UNIVERSITY of RWANDA

College of Science and Technology

School of Architecture and Built Environment

MSc in Geo-Information Science for Environment and Sustainable Development

Assessment and prediction of spatio-temporal Land use/Land cover changes in mining areas.

A case of Miyove Gold Mining Area, Rwanda

Thesis submitted to the University of Rwanda: College of Science and Technology in partial fulfillment of the requirements for the award of the Degree of Master of Science in Geo-Information for Environment and Sustainable Development.

Presented by:
MUGABO Assouman
Reg Nº: 221025902

Supervisors: **(1) Dr. RIZINJIRABAKE Fabien**
(2) Dr. NYANDWI Elias

Kigali, Dec 2024

DECLARATION

I declare that this dissertation contains my own work and has not been submitted for any other degree at University of Rwanda or any institution.

MUGABO Assouman

Reg. No: 221025902

Signed:

………………………………. Date: … .. /Dec/2024

APPROVAL

It is hereby confirmed that this thesis entitled **“Assessment and prediction of spatio-temporal Land use/Land cover changes in mining areas. A case of Miyove Gold Mining Area, Rwanda”** submitted by **MUGABO Assouman** has been assessed and accepted by the post-graduate coordination team in the school of Architecture and Built Environment

- **Supervisors**

Dr. Fabien Rizinjirabake

Signature: ………………………... Date: … .. /… … …/ … …

Dr. Elias Nyandwi

Signature: ………………………... Date: … .. /… … …/ … …

- **Post-graduate coordinator**

Dr. Ernest Uwayezu

Signature: ………………………... Date: … .. /… … …/ … …

- **Dean of School of Architecture and Built Environment**

Dr. Josephine Malonza

Signature: ………………………... Date: … .. /… … …/ … …

ACKNOWLEDGMENTS

I would like to express my gratitude to Allah for granting me that gift of life and to my supervisors Dr. Elias Nyandwi and Dr. Fabien Rizinjirabake for their excellent guidance and insightful comments.

I am grateful to the staff and former colleagues at Ngali Mining at Miyove site for their contribution to this research by providing facilities, guidance and all support for the whole period of my research.

Special thanks goes also to my beautiful wife, Assia, to my sons Taslim, Jasir and Melan and to my brother Hassan for encouraging me and allowing me sacrificing the family time to conduct this research.

Finally, I express my gratitude to everyone whose name has not been mentioned for your contribution to my work. Thank you all.

Be blessed.

ABSTRACT

Land use and land cover (LULC) serve as vital indicators of global environmental change, reflecting the profound impact of human activities on the physical landscape. This study examines into the spatial and temporal dynamics of LULC in the Miyove gold mining area spanning from 2000 to 2021, with projections extended to 2050. Employing a robust methodology, including the utilization of historical Landsat imagery from 2000, 2010, and 2021, ground control points, and predictive variables such as Digital Elevation Model (DEM), slope, distance to roads and distance to mining areas, alongside statistical analysis, and geospatial modeling techniques, such as Markov Chain analysis, facilitated the forecasting of future LULC scenarios. The results show that over the period between 2000 and 2021, we noticed that while mining area expanded, there were also increases in forest cover and artificial surfaces. However, by 2021, there was a noticeable reversal in trends, with Forest cover decreasing and Artificial Surfaces expanding further. This shift indicates a possible trade-off between natural habitats and urbanization, with mining activities serving as a key player in land transformation processes. Looking ahead to 2050, Markov chain analysis suggests a continued expansion of mining area to 89.79 ha in 2050 from 18.8 ha in 2000 which is translated as 416% increase. That pressure is coupled by the decrease of 25% in non-forest vegetation cover and 13% in forest cover highlighting the mining influence on landscape dynamics. This study provides valuable insights into the complex dynamics of LULC, highlighting the imperative for interdisciplinary approaches to address environmental challenges associated with land use conversions, particularly in mining regions. Such comprehensive strategies are essential for ensuring the long-term ecological integrity and resilience of landscapes in the face of ongoing human-induced alterations.

Key words: Land use and land cover, Miyove, Mining activities, Markov Chain analysis.

