo which show that deforestation, expansion of smallholder agriculture, and built-up expansion are among the main proximate drivers of land use changes in this country (Bamba, 2010; Ciza *et al*., 2015, Molinario *et al*., 2020, Shapiro *et al*., 2021). It was also found that the forest land has the largest surface cover over the 1987-2020 period. However, this land cover shows a declining trend, from 56.25% in 1987 to 47.02% in 2020. This corresponds to an annual rate of deforestation of 0.50% per year which is higher than the national estimated rate ranging from 0.2% to 0.3% per year (Kengoum *et al*., 2020). Furthermore, deforestation increased from 0.15% per year (7.95km^2/year) during the 1987-2002 period to 0.36% (14.66km^2/year) per year between 2002-2020, indicating that the pressure on the forest ecosystem has been increasing over time. The decreasing of forest land is associated with the expansion of shrubland, cropland, and built-up land.

Shrubland constitutes the second most prevalent land use category in the study area. Its surfaces increased from 24.56% in 1987 to 28.41% in 2002 and 31.43% in 2020. The increment of shrubland was concomitant to the expansion of forest land, cropland, and wetland. In this region, people practice slash and burning agriculture and when the farmland becomes unproductive, local farmers tend to abandon in favor of other area, especially forest land and old fallows. These lands are perceived as fertile by local farmers and are often choosen as agricultural endeavors. The majority of the shrubland observed in this territory is composed by old fallows that were abandoned by the farmer and where natural regeneration took place. On the other hand, agriculture constitutes the main economic activity that contributes to the livelihoods of local communities in Eastern DR Congo but it is recognized as one of the main drivers of deforestation in DR Congo (Molinario *et al*., 2020, Shapiro *et al*., 2021).

During the 1987-2020 period, the agricultural area underwent significant expansion, increasing from 3.2% to 7.54%. This growth exhibited with an annual increasing rate of 5.68km^2/year or 4.53%/year. The expansion of agriculture led to the encroachment of forestland, shrubland (old fallows), grassland, and wetland which were subsequently drained for cash crop production purposes. In addition, the settlements presents an upward, increasing from 1.89% to 9.36% with an annual growth rate of 11.96%/year or 9.40km^2/year. This consistent increase in both cropland areas and settlement areas is related to the fact that LULC changes are associated with population growth. This region has been subjected to demographic changes with an increase in population since 1994 with the arrival of Rwandan refugees in search of land for agriculture and pasture for livestock. Consequently, there was encroachment of forest land to the benefit of anthropogenic activities. Furthermore, with the boom of artisanal activities in this territory, the mineral wealth and the reputed fertile soil of this territory have attracted people. In addition to that, the high plateau of this region contains pastureland which attracts pastoralists for livestock keeping. This region has an annual population growth rate of 3.3%, characterised by a high population density reaching 300 inhabitants/km^2. In contrast, the western part of the country exhibits a density of around 30 inhabitants/km^2 (Ngeleza, 2012). This ever-increasing population implies that there is an increasing demand for products and services to meet the needs of this population. Furthermore, there is a correlation between deforestation and population growth in DR Congo (Tyukavina *et al*. 2018).

5.2.3. Future trend of LULC changes

The LULC changes projections under the business-as-usual (BAU) scenario portrayed how the future LULC will occur if the past trend continues. Under this scenario, the projected land use pattern indicates that forest land would continue to dominate the land cover with 41.31% in 2030 but it will decrease to 41.20% in 2050 and 38.16% in 2070. These results show that DR Congo will not achieve its REDD+ commitment to stabilizing its forest cover to 63.5% at the national level by 2030 (Kengoum *et al*., 2020). Overall, the LULC projection suggests that the expansion of development activities (cropland and built-up) would continue at the expanses of forest land even in the protected area. Thus, land use conflicts are likely to occur in the future due to an incompatible interest among the land user's stakeholders in this region. Furthermore, the decreasing forest cover will result in the fragmentation of species' habitats, this situation can lead to human-wildlife conflicts and constitutes a threat to the biodiversity of this region. In addition to that, there is a correlation between deforestation and the rate of erosion in the Kivu region (Karamage *et al*., 2016). The Deforestation combined with the expansion of cropland which is the greatest contributor to soil loss by erosion in this area could result in the recrudescence of erosion problems, siltation of rivers, and sediment loads into the aquatic ecosystem. The projected LULC maps show the areas where deforestation, urban expansion, and cropland expansion are likely to occur.

5.2.4. Spatial pattern of underlying drivers of LULC change

The understanding of LULC changes dynamics and theirs underlying drivers is important to design sustainable land management strategies (Opiyo *et al*., 2022). The analysis of the spatial relation between the underling drivers and the majors LULC changes observed in the study area demonstrated that the slope, altitude, soil type, population density, proximity to the road, proximity to artisanal mining, proximity to the locality, and conservation zoning are the major underlying drivers of LULC changes in the Kalehe territory. However, the drivers of LULC changes varied across specific LULC changes. For instance, the susceptibility to deforestation is mainly determined by factors such as the conservation zoning, the proximity to roads, the proximity to artisanal mining, the population density, and soil type. In contrast, the expansion of cropland is contingent upon the slope gradient, the slope aspect, the distance to localities, the distance to artisanal mining and conservation zoning, while the built-up land expansion is determined by the altitude gradient, the soil type, the population density, the proximity to road networks, and the conservation zoning.

The implementation of conservation zoning measures through the implementation of the National Park of Kahuzi-Biega and the Forest Reserve of Sud-Masisi) has a negative influence on deforestation occurrence. However, the increased accessibility to the major's infrastructures and communities' agglomerations (villages) has been found to increase the level of deforestation. Furthermore, the proximity to artisanal mining sites increases the risk of deforestation whereas the zoning of mining concession has no significant effect on deforestation. This observation is in line with the assumption posited by Geist & Lambin (2001) that socio-economics factors are the prominent underlying drivers of tropical deforestation. The deforestation pattern is also influenced by the soil type. For instance, deforestation is high on happlic acrisols compared to humic cambisols and the humic ferrasols. Conversely, the topographic variables such as altitude, slope gradient, and aspect have been observed to be positively associated with deforestation but this relation is not statisticaly significant.

The expansion of built-up areas expands more in areas that are characterized by high altitudes. Although the slope does not significantly influence this expansion, it has a negative effect on the expansion of the built-up area. The soil type has also a positive effect on this expansion. It is the most important factor affecting the expansion of the built-up area with an odd ratio of 2.3 indicating that the expansion of the settlements is likely to occur 2.3 times on happy acrisols compared to humic cambisols and the humic ferrasols. The population density also influences positively the expansion of settlements. This situation can be illustred the observation that the built-up area has increased at a greater rate in regions characterized by high population density. The proliferation of artisanal mining sites in the territory have favored the expansion of settlement around the mining sites. This pattern is also evident in the context of road network, where the settlement expansion is more likely to occur in areas close to road networks compared to areas that are distant from them. However, the presence of conservation zoning has a negative affects on the occurrence of built-up area expansion in the study area.

The expansion of cropland during the 1987-2020 period was found to be positively influenced by the slope gradient. During this period, the cropland underwent an expansion to areas characterized by a high slope gradient. Indeed, due to the scarcity of land and the competition for land resources in the study area, there is an expansion of cropland activities in marginal areas which are subject to erosion and landslides. The insolation has also an influence on cropland expansion as evidenced by the slope aspect which significantly influences the expansion of cropland in this area. With regards to the proximity factors, it has been established that the expansion of cropland is influenced by the proximity to the market which can be considered as a proxy for transportation costs (Serneels & Lambin, 2001). The present study found that the distance to localities is a determining factor of cropland expansion. The results show that cropland has a high probability of expansion in the vicinity of a locality or village. The distance to artisanal mining sites exhibits the same pattern. These results are in adequation with the assumption that the cropland is likely to expand further from the market center into rural areas (Kipkulei *et al*., 2022). However, conservation zoning has a negative influence on the expansion of cropland in the study area due to the restriction on practices of agricultural activities in these areas.

The expansion of shrubland depends on topographic factors such as altitude and slope aspects. The altitude has a negative influence on this expansion whereas the slope aspect influences it positively. The probability of occurrence of shrub land expansion is high at low altitudes compared to high altitudes in the study area. Soil type constitutes an additional biophysical factor that influences this expansion. The expansion of shrubland is more probale on haplic acrisol than in humic cambisols and ferasols. The distance to roads has been demonstrated to positively influences this occurrence. The probability of expansion is directly proportional to the distance from rivers. However, a divergent pattern emerges for proximate drivers, such as the distance to road networks and distances to artisanal mining sites. The presence of shrub land expansion is particularly notable in close proximity to road networks and artisanal mining sites.

A thorough evaluation of the performance of the best fitted models indicated that the AUC has an overall value of 0.746 for the deforestation model, 0.82 for the built-up area expansion model, 0.813 for the cropland expansion model, and 0.685 for the shrubland expansion model. All the developed models have AUC values that are significantly different from 0.5 (p-value<0.001), thereby indicating that the model performs better than the chance (Hossein, 2019) in discriminating the area where there is LULC change from those characterized by no change. In addition to that, the percentage of accurate predictions of the best-fitted model which indicates the percentage of corrected predicted points from the total of points considered in the sample was 87.9% for the deforestation model, 86.2% for the built-up expansion model, 95.1% for the cropland expansion model and 80.1% for the shrubland expansion model.

All the developed models exhibit a percentage of correct prediction that exceeds 50% indicating the outcomes predicted by the model are accurate.

The pseudo-R-square (measured with the Nagelkerke R^2) indicated that the deforestation model explained betweem 17.5% and 18.3% of the variability of forest conversion. In contraste, the built-up expansion model accounted for 28.2% and 29.0% of the variability. On the other hand, the cropland expansion model explained between 19.3% and 21.9% of the observed variability while only 16.7% to 18.2% of variability was explained in the shrubland expansion model. Thus, the variability of LULC changes vary between 16.7% for the weakest model and 29.0% for the best-performing model. The low explanatory power of the developed models can be associated with the fact that many drivers that can explain the LULC changes were not incorporated into the model due to a lack of spatial data. For instance, the cultural drivers (public attitudes, values, and beliefs), institutional drivers (change in land use tenure, policy change), technological factors (technological level of farmers, Agro-technological changes, net agricultural trade per capita, percentage of agricultural production exported, agro-technological changes, use of bioenergy), demographic drivers (population growth or density, urban population growth, rural population growth, migration), economic drivers (GDP per capita, annual income or GDP growth, market growth, poverty, accessibility to markets, distance to roads, distance to urban centers, distance to rivers, travel time center) and biophysical drivers (elevation, aspect, curvature, soil type, soil quality, soil pH, soil CEC, average humidity, rainfall), temperature, geological units, degree of erosion, topographic wetness index) may explain the variability of LULC conversion. However, some drivers were not incorporated into the models due to the absence of spatial data. In particular, there is an interaction between the cultural, political, and economic drivers that influence each other, and is difficult to capture this interaction in the models (Geist & Lambin, 2001). Furthermore, the influence of underlying drivers of LULC change is scale-dependent (Birhanu *et al*., 2021). However, the assessment of the effect of spatial scale on the relationship between LULC changes and their drivers goes beyond the scope of this study. Further study should assess the impact of the scale on the performance of the model and include the LULC change models by including the potential drivers that were not included in this analysis.

5.2.5. Implications of LULC changes on land cover degradation

LULC change is recognized as an indicator of land cover degradation arising from anthropogenic activities (Bär *et al*., 2023). In the Kalehe territory, there are substantive LULC changes that contributed to the loss of green covers such as forest land and grassland as well as the encroachment of wetland at the expanse of anthropogenic land use such as built-up land expansion and cropland expansion. Indeed, during the 1987-2020 period, the highest net area which increased in Kalehe territory were built-up area (349.82km^2), shrubland (285.27km^2), and cropland (187.56km^2) while the highest net losers were forestland (383.17km^2), grassland (315.29km^2) and wetland (75.18km^2). Using the LULC change as an indicator of land degradation, it was found that, between 1987 and 2020, about 34.17% (1424.79km^2) of the study area was subjected to land cover degradation and compared to the baseline situation of 2020, it is projected that 28.28% of the land would be degraded in 2030, 27.28% in 2050, and 33.65% in 2050 if the past trend of land use change continues in the future. This land cover degradation depicts the areas that are vulnerable to adverse processes such as erosion, loss of biodiversity, and other ecological disasters due to the loss of green cover. In particular, the degradation of forest ecosystems can have adverse impacts on the livelihood of the population, biodiversity, and climate (Shapiro *et al*. 2021). when there is a transformation of undisturbed land such as natural forest into more intensive land use such as farming, grazing and timber harvesting, a loss of biodiversity is likely to occurs (Semenchuk *et al*., 2022). Furthermore, the expansion of cropland associated with the increase in food demands contributes to the overexploitation of fragile ecosystems leading to the propagation of land degradation and loss of natural diversity (Kipkulei *et al*., 2022). In the study area, the adverse impact of land cover degradation is already felt by local communities. Such impacts include the scarcity of basic forestry products such as fuel wood, charcoal, and timber, and no forest timber products such as mushrooms, fruits, and medicinal plants. The disturbance of the natural ecosystem due to LULC change have also the potential to reduce carbon sinks; accelerate surface water runoff and soil erosion; to contribute to the disruption of the water cycle, essentially the groundwater recharge and discharge. This demonstrates that there is a need to implement sustainable land use management planning. In this perspective, planning for land degradation neutrality (LDN) implies avoiding, reducing, and reversing land degradation (Cowie *et al*., 2018). In this context, to achieve the LDN target, the implementation of sustainable management practices is important to reduce ongoing degradation and reverse past degradation through restoration and rehabilitation practices in the land already degraded. Currently, this degraded land which needs the rehabilitation of green cover represents 34.17% (1424.79km^2) of the territory. In addition, it is necessary to avoid degradation in the land which are not degrading (stable land) which represents 58.72% (2448.25km^2) of the territory. Therefore, it is necessary to determine the parts of the territory which have a high likelihood of occurrence of land cover degradation. The model of land degradation susceptibility can help to identify the areas that have a high probability of degradation and where the intervention should be priories to prevent the degradation. In this study, a logistic regression model was developed to map the area with high susceptibility to land cover degradation by considering a set of biophysical and socio-economic factors as independent variables. Considering the occurrence of land cover degradation between 1987 and 2020, the model reveals that the odds of land cover degradation increased at high altitudes, in mining concessions, in areas close to locality, rivers, roads, and artisanal mining sites, and in areas characterized by high-density of population but the probability of land cover degradation diminishes in conservation zones. These variables significatively influence the susceptibility of land cover degradation and explain 41.50% of the variability. Considering the underlying drivers of land cover degradation identified in the context of this study, conservation efforts should be focused on the high-altitude zones, the area close to artisanal mining sites, rivers, and roads which are more vulnerable to land cover degradation. Furthermore, the highest susceptibility to land cover degradation was found in the mining concession indicating the necessity for the restoration of degraded land in those areas. These results are consistent with the fact that, land cover degradation is caused by a synergy of natural and anthropogenic factors (Vu *et al*., 2014).

The results of this study indicate that the LULC changes in Kalehe territory are a complex and dynamic process that is driven by multiple factors including the biophysical, conservation, population, and accessibility factors that vary spatially and temporally. The quantification of this dynamic and its causes can help to inform relevant land use policy. Therefore, policy interventions need to target both the indirect and direct drivers of LULC, their spatial and temporal variations, and consider the interactions and feedback among these factors and their impacts on the environment and society. The results also show that the prominent LULC changes are deforestation, built-up area expansion, cropland expansion, and shrubland expansion. These changes have potential impacts on the ecosystem services, biodiversity, carbon stocks, erosion, and greenhouse gas emissions in this region. Therefore, policymakers should design and implement land use management policies that take into account the drivers and patterns of LULC changes at the territorial level in Eastern DR Congo. These policies should aim to promote sustainable land use practices that balance the socio-economic needs of the local communities and the environmental conservation objectives. One of the possible policy options is to implement REDD+ (Reducing Emissions from Deforestation and Forest Degradation) programs. REDD+ is a global mechanism that provides financial incentives for developing countries to reduce greenhouse gas emissions from deforestation and forest degradation, and to enhance forest carbon stocks. REDD+ can help to conserve the forest resources, biodiversity, and ecosystem services in Kalehe territory, as well as to improve the livelihoods of forest-dependent communities through benefit-sharing arrangements. REDD+ can also contribute to achieving the SDGs (Sustainable Development Goals) related to poverty reduction, food security, climate action, and environmental protection. However, the implementation of REDD+ faces several challenges in this region, such as weak governance, land tenure insecurity, lack of data and monitoring systems, and competing land use demands. Therefore, policymakers should address these challenges by strengthening the institutional and legal frameworks, clarifying the land rights and responsibilities, improving the data availability and quality, and engaging the stakeholders in participatory planning and decision-making processes, It is in this context that the spatial modeling results obtained as part of this study can be used to prioritize locations for the implementation of REDD+ policies by determining forest locations likely to be deforested in the future and by developing strategies or action plans to reduce pressure on forest ecosystems in this region. Nevertheless, there is a necessity to improve the LULC prediction by integrating the community perspectives and local knowledge about the land use changes in the spatial analysis through the application of Public Participation GIS (PPGIS) techniques. Policymakers should also consider the spatial variability of the drivers and patterns of LULC changes in this region, and tailor the REDD+ interventions to the specific contexts and needs of different health zones and land use categories. Policymakers should also integrate REDD+ with other land use management policies, such as spatial planning, agricultural intensification, urban development, and mining regulation, to ensure coherence and synergy among different policy objectives. By doing so, policymakers can help to cope with the LULC change problem in Kalehe territory and improve the sustainability of land resources and rural livelihoods in this region.

5.2.6. Extent and drivers of land productivity degradation

This study attempted to quantify the dynamics of land productivity and identify the hotspot of vegetation degradation and its underlying drivers based on the trend of Landsat-derived NDVI during the 1987-2020 period in Eastern DR Congo. Similar approaches have been applied in other African countries. Indeed, an understanding of the trends of land productivity and the driving forces behind these trends is essential to provide informed decision-making about potential interventions and prioritizing efforts to cope with the land degradation problems (Vu *et al*., 2014, Muhoyi *et al*., 2023). The results of this study demonstrated that about 31.25% of the territory presents a decline in land productivity. This proportion is higher compared to the proportion of 15% at the global level and 22% in Africa of land characterized by a decrease in land productivity between 1999 and 2013 (de la Fuente *et al*. 2020). Nevertheless, the land productivity dynamics vary according to the LULC types in the study area as it was found also in Tanzania, Kenya, Ethiopia, and Malawi (Kirui *et al*., 2021). For instance, 40.01% of shrubland, 36.27% of wetland, 31.58% of cropland, 30.36% of grassland, and 20.89% of forestland are characterized by a decrease in productivity. This decrease of land productivity is negatively correlated with the extent of forest cover but positively associated with the extent of bare land, built-up land, shrub and grassland. This result seems to be similar with the results of Lestariningsih *et al*. (2018) in Indonesia who find that the forest cover has a high correlation and regression towards critical and very critical land. Indeed, the forest cover provides a good cover on steeps slopes, resulting in the small land degradation. This supports the finding from Gao and Liu (2010), who states that the deforestation associated with the built-up expansion, overcultivation on steeps slopes, overgrazing, and excessive reclamation of grasslands for farming purposes are among the factors that contributes to land degradation.

The underlying drivers beyond the decrease in land productivity can be ascribed to both biophysical and anthropogenic factors (Muhoyi *et al*., 2023). Understanding these causatives drivers is important to find solution and to design cause-targeted strategies to cope with land degradation (Vu *et al*., 2014). To quantitatively assess the impacts of these factors, the results of the model of land productivity degradation as a function of biophysical and socio-economic factors indicated that the altitude gradient, the proximity to the administrative center, proximity to artisanal mining, proximity to the river, and occurrence of mining concession are the significant factors that contribute to the decrease of land productivity in this area. It was found that the altitude presents a positive relationship with the occurrence of degradation of land productivity. The area located at high altitudes is likely to be affected by land degradation compared to the area located at low altitudes. This result is in accordance with the observation from Lestariningsih *et al*. (2018) who noticed that the high elevation and high slopes gradient often resulted in lightly degradation. The results show that the probability of degradation is high in areas close to the major's administrative center, artisanal mining sites, and rivers. This accessibility factors reflects the effects of anthropogenic factors on the occurrence of land degradation which is recognized to be accelerated by human activities. The high susceptibility associated with the proximity to rivers can be explained by the fact that riparian vegetation is more vulnerable to anthropogenic pressures. On the other hand, the anthropogenic activity exerted by the artisanal miners before doing the mineral extraction such as the clearing of vegetation, and the demand for other land resources such as timbers for camp constructions, firewood energy, or wood to support the mining tunnels contributes to pressures on natural resources in the surrounding of artisanal mining sites (Bucekuderhwa *et al*. 2012; Macháček 2019). Thus, exacerbating the decrease in land productivity. In addition, the administrative center constitutes the economic pools in the study area. It is in this center where the market is localized and these centers are among the highly densely populated. People come from the locality (village) to the center for access to the market. This implies that there is a high demand for natural resources in the surrounding environment of the administrative centers to meet the needs of the population concentrated on their economic activities.

5.2.6. Perceived ecosystem service value variation over LULC changes

While many studies use the biophysical and economic approaches during the valuation of ecosystem services in ecosystem services to identify the priority hotspot for conservation (Raymond *et al*., 2009), this study incorporated local knowledge in the assessment of ecosystem services to provide a perceived ecosystem service value. Considering the advantage of the land use-based decision approach which include the rapidity, simplicity, cost-effectiveness as well as the possibility to assess the effect of land use change on ecosystem service supply (Tasser *et al*. 2020), the LULC maps were considered as the basic spatial information to define the boundary of the ecosystem service to be valued. Thus, the ecosystem service matrix approach was used to map the potential supply of ecosystem service across the Kalehe territory, by using the average potential value perceived by the local community per ecosystem service rather than using the value proposed in the literature considering the data transferability is limited as the ecosystem service assessments are context specific (Luederitz *et al*. 2015). This approach is essential to understanding how humans value the ecosystem and this information can be used for the management of the ecosystem. Although the approach adopted in this study used household survey data to provide an assessment matrix that links local knowledge about the ecosystem service value and LULC, the study has some limitations as it has not taken into account other landscape factors such as geomorphological characteristics and pedoclimatic variables to assess the capacity to supply the ecosystem services. The consideration of these biophysical characteristics in the analysis was beyond the scope of this study. These factors can be integrated into the evaluation by using empirical models like the InVEST model. In addition to that, the valuation of ecosystem services can be perceived differently by stakeholder groups (Koko *et al*., 2020) and it is important to understand the changes in ecosystem services preference by all stakeholders who are engaged in the co-management of natural resources (Kilonzi & Ota, 2019). For instance, Githiora-Murimi *et al*. (2022), found that the score provided by environmental conservation experts in the evaluation of ecosystem services of different LULC types in Yala swamp (Kenya) was significantly higher than the one provided by local resource users such as farmers and fishermen. Thus, it should be necessary to examine to which extent the valuation of ecosystem service differed from different stakeholder perspectives and assess the agreement of the results from the ecosystem service valuation matrix from the results of the empirical modeling. However, local knowledge of indigenous people and local expert opinion is recognized as important in the assessment of ecosystem service management (Esmail *et al*., 2023). Indeed, the incorporation of local knowledge about people's dependency on land cover type in decision-making can help to identify the tradeoffs in land use allocation such as forest versus agriculture land or settlements, and reduce the burden on a particular land cover type (Chaudhary *et al*. 2017). Another limitation of the assessment made in this study concerns the spatial resolution of the images used to obtain the LULC maps. It is important to use images of high spatial resolution such as sentinel and spot to have more details about the spatial pattern of the ecosystem. Notwithstanding these limitations, the ecosystem service matrix-based approach is commonly used in the mapping and assessment of ecosystems in areas where local or regional data for assessment are scarcely available (Martınez-Harms and Balvanera 2012), where data requirements limit the application of more refined methods. Furthermore, this study used the logistic regression model to understand the interaction between the landscape pattern (structure and composition) and the perceived ecosystem value. This approach is useful in establishing models to determine the optimal landscape structure and composition that should be adopted during land use planning to enhance the provision of ecosystem services. Furthermore, a trend analysis of the ecosystem service maps from the past period (1987-2020) and the present period allowed us to identify the areas that were characterized by a decreasing trend, decreasing and stability of ecosystem services supply. This information is important to make informed decisions during future land use planning and to prioritize interventions for conservation.

The analysis of the relationship between LULC categories and ecosystem services value is crucial to clarify the impacts of land use changes on ecosystems considering the change rates of different LULC categories can cause large or small changes in ecosystem services value (Zhang *et al*., 2022). The results of the assessment matrix indicated that the forestland and wetland have the highest ecosystem service value compared to other LULC types, Similar results have been found in another context (Chaudhary *et al*. 2017, Tasser *et al*. 2020, Esmail *et al*. 2023). However, the analysis of the LULC changes from 1987 to 2020 demonstrated that the aerial extent of these ecosystems decreased at the expense of cropland and built-up areas. This situation is expected to continue in the future (2030-2070 period). Our analysis of the impact of LULC change on the potential supply of ecosystem service revealed that the overall supply of ecosystem service has been decreasing over time. During the 1987-2002 period, the overall potential supply decreased by 3.46% while in the 2002-2020 period, it decreased by 5.83%. Overall, during the 1987-2020 period, the supply potential of ecosystem services decreased by 9.09%. The results also revealed that the largest decrease was observed for provisioning service (-12.9%), followed by regulating service (-12.37%) and supporting services (-11.93%). This implies that the availability of natural resources has decreased sharply due to the LULC change occurring in the study area. Furthermore, due to a decrease in regulating and supporting services, hydro-meteorological risks such as floods and erosion have become more recurrent in the study area. Only the cultural service increased by 5.3%. This situation can be associated with the fact that the forestland and wetlands which are perceived to have a high value for different ecosystem services decrease drastically during the study period. Furthermore, people perceived that the supply of provisioning services and supporting services depends mostly on forest land and wetlands, while the supply of the regulating service depends mostly on the wetlands and grasslands. In contrast, a high dependency on built-up are is observed for the supply of cultural services. Although forestland, wetland, and grassland are vital for regulating and supporting services, they decreased during the study period. The frequent flash floods, landslides, and erosions in recent years that occurred in this study area can be associated with the reduction of these services. In fact, the reduction of green cover contributes to the reduction of water infiltration and increases surface water runoff. Similar findings concerning the reduction of regulating and supporting services resulting from changes in LULC were found in other regions of Africa such as Kenya (Wangai *et al*., 2019) and Madagascar (Dave *et al*. 2017).

Since the local knowledge of ecosystem services can be linked to the LULC maps, it is possible to analyze the trend in the supply of ecosystem services to support the decision-making process and to monitor policy by ensuring that the changes implanted on the ground align with the objectives of stakeholders and decision-makers (Esmail *et al*., 2023). The trend analysis of the ecosystem service potential maps shows that, from 1987 to 2020, 28.44% (1177.62km^2) of the territory presented a general decrease in the supply of ecosystem service, indicating that this area is undergone land degradation. It was observed that the area affected by the degradation of ecosystem service increased from 28.74 (1190.26km^2) during the 1987-2002 period to 30.71% (1271.74km^2) of the territory during the 2002-2020 period. Under the business-as-usual scenario, this situation is expected to continue in the future as the degradation of ecosystem service supply potential would increase from 28.44% for the Baseline situation (1987-2020), to 31.37% in the 2020-2030 period, 30.87% in the 2020- 2050 period and 48.79% in the 2020-2070 period indicating that the land degradation neutrality target (situation where the amount of the land degradation is low or equivalent to the baseline situation) will not be reached by the year 2030 and the situation will be worsened by the year

2070. Thus, there is a need for sustainable land use management to avoid this situation to occur.

This study also attempted to assess the influence of the landscape pattern on the potential supply of ecosystem services to determine the optimal landscape structure and composition that should be adopted during the land use planning process to enhance the supply of ecosystem services. The results indicated that both the landscape composition and structure influence the perceived ecosystem service value in this territory. Indeed, the proportion of the forest in the landscape has the most influential positive power on the overall ecosystem service value, emphasizing the need for natural vegetation protection in ecologically fragile ecosystem during urbanization process as suggested by Fang *et al*. (2022). Concerning the landscape structure metrics, among the fragmentation index, both the patch density (PD) and the edge density (ED) are negatively correlated to the potential supply of ecosystem service. These landscape metrics reflect the intensity of human intervention in the landscape and the fragility of the ecosystem (Yushanjiang *et al*., 2018). A similar finding was observed by Chen *et al*. (2022) in China. However, the Aggregation index (AI), the cohesion index (COHESION), the Mean patch size, and the Large Patch Index which indicate the degree of consolidation of land are positively associated with the perceived ecosystem service value. In contrast, the landscape diversity index (Simpson diversity index and Shannon diversity index) is negatively correlated to the ecosystem service supply potential indicating that the increase of landscape heterogeneity and the diversification of anthropogenic activities such as built-up expansion and cropland expansion have negative effects on the ecosystem service supply potential. These results corroborate the finding from Yushanjiang *et al*. (2018) who found that the Patch Density and Shannon diversity index negatively affect the provision of ecosystem service. Within this study, it was also found that the ecosystem service supply potential was positively influenced by the Perimeter-area fractal dimension (PAFRAC) and Shape index (SHAPE_MN) which are indicators of patch shape's complexity, indicating that the more complex and irregular shape of patches, the more the ecosystem supply potential. In addition to that, it was found that the mean Euclidian distance between the landscape patches and the Interspersion and Juxtaposition index (IJI) is negatively correlated to the ecosystem service supply potential, indicating that the isolation of patches has a negative influence on the supply of ecosystem services. The finding of this research aligns with a previous study which indicated that the landscape metrics significantly influence the ecosystem service supply but these effects vary from one location to another. For instance, Liu *et al*. (2020) have found that the increase of the Shannon diversity index in the landscape could contribute to the improvement of the average ecosystem service value while in this study we find a negative influence of the Shannon diversity index on the potential supply of ecosystem services. Since landscape composition, fragmentation, and shape complexity are determinant factors of ecosystem service potential, these parameters should be integrated into landscape planning and land use allocation (Chen *et al*. 2022).