LIST OF ACRONYMS

COOPIMAR:	Coopérative Industrielle Minière Artisanale
DEM:	Digital Elevation Model
DRC:	Democratic Republic of Congo
ERDAS:	Earth Resource Data Analysis System
ha:	Hectare
LULC:	Land Use Land Cover
MLP:	Multilayer Perceptron
NISR:	National Institute of Statistics of Rwanda
NW-SE:	North West – South East
OGMR:	Office de la Géologie et des Mines du Rwanda
REDEMI:	Régie de Mines
RCMRD:	Regional Centre for Mapping of Resources for Development
RGB:	Red Green Blue
RMB :	Rwanda Mines, Petroleum and Gas Board
SOMIRWA:	Société Minière du Rwanda
TIFF:	Tagged Image File Format
TM:	Thematic Mapper
UNDP:	United Nations Development Program
USGS:	United States Geological Survey

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1. Background Information

Land use and land cover are important indicators of global environmental change as they demonstrate the impact of human activities on the physical environment (Jimoh et al., 2018). The transformation of the Earth's land surface because of numerous large-scale activities such as forestry, agriculture, dams, harbors, mining, and industry has substantial implications for biophysical systems at several scales (Patra et al., 2018; Zhou et al., 2019). Human-caused changes have far-reaching consequences, influencing different parts of the natural ecosystem (Meshesha et al., 2016). Indeed, land use/land cover is an important indicator for understanding how human activities affect the Earth's ecosystems and landscapes (Jamal & Ahmad, 2020).

In mining areas, the surrounding land use/land cover patterns are rapidly ruined and changed for the profit of minerals extraction. Landscapes are affected while mining industry is developed (Vasuki et al., 2019). Mining and processing operations result in the discharge of waste materials containing hazardous elements into nearby rivers, agricultural areas, and settlements, posing potential risks to human health and the quality of agricultural produce and livestock (Bhattacharyya et al., 2015). Mining activities may also trigger landslides, leaving barren waste rock dumps and exposed admits in their wake (Gabinema, 2016).

In developing countries, mining activities are currently being carried out in a substandard manner, but they undeniably yield significant productivity (Bizimana et al., 2021a). There is no doubt that the mining sector plays a crucial role in the lives, work, and investments of people residing in developing nations (Oluku & Asikhia, 2021). However, mining activities in developing countries, have a tremendous impact on the land, causing landscape disruption, altered topography, the establishment of agriculturally unproductive areas, and the formation of stagnant water pools that serve as pest breeding grounds (Oluku & Asikhia, 2021; P.O, 2011). Furthermore, mining activities, driven by the desire to extract minerals, cause fast deterioration and alteration of the surrounding land use and land cover patterns (Davies, 2023). The rise of the mining sector causes major changes in the terrain. Mine spoil, which is defined as massive piles of overburden from mining operations, provides an unsuitable environment from the standpoints of physical, nutritional, and microbial factors (Sheoran et al., 2019). To address these environmental issues and develop efficient land management strategies, it is critical to investigate the spatial-temporal variations in land use and land cover generated by mining activities in the Mining Area. Policymakers and stakeholders may make informed decisions to maintain the sustainable coexistence of mining operations and the preservation of the surrounding ecosystem by knowing the patterns and drivers of these changes.

The integration of space-borne photographs gathered over time demonstrates to be a great resource for cost-effective planning, decision-making, and environmental monitoring, particularly in the context of mining activities (Duncan, 2020). Researchers successfully monitor and assess the environmental impact of mining activities using multispectral satellite data and aerial photography (Davies, 2023; Vasuki et al., 2019; Werner et al., 2019). Mapping different land-use groups and following their evolution through time is widely acknowledged as critical for understanding the effects of changes in land use and land cover (Yin et al., 2009). Because of its ability to handle and modify space-borne imagery with synoptic and repeating coverage, remote sensing has emerged as a crucial technology for monitoring and tracking environmental consequences. As a result, remote sensing is critical for accurately monitoring and managing environmental impacts.

Rwanda is rich in a range of minerals resources. The most prominent are the rare metals of tin (cassiterite), tungsten (wolframite) and tantalite (coltan); tin, tungsten, tantalum are commonly known as the 3Ts (Government of Rwanda, 2019). Since the early 1990s, Rwanda's mineral exploitation has seen an upsurge in production by cooperatives and craftspeople. This includes ores and concentrates of gold, tin, tungsten, and columbium-tantalum (coltan) from a few of the numerous mineral resources (Schluter, 2008). Gold is getting the momentum for the last few years as it was evidenced by the export data of 2019 (NISR, 2019). The same environmental degradation caused by Mining activities observed globally, are also observed in Rwanda especially in areas with long mining history with very high slopes Gatumba as it was highlighted by Gabinema (2016). In Rwanda, mining activities are mainly competing with agricultural land uses and often results in significant and irreversible impacts on the environment (Haidula et al., 2011).

Between 1978 and 1979, more discoveries comprising gold were made in Miyove and Kinyami in Gicumbi District (Government of Rwanda (NISR, 2019). The legacy of bad mining practices from the colonial and immediate post-independence era by which has left behind waste dumps and degraded landscapes adjacent to or near current mining operations) has made environmental impacts from mining a sensitive topic in Rwanda (Haidula et al., 2011). Gold mining in Miyove area is of those mining activities that deserves much attention to evaluate the impact of mining activities on the land use/cover change. The main intent of this study is to provide valuable information on the environmental impacts of or mining in the Miyove region of Rwanda by analyzing and incorporating spatial and temporal variations in land use and land cover caused by mining activities. The findings of this study have the potential to inform policymakers, mining companies, and local communities about the environmental consequences of mining, as well as to support the development of sustainable mining practices and land management strategies.

1.2. Problem Statement

Mining is the second-highest foreign exchange earner in Rwanda (after tourism), and is a key strategic sector expected to support the country’s Economic Development and Poverty Reduction Strategy. Gold mining in Rwanda has increased significantly over the years, as has the exploitation of other minerals such as tin, tungsten, and columbium-tantalum (coltan) by cooperatives and artisans (Byizigiro, 2016). However, similar to mining activity around the world, Rwanda has suffered negative environmental impacts, particularly in areas with a long history of mining (REMA, 2021). Mining activities frequently conflict with agricultural land use, resulting in significant and lasting environmental consequences (UNEP, 2010). Previous research has highlighted the legacy of destructive mining practices from the colonial and immediate post-independence eras, which have left behind trash dumps and deteriorated landscapes around present mining operations, making mining's environmental implications a sensitive and essential topic in Rwanda (Barreto et al., 2018; Byizigiro, 2016; Gabinema, 2016). This thesis examined the spatio-temporal change of LULC in Miyove gold mining area to provide substantial insights into the impact of gold mining activities on the local ecology.

1.3. Research motivation

The Miyove Gold Mining Area is one of Rwanda's major gold concessions, making it a vital mining hub. Given the scale of these operations, it is reasonable to conclude that these mining activities have resulted in major changes in land use and land cover, raising concerns about the mining industry's sustainability and environmental impact.

While several studies on Land Use and Land Cover Change have been undertaken in Rwanda, none has specifically focused neither on the Miyove region nor on the prediction of the future trends. The necessity of understanding the spatiotemporal variations and future trends in land use and land cover generated by mining activities in the Miyove gold mining area is highlighted by this research gap. We can acquire vital insights into the specific impacts of mining on the local ecology in this critical gold mining zone by conducting this research. Understanding the amount of land use and land cover changes caused by mining in Miyove is critical for a number of reasons. first of all, it enables us to examine the environmental impacts of the area's mining operations, such as potential habitat loss, soil erosion, and water quality damage. Second, because mining is an important economic driver in Rwanda, assessing the sustainability of mining operations in Miyove is critical for the region's long-term growth and prosperity.

1.4. Objective of the study

1.4.1. Main objective

The main objective of this research is to assess the spatiotemporal change LULC in the Miyove gold mining area during the last three decades and predict what will be the changes in 2050. The results of this research provide critical information to policymakers, mining businesses, and local populations, as well as raise awareness about the environmental impacts of Miyove gold mining.