The analysis of the interaction between the ecosystem service and landscape metrics allows us to understand the effect of landscape patterns on the ecosystem and this information can be used to guide land use planning toward the improvement of ecosystem protection policymaking (Liu *et al*. 2020, Ersoy Tonyaloğlu, 2025). More particularly, in the case of the study area, an emphasis should be placed on the conservation of blue (wetland) and green cover (forestland, shrubland, and grassland) which have a high potential to supply the ecosystem service. Furthermore, during the land use planning process, it is necessary to increase the mean patch area through land consolidation and the aggregation of patches to reduce land fragmentation and enhance the potential of the landscape to supply ecosystem services. At the same time, it is necessary to reduce the diversity or heterogeneity of the land use classes but maintain the shape's complexity and connectivity of landscape patches in the study area. In addition, the developed models which show the relationship between the landscape metrics and the perceived ecosystem service value will allow policymakers to perform continuous tracking and monitoring towards the assessment of the impact of land use transformation on ecosystem services and to determine appropriate management's strategy to reduce the negative impact of anthropogenic activities on ecosystems.

5.3. Soil erosion dynamics

5.3.1. Impact of LULC changes on soil erosion dynamics

High variation in the amount of soil loss was observed in the territory of Kalehe. This variation is induced by the R, K, LS, C, and P factors included in the RUSLE model. The study area is more erosive with an R-factor value of 6025 MJ.mm/ha.h.yr which is greater than the global average of 2100 MJ.mm/ha.h.yr derived by Panagos *et al*. (2017) and 4623 MJ.mm/ha.h.yr in the Lake Kivu basin. This higher value of rainfall erodibility depicts the aggressivity of rainfall to induce erosion in this region. This erosivity increased with the elevation of altitude has the spatial distribution of rainfall in the study area is significantly dependent on the variation of altitude. Thus, the high rainfall erosivity is observed in the northern and southern parts of the territory which is dominated by a high plateau (altitude>2000m) while the lowest erosivity is observed in the lowland plateau observed in the western part of the territory. This territory is also vulnerable to erosion due to the dominance of steep slopes (15-30%) and very steep slopes (>30%) which represent 36.09% and 36.04% of the territory respectively. The value topographic factor LS has a mean value of 5.67 which is higher than the value of

4.79 found in the Lake Kivu basin by Karamage *et al*. (2016). The high value of LS factors is found in the area dominated by the high gradient of slope in the territory. The nature of the soil also constitutes a major factor that influences the dynamic of soil loss by erosion in the territory of Kalehe. The soil erodibility factor K which is related to soil properties has a mean value of 0.018 t.ha.h/ha.MJ.mm at territorial level but it varies according to the soil types in this area. The haplic acrisols which dominate in the northern part and southern part of the territory present the highest erodibility while the lowest erodibility is observed in the humic cambisols which dominate the western part. These natural factors contribute to the soil vulnerability to water erosion in this territory. In addition to these natural factors, anthropogenic factors associated with land use systems have influenced the dynamics of erosion during the 1987-2020 period. This includes the cover management factors (C) and the support practices (P) which depend on the LULC changes. The value of C factors has increased from 0.041 in 1987 to 0.046 in 2002 and 0.058 in 2020, indicating that the land vulnerability to erosion processes has increased over the last 33 years. The increase in C value over time is related to the deforestation at the expanse of cropland and built-up land which are occurring in the study area. Under the business-as-usual scenario, this situation would continue in the future. The C factor would increase from 0.062 in 2030 to 0.063 in 2050 and 0.066 in 2070. This increase in the value of C factors depicts the increase of the vulnerability to erosion as a lower value of C-factor is likely to generate low erosion compared to higher C-value which increases the rate of erosion. Considering the factor P, the implementation of soil and water conservation practices is not effective in the study area. Field observation indicated that the small holders' farmers practice mulching and fallowing as soil and water conservation options but these measures are not effective in controlling erosion in this sector. Taking into account all these factors the average soil loss estimated in the territory of Kalehe moved from 32.08 t/ha/year in 1987 to 44.35 t/ha/year in 2020 and this pattern would continue in the future as a result of LULC change. This increasing pattern of soil erosion associated with the LULC change is in agreement with the observation at global scale (Borrelli *et al*., 2017, Borrelli *et al*., 2020) and regional scale (Karamage *et al*., 2016, Eisenberg & Muvundja, 2020, Chuma *et al*., 2022b). The current rate of erosion in the Kalehe territory is comparable to the rate of 40.4t/ha/year found by Eisenberg & Muvundja (2020) in the Ruzizi basin but it is higher compared to the value of 30 t/ha/year found by Karamage *et al*. (2016) in the Lake Kivu basin and 24 t/ha/year in Chisheke watershed (Territory of Walungu) by Chuma *et al*. (2022b). These similitude and differences can be attributed to the variation of local topographic conditions, and the land use pattern. In the territory of Kalehe, the highest rate of erosion was observed in the barren land and cropland while the lowest level was observed in the forestland, shrubland, and grassland. Additionally, the cropland and shrubland were the highest contributors to soil loss by erosion in this territory. A similar observation was done in this region by previous studies (Kamarage *et al*., 2016, Eisenberg & Muvundja, 2020, Chuma *et al*., 2022b). Thus, there is a necessity to increase the green cover and to implement soil and water conservation measures in agricultural land to reduce the erosion problem in this area. Under the current situation, 50.33% of the territory has an annual soil loss higher than the tolerable limit of 10t/ha/year for the tropical region (Bamutaze, 2015) which should be prioritized for the implementation of soil and water conservation measures. The scenario analysis indicated that strip cropping, agroforestry and terracing are the most effective soil and water conservation practices that should be implemented in the cropland to decrease the rate of erosion in this territory. Since, the cropland and the shrubland are the most contributors to the overall soil loss in this territory, the implementation of agroforestry in cropland, and the conversion of shrubland and bare land to forest plantation constitutes a practical solution to reduce the erosion. These measures have also a potential improve the livelihoods of people. More particularly, the implantation of agroforestry and forest plantation can improve the soil quality and enhance the food security (Lee *et al*., 2017). The vulgarization of these methods is then necessary. Furthermore, this study demonstrated how the LULC change has an impact on past, present, and future patterns of erosion. Even though the LULC changes contributed to the increase of erosion in the study area, it should be noted that the impact of LULC change can also be positive if there is a spatial and temporal increase in vegetation cover (Wijitkosum's, 2012, Kulimushi *et al*., 2021).

5.3.2. Impacts of landscape pattern on soil erosion dynamics

Understanding the interrelation between the landscape metrics and ecological process constitutes one of the core issues in landscape ecology. Indeed, the landscape pattern (structure and composition) is the result of the effects of human and natural factors. Thus, any change in the landscape pattern may impact the ecological process. The results of this study show that the rate of soil erosion within the study area is significantly influenced by the landscape characteristics. Both the fragmentation index (patch density and edge density) and diversity index (Simpson and Shannon diversity index), the interspersion and juxtaposition index are positively correlated with erosion rate. In contrast, there is a negative correlation between the mean patch area, the largest patch index, the cohesion index, and the aggregation index. These results suggest that the intensification of fragmentation of land, the increase of heterogeneity of patches, the increase of the isolation of patches, and the weak connectivity of patches increase the rate of erosion in the study area. Although we find a positive correlation between the diversity index and the rate of erosion, other studies have found a negative correlation (Ouyang *et al*. 2010, Xu *et al*. 2017). Thus, the results are context-specific and highlight the complexity of the relationship between landscape metrics and erosion (Shi *et al*. 2013). In the case of this study, the positive impact of land diversification on erosion can be associated with human-dominated land use such in the landscape as cropland and built-up areas which are more vulnerable to erosion processes. Furthermore, it was found that the shape index is positively correlated to the annual rate of erosion while the mean perimeter area ratio and perimeter-area fractal dimension are negatively correlated to it, indicating that the increase in the complexity of landscape patches contributes to the decrease of erosion rate. These findings follow the assumption that the occurrence of many heterogeneous patches of different LULC categories is likely to accelerate soil erosion at the landscape scale (Shi *et al*. 2013). The positive relation between the land fragmentation indices and the rate of soil erosion indicated that fragile landscape is more prone to erosion. Similar results have been found by Shi *et al*. 2013 and Xu *et al*. (2017) in China. The implication of these findings from a land management perspective is that during the land use planning process, to prevent and control erosion in the future, it should be better to optimize the spatial structure of the landscape by reducing the land fragmentation and the heterogeneity of patches through land consolidation and by increasing the complexity of patches shapes. Considering that these metrics are sensitive to the change in landscape, the model of soil erosion modulus on landscape level index was obtained. The results from the step-wise regression model indicated that the edge density, the mean patch size, the Shannon diversity index, and the mean perimeter-area ratio were the most influential variables in explaining the relationship between the landscape structure and the rate of erosion. These landscape metrics which can be derived from LULC maps can be used to predict and monitor the rate of erosion over time at the watershed level in this territory where the gauging stations are not available. However, the coefficient of determination shows that the landscape structure metrics explained only 34.89% of the variability of erosion rate while the landscape composition has explained 60.9% of variability, indicating that the landscape composition metrics are most influential compared to landscape structure metrics. The remaining variability can be explained by the topographic, climatic, and edaphic factors which were not incorporated in the developed model despite that they influence the dynamics of erosion.

This study demonstrated that the dynamics of erosion are significantly influenced by the landscape composition and structure. However, there are some limitations. First, the RUSLE model was primarily conceived to estimate the soil loss derived from rills and sheet erosion. Besides, the amount of soil erosion derived from the gullies and river bank erosion are not incorporated in this model. Secondly, this study has not assessed the effect of seasonality on the dynamics of erosion despite that the region has a bimodal climate. Thirdly, although we found that the LULC type has a significant influence on the soil erosion dynamics, the effect of landscape metrics on erosion rate has not been determined at the LULC class-scale level. Only landscape scale level metrics and patch scale level metrics were considered in this analysis. Thus, further research should be focused on the assessment of the impact of seasonality and class-level metrics on the dynamics of erosion in this territory.

5.4. Land degradation vulnerability modeling for restoration planning

5.4.1. Land degradation vulnerability assessment

The assessment and modeling of land degradation are essential for the sustainable management of natural resources and conservation planning (Sandeep *et al*., 2021, Das *et al*. 2023). It requires the use of multilayers and multidisciplinary approaches to identify the factors that influence land degradation vulnerability. These factors can be used to model and assess the land degradation vulnerability with good efficiency by using the GIS, remote sensing data, and the Analytical Hierarchy Process (Mzuri *et al*., 2022). In this study, the potential use of the AHP approach in a GIS environment was used to assess the land degradation vulnerability at the territorial level in Eastern DR Congo. This region is severely affected by physical degradation processes such as gully erosions and shallow landslides which have major physical and economic impacts (Heri-Kazi, 2020, Maki *et al*. 2022). Therefore, there is a necessity to identify the hotspot of land degradation where conservation actions are needed.

The land degradation is complex, and it is influenced by a synergy of causes including natural and anthropogenic driving factors (Mzuri *et al*., 2022). In this study, both biophysical and socio-economics factors of vulnerability were used. Thematic layers of these factors were given weight according to their importance using the AHP. For the biophysical factors, the slope gradient, soil type, and rainfall intensity were identified as the most influential factors of vulnerability. The slope gradient was ranked as the most influential factor of the physical degradation process considering that the susceptibility to soil erosion increases with the increase of slope gradient. The study area is dominated by steep slopes which make it vulnerable to erosion and landslides. A high rate was given to the soil type considering that the soil texture plays a significant role in the susceptibility to surface water erosion. The territory is dominated by clayey soil which is characterized by low permeability and is favorable to surface water runoff generation. The mean annual rainfall was selected as the third parameter as the erosion and shallow landslides are triggered by high rainfall intensity in this region. In addition to these natural factors, the primary socio-economic factors of vulnerability are population density, the occurrence of mining concession, the proximity to artisanal mining sites, proximity to locality, and proximity to roads. On the one hand, the increase of population induces a high pressure on natural resources.

The developed model of the land degradation vulnerability index as a function of biophysical and socio-economic factors presented a good accuracy in predicting the area with high vulnerability to physical land degradation processes such as shallow landslides and erosion. The land degradation vulnerability map obtained by using the AHP and the geospatial modeling approach was categorized into five: very low, low, moderate, high, and very high vulnerability zones covering 29.28%, 18.35%, 20.41%, 26.73%, and 5.28% of the territory, respectively. This vulnerability zonation at the territorial level constitutes the basis for the identification of priority areas for the implementation of landscape restoration to cope with the problem of degradation. For restoration planning purposes, the area can be categorized into three priority zones: high priority (high and very high vulnerability), moderate priority (moderate vulnerability), and low priority (low vulnerability).

The very low to low vulnerability zone represents 47.63% of the total surface, predominately covering the western part of the territory. These categories are mainly attributed to the high forest coverage, the low altitude gradient, the low rainfall intensity, and the dominance of cambisols which are least susceptible to soil erosion in this area. Similarly, other researchers have found that very low to low land degradation vulnerability occurs in areas characterized by high vegetation coverage, essentially the dominance of forestland, adequate rainfall, and well-drained soils (Sandeep *et al*., 2021, Yadav *et al*., 2022).

About 20.41% of the territory is prone to a moderate level of vulnerability, essentially at the edge of forest land. This zone is essentially covered by less vegetation coverage dominated by shrubland and grassland, moderate rainfall, and moderate altitude. This is consistent with previous studies on land degradation vulnerability which demonstrated that a moderate level of vulnerability is associated with sparse vegetation cover, little rainfall, and moderate temperature (Mzuri *et al*., 2022, Tolche *et al*. 2022, Yadav *et al*., 2022).

The high and very high vulnerability zones covering about 32.01% of the territory are already affected by a high to very high vulnerability to land degradation. The major degradation occurs in the Eastern and Northern parts of the territory due to erosion accentuated by high rainfall intensity, and rugged terrain dominated by steep slopes and high plateau. In addition to that, this part of the territory is characterized by a high population density which implies a high pressure on natural resources. It was observed that a high level of degradation occurred in the highly populated area which deserves urgent attention for remediation actions. Furthermore, the presence of artisanal mining sites, the intensification of cropland activities on steep slopes, and deforestation have accentuated the land degradation vulnerability in this area. Within the study area, there is a zonation of vulnerability zone which increases with the increase of distance to forest edge and increase of population density suggesting that improper land use is one of the major causes of land degradation in this territory. Similar findings were obtained by Sandeep *et al*. (2021) and Mzuri *et al*. (2022) who reported that inadequate rainfall, less vegetation coverage, problematic soils, high slope gradients, and land of adequate conservation measures are among the primary causes of degradation.

The results derived from the application of the developed land degradation vulnerability model can be used by policymakers to direct attention to the hotspots of land degradation in the study area. During the planning, knowledge about the spatial pattern of land degradation vulnerability zones can be used to assign adequate resources to the more vulnerable areas (Kizito *et al*., 2018). The areas characterized by a high to very high vulnerability constitute the hotspots of degradation where soil and water conservation initiatives and sustainable land resources management should be prioritized (Yadav *et al*., 2022). To achieve land degradation neutrality by 2030, there is a necessity to implement restoration initiatives in the areas characterized by very high and high vulnerability degraded land avoid degradation in areas characterized by very low vulnerability, and improve the land use management to avoid further degradation in the moderate and low vulnerability zones. Considering that improper land use is one of the major causes of land degradation in the study area, there is a necessity to adapt the land use to its land capability to avoid further degradation.

This study provides insight into the capability of MCDA based on the AHP and IPC vulnerability frameworks in predicting the land degradation vulnerability zones in the study area with good accuracy in Eastern DR Congo. However, the performance of the developed model compared to the machine learning model (Random Forest, Classification and Regression Tree, Support Vector Machine, Gradient boosting machine, etc), statistical model (Frequency ratio, logistic regression), or hybrid model combining the AHP and machine learning technics have not been assessed despite that Das *et al*. (2023) have proposed that the combination of the machine learning and AHP would improve the accuracy of the land degradation vulnerability models. Future research should focus on the verification of this assertion to determine the best model adapted to the context of the study area.

5.4.2. Land capability assessment for sustainable land use planning

The evaluation of the land suitability (land use potential) or land classification for specific utilization such as crop, livestock operations, and other purposes is imperative for sustainable land management and land use planning (Beek *et al*., 1997, Taveira *et al*. 2021). Indeed, the understanding of the relation between land use and land capability classification provides some insights in terms of sustainable utilization of natural resources (Gülersoy *et al*., 2015). Thus, failure to use land within its capacity leads to adverse consequences such as land degradation (Gulersoy *et al*., 2017). In the Kalehe territory, the current land use is unsustainable since there is a mismatch between the land capability and their uses. For instance, the land capability classes I to IV which are suitable for farmland activities account for 76.67% of the territory. However, the agricultural land covers only 7.54% of the area as per the current situation of land use. Furthermore, it was observed that 25.40% of farmland is located in the land capability class V despite that this class is suitable for forest plantation as it is located on very steep slopes which are vulnerable to soil instability. It was also found that 77.27% of built-up land was allocated within the high and moderate land capability classes which should be allocated to agriculture. This weak allocation of agricultural land according to its land capability can result in a reduction in cropland productivity (Abou-Najem *et al*., 2019). Considering that most of the lands in Kalehe territory are suitable for agricultural productivity, it is preferable to relocate the built-up land and pasture land to no arable land and low-productive land to support agriculture for the upcoming years. Under the current situation of land use, about 9.97% of the territory that falls under the land capability V is allocated to other land use such as cropland activities, pasture (grassland and shrub), and built-up up despite that this area should be allocated to afforestation. This situation leads to an increase in degradation processes such as landslides and erosion which are reccurent.

The understanding of the difference between the current land use and land capability is an important step in land degradation assessment (Bachri *et al*., 2021). Within the study area, 15.88% of the land is not used within its land capability and has the potential to cause degradation. This mismanagement of land occurs mostly in the eastern part of the territory where there is an expansion of anthropogenic activities such as cropland expansion, pasture expansion, and built-up land expansion. The expansion of these anthropogenic land uses in steep slopes contributes to environmental degradation. This area is already subjected to an increase in shallow landslides, erosion, and flash flooding. The analysis of the frequency ratio of shallow landslides within the land capability classes shows that the landslides are likely to occur in the land capability classes V when they are not covered by forest cover and in land capability IV when soil and water conservation measures are not implemented. Steep slopes, rough soil texture, and low water holding capacity which characterize these classes contribute to the potential occurrence of landslides (Bachri *et al.*, 2021). Therefore, there is a necessity to adapt the current land use to its capability in future land use plans and adopt appropriate conservation measures to reduce the problem of land degradation in the territory.

The land capability maps could provide a good orientation about land use allocation and guide policymakers to develop crop management to increase land productivity and minimize environmental degradation (Abou-Najem *et al.*, 2019, Nguyen *et al.*, 2023). To achieve both the goal of environmental conservation and agricultural productivity within the study area, the current forestland and the wetland should be conserved. The most productive capability class (I to III) should be allocated to agriculture productivity while the least productive land (IV) can be allocated to pasture land and built-up expansion upon land suitability analysis. In contrast, the non-arable classes V should be afforested to increase the forest cover and to protect the steep slopes. By doing so, the current forest cover which is 48.12% of the territory, could increase to 58.09% and the current agriculture land which is 7.29% of the territory could increase to 19.21% with 11.47% of the land allocated to agricultural activities but requiring the implementation of conservation measures to control erosion and 7.11% which doesn't necessary require the implementation of soil erosion control treatments.

5.5. Conceptual model for land degradation management

During the last three decades, the Eastern DR Congo has been subjected to different environmental changes which affect the livelihood of the local community. It is therefore necessary to formulate a policy that takes into account the interplay between environmental, social, and economic factors. The DPSIR framework constitutes a holistic approach to assessing environmental problems for sustainable land use management. It is used to formulate policy based on complex environmental information. Considering the complexity of land degradation in Eastern DR Congo that was depicted in this study through the use of a triangulated approach combining field observation, remote sensing, GIS modeling, and community perception, the DPSIR framework was adopted to develop a conceptual model for land degradation management in the study area. The findings of this research are organized into themes which are presented using the component of the DPSIR framework. Figure 5.1 summarizes the results of the DPSIR framework in the study area with an emphasis on land cover degradation, soil erosion, the decrease in land productivity, and dynamics of perceived ecosystem services value as a proxy of the land degradation process for identifying the driving forces, the current states, the impact and the necessary policy responses to mitigate the land degradation in the study area . After that the different components of the DPSIR framework adapted to the reality of the study area discussed.

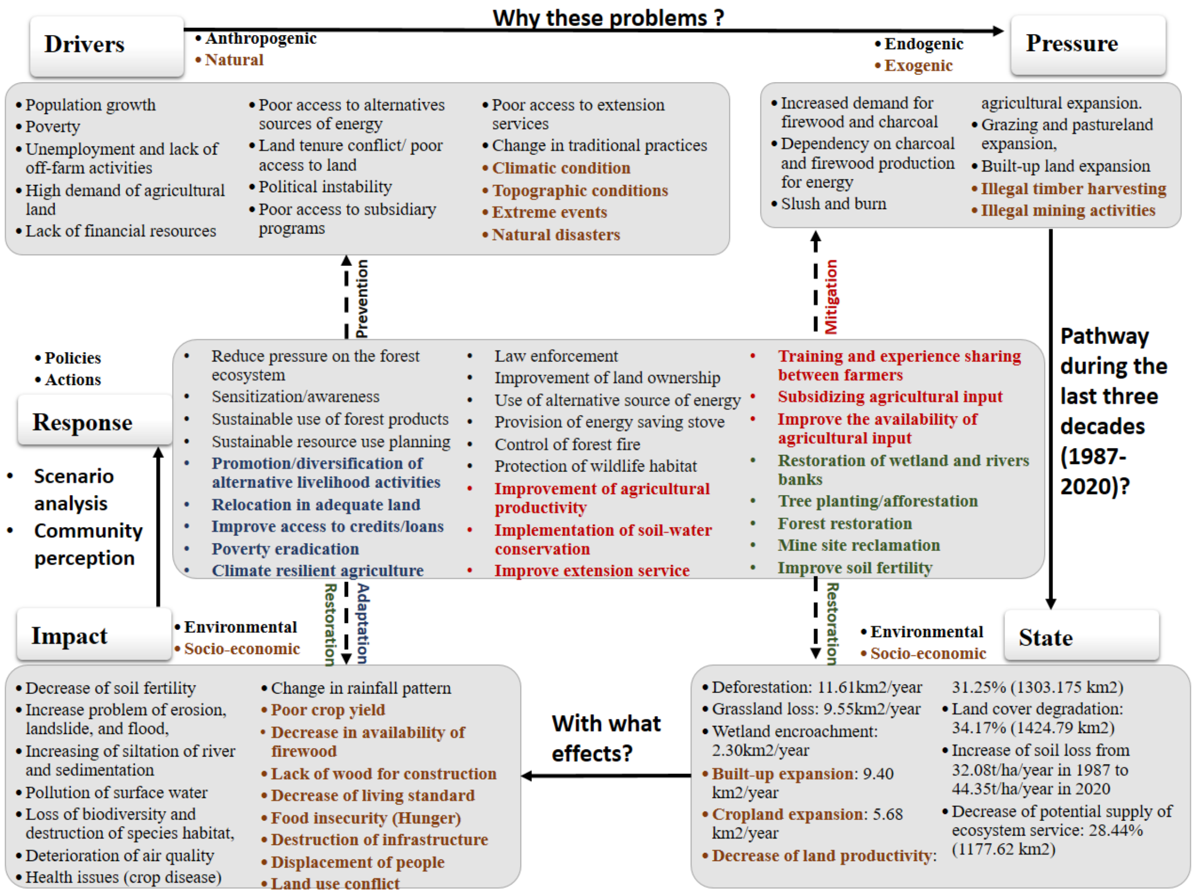


Figure 5.1: Conceptual model of land degradation management in Eastern DR Congo adapted from the DPSIR framework.

5.5.1. Drivers of land degradation

The driving forces of land degradation are the indirect drivers or underlying forces that contribute to activities with a direct impact on the environment. These underlying factors stimulate the proximate or direct causes of environmental change. The land degradation observed in the study area is the result of a combined association of demographic (population growth and immigration), socio-economic (poverty, increased demand for firewood and charcoal, unemployment and lack of off-farm activities, increased demand of agricultural land for food production, lack of financial resources), technological (poor access to alternatives sources of energy), socio-political (land tenure conflict, poor access to land and political instability), biophysical (climatic and topographic conditions), institutional (poor access to subsidiary programs and extension services), educational (lack of information and training about the better conservation options), and cultural (change in traditional practices such as the reduction of fallowing) processes. For instance, the results from the questionnaire survey have indicated that the indirect factors contributing to the forest degradation in the territory of Kalehe can be categorized in a hierarchical way as population growth and immigration, poverty, the increased demand for wood for charcoal production, and firewood which constitute the main source of energy, the lack of off-farm activities which lead to the expansion of agricultural land through the slash and burn practices, poor access to alternatives sources of energy, lack of financial resources, conflict, and political instability. These results resonate with similar study carried in sub-Saharan Africa which reported that population growth, poverty and high demand of natural resources are the main contributors to the LULC change and the associated degradation of ecosystem (Saguye 2017a, Saguye 2017b, Opiyo *et al*., 2022). These factors are intertwined and there is an interplay among them. Indeed, the population growth which is recognized as the main underlying driver of land degradation in this sector occurred with the arrival of immigrants in search of land for agricultural, pasture, and rush for artisanal mining activities following the political instability in this region. Furthermore, due to poverty and lack of off-farm activity, lack of agriculture input, and high cost of agriculture input, people continue to do unsustainable agricultural practices such as slash and burn agriculture which expand to forest land. The increase in population implies that there is an increase in demand for natural resources (Turner, 2009) such as wood energy and more land for agricultural productivity to feed people. In fact, during the flux of refugees in 1994, the population of Kalehe increased, and the pressure on the forest ecosystem due to the high demand for forest products especially firewood and wood for construction as well as forest cutting to obtain land for cultivation, land for settlements implementation and pasture lands. Furthermore, this study shows that in Kalehe territory, 40.9% of households have a household size ranging from 5 to 10 members and 33.1% of households have more than 10 members. This high size of households implies a high demand for natural resources. It was also found that more than 80% of respondents are farmers who depend only on selling their farming products to survive. They are not engaged in off-farm activities which could supplement them with supplement incomes. This situation leads to poverty and more pressure on forest resources which are overexploited. Charcoal production as well as slash-and-burn agriculture were also perceived as direct drivers of forest degradation in this area. People noticed that before the year 1994, charcoal production was not practiced at a large scale in this area. Therefore, forest degradation was low during this period. Only slash and burn activities were considered as a driver of deforestation but the fallow of more than four years was a norm, thus the pressure on the forest was low. However due to the population increase since the years 1994, land became scarce, and people tended to decrease the years of fallow to satisfy the high demand for crop production but this led to the degradation of soil fertility. Furthermore, the forest land which is perceived to have a high fertility came under pressure as people were looking for additional lands to exercise their slash-and-burn agriculture. It was in the year 2000s that charcoal production became prominent in the study area. People noticed that after the 1996 war "of liberation" and many rebellious movements that occurred after this period, people became poor and lost their livestock and other means of livelihood. So, in the 2000s, they found charcoal production as a rapid means to make money. It is in this period that the forest degradation becomes acute. In addition, people became engaged in timber harvesting which was artisanal during the period ranging from the 1990s to the 2000s.

However, in the period 2010s, the forest degradation became acute due to the release by the government of land tenure to “elites’’ who are reported by the respondents as “men with power” in the area. In fact, these “elites” people come with machinery and begun to do timber harvesting in a semi-artisanal way. Therefore, the remaining forest land becomes cleared. According to the respondent, after cutting the forest, the cleared forest was converted into pastureland. Respondent also noticed that “man with power” colonized their land by transforming it into pastureland. In addition to these factors, people indicated that the land tenure system constitutes a factor of land degradation in this study area. The limit and inadequate land are cited as the factors contributing to the decrease in farmland productivity as well as the increase in erosion. Indeed, the territory is characterized by rouged mountainous topography which constitutes a constraint for agricultural production. In consequence, there is pressure on the existing farmland. In addition, with the arrival of immigrants, the land has been scarce which make people exert their agricultural activities on marginal lands such as steep slopes which are prone to degradation process such as erosion and landslides. Furthermore, with population growth, there is land fragmentation because 53.1% of smallholder farmers do their agricultural activities on plots of less than 1ha.

There is also land tenure issues that impede the implementation of conservation practices as some conservation practices such as tree planting and agroforestry are not allowed in renting plot despite that 38.8% of respondents reported that they exert their activities on rented plots. The poor access to subsidiary programs and extension services are among the institutional factors which have been reported by respondents as indirect drivers of land degradation in their entity. Indeed, there is a paucity of information about the better conservation options which can be implemented for nutrient enrichment of soil other than the traditional tillage as well as the slush and burn agriculture which leads to a decrease in agricultural productivity.

The biophysical factors are also considered as an indirect driver of land degradation in the study area. For instance, the unreliable rainfall or inconsistent rainfall along the agricultural seasons and cultivation on the steep slope contribute to the degradation of land within the Kalehe territory. This observation is consistent with the fact that there are longer dryer spills as a consequence of climate change in the Kivu region (Ahana et al., 2024). Furthermore, due to the scarcity of land, farmers practice their activities on inadequate lands such as hillslopes which are prone to erosion. The erosion leads to the loss of topsoil which is important for agricultural activities.

There are also cultural factors like the change in traditional practices such as continued cultivation without fallowing or reduction of the period of fallowing which are contributing to farmland degradation and soil erosion. For instance, in the last time, the minimum duration of fallow was 4 years but due to the population growth and high demand of agricultural land for food production, the period of fallow has been reduced to 1 to 2 years. Other farmers noted that they do not continue to do fallow because of the land scarcity. This change of traditional practices without adequates alternatives leads to the depletion of nutrients in the soil and contributes to the reduction of farmland productivity.

Conflicts and activities of rebellion movements are exemples of socio-political factors which contribute to the massive displacement of the population are also among the cause of land degradation, especially forest degradation in the territory of Kalehe. This aligns with the results of Shapiro *et al*. (2021) who demonstrated that the occurrence of armed conflicts results in higher deforestation and forest degradation in DR Congo.

5.5.2. Pressure of land degradation

The pressure indicator of the DPSIR model indicates the directs effects of drivers or the direct causes of land degradation. They represent the actions or activities that result from the drivers and have a more immediate impact on the environment. They can be influenced by the internal dynamics and needs of the community or region (endogenic pressure) or they can results from external factors or interventions that impact the land and environment from outside (exogenic pressure). For instance, both the both illegal timber harvesting and illegal mining activities that occurs in protected area such as the National park of Kahuzi-Biega can be classified as exogenic pressures because they originate from external actors and forces that impose their activities on the land, leading to environmental degradation. Moreover, mining activities can be considered as exogenic pressure since they are typically initiated and conducted by external entities, such as mining companies, seeking to extract valuable minerals and resources from the land. These activities contributes to land disturbance, erosion, and pollution but the scale and impact of mining activities are often beyond the control of local communities.

The increasing land use pressure that occurred within the study area during the last three decades constitutes the primary force for the degradation of the natural ecosystem. The direct pressure toward vegetation cover degradation in the study area which was highlighted by the local community includes charcoal and firewood production, agricultural expansion, timber harvesting, overgrazing and pastureland expansion, settlements expansion, and expansion of mining activity to natural habitat. These results follow the remote sensing observation which shows that during the 1987-2020 period due to anthropogenic pressure, there was an expansion of cropland, built-up land, and shrubland at the expanse of forestland, grassland, and wetland. This observation aligns with the finding from Shapiro *et al*. (2021) who found that the high level of forest degradation in DR Congo is associated with the built-up area and demonstrated that the expansion of smallholder agricultural activities (Tyukavina *et al*., 2018) contributes to the most to deforestation in this country. Furthermore, the deforestation and destruction of natural habitats have been reported as the main drivers of change in the supply of ecosystem services. The forest land and wetlands are perceived to have the highest ecosystem service potential value. Thus, the destruction of these ecosystems due to expansion of anthropogenic activity leads to degradation. In addition, this land use change is perceived by land users as a direct driver of soil erosion in this area. People noted that the cropland and built-up land are the most vulnerable to erosion process in their entities while the grassland, shrubland, and forest land are the least vulnerable to erosion process. Other direct factors contributing to the exacerbation of soil erosion in the study area include improper tillage and missing or insufficient soil and water conservation measures.

5.5.3. State of land degradation

The state indicator of the DPSIR model indicates the current condition of the land. The LULC change, the land productivity dynamics, the dynamics of ecosystem service, and the dynamics of soil erosion were considered indicators of land degradation in this study. The observed change in LULC for the 1987-2020 period indicated that there is a decrease of forestland, grassland, and wetland at an annual rate of 0.5%/year or 11.61km^2/year, 2.04%/year or 9.55km^2/year and 2.04%/year or 2.30km^2/year. This decrease of green cover and encroachment of wetland is done at the expanse of anthropogenic LULC types such as cropland (4.53%/year or 5.68km^2/year) and built-up area (11.96%/year or 9.40km^2/year). Overall, during the 1987-2020 period, about 34.17% (1424.79km^2) exhibited a green cover degradation. Considering the land productivity dynamics, it was found that 31.25% of the territory is characterized by a decrease in land productivity, indicating that there is a degradation of the land productivity at a rate of 0.95%/year. The decrease in land productivity is variable according to the LULC category. For instance, throughout the analysis, 20.89% of forest land has been characterized by a decrease in land productivity while 31.58% of farmland shows a similar trend. This degradation of productive land is already felt by the local community which reported that there is a decrease in farmland yield productivity (68.8% of respondents) and scarcity of forestry products due to forest degradation (58.1%) which occurs in their entities. Using the trend of the perceived ecosystem service value, it was found that both the provisioning, regulating service, and supporting have decreased by 12.9%, 12.37%, and 11.93% respectively during the 1987-2020 period as a consequence of LULC changes. Overall, 28.44% (1177.62km^2) of the study area is characterized by a decreasing pattern of ecosystem service. Considering the soil erosion dynamics, it was found that the annual soil loss increased from 32.08t/ha/year in 1987 to 44.35t/ha/year in 2020, indicating that the soil is degrading. During this period, 39.10% (1617.33km^2) of the territory was characterized by an increase in soil loss. These spatial observations were confirmed by 61.2% of respondents who noticed that the erosion problem has increased over time in their territory. Furthermore, under the current situation, 29.81% of the territory is characterized by a soil loss which is higher than the tolerable limit of 10t/ha/year. Although the cropland represents only 7.60% of the territory, it contributes to about 37.56% of total soil loss by erosion in this sector due to a lack of appropriate soil and water conservation processes.

5.5.4. Impact of land degradation

The impact indicators of the DPSIR model present the effects of changes of state of the land. Land degradation has several consequences on the livelihood of the population in the territory of Kalehe. The respondent noted that due to the degradation of forest land, there is a decrease in the availability of firewood, scarcity of no timber products, lack of wood for construction, a decrease in soil fertility leading to the decline in crop yield, the increasing problem of erosion, landslide, and flood, the siltation of river, loss of biodiversity, deterioration of air quality, change in rainfall pattern. On the other hand, the increase in erosion contributes to the decrease in land productivity as the soil erosion washes away the topsoil, reduces the soil depth, and contributes to the loss of soil fertility. This exacerbates the problem of food insecurity (hunger) and reduces the living standards in this region as the smallholder farmers become poorer due to the reduction of farmland productivity which constitutes the main livelihood activity in this area. In addition to that, it contributes to the alteration of water quality through the siltation of rivers and sediment loads into surface water. Another consequence is the destruction of infrastructure resulting from the gully erosion and landslides that occur in this area. The increase of surface water runoff and flooding in the study area can also be related to land use change and climate change. Another impact of land degradation is the emergence of land use conflict in the area. Indeed, due to the decrease in agricultural productivity, people look for additional land and they noted that their preference is for forest land, shrubland, and grassland which are perceived as fertile land. This creates conflicts among farmers, pastoralists, and conservationists due to the competition of the land. Although the exploitation of natural resources is prohibited in the national park (National Parc of Kahuzi-Biega), due to poverty and scarcity of forestry resources, there is also some illegal exploitation of mineral resources, production of charcoal, illegal timber harvesting, and illegal hunting to meet the bushmeat demand of people in the landscape of National Park of Kahuzi Biega. Furthermore, there is an expansion of pastureland and agricultural land in the ecological corridor of this park. These activities contribute to the destruction of species habitat, and loss of biodiversity and exacerbate the resource usage conflicts in this territory.

5.5.5. Response to land degradation

The Response indicator refers to the efforts of the society to solve the land degradation problem. In reference to the Land Degradation Neutrality (LDN) principles, the responses to land degradation can be categorized into three main groups: avoiding, reducing, and reversing land degradation (UNCCD, 2018, Cowie *et al*., 2018). The Figure 5.1 presents the responses to land degradation identified in the study area based on these categories. Avoiding land degradation refers to practices aimed at preventing further degradation of land by addressing the drivers of land degradation through appropriate regulation, planning, and sustainable land management practices. The actions of reducing land degradation includes measures that mitigate ongoing degradation on land resources through the application of sustainable land management practices and by reducing the pressure on ecosystems. The actions of reversing land degradation aims to restore or rehabilitating degraded land to its former productivity and ecological function through corrective measures (UNCCD, 2018, Cowie *et al*., 2018). In this perspective, to minimize the impact of land degradation in the study area, different recommendations have been formulated by local communities. Hierarchically, the respondent proposed a set of measures that should be implemented to reduce the problem of forest degradation. These measures include the improvement of agricultural productivity to reduce pressure on the forest ecosystem, the promotion of tree planting through an environmental education program, the promotion of alternative livelihood activities, the sustainable use of forest products, poverty eradication, law enforcement, improvement of land ownership, use of alternative source of energy and provision of energy saving stove, control of forest fire and protection of wildlife habitat. In addition to these proposed measures, people have adopted different strategies to cope with the problem of erosion. The adopted soil and water conservation measures in the study area include fallowing, vegetative cover (mulching), agroforestry and tree planting, trenches and drainage ditches, crop rotation, and grass-bound or brushwood fences. However, the adoption of conservation measures is low in this territory. Only 57% of respondents reported that they adopted at least one soil and water conservation measure. Thus, it is important to address the challenges to the adoption of conservation measures such as the lack of training and technical support through extension services and environmental programs. This study demonstrated that strip cropping, agroforestry, and terracing are the most effective soil and water conservation options in the study area but they are not extensively applied in the territory due to a lack of training, and technical and financial support. Furthermore, some soil conservation techniques such as agroforestry and tree planting are not allowed in rented plots. This call for action to resolve the land tenure issue, facilitating training and experience sharing between farmers, subsidizing agricultural input, improving the availability of agricultural input (seeds, pesticides, fertilizers) to farmers, improving access to credits and loans for smallholders farmers, strengthening and advising farmers to works into cooperatives to facilitate capacity building and financial inclusion, recruit extension workers and implement extension center in the villages. Due to the degradation of farmland, the strategy adopted by farmers includes fallowing, abandonment of land, and search for additional land in the forest and old fallows which are perceived as the most fertile, crop rotation, intercropping, improvement of the fertility of land through manure application and agroforestry. Despite that the adoption of agroforestry is low (20.10%), this study demonstrated that the implementation of agroforestry in cropland and the afforestation of shrubland and bare land constitute effective solution to reduce the erosion by more than 60 percent in the study area. It was observed that there is an encroachment of wetland in the territory although wetland is recognized to play a key role in the regulation of the water cycle, control of water quality, and regulating flood. Thus, it is necessary to restore the degraded river banks in this area. Since the land is not used sustainably, future land use plan should be participative, take into account the land capability, and considers the tradeoff between environmental protection and economic development to avoid further degradation and resource use conflicts.

5.5.6. Determinants of adoption of conservation measures

Although people are aware of the problem of land degradation in their entity, the adoption of conservation measures is low. About 57% of respondents did not adopt any conservation practices to cope with the problem of land degradation. This rate of adoption is low compared to what has been found in Ethiopia where 76% of farmers have adopted a different type of soil and water conservation technologies into their farms (Gedefaw *et al*., 2018). This low rate of adoption of conservation practices within the study area is related to a set of challenges such as lack of training and knowledge about the conservation techniques, lack of technical support to implement the conservation measures, lack of financial support, the small size of farmland, land tenure issues as some techniques like agroforestry are not allowed in rented land. To overcome these constraints there is a need for more awareness and training about the soil and water conservation measures. Respondents proposed a set of strategies to overcome the challenges that they face. Among the proposed strategies, there is a necessity to resolve the land tenure issue and increase farmland sizes, facilitate access to training and experience sharing among farmers, subsidize agricultural input, improve the availability of agricultural input (seeds, pesticides, fertilizers) to farmers, improve access to credits and loans for smallholders farmers, organizing farmers into cooperatives to facilitate capacity building and financial inclusion, recruit extension workers and implement extension center in the villages. In addition to that, evidence from other countries like Kenya has shown that people are more willing to implement conservation options with income generating which tends to be more desirable as the income constitutes an insensitive for farmers to adapt the land management measures (Kizito *et al*., 2021). The implementation of soil and water conservation measures by farmers can increase cropland productivity, reduce soil loss by erosion, control flood, contribute to the improvement of soil fertility, and constitute the source of fuelwood for domestic energy and forage for livestock (Toromo *et al*. 2019, Yifru & Miheretu, 2022). These positive benefits associated with the conservation practices could constitute an incentive for farmers to adopt these measures.

The adoption of soil and water conservation measures to cope with land degradation in the study area depends on the socio-economics characteristics of the respondents. The adoption of conservation measures is significantly influenced by the farming seniority, the size of the household, the education level, access to extension services, and the slope of farmland. However, the age, the stay period, and the distance to farmland have a negative influence on this adoption.

The negative influence of age on the adoption of conservation practices can be explained by the fact that the respondent noted that one of the challenges of adoption is the supplement labor associated with the implementation of conservation activities. More energetic youth people are the ones who adopted the conservation action in their farmland compared to elders. These findings are in line with the results from Cherono *et al*. (2019) in Kenya and Asfew *et al*. (2023) in Ethiopia who reported that the probability of a farmer participating in soil management decreases when their age increases considering that the elderly may not have enough force to maintain the conservation measures. However, it is noted that the seniority in farmland influences positively the adoption while the stay period has a negative influence. Then for the same group age, the adoption of conservation practices depends on the years of experience in farming. A senior farmer is more likely to adopt conservation practices than a junior farmer. This may be explained by the fact that the experienced farmers have identified strategies to adapt to the environmental changes that occur in their entity. In addition, experienced farmers can detect land degradation problems and have a higher chance to participate in conservation measures than inexperienced ones (Nigussie *et al*., 2017, Wordofa *et al*., 2020). The stay period has a negative influence on the adoption of conservation due to the low access to training and extension services in the territory. The immigrants come with new knowledge about land management that they have previously acquired in their area of origin and are the ones who implement the conservation practices compared to the autochthone. Furthermore, the finding of this study reveals that the adoption of conservation practices increases with the size of the household. This is explained by the availability of people to carry out supplement labor work associated with the implementation of conservation practices. This result disagrees with the observations of Bekele & Drake (2002) in Eastern Ethiopia where large family size was negatively correlated to the conservation decision due to the competition between food production and investment in conservation. However, they corroborate with the results of Tadesse & Belay (2004) in southern Ethiopia where the adaption of conservation measures is positively influenced by the number of active people as the implementation of conservation measures was known to be labor intensive. These differences and similitudes are related to the fact that the study area has different agroecological and socio-economic conditions under which the farmers operate. Therefore, it is difficult to generalize the determinants of the adoption of conservation measures (Bekele & Drake, 2002).

The education level of the household head and access to extension services also increase the likelihood of the adoption of conservation measures. This finding corroborates a previous study by Yifru & Miheretu (2022) who stated that the level of education of farmers improves their decision to adopt conservation measures. This is because literate land users and people who have attended training provided by extension services have access to scientific knowledge about conservation and play the role of contact person between their community and extension agents during the dissemination of information about conservation practices. They have access to updated information about the consequences of land degradation and then tend to implement conservation strategies to avoid the adverse impact. This finding agrees with Wordofa *et al*. (2020) who reported that the access to extension services by farmers contributes to their willingness to adopt conservation measures as there is a development of awareness and understanding of soil erosion.

The slope and distance to farmland are the physical factors that influence the adoption of conservation practices within the study area. The slope of the land is one of the physical factors that influence the occurrence of erosion (Tesfahunegn *et al*., 2021) and people who have their plots on the steep slopes are the ones who experience the problem. Then they adopt a strategy to reduce this problem more than people who have their plots on gentle slopes or flat areas. This is consistent with the fact that people who perceive that their land area is at risk of erosion are more likely to invest in the implementation of conservation measures (Tadesse & Belay, 2004, Yifru & Miheretu, 2022). In contrast, the distance of the farmland from the homeland decreases the adoption of conservation practices because farmers don’t frequently go to distant plots and they are tired when they arrive there as they notice that one of the challenges, they face in implementing the conservation practices is that it requires more labor. A similar finding was obtained by Asfew *et al*. (2023) who noted that access to remote plots requires more time and effort. Furthermore, distant plots receive less effort and care regarding the implementation of conservation measures (Saguye 2017b). Thus, it is difficult for farmers to monitor and maintain conservation structures when their farmland is far from their homes.

Considering the above findings, some policy implications for conservation planning arise. The main implication is that any conservation intervention within the study area should be tailored to the socioeconomic characteristics of farmers and the structural characteristics of farmland. Indeed, the development of policies and programs to tackle the effect of land degradation needs to take into account the determinant factors of land farmers' decision to adopt conservation measures. Therefore, the identified factors must be integrated into the conservation plan (Tenge *et al*., 2004). For instance, the findings of this study demonstrated that there is a positive influence of the education level on the adoption of conservation measures. This implies that the stakeholders who want to implement the conservation measures within the study area should use the more educated people as focal points to demonstrate the importance and benefits associated with the implementation of conservation measures (reduction of erosion, increase of crop yield, improvement of soil fertility, production of forage for livestock, fuelwood, etc.) through demonstration plots. Since access to extension services increases the level of adoption, there is a necessity for institutional support to increase the number of extension workers in the village and to implement extension centers in each health center of the territory to reach more people. The findings of this research demonstrated that young people were more likely to implement conservation measures compared to older although older people have more experience. This implies that conservation planners should favorite an experience sharing between older people and young people through the organization of the local community and the young people should be the first target during the training on conservation practices. This can be done through the organization of community forums and exchange visits. The results highlight that the size of households has a positive influence on the adoption of conservation measures. Thus proper management of labor through community actions should be promoted by extension services so that the conservation goals can be attained. Furthermore, it was also found that people are willing to adopt conservation measures when the farm plot is close to their home. This fact should be taken into account by planners to maximize the expected results. Finally, people who identify their farmland plot as at a high risk of degradation (farmland located on a steep slope) are adopting conservation measures. This implies that there is a need to increase awareness about the drivers of land degradation and demonstrate the benefits of adopting conservation measures to reduce the risk of degradation in the study area.

5.5.7. Land degradation management plan

The results of this study demonstrated that the land degradation is a significant and persistent issue in the highlands of eastern DR Congo. In order to alleviate the current degradation and prevent future degradation, it is essential to incorporate the causes and effects of the land degradation into the planning process by linking the driving forces, the pressure, states, and impacts of land degradation as depicted in the previous section on the DPSIR indicators of land degradation within the study area. This could be possible by using a multidisciplinary approach combining field observations, geospatial techniques and participative approach. This participative approach is essential to include all the stakeholders implying in the management of natural resources in this territory in the land use planning process so that the plan can respond to people aspiration. In these perspectives, a comprehensive land degradation management plan has been developed based on the finding from both the spatial modeling approach and the stakeholder opinion (community perception) on land degradation and adoption of conservation measures.

5.5.7.1. Situation analysis and identification of key issues

The hifhlands of Eastern DR Congo face significant land degradation due to a combination of both natural factors (dominance of steeps slopes, high rainfall intensity, and clayey soils) and anthropogenic factors such as population growth, economic development, deforestation, overgrazing, and unsustainable agricultural practices. These drivers have led to severe soil erosion, loss of soil fertility, reduced vegetation cover, and land fragmentation wich resulted in loss of land productivity and negatively affect the community livelihood. The rapid expansion of agricultural land and urban areas in inadequate lands without the implementation of adequate conservation measures has exacerbated the issue, with forests being cleared and wetland drained for farming and development, leading to further environmental degradation. Moreover, due to population growth, there is an increase in land fragmentation and exacerbation of land tenure security which remains a critical issue in the region.

The impacts of land degradation in Kalehe are profound, affecting food security and community livelihood, water quality, and the overall ecological balance of the region. Quantitative data reveals that the soil loss by erosion have increased from 32.08 t/ha/year in 1987 to 44.35 t/ha/year in 2020 due to land use changes, and low adoption of soil and water conservation practices. Many local communities rely on traditional agricultural practices (slush and burn agriculture) and have limited access to resources and training for sustainable land use. Tailoring conservation actions to the socio-economic characteristics of farmers is essential to ensure higher adoption rates and long-term success. Over the same period (1987-2020), 34.17% of the land has been subjected to potential degradation due to unsustainable land use practices which are not in accordance with the land use potential. Additionally, about 32% of the territory is prone to high to very high vulnerability to physical land degradation processes such as erosion and landslides, and 31.25% of the territory has experienced a decrease in land productivity.

To address these challenges, it is crucial to implement sustainable land management practices, promote reforestation, engage local communities in conservation efforts, and improve community livelihoods. However, these efforts require substantial coordination and collaboration among various stakeholders, including the territorial administratives authorities, the ministry of planning, the ministry of environment and sustainable development, the civil society, NGOs, and local development organisations, farmers, community leaders, extension workers, local community, and academic institutions as outlined in the Table 5.1 which summarizes the key issues, activities, and stakeholders involved in addressing land degradation in the highland region of Eastern DR Congo.

Table 5.1: Land degradation management plan

Category	Issues identified	Activities	Stakeholders
Unsustainable land use	Unsustainable agricultural practices and increasing human activities leading to habitat loss	- Adjust land use according to land capability - Implement agroforestry - Forest landscape restoration initiatives - Forest, wetland, and river bank protection	- Territorial Administrative Authorities - Ministry of Planning - Ministry of Environment and Sustainable Development - Farmers and Community Leaders
Soil Erosion	Natural factors (Steep slopes and high rainfall) and unsustainable land use contributing to soil erosion	- Implement soil and water conservation measures - Increase vegetation cover - Promote sustainable farming on less steep areas - Establish demonstration centers	- Civil Society, NGOs, and Local Development Community Organizations - Farmers and Community Leaders - Research Institutions and Universities
Land fragmentation	Unequitable land distribution or access due to population growth and leading to land fragmentation	- Participatory land use planning - Address land conflicts through land consolidation tools and training- Strengthen land tenure systems	- Territorial Administrative Authorities - Ministry of Planning - Civil Society, NGOs, and Local Development Community Organizations
Limited adoption of conservation practices	Lack of awareness and technical knowledge on soil and water conservation measures	- Environmental education and awareness programs - Tailor conservation actions to the socioeconomic characteristics of farmers - Demonstration centers	- Civil Society, NGOs, and Local Development Community Organizations - Farmers and Community Leaders - Research Institutions and Universities
Deterioration of community livelihood standards	Dependence on degrading practices and low agricultural productivity leading to poverty and food insecurity	- Increase agricultural productivity - Promote alternative livelihood activities - Introduce renewable energy solutions - Improve accessibility to subsidiary programs	- Farmers and Community Leaders - Civil Society, NGOs, and Local Development Community Organizations - Ministry of Environment and Sustainable Development
Destruction of sensitive ecosystem	Loss of sensitive ecosystems and wildlife habitats	- Restore forests in critical areas - Implement soil and water conservation measures - Protect wetlands and riverbanks - Increase vegetation cover to protect sensitive ecosystems	- Ministry of Environment and Sustainable Development - Civil Society, NGOs, and Local Development Community Organizations - Research Institutions and Universities

5.5.7.2. Objectives and activities of the management plan

The overall objective of the developped land degradation management plan (Table 5.1) is to reduce land degradation and promote sustainable land use in the highlands of Eastern DR Congo. This plan is designed to address the root causes of land degradation through a combination of sustainable land use planning, conservation measures, restoration initiatives, and community engagement. This integrated approach is expected to contribute to long-term environmental sustainability, improved agricultural productivity, and poverty reduction.

The primary objective of this land management plan is to reduce land degradation by optimizing land use according to land capability, engaging local communities in participatory land use planning, and addressing land conflicts through consolidation tools and training. Additionally, the plan's emphasis on strengthening land tenure systems and promoting equitable land distribution aims to mitigate land use conflicts and foster community participation in conservation efforts.

The second objective of the plan is to increase the public awareness on land conservation practices. Indeed, raising awareness of local community about appropriate soil and water conservation options is crucial for controlling soil erosion and runoff. In the perspective of raising public awareness and increase the adoption of soil and water conservation practices among local communities, there is a necessity to implement demonstration centers as well as the development of environmental education and awareness programs tailored to the local socioeconomic characteristics of farmers and structural characteristics of theirs farmlands. It is also important to involve the civil society organizations and extension workers in these activities as they are vital for disseminating information and best practices.

The third objective of the plan is to restore degraded lands and protect sensitive ecosystems such as forestland and wetland through the implementation of restoration initiatives, such as forest landscape restoration, soil and water conservation measures and protection of wetlands and riverbanks. These measures are designed to restore degraded lands, enhance biodiversity, and protect sensitive ecosystems. By promoting sustainable land use and restoration of degraded lands, the plan aims to enhance the resilience of local ecosystems and communities. However, the capacity building for local communities and territorial administrative authorities is essential for the successful implementation and monitoring of restoration initiatives.

The fouth objective of the management plan is to improve the community livelihoods by increasing the agricultural productivity, promoting alternative livelihood activities, and introducing renewable energy solutions to reduce the community's dependence on degrading practices. This, in turn, can help alleviate poverty and reduce pressure on natural ecosystems. Thus, there is a necessity to provide training on improved farming techniques and resources to farmers to increase the agricultural productivity and ensure that they have access to support and subsidiary programs. The involvement of territorial administrative authorities and civil society organizations is crucial for implementing subsidiary programs and supporting farmers.

5.5.7.3. Implementation of the management plan

The action plan (Table 5.2) contains the strategies that can be implemented in the study area to guide the implementation of conservation measures to reduce the current land degradation and avoid future degradation. The identified key priority actions are the sustainable land management planning, public awareness through the vulgarization of conservation measures, restoration of degraded land and protection of ecological sensitive area, and improvement of community livelihood.

Table 5.2: Proposed action plan for reducing the land degradation vulnerability

Action	Objective and justification	Specific actions	Actors	Corresponding actions
Developing and implementing Sustainable Land Use Management Plans **Implementing period**: Medium term	-Reduce the land degradation -Find a tradeoff between conservation and development -Reduce land use conflicts -Increase the degree of participation of local communities in land use planning	- Adjustment of the land use according to land capability - Participatory land use planning - Land consolidation -Reduction of land diversification -Increasing the patch shape size and complexity -Maintaining the patch connectivity -Improvement of the land tenure security	-Territorial administrative authorities -Ministry of planning -Civil society, NGOs, and local development community organization - Research Institutions and Universities	-Land use zoning -Participative rural appraisal -Participative mapping -Training of territorial level administrates authorities on participative planning -Training of leaders of community-based organization on participative mapping
Public awareness through the vulgarization and implementation of soil and water conservation measures **Implementing period**: Short term	-Raise awareness about appropriate soil and water conservation (SWC) options to control soil erosion and runoff -Increase the adoption of SWC measures	-Implementation of environmental education and awareness programs -Establishment of demonstration centers in each health zone or village -Tailor SWC actions to the socioeconomic characteristics of farmers	-Territorial administrative authorities -Ministry of environment and sustainable development -Civil society, NGOs, and local development community organization -Farmers	-Recruiting and training of extension workers -Production and dissemination of vulgarization guides for best land management practices -Training of civil society staff on best land management practices and land degradation monitoring
Restoring degraded lands and protection of sensitive ecosystems **Implementing period**: Short term	-Reduce the vegetation cover loss -Reduce the runoff, and soil loss by erosion -Increase the infiltration rate of rainfall -Conserve sensitive ecosystems -Wildlife habitat protection	-Implementation of forest landscape restoration initiatives -Forest, wetland and river bank protection - Implement soil and water conservation measures to reduce soil erosion and runoff -Increase vegetation cover and reduce farming activities on steep slope	-Territorial administrative authorities -Ministry of environment and sustainable development -Civil society, NGOs, and local development community organization -Farmers	-Capacity building of local communities on implementation of restoration initiatives -Capacity building of territorial administrates authorities and civil society staff on the monitoring, evaluation and reporting of restoration -Law enforcement programs
Improvement of the community livelihood **Implementing period**: Medium term	-Poverty eradication -Reducing the pressure on natural ecosystem	-Increasing agricultural productivity -Promoting alternatives livelihoods activities,alternatives sources of energy -Improving accessibility to subsidiary programs	-Territorial administrative authorities - Civil society, NGOs, and local development community organization	- Implementation of subsidiary programs to support farmers

CHAPTER SIX

CONCLUSIONS AND RECOMMENDATIONS

6.1. Introduction

This study investigated the LULC dynamics and land degradation in Kalehe territory. This chapter presents the summary of the finding of this research, the policy recommendations that arise from these findings and propose an action plan that should be implemented in the study area to reduce the land degradation vulnerability and avoid futher degradation. Furthermore, the areas for further research to improve the sustainable land management in the study area are explored.

6.2. Conclusion

This study aims to assess the spatial pattern of land degradation in the Kalehe territory as a basis for designing sustainable land management and conservation planning. A mixed approach combining geospatial techniques, remote sensing, and stakeholder consultation was used. The geospatial data was used to assess the land use dynamics, its impact on ecosystem services, land productivity, and soil erosion. Furthermore, a Multicriteria Decision Model was developed to assess the land degradation vulnerability pattern. The results of these geospatial analyses was triangulated with community perception to identify the DPSIR (Drivers-Pressure-State-Impact-Response) indicators toward the land degradation mitigation.

The results indicated that during the last 33 years (1987-2020), the territory of Kalehe has been subjected to rapid environmental changes resulting from the expansion of cropland, built-up area, and shrubland at the expanse of forestland, wetland, and grassland. These changes are expected to continue in the future. For instance, the projected LULC demonstrated that the forest cover will further decreases from 47.02%

in 2020 to 41.30% in 2030, 41.20% in 2050, and 38.16% in 2070 while the cropland, built-up land and shrubland would be expanding. These LULC changes have significantly contributed to the land degradation with the prominent manifestation are the degradation of land cover (34.17% of land), decrease of land productivity (31.25% of land), decrease of ecosystem service value (28.44% of land), and increase of soil erosion (from 32.08 t/ha/year in 1987 to 44.35 t/ha/year in 2020) during the 1987-2020 period. This calls for rethinking the land use management options to ensure that the land use transition is beneficial for human well-being and environmental sustainability.

In order to reverse this ongoing degradation and reach the LDN by 2030, there is a necessity for implementation of sustainable land use management. The scenarios analysis of soil erosion under different conservation practices reveals that terracing, agroforestry and strip cropping are the most effective conservation options to reduce the erosion within the study area. However, these technics are not extensively adopted by land users due to challenges such as lack of knowledge, financial and technical constraints. As an illustration, the agroforestry and forest plantation have a potential to reduce the current rate of erosion by 62.28% but it is adopted by only 20.10% of respondents. Furthermore, the decision of land users to adopt the conservation measures and their perception on the severity of land degradation depend on their socio-economics characteristics. Moreover, the local community is aware of the cause of land degradation which occurs in their locality and they are already experiencing its consequences. Thus, planners and policy makers should consider the determinant factors of perception on land degradation and adoption of conservation measures identified in this study as well as the land user's perspectives on the DPSIR (Drivers-Pressure-State-Impact-Response) indicators of land degradation to develop effectives conservation programs which take into accounts the aspirations of people.

The analysis of the impact landscape characteristics on the dynamics of erosion and ecosystem service supply potential reveals that the proportion of forest land in the landscape is positively correlated to the ecosystem supply potential but negatively correlated to the soil loss by erosion. In contrast, the patch density which is an indicator of land fragmentation is negatively correlated to the ecosystem supply potential but positively correlated to the erosion. Moreover, the most influential landscape structure metrics on both soil erosion and ecosystem supply potential are the Shannon diversity index and the Perimeter-area fractal dimension index which positively influence the erosion dynamics but negatively influence the ecosystem supply potential. This imply that, during land use planning, it is important to maintain a high forest cover, and reduce land fragmentation, and landscape heterogeneity but increase the size of landscape patches and the complexity of their shapes to enhance the ecosystem service supply potential and reduce the erosion risk.