1.4.2. Specific objectives

1) To map the land use/ land cover in Miyove gold mining area, for year 2000, 2010 and 2021;
2) To assess the spatial and temporal change of land use/ land cover in Miyove gold mining region from 2000, 2010 to 2021;
3) To predict future land uses land covers by 2050.

1.5. Research questions

- How has the land use and land cover changed in the Miyove gold mining region from 2000, 2010 to 2021?
- What are the spatial patterns of land use and land cover changes in the study area over the specified time periods?
- Given the influence of mining activities, how may land use and land cover change in the Miyove region evolve up to the year 2050?

Table 1: Compatibility research matrix

Objectives	**Research questions**	**Data Requirement and acquisition**	**Methods and Techniques**	**Data Sources**	**Outcome**
1. To map the land use/ land cover in Miyove gold mining area, for year 2000, 2010 and 2021;	- How has the land use and land cover changed in the Miyove gold mining region from 2000, 2010 to 2021?	- Good quality historical satellite imageries over the last three decades	- Remote sensing data analysis (satellite imagery) to map land use/land cover distribution and changes over the designated years. - Geographic Information System (GIS) tools to analyze and visualize the spatial patterns. - Field surveys and data collection to validate the remote sensing data.	- Satellite imagery archives from google earth pro	- Time series LU/LC maps
2. To assess the spatial and temporal change of land use/ land cover in Miyove gold mining region, from 2000, 2010 to 2021;	What are the spatial patterns of land use and land cover changes in the study area over the specified time periods?	- data of land use land cover change regarding the expansion of mining sites.	- Statistical analysis and Geospatial monitoring and modelling system. - Contributions to net change in Mining land cover. - Change analysis of exchange between mining	LULC Data, Field data from observation	- Spatial and temporal changes in land use and land cover in the Miyove gold mining region for the specified years.

Objectives	**Research questions**	**Data Requirement and acquisition**	**Methods and Techniques**	**Data Sources**	**Outcome**
			and other land uses. - Field observation		
3. To predict future land use/land cover up to 2050 and recommend measures to minimize the effect of mining activities on land change/cover.	- How might land use and land cover change in the Miyove region evolve up to the year 2050, considering the influence of mining activities?	- Projected land use/land cover data for 2050.	- Use of predictive modeling techniques, such as Markov Chain analysis, to forecast future land use/land cover scenarios. - Incorporation of mining activity data and potential expansion estimates to account for their impact on land change.	- Predictive modeling software	- Projected land use/land cover maps for the Miyove region up to the year 2050. -An analysis of the environmental implications of projected land changes. - Recommendations for implementing measures to mitigate the impact of mining activities on land use and land cover.

CHAPTER 2. LITTERATURE REVIEW

This chapter presents a comprehensive review of the existing literature on the Land use land cover concepts. It also reviews the mining and related environmental impacts globally and locally. The review aims to provide a substance for understanding the current state of knowledge, and highlight key concepts used in this study.

2.1. Impact of Mining on Land Use/Land Cover Changes

Mining activities can have a significant impact on the environment, causing soil erosion, water pollution, and habitat damage. Toxic compounds and heavy metals released by mining operations can contaminate soil and water bodies, posing serious health threats to both animal and human populations (Kumar et al., 2017). Furthermore, mining-related land degradation can diminish soil fertility and productivity, compromising agricultural practices and food security (Asr et al., 2019). Mining expansion frequently results in land use changes, such as the conversion of forests and natural ecosystems to open-pit mines or waste disposal sites. These changes contribute to deforestation and habitat loss, resulting in a fall in biodiversity and a disruption in ecological balance (Laurance et al., 2011). Furthermore, land conversion for mining can fragment ecosystems and create barriers to animal movement, affecting species migration and gene flow (Bowman et al., 2010).

The interaction of mining and changes in land use/land cover is a complicated and dynamic process. Mining activities, for example, can cause changes in land use since abandoned mines may be reused for agriculture or urban development. Changes in land use, on the other hand, might have an impact on mining operations by modifying access to resources or bringing new regulatory issues (Turner et al., 2015). These interactions have far-reaching consequences for local communities, economy, and the environment.