In order to determine the priority area for landscape restoration at territorial level in Eastern DR Congo, a model of land degradation vulnerability which take into account the natural and anthropogenic factors of degradation was developed based on the MCDA analysis approach. This model was tested in the Kalehe territory to identify the hotspot of land degradation vulnerability at territorial level and to prioritize watershed for implementation of landscape restoration initiatives. It was demonstrated that the developed model of land degradation has an overall accuracy of 77.82% for predicting the area with high susceptibility to occurrence of physical land degradation processes such as erosion and landslides which are more recurrent in the study area. The results of this model show that 32.01% of the territory is characterized by a high vulnerability and thus requires urgent measures for restoration. This vulnerability to land degradation is accentuated by the fact that the land is not used according to its capability. This imply that there is a necessity to adapt the LULC to its capability to avoid further degradation. In this perspective, an adaptative land use scenario of the study area was developed to serve as a basis for discussion with local community during the participative land use planning.

6.3. Policy recommendations

This study reveals that the territory requires the implementation of measures and strategies to reduce the land degradation vulnerability. Based on the proposed action action plan, the policy recommendation to reduce the land degradation in Kalehe territory an beyond are presented below:

6.3.1. Developing and implementing Sustainable Land Use Management Plans: As the current land use is not sustainable, there is a necessity to implement a new land use plan that is adapted to the land's capability to reduce land degradation vulnerability and improve existing land management practices. As there is competition between the use of land for agricultural production, pasture activities and settlements in one hand and the conservation of forest land and wetlands in other hand, a tradeoff between these land uses should be found through the consultation of land users by recognizing that people are integral agents of conservation outcomes. A zoning is then necessary to avoid land use conflict. The land capability maps provided in this study can serve as a basis for discussion during participatory land use planning through the application of participatory rural appraisals tools and GIS-based participatory tools. A prerequisite for that is the capacity building and training of administrates authorities on participative planning. Furthermore, in the study area, the landscape characteristics influence the dynamics of erosion and the supply of ecosystem services. To reduce the problem of erosion and enhance the provision of ecosystem services, it is important to reduce land fragmentation and land diversification while increasing the patch shape size and complexity as well as maintaining the patch connectivity in the future land use plan. In doing so, the land use plan will improve the management of natural resources in the territory for both human and environmental sustainability.

6.3.2. Vulgarization and implementation of soil and water conservation measures: There is a necessity for the vulgarization of proper cultivation techniques to control runoff and soil erosion in this territory. The scenario analysis of soil erosion under different soil and water conservation practices has demonstrated that terracing, agroforestry, and strip cropping are the most appropriate techniques to reduce soil loss by erosion in the study area. However, these techniques are not extensively applied by farmers due to a lack of knowledge about the techniques. Considering that effective education and awareness programs are the foundation for behavior change at community level, there is a necessity to produce and disseminates vulgarizations materials (guides, books, leaflets, flyers, videos) about the best land management practices, establish demonstration centers in each health zone or village of the study area to educate and mobilize farmers on the application of best soil and water conservation practices. Since the adoption of conservation technics depends on the socio-economics characteristics of people, any conservation intervention within the study area should be tailored to the socioeconomic characteristics of farmers and the structural characteristics of farmland. Additionally, training of extension officer and staff of the civil society organization about the application of land capability/land suitability maps as well as the land degradation vulnerability maps, the best land use management options and the monitoring and reporting of landscape restoration programs will be necessary for an effective implementation of conservation programs. Moreover, since certain conservation technics like the tree planting are not adopted in rented land, there is a need to improve the land ownership (land tenure security) in this territory.

6.3.3. Restoration of degraded lands and protection of sensitive ecosystems: The territory is dominated by an area with steep slopes in the eastern part of the region where deforestation is very high. These areas are more vulnerable to land degradation processes such as erosion and landslides due to both anthropogenic and natural factors. Other sensitive areas that should be considered for restoration purposes include the riparian area of the water body (rivers banks and lake shore) and wetland which plays a great role in flood regulation. The encroachment of these sensitives area should be discouraged through the enforcement of law. Furthermore, the study area is characterized by a decrease in green cover especially forest land and grassland which should be restored. There is a necessity for increasing the vegetation cover in the area characterized by the high vulnerability to reduce the runoff, and soil loss by erosion and increase the infiltration rate of rainfall. Thus, from a restoration perspective, the land degradation vulnerability map produced in this study can be used to identify the hotspots of land degradation where restoration measures such as forest landscape restoration initiatives could be prioritized. Furthermore, there is a need for law enforcement to improve the protection of natural resources.

6.3.4. Improvement of the community livelihood: There is a high demands of forest resources especially the wood energy which is the most used energy in the study area. Furthermore, people practice slash and burn agriculture which contributes to forest cover loss. To reduce pressure on natural ecosystem, there is a necessity to enhance the agricultural productivity by improving the accessibility to agriculture impute and subsidiary programs, promote alternative sources of energy, and promote alternative livelihood activities for poverty eradication.

6.4. Research perspectives

Although this study contributes to knowledge about the land degradation processes in Eastern D.R. Congo, it presents some limits that should be filled by feature research. Considering the scope of this study and the outcomes, there is a set of future research that should be done to enhance the sustainable management of natural resources in this region:

6.3.1. Assessment of the impact of landscape dynamics on surface water runoff: The study used the dynamics of LULC change, soil erosion, land productivity, and ecosystem service as a proxy of land degradation. Although the study area is currently subjected to flooding, this study has not analyzed the impact of landscape dynamics and climate change on the surface water runoff dynamics. Thus, future research should evaluate this impact, determine the hotspots of surface water generation, and suggest effective soil and water conservation options to control the dynamics of surface water runoff in Eastern DR Congo.

6.3.2. Assessment of the extent of chemical land degradation: This study focused on the physical land degradation process related to erosion and their interrelation with LULC changes in Eastern DR Congo. Other aspects of land degradation such as chemical degradation was not assessed in this study. For instance, the impact of soil erosion and LULC changes on the chemical properties of soil and water bodies has not been evaluated. Thus, it will be important to develop spatial models for predicting the soil and water quality vulnerability to land degradation processes at the territorial level, assess the water quality index, soil quality index, and sediment contamination under different land uses.

6.3.3. Development of a public participation GIS (PPGIS) to incorporate local knowledge perspective of land degradation and restoration in future land use decision-making process: The LULC changes detection analysis performed in this study provides insight into the past, present, and possible future land development in the study area. It demonstrated the trends of past land use development and how the land cover is likely to be degraded in the future. However, the information provided by the remote sensing images used in this study is constrained by the spatial resolution of Landsat images (30 m) which prevents the acquisition of more details. Furthermore, the remote sensing classification error can potentially propagate in the land use change projection. To improve the spatial analysis of LULC dynamics and to get more details about the past, current, and possible future land use in the study area, it can be necessary to use images with high spatial resolution such as Sentinel or Spot. Furthermore, there is a necessity to engage the stakeholders implied in the land use management for a better land use change and land degradation assessment. The PPGIS approach can be used in future studies to incorporate local knowledge perspective on land degradation and restoration in future land use decision-making process and to identify the land use conflict which can result in future land use allocation according to the variables interests of different stakeholders

6.3.4. Comparison of the outcomes of different ecosystem services monitoring approaches for land degradation assessment: The assessment of the impact of LULC changes on ecosystem services was based on the land user's valuation through the "matrix model". In the future it will be necessary to evaluate the agreement of the perceived ecosystem services value by land users with the monetary valuation of ecosystem service (economic valuation of ecosystem service) as suggested by Costanza *et al*. (1997) and the Economics of Ecosystems and Biodiversity (TEEB) database (Van der Ploeg & de Groot, 2010) and empirical valuation derived from the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) tools.

6.3.5. Assessment of the performance of data-driven model compared to knowledge-based models in the assessment of land degradation: This study demonstrated that the MCDA approach can be used to model the vulnerability to physical land degradation processes at a territorial level in Eastern DR Congo with a good performance in predicting the area which is susceptible to physical degradation processes such as erosion and landslides. However, the performance of this knowledge-driven approach compared to the data-driven approach has not been assessed. Therefore, future studies should be focused on the evaluation of the performance of data-driven methods such as machine learning techniques (Random Forest, Classification and Regression Tree, and Support Vector Machine, etc.) and statistical methods (Frequency ratio, weight of evidence, regression, etc.) compared to knowledge driven approach related to MCDA in predicting the land degradation vulnerability at territorial level in Eastern DR Congo. This will help to determine the best approach for spatial modeling of land degradation vulnerability in this region.

REFERENCES

AbdelRahman, M. A. (2023). An overview of land degradation, desertification and sustainable land management using GIS and remote sensing applications. *Rendiconti Lincei. Scienze Fisiche e Naturali*, *34*(3), 767-808.

Abdi, A. M., Boke-Olén, N., Jin, H., Eklundh, L., Tagesson, T., Lehsten, V., & Ardö, J. (2019). First assessment of the plant phenology index (PPI) for estimating gross primary productivity in African semi-arid ecosystems. *International Journal of Applied Earth Observation and Geoinformation*, 78, 249-260.

Abdulkadir, T. S., Muhammad, R. U. M., Yusof, K. W., Ahmad, M. H., Aremu, S. A., Gohari, A., & Abdurrasheed, A. S. (2019). Quantitative analysis of soil erosion causative factors for susceptibility assessment in a complex watershed. Cogent Engineering, 6 (1), 1594506.

Abou-Najem, S., Palacios-Rodríguez, G., Darwish, T., Faour, G., Kattar, S., Clavero Rumbao, I., & Navarro-Cerrillo, R. M. (2019). Land Capability for Agriculture, Hermel District, Lebanon. *Journal of Maps*, *15*(2), 122-130.

Abuzaid, A. S., AbdelRahman, M. A., Fadl, M. E., & Scopa, A. (2021a). Land degradation vulnerability mapping in a newly-reclaimed desert oasis in a hyper-arid agro-ecosystem using AHP and geospatial techniques. *Agronomy*, *11*(7), 1426.

Abuzaid, A.S.; Abdellatif, A.D.; Fadl, M.E. (2021) Modeling soil quality in Dakahlia Governorate, Egypt using GIS techniques. *Egypt. J. Remote Sens. Space Sci.* **2021**, *24*, 255–264.

Achille, L. S., Zhang, K., & Anoma, C. J. K. (2021). Dynamics of deforestation and degradation of forests in the Democratic Republic of Congo from 1990 to 2018. *Open Journal of Ecology*, *11*(5), 451-461.

Adidja M.W (2014), Soil, runoff and nutrient losses under maize and banana cropping systems in the Lwiro micro catchment, DRC, Master Dissertation, Integrated Watershed Management, Makerere University, December 2014, 82p

Adidja, M. W., Majaliwa, M. J. G., Tenywa, M. M., & Somora, M. P. (2016). Soil and water conservation practices and soil erosion intensity in the Lake Kivu Basin, Democratic Republic of Congo. *RUFORUM Working Document Series (ISSN 1607-9345) No*, *14*(3), 77-85.

AGNES (2020), Land Degradation and Climate Change in Africa, Policy Brief No. 2, https://hdl.handle.net/10568/107809

Aguirre-Salado, C. A., Miranda-Aragón, L., Pompa-García, M., Reyes-Hernández, H., Soubervielle-Montalvo, C., Flores-Cano, J. A., & Méndez-Cortés, H. (2017). Improving identification of areas for ecological restoration for conservation by integrating USLE and MCDA in a GIS-environment: A pilot study in a priority region Northern Mexico. *ISPRS International Journal of Geo-Information*, 6(9), 262.

Agyemang, I., McDonald, A., & Carver, S. (2007, August). Application of the DPSIR framework to environmental degradation assessment in northern Ghana. In *Natural Resources Forum* (Vol. 31, No. 3, pp. 212-225). Oxford, UK: Blackwell Publishing Ltd.

Ahana, B. S., Posite, V. R., Maouly, D. K., Abdelbaki, C., Kantoush, S. A., Nguyen, B. Q., & Kumar, N. (2024). Changing rainfall patterns in the Northeastern South Kivu Region, Democratic Republic of the Congo: a detailed analysis using CHIRPS Rainfall Data (1981–2023). *Earth Systems and Environment*, *8*(4), 1733-1750.

Akayezu, P., Musinguzi, L., Natugonza, V., Ogutu-Ohwayo, R., Mwathe, K., Dutton, C., & Manyifika, M. (2020). Using sediment fingerprinting to identify erosion hotspots in a sub-catchment of Lake Kivu, Rwanda. *Environmental Monitoring and Assessment*, *192*(12), 806.

Al Sayah, M. J., Abdallah, C., Khouri, M., Nedjai, R., & Darwich, T. (2021). On the use of the Land Degradation Neutrality concept in mediterranean watersheds for land restoration and erosion counteraction. *Journal of Arid Environments*, *188*, 104465.

Al Sayah, M. J., Abdallah, C., Khouri, M., Nedjai, R., Darwish, T., & Khatib, H. (2022). A GIS framework for the application of the land degradation neutrality concept in Mediterranean landscapes. *Geocarto International*, 1-31.

Alemu, B. (2015). The effect of land use land cover change on land degradation in the highlands of Ethiopia. *Journal of Environment and Earth Science*, *5*(1), 1-13.

Alexandridis, T.K., Sotiropoulou, A.M., Bilas, G., Karapetsas, N., and Silleos, N.G., 2014, « The effects of seasonality in estimating the C-factor of soil erosion studies », *Land Degradation and Development*, 16 p. DOI: 10.1002/ldr.2223.

Alongo, S., Visser, M., Drouet, T., Kombele, F., Colinet, G., & Bogaert, J. (2013). Effets de la fragmentation des forêts par l'agriculture itinérante sur la dégradation de quelques propriétés physiques d'un Ferralsol échantillonné à Yangambi, RD Congo. *Tropicultura*, *31*(1), 36-43.

Amdihun, A., Gebremariam, E., Rebelo, L. M., & Zeleke, G. (2014). Suitability and scenario modeling to support soil and water conservation interventions in the Blue Nile Basin, Ethiopia. *Environmental Systems Research*, *3*(1), 1-13.

Amer, M., Daim, T. U., & Jetter, A. (2013). A review of scenario planning. *Futures*, *46*, 23-40.

Anderson J.R., Ernest E. Hardy, John T. Roach, and Richard E. Witmer, (1976). *A Land Use And Land Cover Classification System For Use With Remote Sensor Data-* Geological Survey Professional Paper 964 - A revision of the land use classification system as presented in U.S. Geological Survey Circular 671.United States Government Printing Office, Washington: 1976

Anley, Y., Bogale, A., & Haile-Gabriel, A. (2007). Adoption decision and use intensity of soil and water conservation measures by smallholder subsistence farmers in Dedo district, Western Ethiopia. *Land degradation & development*, *18*(3), 289-302.

Arnold, J.G., Srinivasan, R., Muttiah, R.S., Williams, J.R., (1998). Large area hydrologic modeling and assessment part I: model development. J. Am. Water Resour. Assoc. 34, 73–89.

Asfew, M., Bakala, F., & Fite, Y. (2023). Adoption of soil and water conservation measures and smallholder farmers' perception in the Bench-Sheko Zone of Southwest Ethiopia. *Journal of Agriculture and Food Research*, *11*, 100512.

Assefa, F., Elias, E., Soromessa, T., & Ayele, G. T. (2020). Effect of changes in land-use management practices on soil physicochemical properties in Kabe Watershed, Ethiopia. *Air, soil and water research*, *13*, 1178622120939587.

Azanga E., O., Majaliwa, M., Kansiime, F., Mushagalusa, N., Karume, K., & Tenywa, M. M. (2016). Land-use and land cover, sediment and nutrient hotspot areas changes in Lake Tanganyika Basin. *African Journal of Rural Development (AFJRD)*, *1*(1978-2017-2066), 75-90.

Bachri, S., Irawan, L. Y., Fathoni, M. N., Fawaid, A. M., Nuraini, S. G., Utomo, K. S. B., & Aldianto, Y. E. (2021). Developing land capability to reduce land degradation and disaster incident in Bendo Watershed, Banyuwangi. In *IOP Conference Series: Earth and Environmental Science* (Vol. 630, No. 1, p. 012004). IOP Publishing.

Bai ZG, Dent DL, Olsson L and Schaepman ME 2008. Global assessment of land degradation and improvement. 1. Identification by remote sensing. Report 2008/01, ISRIC – World Soil Information, Wageningen

Balandi, J. B., To Hulu, J. P. P. M., Sambieni, K. R., Sikuzani, Y. U., Bastin, J. F., Musavandalo, C. M., ... & Bogaert, J. (2024). Anthropogenic Effects on Green Infrastructure Spatial Patterns in Kisangani City and Its Urban–Rural Gradient. *Land*, *13*(11), 1794.

Balandi, J. B., To Hulu, J. P. P. M., Sambieni, K. R., Sikuzani, Y. U., Bastin, J. F., Musavandalo, C. M., ... & Bogaert, J. (2023). Urban sprawl and changes in landscape patterns: the case of Kisangani city and its Periphery (DR Congo). *Land*, *12*(11), 2066.

Bamba I. (2010), Anthropisation et dynamique spatio-temporelle de paysages forestiers en République Démocratique du Congo, Thèse présentée en vue de l'obtention du grade de Docteur en Sciences, Service d'Écologie du Paysage et Systèmes de Production Végétale, Ecole Interfacultaire de BioIngénieurs, Faculté des Sciences, Université Libre de Bruxelles, 205p

Bamutaze, Y. (2015). Revisiting socio-ecological resilience and sustainability in the coupled mountain landscapes in Eastern Africa. *Current opinion in environmental sustainability*, *14*, 257-265.

Bamutaze, Y., Mukwaya, P., Oyama, S., Nadhomi, D., & Nsemire, P. (2021). Intersecting RUSLE modelled and farmers perceived soil erosion risk in the conservation domain on mountain Elgon in Uganda. *Applied Geography*, *126*, 102366.

Bär, V., Akinyemi, F. O., & Speranza, C. I. (2023). Land cover degradation in the reference and monitoring periods of the SDG Land Degradation Neutrality Indicator for Switzerland. *Ecological Indicators*, *151*, 110252.

Basnet, B., & Vodacek, A. (2015). Tracking land use/land cover dynamics in cloud prone areas using moderate resolution satellite data: A case study in Central Africa. *Remote Sensing*, *7*(6), 6683-6709.

Batjes, H.B., 2007, *SOTER-based soil parameter estimates for Central Africa-DR of Congo, Burundi and Rwanda (SOTWIScaf, version 1.0)*. Report 2007/02, ISRIC-Word Soil Information, Wageningen. URL: http://www.isric.org/isric/webdocs/docs/isric_report_2007_02.pdf

Bavaghar, M. P. (2015). Deforestation modelling using logistic regression and GIS. *Journal of Forest Science*, *61*(5), 193-199.

Beek, K. J., De Bie, C. A., & Driessen, P. M. (1997). *Land evaluation for sustainable land management*. Enschede, The Netherlands: ITC.

Beilin, R., Lindborg, R., Stenseke, M., Pereira, H. M., Llausàs, A., Slätmo, E., ... & Queiroz, C. (2014). Analysing how drivers of agricultural land abandonment affect biodiversity and cultural landscapes using case studies from Scandinavia, Iberia and Oceania. *Land use policy*, *36*, 60-72.

Bekele, W., & Drake, L. (2002). Adoption of soil and water conservation measures (SWCM) by subsistence farmers in the eastern Ethiopia. In *World congress of soil science* (pp. 1747-1749).

Bekele, W., & Drake, L. (2003). Soil and water conservation decision behavior of subsistence farmers in the Eastern Highlands of Ethiopia: a case study of the Hunde-Lafto area. *Ecological economics*, *46*(3), 437-451.

Bekele-Tesemma, A. (1997). *A participatory agroforestry approach for soil and water conservation in Ethiopia*. Wageningen University and Research.

Belayneh, M.,Yirgu, T. and Tsegaye. D., 2019, Potential soil erosion estimation and area prioritization for better conservation planning in Gumara watershed using RUSLE and GIS techniques, *Environmental Systems Research* [en ligne], 8:20, 17 p., DOI: https://doi.org/10.1186/s40068-019-0149-x

Benavidez R, Jackson B, Maxwell D, Norton K (2018) A review of the (Revised) Universal Soil Loss Equation ((R) USLE): with a view to increasing its global applicability and improving soil loss estimates. *Hydrol Earth Syst Sci* 22:6059–6086. https://doi.org/10.5194/hess-22-6059-2018

Benavidez, R. A. (2018). Understanding the effect of changing land use on floods and soil erosion in the Cagayan de Oro catchment, (Unpublished doctoral dissertation), Victoria University of Wellington, New Zealand, 2018.

Bennett, S.N., Wheaton, J.M., Bouwes, N., Jordan, C.E., Macfarlane, W.W., Maestas, J.D., Portugal, E. and Shahverdian, S.M., (2019). Chapter 3 – Planning for Low-Tech Process-Based Restoration. In: J.M. Wheaton, S.N. Bennett, N. Bouwes, J.D. Maestas and S.M. Shahverdian (Editors), Low-Tech Process-Based Restoration of Riverscapes: Design Manual. Utah State University Restoration Consortium, Logan, Utah. pp. 57.

Berliner, D. D. (2009). Systematic Conservation Planning for South Africa's Forest Biome: An assessment of the conservation status of South Africa's.

Bhattacharjee, S., & Ghosh, S. K. (2015). Spatio-temporal change modeling of LULC: a semantic kriging approach. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *2*(4), 177.

Birhanu, A., Adgo, E., Frankl, A., Walraevens, K., & Nyssen, J. (2021). Modelling spatial relationships between land cover change and its drivers in the Afro-alpine belt of Mount Guna (Ethiopia). *Land Degradation & Development*, *32*(14), 3946-3961.

Blomme, G., Ntamwira, J., Kearsley, E., Bahati, L., Amini, D., Safari, N., & Ocimati, W. (2020). Sensitivity and tolerance of different annual crops to different levels of banana shade and dry season weather. *Frontiers in Sustainable Food Systems*, *4*, 545926.

Boo G., Hosner R., Akilimali P.Z., Darin E., Chamberlain H.R., Jochem W.C., Jones P., Shulungu Runika R., Kazadi Mutombo H.M., Lazar A.N. and Tatem A.J. (2021). Modelled gridded population estimates for the HautKatanga, Haut-Lomami, Ituri, Kasaï, Kasaï-Oriental, Lomami and Sud-Kivu provinces in the Democratic Republic of the Congo (2021), version 3.0. WorldPop, University of Southampton, Flowminder Foundation, École de Santé Publique de Kinshasa, Bureau Central du Recensement and Institut National de la Statistique. doi:10.5258/SOTON/WP00720

Book Ruth (2019), NRCS Conservation Planning. *Concepts and Tools*. Illinois Sustainable Ag Partnership – June 19, 2019. U.S. Department of Agriculture (USDA), Washington DC. Available at https://ilsustainableag.org/wp-content/uploads/2019/08/Presentation-3_Book_NRCS-Conservation-Planning-Concepts-Tools.pdf

Borrelli P., Robinson D.A., Fleischer L.R., Lugato E., Ballabio C., Alewell C., Meusburger K., Modugno, S., Schutt, B. Ferro, V. Bagarello, V. Van Oost, K., Montanarella, L., Panagos P. (2017). An assessment of the global impact of 21st century land use change on soil erosion. *Nature Communications,* 8 (1): art. no. 2013

Borrelli, P., Robinson, D. A., Panagos, P., Lugato, E., Yang, J. E., Alewell, C., ... & Ballabio, C. (2020). Land use and climate change impacts on global soil erosion by water (2015-2070). *Proceedings of the National Academy of Sciences*, *117*(36), 21994-22001.

Brown, G. (2013). The relationship between social values for ecosystem services and global land cover: an empirical analysis. *Ecosystem Services*, *5*, 58-68.

Bucekuderhwa CB, Bidubula G, Balemba E (2012) Vulnérabilité et stratégies de gestion des risques dans les zones d'exploitation minière artisanale. *Conjonctures congolaises* 2012:89

Burgess, N., D'Amico Hales, J., Underwood, E., Dinerstein, E., Olson, D., Itoua, I., Schipper, J., Ricketts, T., Newman, K., 2004. *Terrestrial Ecoregions of Africa and Madagascar: a continental assessment.* Island Press, Washington DC. p. 550.

Burkhard B, Maes J, editors. (2017). Mapping ecosystem services. Sofia: Pensoft Publishers: 374 pp.

Butsic, V., Baumann, M., Shortland, A., Walker, S., & Kuemmerle, T. (2015). Conservation and conflict in the Democratic Republic of Congo: The impacts of warfare, mining, and protected areas on deforestation. *Biological conservation*, *191*, 266-273.

Byenda B. M (2016), Dégradation des agroécosystèmes d'exploitation familiale : menace et défi des générations au Sud Kivu, *International Journal of Innovation and Applied Studies*, Vol. 17 No. 1 Jul. 2016, pp. 43-56

Carr, E. R., Wingard, P. M., Yorty, S. C., Thompson, M. C., Jensen, N. K., & Roberson, J. (2007). Applying DPSIR to sustainable development. *International journal of sustainable development & world ecology*, *14*(6), 543-555.

Casado A. (2007), Etude de la structure et de la dynamique des paysages de montagne. Exemple du bassin versant de La Voireuze, affluent de l'Alagnon entre 1948 et 2000, Mémoire, Master 2 Géoenvironnement, Laboratoire de géographie physique UMR 6042 – CNRS, Département de Géographie, Université Blaise Pascal, 51p

Chaudhary, S., N. Chettri, K. Uddin, T. B. Khatri, M. Dhakal, B. Bajracharya, and W. Ning. (2016). "Implications of Land Cover Change on Ecosystems Services and People's Dependency: A Case Study from the Koshi Tappu Wildlife Reserve, Nepal." *Ecological Complexity* 28: 200–211. doi:10.1016/j.ecocom.2016.04.002.

Checkland, P. (1994). Systems theory and management thinking. *American Behavioral Scientist*, *38*(1), 75-91.

Chen, W., Jiang, C., Wang, Y., Liu, X., Dong, B., Yang, J., & Huang, W. (2022). Landscape patterns and their spatial associations with ecosystem service balance: insights from a rapidly urbanizing coastal region of southeastern China. *Frontiers in Environmental Science*, *10*, 1002902.

Cherono, J., Saina E. , Kebeney S. & Chepng'eno W. (2019). Socio-economic factors influencing participation by farm households in soil erosion management in Chepareria Ward, West Pokot County, Kenya. *Journal of Agriculture and Environmental Sciences*, December 2019, Vol. 8, No. 2, pp. 75-85

Chishugi, D. U., Sonwa, D. J., Kahindo, J. M., Itunda, D., Chishugi, J. B., Félix, F. L., & Sahani, M. (2021). How climate change and land use/land cover change affect domestic water vulnerability in Yangambi watersheds (DR Congo). *Land*, *10*(2), 165.

Christensen, M., & Jokar Arsanjani, J. (2020). Stimulating implementation of sustainable development goals and conservation action: predicting future land use/cover change in Virunga National Park, Congo. *Sustainability*, *12*(4), 1570.

Chuma, G. B., Bora, F.S., Ndeko, A.B., Mugumaarhahama, Y., Cirezi, N.C., Mondo, J.M., Bagula, E.M., Karume, K., Mushagalusa, G.N., Schimtz, S. (2022b), Estimation of soil erosion using RUSLE modeling and geospatial tools in a tea production watershed (Chisheke in Walungu), eastern Democratic Republic of Congo, *Modeling Earth System and Environment*, 8, 1273-1289.

Chuma, G. B., Cirezi, N. C., Mondo, J. M., Mugumaarhahama, Y., Ganza, D. M., Katcho, K., ... & Schmitz, S. (2021). Suitability for agroforestry implementation around Itombwe Natural Reserve (RNI), eastern DR Congo: Application of the Analytical Hierarchy Process (AHP) approach in geographic information system tool. *Trees, Forests and People*, *6*, 100125.

Chuma, G. B., Mondo, J. M., Ndeko, A. B., Bagula, E. M., Lucungu, P. B., Bora, F. S., ... & Bielders, C. L. (2022a). Farmers' knowledge and Practices of Soil Conservation Techniques in Smallholder Farming Systems of Northern Kabare, East of DR Congo. *Environmental Challenges*, *7*, 100516.

Ciza, S. K., Mikwa, J. F., Malekezi, A. C., Gond, V., & Bosela, F. B. (2015). Identification des moteurs de déforestation dans la région d'Isangi, République démocratique du Congo. BOIS & FORETS DES TROPIQUES, 324, 29-38.

Claessens, L., Van Breugel, P., Notenbaert, A., Herrero, M., Van De Steeg, J., 2008, Mapping potential soil erosion in east Africa using the universal soil loss equation and secondary data, *IAHS Publ*. 2008, pp. 398-407.

Colman C.B., Guerra A., de Oliveira Roque F., *et al*. (2021), Identifying priority regions and territorial planning strategies for conserving native vegetation in the Cerrado (Brazil) under different scenarios of land use changes, *Science of the Total Environment* (2021), https://doi.org/10.1016/j.scitotenv.2021.150998

COMIFAC and CEEAC (2007), Programme d'action Sous-Régional de lutte contre la dégradation des terres et la désertification en Afrique centrale (PASR / LCD – AC), Juin 2007, 65p

Congedo, L. (2016). Semi-automatic classification plugin documentation. *Release*, *4*(0.1), 29.

Cooper, P. J. M., Leakey, R. R., Rao, M. R., & Reynolds, L. (1996). Agroforestry and the mitigation of land degradation in the humid and sub-humid tropics of Africa. *Experimental agriculture*, *32*(3), 235-290.

Cooper, P. J. M., Leakey, R. R., Rao, M. R., & Reynolds, L. (1996). Agroforestry and the mitigation of land degradation in the humid and sub-humid tropics of Africa. *Experimental agriculture*, *32*(3), 235-290.

Corbera E, Schroeder H (2011) Governing and implementing REDD+. *Environmental Science and Policy* 14: 89–99

Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B., ... & Van Den Belt, M. (1997). The value of the world's ecosystem services and natural capital. *nature*, 387(6630), 253-260.

Cowie, A.L.; Orr, B.J.; Sanchez, V.M.C.; Chasek, P.; Crossman, N.D.; Erlewein, A.; Louwagie, G.; Maron, M.; Metternicht, G.I.; Minelli, S.; *et al*. (2018), Land in balance: The scientific conceptual framework for land degradation neutrality. *Environ. Sci. Policy* 2018, 79, 25–35.

Das, B., Desai, S., Daripa, A., Anand, G. C., Kumar, U., Khalkho, D., ... & Kumar, P. (2023). Land degradation vulnerability mapping in a west coast river basin of India using analytical hierarchy process combined machine learning models. *Environmental Science and Pollution Research*, 1-16.

Das, S., Deb, P., Bora, P. K., & Katre, P. (2020). Comparison of RUSLE and MMF soil loss models and evaluation of catchment scale best management practices for a mountainous watershed in India. *Sustainability*, *13*(1), 232.

Dave, R., Tompkins, E. L., & Schreckenberg, K. (2017). Forest ecosystem services derived by smallholder farmers in northwestern Madagascar: Storm hazard mitigation and participation in forest management. *Forest Policy and Economics*, *84*, 72-82.

David, W. P.: Soil and Water Conservation Planning: Policy Issues and Recommendations, J. Philipp. Dev., 15, 47–84, 1988.

Davison, C. W., Rahbek, C., & Morueta-Holme, N. (2021). Land‐use change and biodiversity: Challenges for assembling evidence on the greatest threat to nature. *Global Change Biology*, *27*(21), 5414-5429.

De Jong, B. (2012), Assessment of Land Use Change Impact on Ecohydrological Parameters Using Remote Sensing in the Sub-Catchments of the Patish Watershed, Israel. MSc. Thesis. Land Degradation and Development Group, Wageningen University, 62p

de la Fuente B., Weynants, M., Bertzky, B., Delli, G., Mandrici, A., Garcia Bendito, E., & Dubois, G. (2020). Land productivity dynamics in and around protected areas globally from 1999 to 2013. *Plos one*, *15*(8), e0224958.

De Wasseige C, Devers D, de Marken P, Eba'a Atyi R, Nasi R and Mayaux P, eds. 2009.
Les forêts du bassin du Congo: État des forêts 2008. Luxemburg: Publications Office of the European Union.

Dee, L. & Gerber, L. (2012) Applications of Decision Theory to Conservation Planning and Management. *Nature Education Knowledge* 3(10):11

Deepak Khare K, Dhore T (2007) Watershed prioritization considering soil erosion status: a case study of India. ASABE International Conference on Watershed Management to Meet Water Quality Standards and TMDLs March 10–13, in San Antonio (TX). pp. 533–540. doi:10.13031/2013.22487.

Depicker A., & Dewitte O. (2021). Shallow landslide inventory for 2000-2019 (eastern DRC, Rwanda, Burundi) (v1.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.5027004

Depicker, A., Jacobs, L., Mboga, N., Smets, B., Van Rompaey, A., Lennert, M., ... & Govers, G. (2021). Historical dynamics of landslide risk from population and forest-cover changes in the Kivu Rift. *Nature Sustainability*, *4*(11), 965-974.

Desmet, P. and Govers, G.A. (1996). GIS procedure for automatically calculating the ULSE LS factor on topographically complex landscape units, *J. Soil Water Conserv*. 1996, 51, pp. 427-433.

Dollinger, J., & Jose, S. (2018). Agroforestry for soil health. *Agroforestry Systems*, *92*(2), 213-219.

Dumont, E. S., Bonhomme, S., Pagella, T. F., & Sinclair, F. L. (2019). Structured stakeholder engagement leads to development of more diverse and inclusive agroforestry options. *Experimental Agriculture*, *55*(S1), 252-274.

Ebrahim, E.H.; Mohamed, A. (2017). Land use/cover dynamics and its drivers in Gelda catchment, Lake Tana watershed, Ethiopia. *Environ. Syst. Res*. 2017, 6, 1–13

ECA (2007). Africa Review Report on Drought and Desertification in Africa. Economic Commission for Africa, United Nations Economic and Social Council. Fifth Meeting of the Africa Committee on Sustainable Development (ACSD-5) Regional Implementation Meeting (RIM) for CSD-16 Addis Ababa 22-25 October 2007

Eisenberg, J., & Muvundja, F. A. (2020). Quantification of erosion in selected catchment areas of the ruzizi river (DRC) using the (R) USLE model. *Land*, *9*(4), 125.

Ekka, P., Patra, S., Upreti, M., Kumar, G., Kumar, A., & Saikia, P. (2023). Land Degradation and its impacts on Biodiversity and Ecosystem services. *Land and Environmental Management through Forestry*, 77-101.

Elbouqdaoui K., Ezzine H., Badrahoui M., Rouchdi M., Zahraoui M., Ozer A. (2005), Approche méthodologique par télédétection et SIG de l'évaluation du risque potentiel d'érosion hydrique dans le bassin versant de l'Oued Srou (Moyen Atlas, Maroc), *Geo-Eco-Trop*, 2005, 29: 25-36

ELD Initiative (2013) Opportunity lost: Mitigating risk and making the most of your land assets. An assessment of the exposure of business to land degradation risk and the opportunities inherent in sustainable land management. Available from: www.eld-initiative.org

Elgubshawi, A. A. (2008). Soil degradation. Its aspects and modelling a case study of northeast Nuba Mountain, South Kordofan state, Sudan. *Institute of G. Ecology and E. protection Prof. Dr. R. Gloaguen TU Bergakademie, Institute of Geology*.

Ersoy Tonyaloğlu, E. (2025). Future land use/land cover and its impacts on ecosystem services: case of Aydın, Turkey. *International Journal of Environmental Science and Technology*, *22*(6), 4601-4617.

Ersoy Tonyaloğlu, E. (2025). Future land use/land cover and its impacts on ecosystem services: case of Aydın, Turkey. *International Journal of Environmental Science and Technology*, *22*(6), 4601-4617.

Esmail, B., Cortinovis, C., Wang, J., Geneletti, D., & Albert, C. (2023). Mapping and assessing ecosystem services for sustainable policy and decision-making in Eritrea. *Ambio*, 1-18.

Espiritu, K. (1997). Development of a Computerized Version of the Universal Soil Loss Equation and the USGS Pollutant Loading Functions.

Eswaran, H., Almaraz, R., van den Berg, E., & Reich, P. (1997). An assessment of the soil resources of Africa in relation to productivity. *Geoderma*, *77*(1), 1-18.

Faludi, A. (2013). *A reader in planning theory* (Vol. 5). Elsevier.

Fang, Z., Ding, T., Chen, J., Xue, S., Zhou, Q., Wang, Y., ... & Yang, S. (2022). Impacts of land use/land cover changes on ecosystem services in ecologically fragile regions. *Science of the Total Environment*, *831*, 154967.

FAO (1976) A framework for land evaluation. Soils Bulletin 32. Food and Agriculture Organization of the United Nations, Rome, Italy. ISBN 92-5-100111-1. https://www.fao.org/3/x5310e/x5310e00.htm.

FAO (Food and Agriculture Organization) 2015 : *État des ressources en sols dans le monde. Résumé technique, Groupe technique intergouvernemental sur les sols 2016*. www.FAO.org. Consulted 23th August 2022

Farashi, A., Naderi, M. & Parvian, N., 2016. Identifying a preservation zone using multi–criteria decision analysis. *Animal Biodiversity and Conservation*, 39.1: 29–36, https://doi.org/10.32800/abc.2016.39.0029

Feng, S., Zhao, W., Zhan, T., Yan, Y., & Pereira, P. (2022). Land degradation neutrality: A review of progress and perspectives. *Ecological Indicators*, *144*, 109530.

Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1‐km spatial resolution climate surfaces for global land areas. *International journal of climatology*, *37*(12), 4302-4315.

Flanagan, D.C., Ascough, J.C., Nearing, M.A., Laflen, J.M., (2001). The water erosion prediction project (WEPP) model. In: Harmon, R.S., Doe, W.W. (Eds.), Landscape Erosion and Evolution Modelling. Springer, Boston, MA, pp. 145–199.

Fokeng, R. M., & Fogwe, Z. N. (2022). Landsat NDVI-based vegetation degradation dynamics and its response to rainfall variability and anthropogenic stressors in Southern Bui Plateau, Cameroon. *Geosystems and Geoenvironment*, *1*(3), 100075.

Foltête, J. C., Clauzel, C., Joly, D., Philibert, A., Roy, D., Sahraoui, Y., ... & Youssoufi, S. (2015). *Dynamique des paysages et potentiel écologique de la région Franche-Comté (D2PE)* (Doctoral dissertation, MSHE Claude Nicolas Ledoux; Université Bourgogne Franche-Comté).

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote sensing of environment*, 80(1), 185-201.

Fu B, Chen L, Ma K, Zhou H, Wang J (2000). The relationships between land use and soil conditions in the hilly area of the Loess Plateau in northern Shaanxi, China. *CATENA* 36:69–78

Fumy, F., & Fartmann, T. (2021). Climate and land‐use change drive habitat loss in a mountain bird species. *Ibis*, *163*(4), 1189-1206.

Ganasri, B.P. and Ramesh H., 2015, « Assessment of soil erosion by RUSLE model using remote sensing and GIS - A case study of Nethravathi Basin », *Geoscience Frontiers* (2015). http://dx.doi.org/10.1016/j.gsf.2015.10.007

Gao, J. and Liu, Y. (2010). Determination of land degradation causes in Tongyu County, Northeast China via land cover change detection. *International Journal of Earth Observations and Geoinformation* 12:9-16.

Gashaw, T., Tulu, T. and Argaw, M. (2017). Erosion risk assessment for prioritization of conservation measures in Geleda watershed, Blue Nile basin, Ethiopia, *Environmental Systems Research*, (2017) 6:1, 14p. https://doi.org/10.1186/s40068-016-0078-x

Gashaw, T., Tulu, T., Argaw, M., & Worqlul, A. W. (2018). Land capability classification for planning land uses in the Geleda watershed, Blue Nile Basin, Ethiopia. *Modeling Earth Systems and Environment*, *4*, 489-499.

Gayen, A., Saha, S., & Pourghasemi, H. R. (2020). Soil erosion assessment using RUSLE model and its validation by FR probability model. *Geocarto International*, *35*(15), 1750-1768.

Gavrilovic Z. (1988). The use of an empirical method (Erosion Potential Method) for calculating sediment production and transportation in unstudied or torrential streams, Proceedings of the International Conference On River Regime, Wallingford, UK. Hydraulics Research Limited, Wallingford, Oxon UK. 1988.

Gebre, S. L., Cattrysse, D., Alemayehu, E., & Van Orshoven, J. (2021). Multi-criteria decision making methods to address rural land allocation problems: A systematic review. *International Soil and Water Conservation Research*, *9*(4), 490-501.

Gedefaw, M., Denghua, Y., Hao, W., Alemu, B., Chanie, M., & Agitew, G. (2018). Evaluation of adoption behavior of soil and water conservation practices in the Simein Mountain National Park, Highlands of Ethiopia. *Cogent food & agriculture*, *4*(1), 1513782.

Geist, H. J., & Lambin, E. F. (2001). What drives tropical deforestation. *LUCC Report series*, *4*, 116.

Gessesew, W. S. (2017). Application of DPSIR framework for assessment of land degradation: a review. *Forest*, *3*(1), 4-000.

Githiora-Murimi, Y. W., Owuor, M. A., Abila, R., Olago, D., & Oriaso, S. (2022). Integrating stakeholder preferences into ecosystem services mapping in Yala wetland, Kenya. *Ecosystems and People*, *18*(1), 146-163.

Gold, M. A., & Garrett, H. E. (2009). Agroforestry nomenclature, concepts, and practices. *North American agroforestry: an integrated science and practice*, 45-56.

Gomes, E., Inácio, M., Bogdzevič, K., Kalinauskas, M., Karnauskaitė, D., & Pereira, P. (2021). Future land-use changes and its impacts on terrestrial ecosystem services: A review. *Science of The Total Environment, 781*, 146716.

Grinand C, Vieilledent G, Razafimbelo T, Rakotoarijaona J-R, Nourtier M, Bernoux M. (2020). Landscape-scale spatial modelling of deforestation, land degradation, and regeneration using machine learning tools. *Land Degrad Dev*. 2020;1–14. https://doi.org/10.1002/ldr.3526

Grober-Dunsmore, R., Pittman, S. J., Caldow, C., Kendall, M. S., & Frazer, T. K. (2009). A landscape ecology approach for the study of ecological connectivity across tropical marine seascapes. *Ecological connectivity among tropical coastal ecosystems*, 493-530.

GTAC, 2002, EXERCISE 1 Creating a Cloud-free Landsat Composite in Google Earth Engine, https://fsapps.nwcg.gov/gtac/CourseDownloads/Training/Remote_Sensing/DigitalSoilMapping_EarthEngine_NRCS/01_Exercises/Exercises_PDFs/01_DigitalSoilMappingEarthEngine_LandsatComposite.pdf , accessed on 5 January 2023

Guder, A. C., & Kabeta, W. F. (2025). Evaluation of future land use change impacts on soil erosion for holota watershed, Ethiopia. *Scientific Reports*, *15*(1), 6782.

Gulersoy, A. L. İ., Gumus, N., Celik, M., & Ilhan, A. (2017). Relationship between land use and land classification in the Tahtali Dam Protection Basin (Izmir, Turkey). *Journal of Environmental Biology*, *38*(5).

Gülersoy, A. L. İ., Gümüş, N., Sonmez, M., & Gunduzoglu, G. (2015). Relations between the land use and land capability classification in Kucuk Menderes River Basin. *Journal of Environmental Biology*, *36*(1).

Gurjeet S. and Rabindra K. P. (2017), Grid-cell based assessment of soil erosion potential for identification of critical erosion-prone areas using USLE, GIS and remote sensing: A case study in the Kapgari watershed, India, *International Soil and Water Conservation Research* 5 (2017) 202–211

Halbac-Cotoara-Zamfir, R., Polinesi, G., Chelli, F., Salvati, L., Bianchini, L., Marucci, A., & Colantoni, A. (2022). Found in Complexity, Lost in Fragmentation: Putting Soil Degradation in a Landscape Ecology Perspective. *International Journal of Environmental Research and Public Health*, *19*(5), 2710.

Hansson, S. O. (1994). Decision theory. *A brief introduction. Department of Philosophy and the History of technology. Royal Institute of Technology. Stockholm*.

Harfoot, M. B., Johnston, A., Balmford, A., Burgess, N. D., Butchart, S. H., Dias, M. P., ... & Geldmann, J. (2021). Using the IUCN Red List to map threats to terrestrial vertebrates at global scale. *Nature Ecology & Evolution, 5*(11), 1510-1519.

Hasan, S. S., Zhen, L., Miah, M. G., Ahamed, T., & Samie, A. (2020). Impact of land use change on ecosystem services: A review. *Environmental Development*, *34*, 100527.

Hateffard, F., Mohammed, S., Alsafadi, K., Enaruvbe, G. O., Heidari, A., Abdo, H. G., & Rodrigo-Comino, J. (2021). CMIP5 climate projections and RUSLE-based soil erosion assessment in the central part of Iran. *Scientific reports*, *11*(1), 1-17.

Head, J. S., Boesch, C., Robbins, M. M., Rabanal, L. I., Makaga, L., & Kühl, H. S. (2013). Effective sociodemographic population assessment of elusive species in ecology and conservation management. *Ecology and Evolution*, *3*(9), 2903-2916.

Hengl T., G.B.M. Heuvelink, B. Kempen, J.G.B. Leenaars, M.G. Walsh, K.D. Shepherd, A. Sila, R.A. MacMillan, J. Mendes de Jesus, L.T. Desta, J.E. Tondoh, 2015. Mapping Soil Properties of Africa at 250 m Resolution: Random Forests Significantly Improve Current Predictions. *PLoS ONE* 10(6)

Heri-Kazi Bisimwa, A. (2020). *Caractérisation de l'état de dégradation des terres par l'érosion hydrique dans le Sud-Kivu montagneux à l'Est de la RD Congo* (Doctoral dissertation, UCL-Université Catholique de Louvain).

Heri-Kazi, A. B., & Bielders, C. L. (2021a). Erosion and soil and water conservation in South-Kivu (eastern DR Congo): The farmers' view. *Land Degradation & Development*, *32*(2), 699-713.

Heri-Kazi, A. B., & Bielders, C. L. (2021b). Cropland characteristics and extent of soil loss by rill and gully erosion in smallholder farms in the KIVU highlands, DR Congo. *Geoderma Regional*, *26*, e00404.

Hermans, K., & McLeman, R. (2021). Climate change, drought, land degradation and migration: exploring the linkages. *Current opinion in environmental sustainability*, *50*, 236-244.

Hernando, D., & Romana, M. G. (2015). Development of a soil erosion classification system for cut and fill slopes. *Transportation Infrastructure Geotechnology*, *2*(4), 155-166.

Hersperger, A. M. (1994). Landscape ecology and its potential application to planning. *Journal of Planning Literature*, *9*(1), 14-29.

Herzberg, R., Pham, T. G., Kappas, M., Wyss, D., & Tran, C. T. M. (2019). Multi-criteria decision analysis for the land evaluation of potential agricultural land use types in a hilly area of Central Vietnam. *Land*, *8*(6), 90.

Hossein, S.-M. (2019). Improving spatial accuracy of urban growth simulation models using ensemble forecasting approaches. *Computers, Environment and Urban Systems*, 76, pp. 91-100.

Hu, T., Yang, J., Li, X., & Gong, P. (2016). Mapping urban land use by using landsat images and open social data. *Remote Sensing*, *8*(2), 151.

Hurni, H., Abate, S., Bantider, A., Debele, B., Ludi, E., Portner, B., ... & Zeleke, G. (2010). Land degradation and sustainable land management in the highlands of Ethiopia.

Hurni, H., Herweg, K., Portner, B., & Liniger, H. (2008). Soil erosion and conservation in global agriculture. *Land use and soil resources*, 41-71.

Ilunga L. (1991), Morphologie, volcanisme et sédimentation dans le rift du Sud-Kivu, *Bulletin de la Société géographique de Liège*, 27, 209-228

Institute for Environmental Security (2008), Mining, forest change and conflict in the Kivu, eastern Democratic Republic of Congo, Outcome of a short study within the IES-ESPA programme, May 2008, Institute for Environmental Security (IES), The Hague, The Netherlands, 22p

IPCC (2014). Summary for policymakers In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change ed C B Field *et al* (Cambridge)(Cambridge University Press)(Cambridge, United Kingdom and New York, NY, USA) pp 1–32

IPCC (2014). Summary for policymakers. In: [Field CB, Barros VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi YL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds)]. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK and New York, USA. pp 1–32

IRP (2017). Assessing global resource use: A systems approach to resource efficiency and pollution reduction. Bringezu, S., Ramaswami, A., Schandl, H., O'Brien, M., Pelton, R., Acquatella, J., Ayuk, E., Chiu, A.S.F., Flanegin, R., Fry, J., Giljum, S., Hashimoto, S., Hellweg, S., Hosking, K., Hu, Y., Lenzen, M., Lieber, M., Lutter, S., Miatto, M., Singh Nagpure, A., Obersteiner, M., van Oers, L., Pfister, S., Pichler, P., Russell, A., Spini, L., Tanikawa, H., van der Voet, E., Weisz, H., West, W., Wijkman, A., Zhu, B., and Zivy, R. A Report by the International Resource Panel. United Nations Environment Programme, Nairobi, Kenya. [100 pp.]

IUCN (2015), Land Degradation Neutrality: implications and opportunities for conservation, Technical Brief 2nd Edition, November 2015. Nairobi: IUCN. 19p.

Jaeger, J. A., Soukup, T., Schwick, C., Madriñán, L. F., & Kienast, F. (2016). Landscape fragmentation in Europe. In *European Landscape Dynamics* (pp. 187-228). CRC Press.

Jaiswal, R. K., Ghosh, N. C., Galkate, R. V., & Thomas, T. (2015). Multi criteria decision analysis (MCDA) for watershed prioritization. *Aquatic procedia*, *4*, 1553-1560.

Jara-Rojas, R., Bravo-Ureta, B. E., & Díaz, J. (2012). Adoption of water conservation practices: A socioeconomic analysis of small-scale farmers in Central Chile. *Agricultural Systems*, *110*, 54-62.

Javed A., Jamal S., Khandey Y.M. (2012), Climate Change Induced Land Degradation and Socio-Economic Deterioration: A Remote Sensing and GIS-Based Case Study from Rajasthan, India, *Journal of Geographic Information System*, 2012, 4, 219-228 http://dx.doi.org/10.4236/jgis.2012.43026

Jhariya D. C., Tarun Kumar & Pandey H. K. (2018): Watershed prioritization based on soil and water hazard model using remote sensing, geographical information system and multi-criteria decision analysis approach, *Geocarto International*, DOI: 10.1080/10106049.2018.1510039

Josh CS, Dash DC. (1982). Geomorphic prediction models for sediment production rate and intensive priorities of watersheds in Mayurakshi catchment. Proceedings of International Symposium on Hydrological Aspects of Mountainous Watersheds. Vol. 1. Roorkee: School of Hydrology, University of Roorkee; p. 15–23.

Kabonyi C.N., Salmon M. et Roche E. (2011), Le Parc National de Kahuzi - Biega (R. D. Congo), patrimoine en péril ? Le secteur « Haute Altitude », situation et perspectives, *Geo-Eco-Trop*., 2011, 35: 1 – 8

Kabuanga, J. M., Adipalina Guguya, B., Ngenda Okito, E., Maestripieri, N., Saqalli, M., Rossi, V., & Iyongo Waya Mongo, L. (2020). Suivi de l'anthropisation du paysage dans la région forestière de Babagulu, République Démocratique du Congo. *VertigO-la revue électronique en sciences de l'environnement*, *20*(2).

Kabuanga, J. M., Koy, J. K., Wardell, D. A., Mikwa, J. F., Kabuanga, J. M., Ngonga, A. M. M., ... & Doumenge, C. (2019). Dynamique de la déforestation dans la Réserve de biosphère de Yangambi (République démocratique du Congo): variabilité spatiale et temporelle au cours des 30 dernières années. *Bois et Forêts des Tropiques*, *341*, 15.

Kabulu Djibu, J. P., Bamba, I., Munyemba Kankumbi, F., Defourny, P., Vancutsem, C., Nyembwe, N. S., ... & Bogaert, J. (2008). Analyse de la structure spatiale des forêts au Katanga. *Annales de la Faculté des Sciences Agronomiques de l'Université de Lubumbashi*, *1*.

Kadam A., Rajasekhar M, Umrikar B., Bhagat V., Wagh V. & Sankua R. N. (2021), Land Suitability Analysis for Afforestation in Semi-arid Watershed of Western Ghat, India: A Groundwater Recharge Perspective, *Geology, Ecology, and Landscapes*, 5:2, 136-148, DOI: 10.1080/24749508.2020.1833643

Karamage F., Shao H., Chen X., Ndayisaba F., Nahayo L., Kayiranga A., Kehinde O.J., Liu T. and Zhang C. (2016), Deforestation Effects on Soil Erosion in the LakeKivu Basin, DR Congo-Rwanda, *Forests* 2016, 7, 281, 17p

Kengoum Djiegni, F., Pham, T. T., Moeliono, M., Dwisatrio, B., & Sonwa, D. J. (2020a). Le contexte de la REDD+ en République Démocratique du Congo: Causes, agents et institutions [2e édition] (Vol. 211). CIFOR.

Kengoum F, Pham TT, Moeliono M, Dwisatrio B, Sonwa DJ. 2020. *The context of REDD+ in the Democratic Republic of Congo: Drivers, agents and institutions. 2nd edition*. Occasional Paper 207. Bogor, Indonesia: CIFOR.

Kevin, M. (2015) *Fragstats Help*; University of Massachusetts: Amherst, MA, USA, 2015

Kilonzi, F., & Ota, T. (2019). Ecosystem service preferences across multilevel stakeholders in co-managed forests: Case of Aberdare protected forest ecosystem in Kenya. *One Ecosystem*, *4*, e36768.

Kindu Mengesha, M. (2017). *Landscape Level Modelling of the Ethiopian Highland Resources: A geo-informatics application to their sustainable management, use and conservation*. Technische Universitat Munchen.

Kindu, M., Schneider, T., Teketay, D., & Knoke, T. (2016). Changes of ecosystem service values in response to land use/land cover dynamics in Munessa–Shashemene landscape of the Ethiopian highlands. *Science of the Total Environment*, 547, 137-147.

Kipkulei, H. K., Bellingrath-Kimura, S. D., Lana, M., Ghazaryan, G., Boitt, M., & Sieber, S. (2022). Modelling cropland expansion and its drivers in Trans Nzoia County, Kenya. *Modeling Earth Systems and Environment*, *8*(4), 5761-5778.

Kiptot, E., Franzel, S., & Degrande, A. (2014). Gender, agroforestry and food security in Africa. *Current Opinion in Environmental Sustainability*, *6*, 104-109.

Kirui, O. K., Mirzabaev, A., & von Braun, J. (2021). Assessment of land degradation 'on the ground' and from 'above'. *SN Applied Sciences*, *3*, 1-13.

Kizito F; Tamene L; Koech N; Pondi B; Nganga K. (2018). *Land degradation assessments using multiscale hierarchical approaches for agroecosystem restoration and improved food security: The case for Kenya and Burkina Faso*. CIAT Publication. International Center for Tropical Agriculture (CIAT) and TMG-Think Tank for Sustainability. Nairobi, Kenya. 56 p.

Koech, G., Winowiecki, L. A., Westermann, O., Bourne, M., Wamawungo, D., Carsan, S., ... & Chomba, S. (2020). Regreening Africa: A bottom-up transformation of degraded lands. *ETFRN News*, 219-226.

Koko, I. A., Misana, S. B., Kessler, A., & Fleskens, L. (2020). Valuing ecosystem services: stakeholders' perceptions and monetary values of ecosystem services in the Kilombero wetland of Tanzania. *Ecosystems and People*, *16*(1), 411-426.

Kothari C.R. (2004), *Research Methodology: Methods and Techniques*, second ed., New Age International Publisher, Delhi, India, 401p

Kouriati, A., Tafidou, A., Lialia, E., Prentzas, A., Moulogianni, C., Dimitriadou, E., & Bournaris, T. (2024). A Multicriteria Decision Analysis Model for Optimal Land Uses: Guiding Farmers under the New European Union's Common Agricultural Policy (2023–2027). *Land*, *13*(6), 788.

Kpadonou, R. A. B., Owiyo, T., Barbier, B., Denton, F., Rutabingwa, F., & Kiema, A. (2017). Advancing climate-smart-agriculture in developing drylands: Joint analysis of the adoption of multiple on-farm soil and water conservation technologies in West African Sahel. *Land use policy*, *61*, 196-207.

Kristensen, P. (2004). The DPSIR Framework [Paper presentation]. In *Workshop on a Comprehensive/Detailed Assessment of the Vulnerability of Water Resources to Environmental Change in Africa using River Basin Approach, Nairobi, Kenya. https://wwz. ifremer. fr/dce/content/download/69291/913220/DPSIR.pdf*.

Kulimushi, L. C., Choudhari, P., Maniragaba, A., Elbeltagi, A., Mugabowindekwe, M., Rwanyiziri, G., ... & Singh, S. K. (2021). Erosion risk assessment through prioritization of sub-watersheds in Nyabarongo River catchment, Rwanda. *Environmental Challenges*, *5*, 100260.

Kulimushi, L. C., Maniragaba, A., Choudhari, P., Elbeltagi, A., Uwemeye, J., Rushema, E., & Singh, S. K. (2021). Evaluation of soil erosion and sediment yield spatio-temporal pattern during 1990–2019. *Geomatics, Natural Hazards and Risk*, *12*(1), 2676-2707.

Kumar, S., Singh, D. R., Jha, G. K., Mondal, B., & Biswas, H. (2021). Key determinants of adoption of soil and water conservation measures: A review. ICAR. *Indian Journal of Agricultural Sciences* 91 (1): 08–15.

Kupfer, J. A. (2012). Landscape ecology and biogeography: rethinking landscape metrics in a post-FRAGSTATS landscape. *Progress in physical geography*, *36*(3), 400-420.

Labrière, N., Locatelli, B., Laumonier, Y., Freycon, V., & Bernoux, M. (2015). Soil erosion in the humid tropics: A systematic quantitative review. *Agriculture, Ecosystems & Environment*, *203*, 127-139.

Lal, R., Hall, G. F., & Miller, F. P. (1989). Soil degradation: I. Basic processes. *Land Degradation & Development*, *1*(1), 51-69.

Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. W., ... & Xu, J. (2001). The causes of land-use and land-cover change: moving beyond the myths. *Global environmental change*, *11*(4), 261-269.

Lamy, T., Liss, K. N., Gonzalez, A., & Bennett, E. M. (2016). Landscape structure affects the provision of multiple ecosystem services. *Environmental Research Letters*, *11*(12), 124017.

Land Degradation Assessment in Drylands (LADA). 2011. Land degradation assessment in drylands: methodology and results. Food and Agriculture Organization of the United Nations, Rome, Italy. https://www.fao.org/3/i3241e/i3241e.pdf

Le, Q. B., Nkonya, E., & Mirzabaev, A. (2016). Biomass productivity-based mapping of global land degradation hotspots. *Economics of land degradation and improvement–A global assessment for sustainable development*, *55*.

Le, Q. B., Tamene, L., & Vlek, P. L. (2012). Multi-pronged assessment of land degradation in West Africa to assess the importance of atmospheric fertilization in masking the processes involved. *Global and Planetary Change*, *92*, 71-81.

Lee, E., Ahn, S., lm, S. (2017), Estimation of soil erosion rate in the Democratic People's Republic of Korea using the RUSLE model. *Forest science and technology*, *13*(3), 100-108.

Lee, S. W., Hwang, S. J., Lee, S. B., Hwang, H. S., & Sung, H. C. (2009). Landscape ecological approach to the relationships of land use patterns in watersheds to water quality characteristics. *Landscape and Urban Planning*, *92*(2), 80-89.

Lefévère J. (2003), Analyse et interprétation du canevas lithostratigraphique et tectonique du synclinal de l'Itombwe (Sud Kivu-République Démocratique du Congo) à l'aide des données satellitaires et radar, Mémoire de fin d'étude, Université Libre de Bruxelles

Leh, M., Bajwa, S., & Chaubey, I. (2013). Impact of land use change on erosion risk: an integrated remote sensing, geographic information system and modeling methodology. *Land Degradation & Development*, *24*(5), 409-421.