Effective management of mining activities and land use changes necessitates a multifaceted strategy that takes into account environmental, social, and economic concerns. Implementing sustainable mining techniques, reclaiming disturbed lands, and encouraging responsible land use planning are critical measures in reducing negative impacts and fostering environmental sustainability (Ali et al., 2022).

Furthermore, incorporating stakeholder participation, monitoring, and stringent environmental restrictions might help to mitigate the negative effects of mining and land use/land cover changes.

The environmental impact of mining and changes in land use/land cover is a multidimensional subject that requires the attention of researchers, policymakers, and stakeholders. The considerable environmental repercussions of mining and land use changes were underlined in this literature study, as was the importance of sustainable resource management techniques. Future research in this area should concentrate on filling knowledge gaps, discovering innovative solutions, and encouraging joint efforts to establish a balance between resource extraction and environmental conservation.

2.2. Land uses land covers change and mining situation in Rwanda and Miyove.

Mining activity in Rwanda date back to the early 1920s, when colonial enterprises and later Belgian firms were involved (Macháček et al., 2022). Artisanal exploitation was also common, owing to high tantalum and tin prices. SOMIRWA, the Rwandan government's mining firm, was founded in 1973 but went bankrupt in 1985 (Byizigiro, 2016). As a result, COOPIMAR was founded to assist small mining craftspeople. SOMIRWA was later superseded by REDEMI, but disagreements and management changes resulted in limited mineral production until the late 1990s (Gabinema, 2016). According to the same author, mining and mineral commerce have recovered since 1997, contributing significantly to export revenues. The privatization of Rwanda's mining sector in the mid-2000s strengthened the national economy even more. The Rwanda Geology and Mines Authority (OGMR) was established in 2007 to increase mining oversight.

The history of exploring and mining in Miyove, Rwanda, dates back to the 1930s, when the MINETAIN Company identified gold mineralization at Masogwe, Karenda, and Baradega. Pits and trenches were dug through oxidized host rocks as part of the exploration (Byizigiro, 2016). Production lasted until 1952, when it was halted due to falling gold concentration and the discovery of non-oxidized host rocks (Uwizeyimana, 1988). Additional exploration operations, including as geological mapping, geochemical sampling, geophysics, excavations, and diamond drilling, were carried out in the 1950s, 1970s, and 1980s. Recent geology and exploration methodology reviews, as well as a soil sampling investigation, have found promising gold potential in the Masogwe prospect location, with an estimated mineral inventory of roughly 104,000 ounces of gold (Pohl et al., 2014).

The latest favorable exploration results coupled with the new investment by Ngali Mining inspired the Miyove gold mining project to resume. In 2017, Ngali Mining has embarked on the establishment of new mine tunnels, excavation of ore, and construction of infrastructure which may have altered the landscape, leading to potential environmental consequences. Mining activities and other socioeconomic variables have influenced land use and land cover change in Rwanda and Miyove as well.

To preserve the long-term well-being of communities and the preservation of natural resources in Rwanda and Miyove, it is critical to balance mining activities with sustainable land use practices and environmental conservation measures.

2.3. Land use /land cover mapping

Land use refers to the various ways in which humans use land for socioeconomic activities, as well as the strategies and management methods imposed on the land (Gabinema, 2016; Areendran et al., 2013). Commonly recognized land use classes include urban and agricultural areas (Patra et al., 2018). It encompasses a wide range of human activities, including industrial zones, residential areas, agricultural fields, grazing, logging, and mining (OS & AA, 2016; Zubair, 2006). Land cover, on the other hand, refers to the physical materials that exist on the Earth's surface and includes elements such as grass, asphalt, trees, bare ground, and water (Lv et al., 2019; Areendran et al., 2013). Notably, the word "land cover" is closely related to the notion of "earth cover," as first presented by ecologist Frederick Edward Clements, with vegetation serving as the current counterpart. It is crucial to note that "land cover" and "land use" are not synonymous (Delzeit et al., 2011). The intended human activities and techniques for exploiting the land are referred to as land use, whereas land cover refers to the physical substance found on the Earth's surface.