Lestariningsih, I.D., Widianto, Agustina, C., Sudarto, Kurniawan, S. (2018), Relationship between land degradation, biophysical and social factors in Lekso Watershed, East Java, Indonesia. *Journal of degraded and mining lands management*, 5 (3), 1283-1291

Li, J., Zhou, Y., Li, Q., Yi, S., & Peng, L. (2022). Exploring the Effects of Land Use Changes on the Landscape Pattern and Soil Erosion of Western Hubei Province from 2000 to 2020. *International Journal of Environmental Research and Public Health*, 19(3), 1571.

Li, Z., Liu, W., & Zheng, F. (2013). The land use changes and its relationship with topographic factors in the Jing River catchment on the Loess Plateau of China. In *SpringerPlus* (Vol. 2, No. 1, pp. 1-6). SpringerOpen.

Liu, L., Chen, X., Chen, W., & Ye, X. (2020). Identifying the impact of landscape pattern on ecosystem services in the Middle Reaches of the Yangtze River Urban Agglomerations, China. *International journal of environmental research and public health*, *17*(14), 5063

Lo, A., El-Swaify, S.A., Dangler, E.W., Shinshiro, L. (1985), Effectiveness of El30 as an erosivity index in Hawaii, dans: *Soil Erosion and Conservation*; E1-Swaify, S.A., Moldenhauer, W.C., Lo, A., Eds.; Soil Conservation Society of America: Ankeny, IA, USA, 1985; pp. 384-392.

Loukrakpam, C., & Oinam, B. (2021). Linking the past, present and future scenarios of soil erosion modeling in a river basin. *Global Journal of Environmental Science and Management*, *7*(3), 457-472.

Lucia, M.-B.; Lyons, M.B.; Phinn, S.R.; Roelfsema, C.M. (2019). Trends in remote sensing accuracy assessment approaches in the context of natural resources. *Remote Sens.* 2019, 11, 1–16.

Luederitz, C., E. Brink, F. Gralla, V. Hermelingmeier, M. Meyer, L. Niven, L. Panzer, S. Partelow, *et al*. (2015). A review of urban ecosystem services: Six key challenges for future research. *Ecosystem Services* 14: 98–112. https://doi.org/10.1016/j.ecoser.2015.05.001.

Lufafa, A., Tenywa, M. M., Isabirye, M., Majaliwa, M. J. G., & Woomer, P. L. (2003). Prediction of soil erosion in a Lake Victoria basin catchment using a GIS-based Universal Soil Loss model. *Agricultural Systems*, 76(3), 883e894. https://doi.org/10.1016/S0308-521X(02)00012-4

Lulseged T., Zenebe A., Ermias A., Tesfaye Y. (2017), Estimating landscape susceptibility to soil erosion using a GIS-based approach in Northern Ethiopia, *International Soil and Water Conservation Research*, 5 (2017), p221–230http://dx.doi.org/10.1016/j.iswcr.2017.05.002

Macháček J (2019). Typology of environmental impacts of artisanal and small-scale mining in African Great Lakes Region. Sustainability 11(11):3027

Mahamba, J. A., Kayitoghera, G. M., Musubao, M. K., Chuma, G. B., & Sahani, W. M. (2023). Evolution of gully erosion and susceptibility factors in the urban watershed of the Kimemi (Butembo/DR Congo). *Geography and Sustainability*, *4*(3), 268-279.

Maitima M.J., Mugatha M.S., Reid S.R., Gachimbi N.L., Majule A., Lyaruu H., Pomery D., Mathai S. and Mugisha S. (2009), The linkages between land-use change, land degradation and biodiversity across East Africa, *African Journal of Environmental Science and Technology* Vol. 3 (10), pp. 310-325

Majaliwa (2008), *Land use and climate change effects on livelihoods and sediments and carbon loading in the Lake Tanganyika Region*, Technical Report, ISP/BUKAVU, November 2008, 20p

Majaliwa J.G.M. Bashwira, S.Tenywa, M. & Kansiime, F. (2012), An overview of pollution loading into Lake Kivu basin, Third RUFORUM Biennial Meeting 24 - 28 September 2012, Entebbe, Uganda, *Research Application Summary*, p863-868

Majoro, F., Wali, U. G., Munyaneza, O., Naramabuye, F. X., Bugenimana, E. D., & Mukamwambali, C. (2020). Sediment transport and its impacts on lake kivu, gihira water treatment plant and various hydropower plants along Sebeya River in Rwanda. *Journal of Water Resource and Protection*, *12*(11), 934-950.

Maki Mateso, J. C. (2014). Inventaire de glissements de terrain et étude des éléments à risque dans le rift ouest du bassin du lac Kivu. *Travail de fin d'études de Master complémentaire en gestion des risques naturels, Faculté des Sciences*.

Maki Mateso, J. C. (2023). *Interactions between landslides, land use and management: a case study on the rift flanks west of Lake Kivu (DR Congo)* (Doctoral dissertation, UCL-Université Catholique de Louvain). https://dial.uclouvain.be/pr/boreal/object/boreal:274386

Maki Mateso, J. C., Bielders, C., Monsieurs, E., Depicker, A., Smets, B., Tambala, T., ... & Dewitte, O. (2021). Natural and human-induced landslides in a tropical mountainous region: the Rift flank west of Lake Kivu (DR Congo). *Natural Hazards and Earth System Sciences Discussions*, *2021*, 1-26.

Malczewski, J. (1999). *GIS and multicriteria decision analysis*. John Wiley & Sons.

Mame Aissatou Toure, Mamadou Lamine Ndiaye, Vieux Boukhaly Traore, Guilgane Faye, Boubacar Cisse, Aminata Ndiaye and Cheikh Tidiane Wade (2016), Dynamics Analysis and Factors in Landscape Units Evolution in Senegal River Delta Ecosystems, *Journal of Geography*, *Environment and Earth Science International* 7(1): 1-12, 2016; Article no.JGEESI.27909 DOI: 10.9734/JGEESI/2016/27909

Mardani A, Jusoh A, Norkm, Khalifah Z, Zakwan N, Valipour A. (2015). Multiple criteria decision-making techniques and their applications—a review of the literature from 2000 to 2014. Econ.-Res. Istraz. 28:516–571.

Margules, C., Pressey, R. Systematic conservation planning. *Nature* **405,** 243–253 (2000). https://doi.org/10.1038/35012251

Marques, A., Martins, I. S., Kastner, T., Plutzar, C., Theurl, M. C., Eisenmenger, N., ... & Pereira, H. M. (2019). Increasing impacts of land use on biodiversity and carbon sequestration driven by population and economic growth. *Nature ecology & evolution*, *3*(4), 628-637.

Martınez-Harms, M.J., and P. Balvanera. (2012). Methods for mapping ecosystem service supply: A review. International Journal of Biodiversity Science, *Ecosystem Services & Management* 8: 17–25. https://doi.org/10.1080/21513732.2012.663792

Mashame, G., & Akinyemi, F. (2016). Towards a remote sensing based assessment of land susceptibility to degradation: Examining seasonal variation in land use-land cover for modelling land degradation in a semi-arid context. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *3*, 137.

Mashimango B. (2015), Sediment and nutrient loading into lake kivu: a case study lwiro micro-catchment, democratic republic of Congo, Msc Thesis, integrated watershed management, Makerere University, June, 2015, 75p.

Mateso, J. M., Monsieurs, E., Bielders, C., & Dewitte, O. (2018). Landslides, land use and the anthropization of a rural environment: focus on the Rift flanks west of Lake Kivu (DR Congo).

Mayaux P., Pekel J.-F., Desclée B., Donnay F., Lupi A., Achard F., Clerici M., Bodart C., Brink A., Nasi R., Belward A. (2013), State and evolution of the African rainforests between 1990 and 2010. Philos. Trans. R. Soc. Lond. B Biol. Sci. 368, 20120300 (2013).

Mays L. W., *Water Resources Engineering*, John Wiley & Sons, 2005.

Mburu D.M. (2015), Effects of land-use and land-cover change on land degradation in Kijabe – Longonot catchment, Kenya, *International Journal of Scientific Research and Innovative Technology*, ISSN: 2313-3759, Vol. 2 No. 10, p22-36

McGarigal, K., Cushman, S.A., Ene, E., 2012. FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical Maps. Computer Software Program Produced by the Authors at the University of Massachusetts, Amherst. <http://www.umass.edu/landeco/research/fragstats/fragstats.html>.

McGlue, M. M., Yeager, K. M., Soreghan, M. J., Behm, M., Kimirei, I. A., Cohen, A. S., ... & McInytre, P. B. (2021). Spatial variability in nearshore sediment pollution in Lake Tanganyika (East Africa) and implications for fisheries conservation. *Anthropocene*, *33*, 100281.

McInnes J. , Vigiak O. and Roberts A.M. (2011), Using Google Earth to map gully extent in the West Gippsland region (Victoria, Australia), 19th International Congress on Modelling and Simulation, Perth, Australia, 12–16 December 2011, p3370-3376 http://mssanz.org.au/modsim2011

McIntosh E.J., Pressey R.L, Lloyd S., Smith R.J., Grenyer R. (2017). The impact of systematic conservation planning. Annual Review of Environment and Resources 42:677–97. Doi: 10.1146/annurev-environ-102016-060902

McNeely, J. A., & Schroth, G. (2006). Agroforestry and biodiversity conservation–traditional practices, present dynamics, and lessons for the future. *Biodiversity & Conservation*, *15*, 549-554.

Megevand C, Mosnier A, Hourticq J, Sanders K, Doetinchem N and Streck C. 2013. *Dynamiques de déforestation dans le bassin du Congo: Réconcilier la croissance économique et la protection de la forêt Environnement et développement durable*. Washington, DC: World Bank. doi:10.1596/978-0-8213-9827-2. https://openknowledge.worldbank.org/bitstream/handle/10986/12477/9780821398272.pdf

Mekuriaw, A., Heinimann, A., Zeleke, G., & Hurni, H. (2018). Factors influencing the adoption of physical soil and water conservation practices in the Ethiopian highlands. *International soil and water conservation research*, *6*(1), 23-30.

Menon, S., & Bawa, K. S. (1997). Applications of geographic information systems, remote-sensing, and a landscape ecology approach to biodiversity conservation in the Western Ghats. *Current science*, 134-145.

Millennium Ecosystem Assessment (2005). Ecosystems and human wellbeing: wetlands and water. Washington D.C: World Resources Institute.

Miller VC. (1953) A quantitative geomorphic study of drainage basin characteristics in the Clinch Mountain area. Virginia and Tennessee. Department Geology Columbia University. (ONR Project Tech – Report NT 389-042, No. 3) p. 189–200.

Milt, Austin Walker (2015), "Conservation Planning in a Changing World. " PhD diss., University of Tennessee, 2015. https://trace.tennessee.edu/utk_graddiss/3514

Ministry of Environment and Sustainable Development of DR Congo (2018). *République Démocratique du Congo : Programme de définition des cibles de la neutralité en matière de dégradation des terres (PDC/NDT)*. Rapport final. Décembre 2018. 37 pages.

Mishra, V.N.; Rai, P.K. (2016). A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India. Arab. J. Geosci. 2016, 9, 1–18.

Mohieldin, M., & Caballero, P. (2015). Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss. *UN Chronicle*, *51*(4), 34-35.

Molinario, G., Hansen, M., Potapov, P., Tyukavina, A., & Stehman, S. (2020). Contextualizing landscape-scale forest cover loss in the Democratic Republic of Congo (DRC) between 2000 and 2015. *Land*, *9*(1), 23.

Monjardin-Armenta, S. A., Plata-Rocha, W., Pacheco-Angulo, C. E., Franco-Ochoa, C., & Rangel-Peraza, J. G. (2020). Geospatial Simulation Model of Deforestation and Reforestation Using Multicriteria Evaluation. *Sustainability*, *12*(24), 10387.

Monserud R (1990) Methods for comparing global vegetation maps, Report WP-90-40. IIASA, Laxenburg

Moonen, P. C., Verbist, B., Schaepherders, J., Meyi, M. B., Van Rompaey, A., & Muys, B. (2016). Actor-based identification of deforestation drivers paves the road to effective REDD+ in DR Congo. *Land use policy*, 58, 123-132.

Moore ID, Wilson JP. (1992). Length-slope factors for the revised universal soil loss equation: Simplified method of estimation. *J Soil Water Conserv*. 47:423–428.

Morgan, R.P.C., Quinton, J.N., Smith, R.E., Govers, G., Poesen, J.W.A., Auerswald, K., Chisci, G., Torri, D., Styczen, M.E., Folly, A.J.V., (1998). The European Soil Erosion Model (EUROSEM): Documentation and User Guide, p. 124.

Mosnier A, Mant R, Pirker J, Makoudjou A, Bokelo Bile D, Bodin B, Tonga P, Havlík P, Bocqueho G, Maukonen P, Obersteiner, M, Kapos V, Tadoum M (2016): Modelling Land Use Changes in the Democratic Republic of the Congo 2000–2030. A report by the REDD-PAC project. Available online: www.redd-pac.org

Mottet, A., Ladet, S., Coqué, N., & Gibon, A. (2006). Agricultural land-use change and its drivers in mountain landscapes: A case study in the Pyrenees. *Agriculture, ecosystems & environment*, *114*(2-4), 296-310.

Msofe, N. K., Sheng, L., Li, Z., & Lyimo, J. (2020). Impact of land use/cover change on ecosystem service values in the kilombero valley floodplain, southeastern tanzania. *Forests*, *11*(1), 109.

Msoffe, F. U., Said, M. Y., Ogutu, J. O., Kifugo, S. C., de Leeuw, J., van Gardingen, P., & Reid, R. S. (2011). Spatial correlates of land-use changes in the Maasai-Steppe of Tanzania: Implications for conservation and environmental planning. *International Journal of Biodiversity and Conservation*, *3*(7), 280-290.

Muhammad, R.; Zhang, W.; Abbas, Z.; Guo, F.; Gwiazdzinski, L (2022).. Spatiotemporal Change Analysis and Prediction of Future Land Use and Land Cover Changes Using QGIS MOLUSCE Plugin and Remote Sensing Big Data: A Case Study of Linyi, China. *Land* 2022, *11*, 419. https://doi.org/10.3390/land11030419

Muhoyi, H., & Muhoyi, E. (2023). Potential of GIS and remote sensing in mapping land degradation: catchment of the Manyame River, Zimbabwe. *Water Practice and Technology*, *18*(3), 455-469.

Müller, F. (1997). State-of-the-art in ecosystem theory. *Ecological modelling*, *100*(1-3), 135-161.

Munthali, M. G. (2020). *Analysis of land use and land cover dynamics and its implications on natural resources in Dedza District Malawi* (Doctoral dissertation, University of Pretoria).

Munyemba K. F. (2010), Quantification et modélisation de la dynamique paysagère dans la région de Lubumbashi: évaluation de l'impact écologique des dépositions issues de la pyrométallurgie, Thèse présentée et soutenue en vue de l'obtention du grade de Docteur en Sciences Agronomiques, orientation: Faune et Flore, Département de Gestion des Ressources Naturelles, Faculté des Sciences Agronomiques, Université de Lubumbashi, 284p

Musavandalo, C. M., Essouman, P. F. E., Ndjadi, S. S., Balandi, J. B., Nguba, T. B., Sodalo, C., ... & Bogaert, J. (2025). Anthropogenic Disturbances in Northwestern Virunga Forest Amid Armed Conflict. *Land*, *14*(4), 732.

Musavandalo, C. M., Sambieni, K. R., Mweru, J. P. M., Bastin, J. F., Ndukura, C. S., Nguba, T. B., ... & Bogaert, J. (2024). Land cover dynamics in the northwestern Virunga landscape: An analysis of the past two decades in a dynamic economic and security context. *Land*, *13*(5), 566.

Mushi, C. A., Ndomba, P. M., Trigg, M. A., Tshimanga, R. M., & Mtalo, F. (2019). Assessment of basin-scale soil erosion within the Congo River Basin: A review. *Catena*, *178*, 64-76.

Mzuri, R. T., Mustafa, Y. T., & Omar, A. A. (2022). Land degradation assessment using AHP and GIS-based modelling in Duhok District, Kurdistan Region, Iraq. *Geocarto International*, *37*(25), 7908-7926.

Nabuurs, G-J., R. Mrabet, A. Abu Hatab, M. Bustamante, H. Clark, P. Havlík, J. House, C. Mbow, K.N. Ninan, A. Popp, S. Roe, B. Sohngen, S. Towprayoon, 2022: Agriculture, Forestry and Other Land Uses (AFOLU). In IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA. doi: 10.1017/9781009157926.009

Nachtergaele F.O. (2017), Classification Systems: FAO in *Reference Module in Earth Systems and Environmental Sciences*, Elsevier Inc.: Amsterdam, The Netherlands, 2017, ISBN 9780124095489, https://doi.org/10.1016/B978-0-12-409548-9.10520-2.

Nachtergaele, F., R. Biancalani, S. Bunning, and H. George. 2010. Land degradation assessment: the LADA approach. Pages 72-75 in 19th World Congress of Soil Science, Symposium 3.1.1, Further development of soil evaluation methods, Soil Solutions for a Changing World, 1–6 August, Brisbane, Australia.

Nacishali Nteranya, J. (2021). Cartographie de l'érosion hydrique des sols et priorisation des mesures de conservation dans le territoire d'Uvira (République démocratique du Congo). *VertigO-la revue électronique en sciences de l'environnement*, *20*(3).

Nackoney J. and Williams D. (2012), Conservation prioritization and planning with limited wildlife data in a Congo Basin Forest landscape: assessing human threats and vulnerability to land use change, *Journal of Conservation Planning* Vol 8 (2012) 25 – 44

Nampindo, S. (2014). Integrated Modeling of Land Use and Climate Change Impacts on Ecosystems of Central African watersheds. PhD thesis, Department of Environmental Conservation University of Massachusetts Amherst, USA

Ndolo G.P. (2015). GIS-based soil erosion modeling and sediment yield of the N'djili river basin, Democratic Republic of Congo, Master degree thesis, Degree of Master of Science, Colorado State University, Fort Collins, Colorado, Summer 2015, 220p

Ngeleza, R. (2012). Le Paysage Maiko-Tayna-Kahuzi-Biega : Maiko-Tayna-Kahuzi-Biega Landscape. COBAM Brief Bogor, Indonesia: Center for International Forestry Research (CIFOR). http://dx.doi.org/10.17528/cifor/003927

Nguyen, Q. V., Liou, Y. A., Nguyen, K. A., & Tran, D. P. (2023). Enhancing basin sustainability: Integrated RUSLE and SLCC in land use decision-making. *Ecological Indicators*, *155*, 110993.

Nguyen, T. A., Le, P. M. T., Pham, T. M., Hoang, H. T. T., Nguyen, M. Q., Ta, H. Q., ... & Hens, L. (2019). Toward a sustainable city of tomorrow: a hybrid Markov–Cellular Automata modeling for urban landscape evolution in the Hanoi city (Vietnam) during 1990–2030. *Environment, development and sustainability*, *21*(1), 429-446.

Nigussie, Z., Tsunekawa, A., Haregeweyn, N., Adgo, E., Nohmi, M., Tsubo, M., ... & Abele, S. (2017). Farmers' perception about soil erosion in Ethiopia. *Land degradation & development*, *28*(2), 401-411.

Nwer Bashir Ahmad Bashir (2005), *The Application of Land Evaluation Technique in the north-east of Libya*, Cranfield University, Faculty of Environment, National Soil Resources Institute, PhD thesis.

Nyeko, M. (2012). GIS and multi-criteria decision analysis for land use resource planning. *Journal of Geographic Information System*, 2012, 4, 341-348 doi:10.4236/jgis.2012.44039 Published Online August 2012 (http://www.SciRP.org/journal/jgis)

Obubu, J. P., Odong, R., Alamerew, T., Fetahi, T., & Mengistou, S. (2022). Application of DPSIR model to identify the drivers and impacts of land use and land cover changes and climate change on land, water, and livelihoods in the L. Kyoga basin: implications for sustainable management. *Environmental Systems Research*, *11*(1), 1-21.

Oldeman, L. R. (1991). World map of the status of human-induced soil degradation, An explanatory note, Global assessment of soils degradation, GLASOD. *The Map Sheets*.

Oldeman, L. R., Hakkeling, R. T. A., & Sombroek, W. G. (1990). *World map of the status of human-induced soil degradation: an explanatory note*. International Soil Reference and Information Centre.

Oliveira, J.D.A., Dominguez, J.M.L., Nearing, M.A., Oliveira, P.T., 2015, « A GIS-based procedure for automatically calculating soil loss from the universalsoil loss equation Gisus-m. », *Appl. Eng. Agric.* 2015, 31, 907. doi: 10.13031/aea.31.11093

Olsson, L., H. Barbosa, S. Bhadwal, A. Cowie, K. Delusca, D. Flores-Renteria, K. Hermans, E. Jobbagy, W. Kurz, D. Li, D. J. Sonwa, L. Stringer. 2019. Land degradation. Chapter 4 in P. R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, editors. Climate change and land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. https://www.ipcc.ch/srccl/chapter/chapter-4/

Ongezo M. S., Joel Norbert, Mtalo F. and Ndomba M. P. (2014), Sediment yields estimation and sources identification in Lake Tanganyika basin- the case of Mulongwe sub catchment – Uvira city – DR Congo, *Standard Global Journal of Geology and Explorational Research* Vol 1(2): 032- 042

Opiyo, S. B., Opinde, G., & Letema, S. (2022). Dynamics and drivers of land use and land cover changes in Migori River Watershed, western Kenya region. *Watershed Ecology and the Environment*, *4*, 219-232.

Orr, B. J., Cowie, A. L., Castillo Sanchez, V. M., Chasek, P., Crossman, N. D., Erlewein, A., ... & Welton, S. (2017). Scientific conceptual framework for land degradation neutrality. In *A report of the science-policy interface. United Nations Convention to Combat Desertification (UNCCD), Bonn, Germany* (pp. 1-98).

Ouyang, W., Skidmore, A. K., Hao, F., & Wang, T. (2010). Soil erosion dynamics response to landscape pattern. *Science of the Total Environment*, *408*(6), 1358-1366.

Panagos P., Borrelli P. and Meusburger K., 2015, « A New European Slope Length and Steepness Factor (LS-Factor) for Modeling Soil Erosion by Water », *Geosciences* 2015, 5, pp. 117-126. doi:10.3390/geosciences5020117

Panagos, P., Ballabio, C., Meusburger, K., Spinoni, J., Alewell, C., & Borrelli, P. (2017). Towards estimates of future rainfall erosivity in Europe based on REDES and WorldClim datasets. Journal of Hydrology, 548, 251-262.

Panagos, P., Borrelli, P., Meusburger, K., Yu, B., Klik, A., Jae Lim, K., ... & Ballabio, C. (2017). Global rainfall erosivity assessment based on high-temporal resolution rainfall records. *Scientific reports*, *7*(1), 4175.

Pandit R., Parrotta J.A., Chaudhary A.K., Karlen D.L., Vieira D.L.M., Anker Y., Chen R., Morris J., Harris J. & Ntshotsho P. (2020) A framework to evaluate land degradation and restoration responses for improved planning and decision-making, *Ecosystems and People*, 16:1, 1-18, DOI:10.1080/26395916.2019.1697756

Pereira, L. F., & Guimarães, R. M. F. (2019). Mapping land uses/covers with Semi-automatic Classification Plugin: Which data set, classifier and sampling design?. *Nativa: Pesquisas Agrárias e Ambientais*, *7*(1), 70-76.

Peterson, G. D., Cumming, G. S., & Carpenter, S. R. (2003). Scenario planning: a tool for conservation in an uncertain world. *Conservation biology*, *17*(2), 358-366.

Plumptre, A.J., Ayebare, S. & Kujirakwinja, D. (2015). *Priority Areas for Conservation in the Maiko, Tayna, Kahuzi Biega Landscape.* Unpublished Report for USAID and USFWS

Pradhan, B., A. Chaudhari, J. Adinarayana et M. F. Buchroithner, 2012, Soil erosion assessment and its correlation with landslide events using remote sensing data and GIS: a case study at Penang Island, Malaysia, *Environ Monit Assess* [en ligne], 184, pp. 715-727, DOI :https://doi.org/10.1007/s10661-011-1996-8

Pressey, R. L., Cabeza, M., Watts, M. E., Cowling, R. M., & Wilson, K. A. (2007). Conservation planning in a changing world. *Trends in ecology & evolution*, *22*(11), 583-592.

Pueyo, Y., Alados, C. L., & Barrantes, O. (2006). Determinants of land degradation and fragmentation in semiarid vegetation at landscape scale. *Biodiversity & Conservation*, *15*, 939-956.

Quantum GIS Development Team, 2022. *Quantum GIS Geographic Information System*, Open Source Geospatial Foundation Project. Available at: http://qgis.osgeo.org.

R Core Team, 2022. *R: A Language and Environment for Statistical Computing*, Vienna, Austria: R Foundation for Statistical Computing. Available at: http://www.R-project.org.

Ramankutty N, Foley JA. (1999), Estimating historical changes in global land cover: croplands from 1700 to 1992. *Global Biogeochemical Cycles* 13(4): 997–1027.

Raymond, C. M., Bryan, B. A., MacDonald, D. H., Cast, A., Strathearn, S., Grandgirard, A., & Kalivas, T. (2009). Mapping community values for natural capital and ecosystem services. *Ecological economics*, *68*(5), 1301-1315.

Renard, K.G., Foster, G.R., Weesies, G.A., McCool, D.K., Yoder, D.C., 1997. Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE). Agric. Handb., vol. 703. US Department of Agriculture, Washington, DC, pp. 1 –251

Renard, K.G., J.R. Freimund, 1994, Using monthly precipitation data to estimate the R factor in the revised USLE, *Journal of Hydrology*, 157(1), pp. 287-306.

RIITTERS, K., WICKHAM, J., O'NEILL, R., JONES, B. & E. SMITH (2000): Global-scale patterns of forest fragmentation. – *Conservation Ecology* 4(2): 3. [online] URL: http://www.consecol.org /vol4/iss2/art3

Rinos, M. M., Aggarwal, S. P., & De Silva, R. P. (2003). Application of Remote Sensing and GIS on soil erosion assessment at Bata River Basin, India. Proceeding of the 4TH Annual International Conference and Exhibition on GIS, GPS, and Remote Sensing, India. Available at https://www.geospatialworld.net/article/application-of-remote-sensing-and-gis-on-soil-erosion-assessment-at-bata-river-basin-india/ Accessed on 27th January 2024.

Robbins, M. M., & McNeilage, A. (2003). Home range and frugivory patterns of mountain gorillas in Bwindi Impenetrable National Park, Uganda. *International Journal of Primatology*, *24*(3), 467-491.

Robin, X., Turck, N., Hainard, A., Tiberti, N., Lisacek, F., Sanchez, J. C., & Müller, M. (2011). pROC: An open-source package for R and S+ to analyze and compare ROC curves. BMC Bioinformatics, 12, 77. https://doi.org/10.1186/1471-2105-12-77

Rojas E *et al*. (2021). Deforestation risk in the Peruvian Amazonbasin. Environmental Conservation 48: 310–319. doi: 10.1017/S0376892921000291

Romshoo, S. A., Amin, M., Sastry, K. L. N., & Parmar, M. (2020). Integration of social, economic and environmental factors in GIS for land degradation vulnerability assessment in the Pir Panjal Himalaya, Kashmir, India. *Applied Geography*, *125*, 102307.

Saaty, T.L. (2008). Decision making with the analytic hierarchy process. *Int. J. Serv. Sci*., 1, 83–98.

Saaty, Tl. (1980). The analytic hierarchy process. New York: McGraw-Hill

Saguye, T. S. (2017a). An Empirical Analysis of Land Degradation Risk from Local Community Knowledge Perspective: The Case of Geze Gofa District, Southern Ethiopia. *Journal of Culture, Society and Development*, *28,* 48-64.

Saguye, T. S. (2017b). Analysis of farmers perception on the impact of land degradation hazard on agricultural land productivity in Jeldu district in West Shewa Zone, Oromia, Ethiopia. *Journal of Agricultural Extension and Rural Development*, *9*(6), 111-123.

Sandeep, P.; Reddy, G.P.O.; Jegankumar, R.; Kumar, K.C.A. Modeling and Assessment of Land Degradation Vulnerability in Semi-arid Ecosystem of Southern India Using Temporal Satellite Data, AHP and GIS. *Environ. Model. Assess.* 2021, *26*, 143–154

Sarathi, B. S., and Pani P., 2015, « Estimation of soil erosion using RUSLE and GIS techniques: a case study of Barakar River basin, Jharkhand, India », *Model. Earth Syst. Environ*. 2015, 1:42, 13 p. DOI 10.1007/s40808-015-0040-3

Semenchuk, P., Plutzar, C., Kastner, T., Matej, S., Bidoglio, G., Erb, K. H., ... & Dullinger, S. (2022). Relative effects of land conversion and land-use intensity on terrestrial vertebrate diversity. *Nature communications*, *13*(1), 615.

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.

Shapiro, A. C., Aguilar-Amuchastegui, N., Hostert, P., & Bastin, J. F. (2016). Using fragmentation to assess degradation of forest edges in Democratic Republic of Congo. *Carbon balance and management*, *11*(1), 1-15.

Shapiro, A. C., Bernhard, K. P., Zenobi, S., Müller, D., Aguilar-Amuchastegui, N., & d'Annunzio, R. (2021). Proximate causes of forest degradation in the Democratic Republic of the Congo vary in space and time. *Frontiers in Conservation Science*, *2*, 690562.

Sharma, J., & Ravindranath, N. H. (2019). Applying IPCC 2014 framework for hazard-specific vulnerability assessment under climate change. *Environmental Research Communications*, *1*(5), 051004.

Sharma, R., Rimal, B., Baral, H., Nehren, U., Paudyal, K., Sharma, S., ... & Kandel, P. (2019). Impact of land cover change on ecosystem services in a tropical forested landscape. *Resources*, 8(1), 18.

Sharma, T., & Singh, O. (2017). Soil erosion susceptibility assessment through geo-statistical multivariate approach in Panchkula district of Haryana, India. *Modeling Earth Systems and Environment*, *3*, 733-753.

Shi Z.H., Ai L., Li X., Huang X.D., Wu G.L., Liao W. (2013), Partial least-squares regression for linking land-cover patterns to soil erosion and sediment yield in watersheds, *Journal of Hydrology* 498 (2013) 165–176

Shi Z.H., Cai C.F., Ding S.W., Wang T.W., Chow T.L. (2004), Soil conservation planning at the small watershed level using RUSLE with GIS: a case study in the Three Gorge Area of China, *Catena* 55 (2004) 33–48, doi:10.1016/S0341-8162(03)00088-2

Shirvani Z., Abdi O., Buchroithner M.F., Phradhan B. (2017), Analysing spatial and statistical dependencies of deforestation affected by residential growth: Gorgnrood basin, Northeast Iran, *Land Degradation & Development*, 28:7, 2176-2190

Simeonakis E., Calvo-Cases A., Arnau-Rosalen (2007), Land Use Change and land degradation in Southeastern Mediterranean Spain, *Environm Manage* (2007), 40:80-94

Sims, N. C., England, J. R., Newnham, G. J., Alexander, S., Green, C., Minelli, S., & Held, A. (2019). Developing good practice guidance for estimating land degradation in the context of the United Nations Sustainable Development Goals. *Environmental Science & Policy*, *92*, 349-355.

Sirengo, R. K., Mundia, C. N., & Sichangi, A. W. (2018). Modelling Land Degradation in Migori County. *SSRG International Journal of Agriculture & Environmental Science* 5(2), 32-44.

Sklenicka, P., Janovska, V., Salek, M., Vlasak, J., & Molnarova, K. (2014). The Farmland Rental Paradox: Extreme land ownership fragmentation as a new form of land degradation. *Land use policy*, *38*, 587-593.

Srivastava, R. K., Sharma, H. C., & Raina, A. K. (2010). Suitability of soil and water conservation measures for watershed management using geographical information system. *Journal of Soil and Water Conservation*, *9*(3), 148-153.

Stattersfield, A.J., Crosby, M.J., Long, A.J., & Wege, D.C. 1998. *Endemic Bird Areas of the World: priorities for biodiversity conservation.* BirdLife International Conservation series No. 7. BirdLife International, Cambridge.

Steffen, W., Grinevald, J., Crutzen, P., & McNeill, J. (2011). The Anthropocene: conceptual and historical perspectives. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *369*(1938), 842-867.

Tadesse, M., & Belay, K. (2004). Factors influencing adoption of soil conservation measures in southern Ethiopia: the case of Gununo area. *Journal of Agriculture and Rural Development in the Tropics and Subtropics (JARTS)*, *105*(1), 49-62.

Tadesse, T. B., & Tefera, S. A. (2020). Comparing potential risk of soil erosion using RUSLE and MCDA techniques in Central Ethiopia. *Modeling Earth Systems and Environment*, 1-13.

Tagore, G. S., Bairagi, G. D., Sharma, N. K., Sharma, R., Bhelawe, S., & Verma, P. K. (2012). Mapping of degraded lands using remote sensing and GIS techniques. *Journal of Agricultural physics*, 12, 29–36.

Tahir, Z., Haseeb, M., Mahmood, S. A., Batool, S., Abdullah-Al-Wadud, M., Ullah, S., & Tariq, A. (2025). Predicting land use and land cover changes for sustainable land management using CA-Markov modelling and GIS techniques. *Scientific Reports*, *15*(1), 3271.

Tasser, E., Schirpke, U., Zoderer, B. M., & Tappeiner, U. (2020). Towards an integrative assessment of land-use type values from the perspective of ecosystem services. *Ecosystem Services*, *42*, 101082.

Taveira, L. R., Weindorf, D. C., De Menezes, M. D., de Carvalho, T. S., Da Motta, P. E. F., Teixeira, A. F. D. S., & Curi, N. (2021). Land use capability classification adaptation in low and intermediate technology farming systems: A soil erosion indicator. *Soil Use and Management*, *37*(1), 164-180.

Tchatchou B, Sonwa DJ and Tiani AM. 2015. *Déforestation et dégradation des forêts dans le Bassin du Congo État des lieux, causes actuelles et perspectives.* Bogor, Indonesia: CIFOR. http://www.cifor.org/publications/pdf_files/OccPapers/OP-120.pdf

Tehrany, M. S., Shabani, F., Javier, D. N., & Kumar, L. (2017). Soil erosion susceptibility mapping for current and 2100 climate conditions using evidential belief function and frequency ratio. *Geomatics, Natural Hazards and Risk*, *8*(2), 1695-1714.

Temesgen, G.; Amare, B.; Abraham, M. (2014) Evaluations of land use/land cover changes and land degradation in Dera District, Ethiopia: GIS and Remote Sensing Based Analysis. *Int. J. Sci. Res. Environ. Sci*. 2014, 2, 199–208.

Tenge, A. J., De Graaff, J., & Hella, J. P. (2004). Social and economic factors affecting the adoption of soil and water conservation in West Usambara highlands, Tanzania. *Land Degradation & Development*, *15*(2), 99-114.

Tesfahunegn, G. B., Ayuk, E. T., & Adiku, S. G. K. (2021). Farmers' perception on soil erosion in Ghana: Implication for developing sustainable soil management strategy. *PLoS One*, *16*(3), e0242444.

Tesfahunegn, G.B.B., Ayuk, E., Adiku, K.G.S. (2020). Farmers' perception on forest degradation in Eastern and Northern Regions of Ghana: implication for developing sustainable forest management strategy. *Research Square*. DOI: 10.21203/rs.3.rs-91191/v1

Tessema, Y. M., Jasińska, J., Yadeta, L. T., Świtoniak, M., Puchałka, R., & Gebregeorgis, E. G. (2020). Soil loss estimation for conservation planning in the welmel watershed of the Genale Dawa Basin, Ethiopia. *Agronomy*, *10*(6), 777.

Thiombiano, L., & Tourino-Soto, I. (2007). Status and trends in land degradation in Africa. *Climate and land degradation*, 39-53.

Thomas R. J, Clifton K., Appadurai A.N, Zucca C., Kodsi E., Sircely J., Haddad F., von Hagen C., Mapedza E., Wolderegay K., Shalander K., Bellon M., Le Q.B, Mabikke S., Alexander S., Leu S., Schlingloff S., Lala-Pritchard T., Mares V. (2017), Scaling up sustainable land management and restoration of degraded land, Global Land Outlook, UNCCD, Working paper, September 2017, 25p

Thomlinson JR, Bolstad PV, Cohen WB (1999) Coordinating methodologies for scaling land cover classifications from site-specific to global: steps toward validating imaging. LLC, Norcross.

Tolche, A. D., Gurara, M. A., Pham, Q. B., & Anh, D. T. (2021b). Modelling and accessing land degradation vulnerability using remote sensing techniques and the analytical hierarchy process approach. *Geocarto International*, 1-21.

Tolche, A. D., Gurara, M. A., Pham, Q. B., & Anh, D. T. (2022). Modelling and accessing land degradation vulnerability using remote sensing techniques and the analytical hierarchy process approach. *Geocarto International*, *37*(24), 7122-7142.

Toromo, A. K., Ucakuwun, E. K., & Kipkorir, E. C. (2019). Perception and Adoption of Famers to Soil and Water Conservation Practices in Upper Turkwel Watershed in Kenya. *Africa Environmental Review Journal*, *3*(2), 77-89.

Traore, S. S., Landmann, T., Forkuo, E. K., & Traore, P. C. S. (2014). Assessing long-term trends in vegetation productivity change over the Bani River Basin in Mali (West Africa). *Journal of Geography and Earth Sciences*, *2*(2).

Tshikeba, K.M., Muamba, T.R., Onema K.J-M., Gumindoga, W., and Tshimpampa, B.J., 2018, A GIS-based estimation of soil erosion parameters for soil loss potential and erosion hazard in the city of Kinshasa, the Democratic Republic of Congo, *Proc. IAHS*, 378, pp. 51-57, DOI : https://doi.org/10.5194/piahs-378-51-2018

Turner, A. (2009). Population priorities: the challenge of continued rapid population growth. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364* (1532), 2977-2984.

Tyukavina, A., Hansen, M. C., Potapov, P., Parker, D., Okpa, C., Stehman, S. V., ... & Turubanova, S. (2018). Congo Basin forest loss dominated by increasing smallholder clearing. *Science advances*, *4*(11), eaat2993.

UNCCD (2013). Background Document: The Economics of Desertification, Land Degradation and Drought: Methodologies and Analysis for Decision-Making. Bonn, Germany, United Nations Convention to Combat Desertification.

UNCCD (2016). Framework and guiding principles for a land degradation indicator. Outcomes of the expert meeting report (p. 20). Washington, DC

UNCCD (2017), Perspectives territoriales mondiales, Première Edition, 340 p

UNCCD (2022). The Global Land Outlook, Second edition. UNCCD, Born, Germany. https://www.unccd.int/resources/global-land-outlook/global-land-outlook-2nd-edition

UNCCD-GM (2016). Achieving Land Degradation Neutrality at the country level: Building blocks for LDN target setting. Global Mechanism (GM) of the United Nations Conventions to Combat Desertification (UNCCD), Bonn, Germany Available online: http://www2.unccd.int/sites/default/files/documents/160915_ldn_rgb_small%20%281%29.pdf

UNDESA, Population Division (2014). World Urbanization Prospects: The 2014 Revision, CDROM Edition.

UNEP (2014), The Emissions Gap Report 2014. United Nations Environment Programme (UNEP), Nairobi.

UNEP (2016) Unlocking the Sustainable Potential of Land Resources: Evaluation Systems, Strategies and Tools. A Report of the Working Group on Land and Soils of the International Resource Panel. Herrick, J.E., O. Arnalds, B. Bestelmeyer, S. Bringezu, G. Han, M.V. Johnson, D. Kimiti, Yihe Lu, L. Montanarella, W. Pengue, G. Toth, J. Tukahirwa, M. Velayutham, L. Zhang.

United Nations (UN). *Revised list of global Sustainable Development Goal Indicators. Report of the Inter-Agency and Expert Group on Sustainable Development Goal Indicators (E/CN.3/2017/2)*; Annex III; UN: New York, NY, USA, 2017; Available online:https://unstats.un.org/sdgs/indicators/Official%20Revised%20List%20of%20global%20SDG%20indicators.pdf .

United Nations Convention to Combat Desertification (UNCCD). 2017. The Global Land Outlook, first edition. Bonn, Germany.

United Nations Department of Economic and Social Affairs, Population Division (2021). Global Population Growth and Sustainable Development. UN DESA/POP/2021/TR/NO. 2.

Uribe, D., Geneletti, D., Del Castillo, R. F., & Orsi, F. (2014). Integrating stakeholder preferences and GIS-based multicriteria analysis to identify forest landscape restoration priorities. *Sustainability*, *6*(2), 935-951.

USAID (2018), Conflicts in Mbinga-Nord, DRC: invisible factors and possibilities for transformation. DRC Solution for Peace and Recovery. www.usaid.gov

Van der Ploeg, S., & de Groot, R. S. (2010). The TEEB Valuation Database–a searchable database of 1310 estimates of monetary values of ecosystem services. Foundation for Sustainable Development, Wageningen, The Netherlands.

Veldkamp, A., & Lambin, E. F. (2001). Predicting land-use change. Agriculture, Ecosystems and Environment, 85, 1–6. https://doi.org/10.1016/S0167-8809(01)00199-2

Verchot, L. V., Van Noordwijk, M., Kandji, S., Tomich, T., Ong, C., Albrecht, A., ... & Palm, C. (2007). Climate change: linking adaptation and mitigation through agroforestry. *Mitigation and adaptation strategies for global change*, *12*(5), 901-918.

von Keyserlingk, J., Thieken, A. H., & Paton, E. N. (2023). Approaches to assess land degradation risk: a synthesis. *Ecology and Society*, *28*(1)

Vu, Q.M, Le, Q.B., Frossard, E., Vlek, P.L.G. (2014), Socio-economic and biophysical determinants of land degradation in Vietnam: An integrated causal analysis at national level, *Land Use Policy*, 36 (2014), 605-617.

Vulević, T., Dragović, N., Kostadinov, S., Simić, S. B., & Milovanović, I. (2015). Prioritization of Soil Erosion Vulnerable Areas Using Multi-Criteria Analysis Methods. *Polish Journal of Environmental Studies*, *24*(1).

Wallace, K. J. (2007). Classification of ecosystem services: problems and solutions. *Biological conservation*, *139*(3-4), 235-246.

Walz, U. (2011). Landscape structure, landscape metrics and biodiversity. *Living reviews in landscape research*, *5*(3), 1-35.

Wang, J., Bretz, M., Dewan, M. A. A., & Delavar, M. A. (2022). Machine learning in modelling land-use and land cover-change (LULCC): Current status, challenges and prospects. *Science of the Total Environment*, *822*, 153559.

Wang, L., & Yang, Z. L. (2020). Changes in land use influenced by anthropogenic activity. In *Oxford research encyclopedia of environmental science*.

Wangai, P. W., Burkhard, B., & Müller, F. (2019). Quantifying and mapping land use changes and regulating ecosystem service potentials in a data-scarce peri-urban region in Kenya. *Ecosystems and People*, *15*(1), 11-32.

Wijitkosum, S. (2012). Impacts of land use changes on soil erosion in Pa Deng sub-district, adjacent area of Kaeng Krachan National Park, Thailand. *Soil and Water Research*, *7*(1), 10-17.

Williams, J., 1995, *The EPIC model, in Computer Models of Watershed Hydrology*, edited by V. P. Singh, pp. 909-1000., Colorado, USA.

Wischmeier, W.H., Smith, D.D., 1978. Predicting rainfall erosion losses, a guide to conservation planning. Agric. Handb., vol. 537. US Department of Agriculture, Washington, DC. 58 pp.

Woldeamlak B (2002), Land cover dynamics since the 1950s in Chemoga watershed, Blue Nile basin, Ethiopia. *Mt Res Dev* 22(3):263–269

Woodfine, A. (2009). Using sustainable land management practices to adapt to and mitigate climate change in sub-Saharan Africa: Resource Guide Version 1.0. *TerrAfrica, Washington DC, USA.*

Wordofa, M. G., Okoyo, E. N., & Erkalo, E. (2020). Factors influencing adoption of improved structural soil and water conservation measures in Eastern Ethiopia. *Environmental Systems Research*, *9*, 1-11.

World Bank Group (2021), Climate Risk Profile: Congo, Democratic Republic (2021): The World Bank Group. Washington DC.

World Resources Institute (2016). African countries launch AFR100 to restore 100 million hectares of land. http://www.wri.org/news/2015/12/release-african-countries-launch-afr100-restore-100-million-hectares-land.

WorldPop (www.worldpop.org - School of Geography and Environmental Science, University of Southampton; Department of Geography and Geosciences, University of Louisville; Departement de Geographie, Universite de Namur) and Center for International Earth Science Information Network (CIESIN), Columbia University (2018). Global High Resolution Population Denominators Project - Funded by The Bill and Melinda Gates Foundation (OPP1134076). https://dx.doi.org/10.5258/SOTON/WP00674

Xu, Y., Tang, H., Wang, B., & Chen, J. (2017). Effects of landscape patterns on soil erosion processes in a mountain–basin system in the North China. *Natural Hazards*, *87*, 1567-1585.

Yadav, B., Malav, L. C., Jiménez-Ballesta, R., Kumawat, C., Patra, A., Patel, A., ... & Mina, B. L. (2022). Modeling and assessment of land degradation vulnerability in arid ecosystem of Rajasthan using analytical hierarchy process and geospatial techniques. *Land*, *12*(1), 106.

Yahya F., Zregat D., Anbar A. (2015), Assessing Farmers' Perception of Soil Erosion Risk in Northern Jordan, *Journal of Environmental Protection*, 2015, 6, 867-884, http://dx.doi.org/10.4236/jep.2015.68079

Yang, D., Kanae, S., Oki, T., Koike, T., & Musiake, K. (2003). Global potential soil erosion with reference to land use and climate changes. *Hydrological processes*, *17*(14), 2913-2928.

Yesuph, A. Y., & Dagnew, A. B. (2019). Land use/cover spatiotemporal dynamics, driving forces and implications at the Beshillo catchment of the Blue Nile Basin, North Eastern Highlands of Ethiopia. *Environmental Systems Research*, *8*(1), 1-30.

Yifru, G. S., & Miheretu, B. A. (2022). Farmers' adoption of soil and water conservation practices: the case of lege-lafto watershed, dessie zuria district, south wollo, Ethiopia. *PloS one*, *17*(4), e0265071

Young, A., & International Council for Research in Agroforestry. (1989). Agroforestry for soil conservation.

Yu, J., Castellani, K., Forysinski, K., Gustafson, P., Lu, J., Peterson, E., ... & Brauer, M. (2021). Geospatial indicators of exposure, sensitivity, and adaptive capacity to assess neighbourhood variation in vulnerability to climate change-related health hazards. *Environmental Health*, *20*, 1-20.

Yushanjiang, A., Zhang, F., & Yu, H. (2018). Quantifying the spatial correlations between landscape pattern and ecosystem service value: A case study in Ebinur Lake Basin, Xinjiang, China. *Ecological Engineering*, *113*, 94-104.

Zaidi, S. M., Akbari, A., Abu Samah, A., Kong, N. S., Gisen, A., & Isabella, J. (2017). Landsat-5 Time Series Analysis for Land Use/Land Cover Change Detection Using NDVI and Semi-Supervised Classification Techniques. *Polish Journal of Environmental Studies*, *26*(6).

Zeleke, G., & Hurni, H. (2001). Implications of land use and land cover dynamics for mountain resource degradation in the Northwestern Ethiopian highlands. *Mountain research and development*, *21*(2), 184-191.

Zhang, H., Zhang, J., Zhang, S., Yu, C., Sun, R., Wang, D., ... & Zhang, J. (2020). Identification of Priority Areas for Soil and Water Conservation Planning Based on Multi-Criteria Decision Analysis Using Choquet Integral. *International journal of environmental research and public health*, *17*(4), 1331.

Zhang, L., Zhou, X., Zhou, Y., Zhou, J., Guo, J., Zhai, Z., ... & Qiao, Y. (2022). Surface coal mining impacts on land use change and ecological service value: a case study in Shengli coalfield, Inner Mongolia. *International Journal of Coal Science & Technology*, *9*(1), 65.

Zhang, S., Fan, W., Li, Y., & Yi, Y. (2017). The influence of changes in land use and landscape patterns on soil erosion in a watershed. *Science of the Total Environment*, 574, 34-45.

Zhao, L., & Liu, F. (2020). Land-use planning adaptation in response to SLR based on a vulnerability analysis. *Ocean & Coastal Management*, *196*, 105297.

Zhao, Y., Zhao, X., Fan, D., & Qiu, Y. (2023). A comprehensive method for refining essential SDGs variables for land degradation monitoring based on the DPSIR framework. *International Journal of Digital Earth*, *16*(1), 741-761.

Zhi Li, WenZhao Liu, FenLi Zheng (2013). The land use changes and its relationship with topographic factors in the Jing River catchment on the Loess Plateau of China. *SpringerPlus* 2013 2(Suppl 1): S3, 6p

Zhou, J., Wu, J., & Gong, Y. (2020). Valuing wetland ecosystem services based on benefit transfer: A meta-analysis of China wetland studies. *Journal of Cleaner Production*, *276*, 122988.

Zorn, M., Komac, B. (2013). Land Degradation. In: Bobrowsky, P.T. (eds) Encyclopedia of Natural Hazards. Encyclopedia of Earth Sciences Series. Springer, Dordrecht. https://doi.org/10.1007/978-1-4020-4399-4_207

APPENDICES

APPENDIX I: HOUSEHOLD QUESTIONNAIRE

The information provided will be used to analyze the community perception of the interrelation between land-use change and land degradation, their impacts on ecosystem services, and the conservation practices of natural resources in Kalehe territory, Sud-Kivu province, Democratic Republic of Congo. The information obtained through this interview will be kept strictly confidential and used solely for this research. Your cooperation and contributions are highly appreciated.

A. GENERAL INFORMATION

Date……………………Name of interviewer……………………Questionnaire No………

Collectivity/Chefferie: (1) Buhavu (2) Buloho

Village/Groupement………… GPS location of village…………

B. HOUSEHOLDS CHARACTERISTICS

1. Age of the respondent ….. (0) 20-30 (1) 30-50 (2) > 50
2. Sex of the respondent: (0) Male (1) Female
3. Marital status (0) Single (1) Married (2) Divorced/Widowed/Separated
4. Size of the household…… (0) <5 (1) 5-10 (2) More than 10
5. The main source of livelihood: (0) Cropping and livestock (1) State agent (2) Small business and trade (3) Others (specify)…………………
6. Level of education: (0) none (1) Primary (2) Secondary (3) Tertiary (4) Others ……………………………………………………………………………………….
7. How long have you lived in this area? (0) 10-20 (1) 20-30 (2) More than 30 years

C. FARMLAND CHARACTERISTICS AND PERCEPTION ON THE DEGRADATION OF AGRICULTURAL LAND

8. Size of farmland........... (0) Less than 1 Ha (1)1-2 Ha (2) More than 2 Ha
9. Distance to farmland (Time of walking in minutes) .... (0) Less than 30 min (1) 30-60 min (2) More than 60 Min
10. Land ownership: (0) Inherited (1) Bought (2) Rented/Leased (3) Others (specify)
11. For how many years have you exerted farming activities? .... (0) 0-10 (1) 10-20 (2) 20-30 (3) >30 years

12. What is the slope of your farmland? (0) flat (1) gentle/moderate (2) Steep
13. What is the current crop productivity in your land compared to the last 10 years (1) Decreased (2) Increased (3) No change
14. If the crop production decreased what is the main reason (0) Soil erosion (1) Loss of fertility (2) Unreliable rainfall (3) Crop diseases (4) Limited or inadequate land (5) Lack of agriculture input/High cost of agricultural input (6) Inadequate labor (7) Poor access to the subsidiary program (8) continuous cultivation without fallow (10) Others (specify)……………………………………………………
15. What have you done in the past when the crop production of your land decreased (0) Looked for additional land (1) Improve the fertility of the land (2) Fallow (3) Crop succession rotation (4) Intercropping/Multiple cropping (5) Agroforestry (6) others (specify)…………………………………………………………………..…
16. If you look for additional land for crop production, what kind of land do you look for (0) Forest land (1) Fallow land (2) Grassland (3) Others (specify)………

D. PERCEPTION ON SOIL EROSION AND ADOPTION OF CONSERVATION PRACTICES

17. Is soil erosion a problem on your land? (0) No (1) Yes
18. What features lead you to believe that such a problem exists in your land, or what is the indicator of erosion in your land? (0) Rill's formation (1) gullies formation (2) Landslides (3) deposits of soil in rivers banks (4) soil loss (5) Change of soil coloration (6) stone lines (7) roots pedestal (exposition of roots due to erosion) (8) others (specify) ………
19. Which category of land-use type is most affected by erosion in your locality? (0) Grazing land (1) homeland (settlements) (2) cropland (3) Forestland (4) All types of land others
20. How the problem of erosion has evolved over the last 10 years in your area? (0) Increase (1) Decrease (2) No change
21. What do you think is the main cause of erosion in your locality? (0) Nature of soil (1) Deforestation (2) Heavy rainfall and runoff (3) Steep slope (4) Runoff (5) Improper tillage (6) Livestock pressure and over-grazing (7) Lack of conservation structures (8) Improper farming (over-cultivation) (9) Not aware (10) Others (Specify)…………

22. What is the *main* effect (consequence) of soil erosion on your locality? (1) Soil loss from farmland (2) loss of fertility (3) Decrease in productivity of the land (4) reduction of soil depth (shallow soil depth) (5) Decrease quality of stream water (waterlogging, siltation of rivers) (6) Soil become coarser and stony (7) Reduction of farm plots size (8) flooding (9) Destruction of infrastructure and habitation (10) Not aware (11) Others (specify)……………
23. Do you use one of these soil and water conservation measures to control or reduce soil erosion of your land?

Soil and water conservation practices	No	Yes
(0) Agroforestry		
(1) vegetative cover/mulching		
(2) Grassed bounds/ Brushwood fence		
(3) Tree planting		
(4) Trenches and drainage ditches		
(5) weeding/fallow		
(6) Intercropping/Multiple cropping		
(7) Crop rotation		
(8) others (specify)……..		
(9) I don't use any of them **(*Go to question 24 and choose (0) No, otherwise if the respondent choose one or more of conservation practice select (1) Yes for question 24*)**		

24. Adoption of conservation measure by the farmer (based on the response to the question above): (0) No (1) Yes
25. What is the main challenge you experience that might hinder you to adopt soil and water conservation practices? (0) requires investment (money, equipment) (1) requires more labor (work) (2) Lack of technical support (3) reduced cropland (small farm size) (4) Lack of training (not familiar with the technique) (5) Technique not allowed in the rented plot (6) Large distance from the house to the plot (7) Others (specify)……….
26. Have you received or participated in training related to soil and water conservation? (0) Non (1) Yes

27. If yes where, which of these institutions have visited your farm/trained you in SWC? (0) Religious institutions (1) NGO (3) Community-based organization (4) Government institution (5) Research institution (6) None (7) Others (Specify)

E. PERCEPTION ON THE DEGRADATION OF FOREST LANDS

28. How has the forest cover changed in your community over the last 10 years? (0) increased (1) Decreased (2) No change
29. If the forest cover decreased, what is the major shift of forest cover change that occurred during the last 10 years in your locality
    (1) Natural forests have been converted to agricultural land (cropland)
    (2) Natural forests have been converted to grassland (pasture land)
    (3) Natural forests have been converted into human settlements
    (4) Mining activities have been expanded to natural forest
30. How do you judge the evolution of the status of forest land in your community over the last 10 years? (1) The forest landscape is degraded (2) The forest landscape is intact (3) others

Justification…………………………………………………………………………………

31. If there is a degradation of the forest landscape, how do you rate the level of degradation?
    (1) Low (2) Moderate (3) High

Justification…………………………………………………………………………………

32. What would be the direct cause of LULC change and forest degradation (proximate causes)? *(Cite the possible cause and select all the assertions for which the respondent says yes)*

Direct cause	No	Yes
(0) Charcoal production and firewood collection		
(1) Agriculture expansion and shifting cultivation on slash and burn		
(2) Settlements expansion		
(3) Mining activities		
(4) Bushfire/Forest fire		
(5) Migrant activities		
(6) Overgrazing		
(7) Colonization of land by immigrants		

(8) Timber harvesting /Forest logging		
(9) Hunting activities		
(10) Development of infrastructures (roads)		
(11) others (specify)……..		

33. What could be the indirect cause (underlying causes) of LULC Change and forest degradation? *(Cite the possible cause and select all the assertions for which the respondent says yes)*

Indirect cause	No	Yes
(0) Lack of off-farm activity		
(1) Poverty		
(2) population growth		
(3) urbanization		
(4) lack of law enforcement		
(5) Poor access to other alternative sources of energy		
(6) High demand for timber		
(7) political instability (rebellion, conflicts, war)		
(8) lack of financial resource		
(9) lack of agricultural input		
(10) others (Specify) ……………..		

34. What are the main consequences of forest degradation in your community? (0) Scarcity of no forest timber product (bushmeat, fruits, etc) (1) lack of firewood (2) lack of wood for construction (3) floods (4) depletion of water resources (5) soil erosion and landslides (6) Change in rainfall pattern (7) loss of soil fertility (8) Wild animal has been scarce (9) Siltation of rivers (10) others (Specify)…….
35. What do you think should be done to reduce the rate of forest degradation in your community? (0) Improve agricultural productivity (1) Law enforcement (2) promote tree planting (3) Sustainable use of forest resources (4) use alternative sources of energy (5) Control the forest fire (6) improve ownership of land (7) promote alternative livelihood (8) Poverty eradication (9) Protect the wildlife habitat (10) Control mining activities (11) others (Specify) …………………

F. COMMUNITY PERCEPTION ON THE DRIVERS OF ECOSYSTEM SERVICES CHANGES

36. A. What are the important products that you get from forest land (F), agricultural land (cropland) (A), settlements (Built-up area) (S), Waterbody (wetland) (W), grassland (shrub) (G), and bare land (B)? How do you judge the evolution of the availability of these products over the last 10 years? What could be the reason for the changes?

Provisioning service	LULC	Trend (0=No change, 1= Increase, 2= decrease decrease,)	Driver of change
Bushmeat			
Firewood			
Timber			
Bamboo			
Grass for house construction			
Grass for livestock			
Fishes			
Edibles vegetables			
Mushroom			
Edibles fruits			
Medicinal plant			
Drinking water			
Water for bathing			
Water for livestock			
Honey			

B. Justification (reason for change or drivers of changes):

(0) Deforestation (1) Illegal activities (3) Overexploitation (4) High demands (5) Climate change (6) Pollution and siltation of river (7) Burning of forest (8) Changes of traditional practices (9) Destruction of the natural habitat of wild species (11) overgrazing and expansion of pastureland (12) Others (specify)…………………

G. PERCEPTION ON THE IMPORTANCE (VALUE) OF ECOSYSTEM SERVICE PROVIDED BY EACH LULC TYPE

Instruction: *the stakeholder will be asked to use a scale of 0 to 3 and rate the importance or value of each LULC type in terms of availability and/or accessibility to each ecosystem service.*

Provisioning service

37. How do you judge the importance (value) of each LULC in providing this provisioning ecosystem service? (0) Not important (1) least important (2) moderately important (3) Very important

Provisioning service	Forest land	Cropland	Grassland and Shrub	Wetland	Settlements (homeland)	Barreland
Bushmeat						
Firewood						
Timber						
Bamboo						
Grass for livestock						
Grass for house construction						
Fishes						
Edibles plants						
Mushroom						
Edibles fruits						
Medicinal plant						
Drinking water						
Water for bathing						

Water for livestock						
Honey						
Comment if any						

Regulating service

38. How do you judge the importance of each LULC in providing regulating services?

Regulating service	Forest land	Agriculture land	Grassland and shrub	Wetland	Settlements (homeland)	Bare land
Erosion control						
Flood control						
Fresh air (clean air)						
Water purification						
Disease control						
Pollination						
Comment if any						

Supporting services

39. How do you judge the importance of each LULC in providing supporting services?

Supporting service	Forest land	Agriculture land	Grassland and shrub	Wetland	Settlements (homeland)	Bare land
Biodiversity conservation						
Conservation of water						
Conservation of soil fertility (Fertile soil)						
Comment if any						

Cultural service

40. How do you judge the importance of each LULC in providing cultural services?

Cultural service	Forest	Agriculture land	Grassland and Shrub	Wetland	Settlements (homeland)	Bare land
Spiritual belief						
Historical importance						
Aesthetic values						
Recreation						
Social relations						
Educational values						
Comment if any						

H. MISCELLANEOUS

41. Do you have any comment, observation, or recommendation related to land management that will be helpful to address the problem of land degradation in your locality?

APPENDIX II: RESEARCH PERMIT

République Démocratique du Congo

RSIT

Ministère de La Recherche Scientifique
et Innovation Technologique
Le Secrétaire Général

PERMIS DE RECHERCHE N° MIN.RSIT/SG-RSIT/182/180/024/2023

Conformément à l'arrêté interministériel N°119/CAB.MIN RSIT/DMK/DK/2019 et N°CAB/MIN/FINANCES2019/125 du 05/12/2019 portant fixation des droits, taxes et redevance à percevoir à l'initiative du Ministère de la Recherche Scientifique et Innovation Technologique ;

Vu le dossier introduit par Monsieur **NACISHALI NTERANYA Jean** de Nationalité **Congolaise**, qualité : ***CHERCHEUR***

Nous, soussigné, Monsieur **NDAMBU MWALANGA Odon**, Secrétaire Général à la Recherche Scientifique et Innovation Technologique, délivrons le présent **Permis de recherche** au chercheur ci-haut identifié en vue d'entreprendre des recherches scientifiques dans la Province du Sud-Kivu sur : « **MODELISATION DE LA DEGRADATION DES TERRES POUR LA PLANIFICATION DE LA CONSERVATION DANS LE TERRITOIRE DE KALEHE A L'EST DE LA RDC** ».

Durée : **06** Mois du 11 Juillet 2023 au 11 Janvier 2024

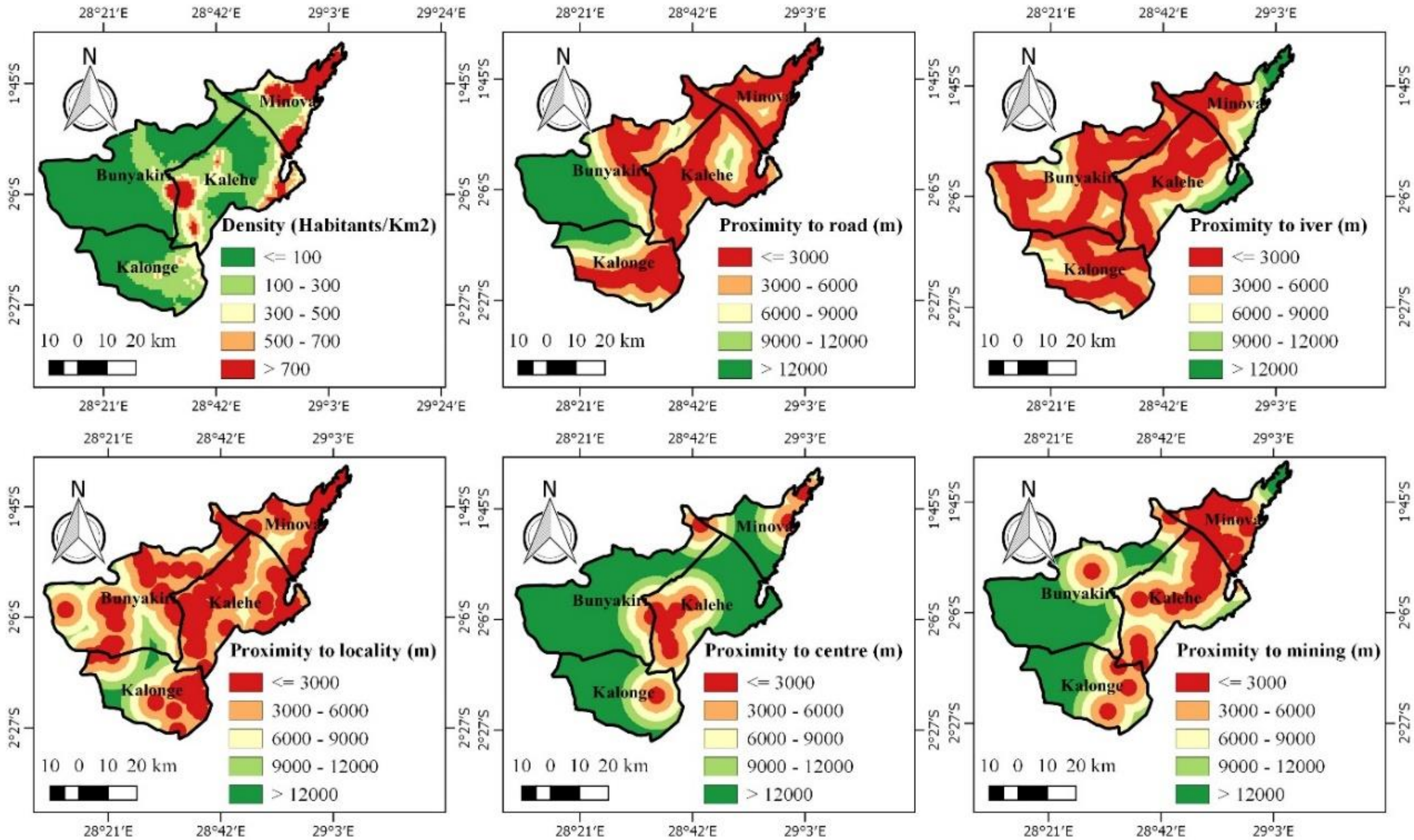
Les autorités tant Civiles que Militaires et celles de la Police Nationale sont priées de lui apporter assistance en toute circonstance en cas de nécessité.

Fait à Kinshasa, le 12 JUIL 2023

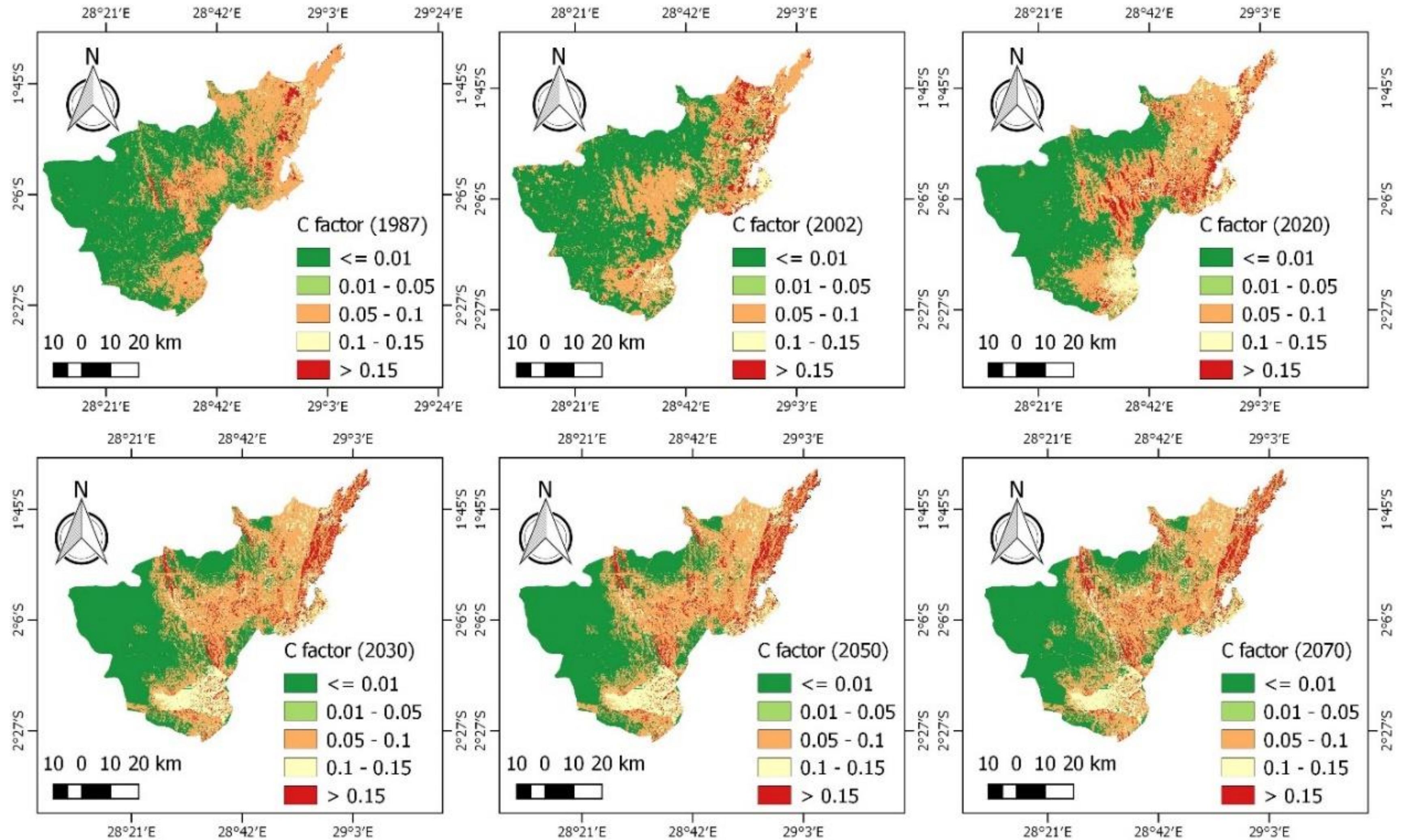
NDAMBU MWALANGA Odon

(1) Domaine précis de recherche
(2) Biffer la mention inutile

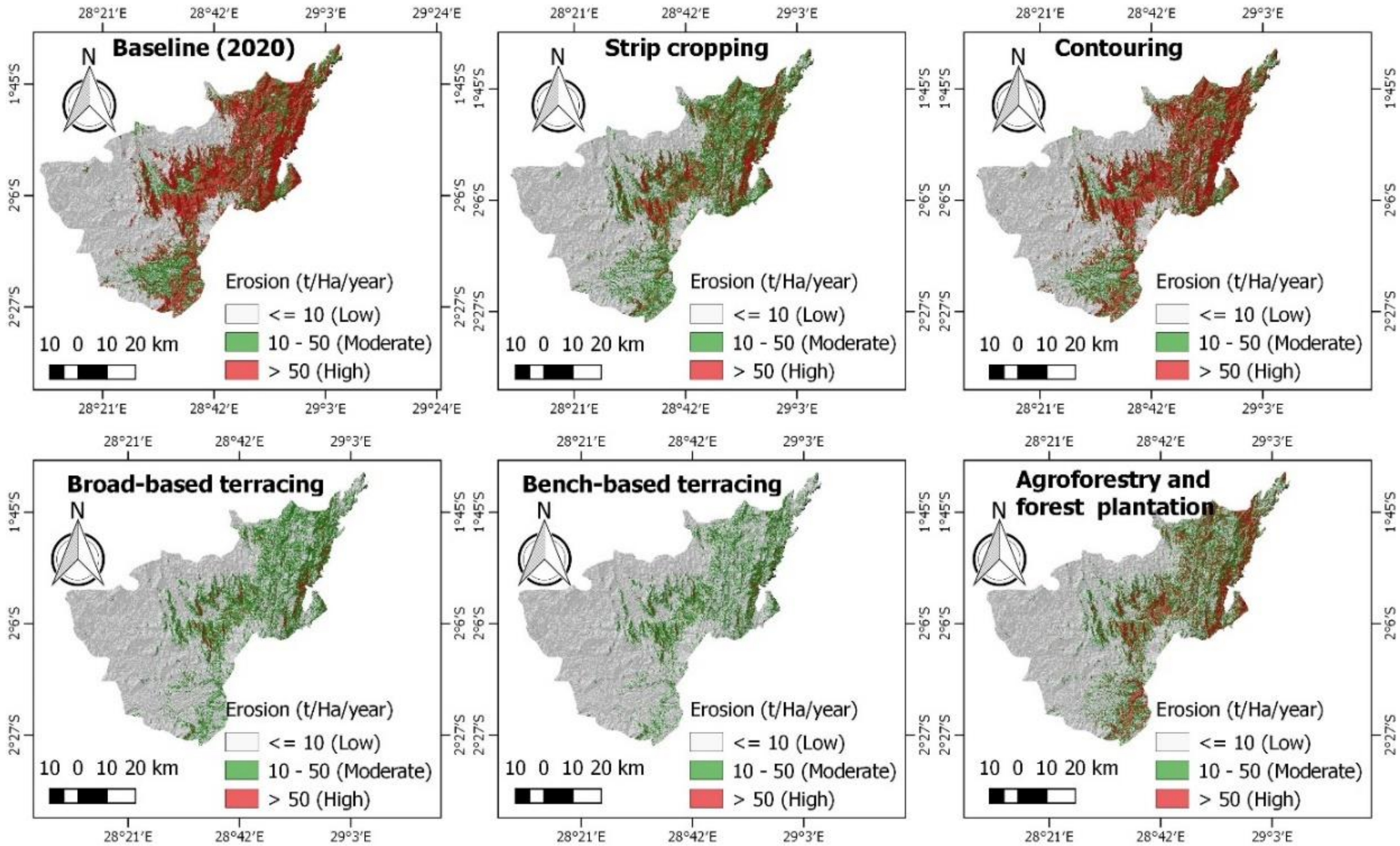
APPENDIX III: MAPS SHOWING THE POPULATION DENSITY, AND PROXIMITY FACTORS



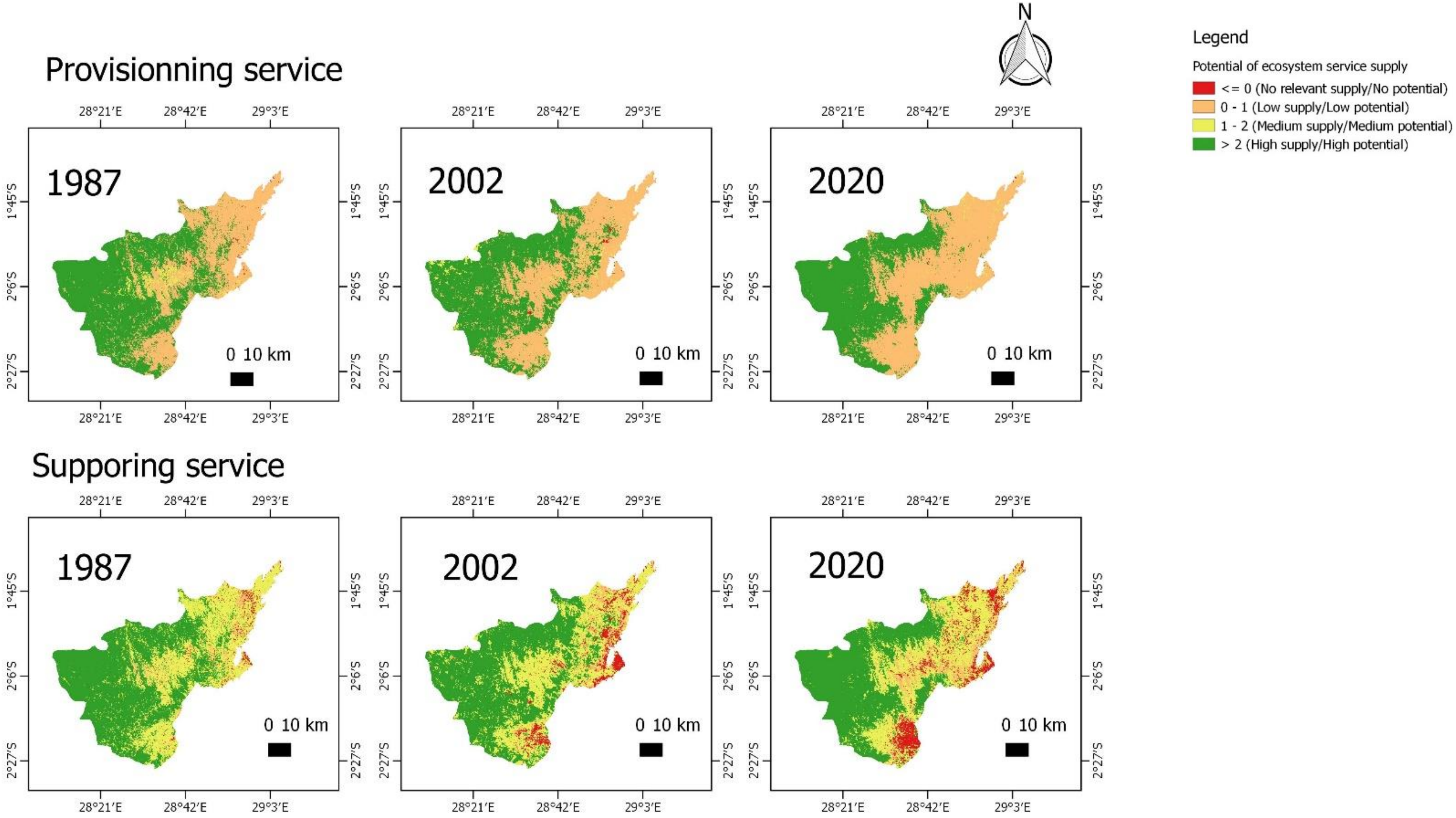
APPENDIX IV: MAPS SHOWING THE SPATIAL AND TEMPORAL VARIATION OF C FACTOR

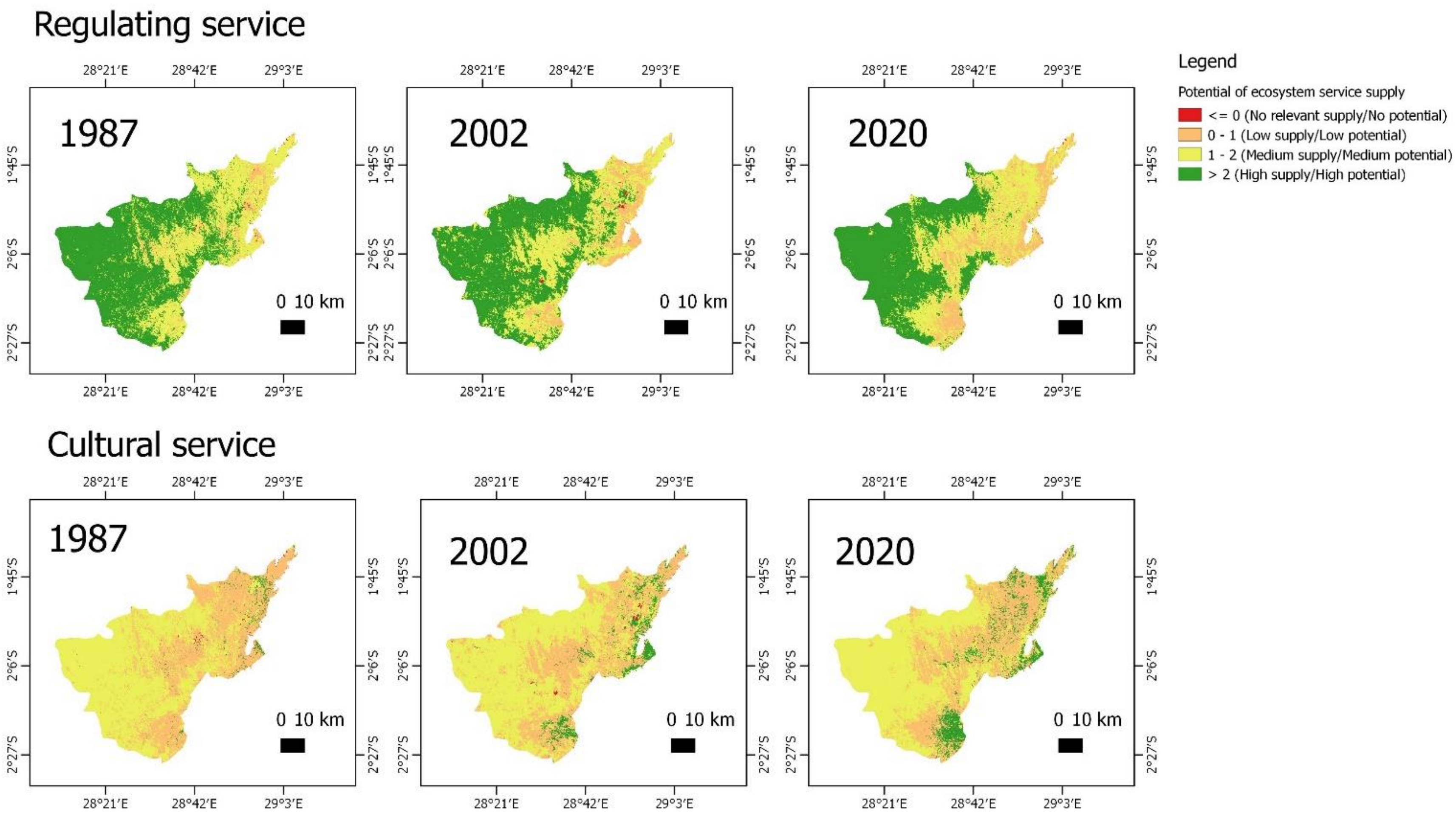


APPENDIX V: MAPS SHOWING THE EROSION DYNAMICS UNDER CONSERVATION SCENARIO



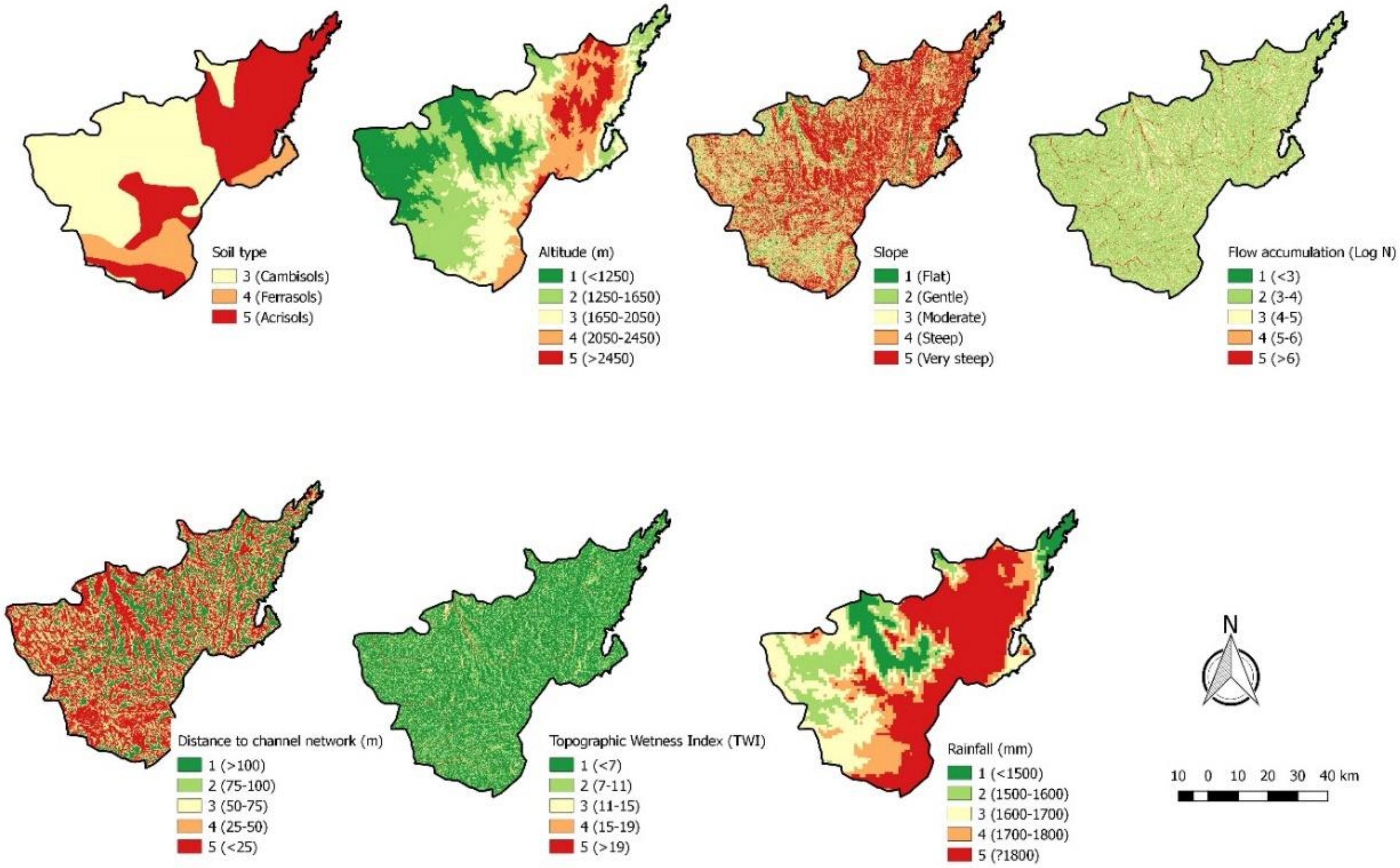
APPENDIX VI: MAPS OF ECOSYSTESM SERVICE SUPPLY POTENTIAL FOR 1987-2020



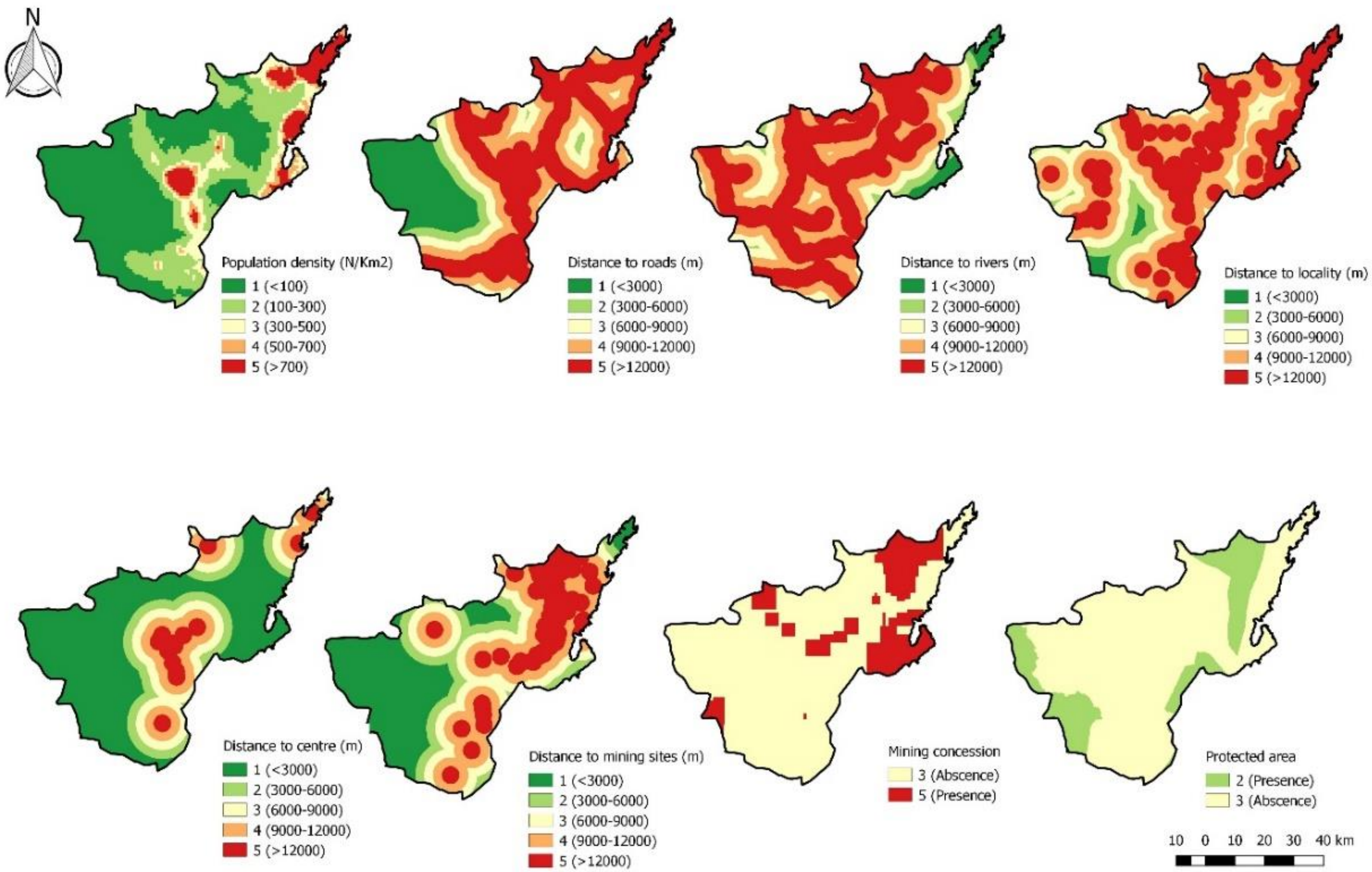


Regulating service
1987
2002
2020
Cultural service
1987
2002
2020
0 10 km
28°21′E
28°42′E
29°3′E
1°45′S
2°6′S
2°27′S
Legend
Potential of ecosystem service supply
<= 0 (No relevant supply/No potential)
0 - 1 (Low supply/Low potential)
1 - 2 (Medium supply/Medium potential)
> 2 (High supply/High potential)

APPENDIXE VII: **MAPS SHOWING THE BIOPHYSICAL FACTORS OF LAND DEGRADATION VULNERABILITY**



APPENDIXE VIII: MAPS SHOWING THE SOCIO-ECONOMICS FACTORS OF LAND DEGRADATION VULNERABILITY



APPENDIX IX: SIMILARITY REPORT

University of Eldoret

University of Eldoret

Certificate of Plagiarism Check for Thesis

Author Name	NACISHALI NTERANYA JEAN SENV/EPM/P/001/21
Course of Study	Type here...
Name of Guide	Type here...
Department	Type here...
Acceptable Maximum Limit	Type here...
Submitted By	similarity@uoeld.ac.ke
Paper Title	MODELING LAND DEGRADATION FOR CONSERVATION PLANNING IN KALEHE TERRITOR, EASTERN D.R. CONGO
Similarity	9%
Paper ID	4623354
Total Pages	435
Submission Date	2025-11-04 21:22:56

Signature of Student

Jean

Signature of Guide

Head of the Department

University Librarian

Director of Post Graduate Studies

* This report has been generated by DrillBit Anti-Plagiarism Software