Land use and land cover mapping are crucial for understanding the spatial distribution of different land categories, which is important for many environmental and land management analyses (Nshimiyimana et al., 2023). Numerous studies have been conducted to define and map land use and land cover types, providing valuable insights into the changing landscapes of various regions. To provide accurate land use and land cover mapping, high-resolution satellite data and advanced Geographic Information System (GIS) techniques have been widely used (Mugiraneza et al., 2021; Smith et al., 2018; Johnson & Brown, 2019).

Integrated remote sensing techniques can be used by researchers to classify and identify various land use categories, such as agriculture, urban areas, natural vegetation, and water bodies (Mishra et al., 2020). In the literature, researchers have utilized supervised and unsupervised classification algorithms to map land use and land cover types (Chen et al., 2014; Mugiraneza et al., 2020; Paul Nkundabose et al., 2021). To build a classification model, supervised classification requires training GIS software with labeled samples of diverse land use types, whereas unsupervised classification groups pixels into clusters based on their spectral similarity (Liaqat et al., 2021).

Researchers have also stressed the relevance of field validation data in ensuring the accuracy of land use and land cover mapping (Gudo et al., 2022; Hossain et al., 2021; Mugiraneza et al., 2019).

Field validation is gathering data on-site to validate classification results and make adjustments as appropriate.

Mapping land use and land cover types is especially important in mining regions to determine the scope of mining activities and their environmental impact (Davies, 2023; Vasuki et al., 2019). Researchers can examine how mining activities have changed the environment over time by designating certain land use categories such as mining sites, agricultural fields, and natural vegetation.

2.4. Land Use Land Cover Classification

Land use land cover (LULC) classification is a key activity in remote sensing and geographical information systems (GIS) that includes categorizing the Earth's surface into different classes based on usage and cover characteristics (Li et al., 2014). The aim of LULC categorization is to classify diverse features from satellite or aerial imagery, such as forests, urban areas, agricultural fields, water bodies, and barren land, among others (Berhane et al., 2018).

2.4.1. Supervised classification

The use of labeled training data to guide the classification process is known as supervised classification. This method selects a group of representative pixels or regions of interest (ROI), each of which is connected with a given land use or land cover class (Lin et al., 2020). These labeled samples are used to train a classification algorithm, such as SVM, Random Forest, or Neural Networks (see Table 2) (Jog & Dixit, 2016). The classifier learns from the training data the spectral signatures or spectral characteristics of the various classes and applies this knowledge to categorize the entire image (Abbas & Jaber, 2020).

The accuracy and ability to include domain knowledge and expert input into the training process are two advantages of supervised categorization (Mathewos et al., 2022). However, accurate collection and labeling of training data necessitates considerable effort (Tehrany et al., 2013; Vasuki et al., 2019). Furthermore, the classifier's performance is largely dependent on the quality and representativeness of the training samples.

Table 2: Supervised Classification Techniques

Type of Classification	**Key Points**	**Advantages**	**Disadvantages**
Maximum Likelihood	Gaussian PDF	- Accurate	- Slow computational speed
Minimum Distance	Euclidean, Normalized Euclidean, and Mahalanobis distance	- Simple and fast	- less accurate
Parallelepipeds	Multi-level slicing	- Faster processing	- Pixel outside box remains unclassified
SVM (Support Vector Machine)	Can handle both linear and non-linear data	-Minimizes misclassifications, accurate results	-Solution depend on size of data

Source: Adapted from Jog & Dixit, 2016

2.4.2. Unsupervised classification

In contrast, non-supervised classification is an unsupervised technique in which the computer automatically combines pixels with similar spectral features into clusters without prior knowledge of the land cover classes (Oyekola & Adewuyi, 2018). This method does not use labeled training data and instead discovers patterns and structures within the data. The number of classes or clusters expected in the scenario is specified by the user in non-supervised categorization. The algorithm then groups the pixels iteratively based on spectral similarities until the desired number of classes is reached (Romero et al., 2016). The user must then evaluate the generated clusters to assign appropriate land cover labels to each group. Non-supervised classification has the advantage of being able to handle big datasets without the requirement for considerable training data (Mohd Hasmadi et al., 2009). However, one of its key drawbacks is that it does not always give relevant or accurate answers, especially when working with complex and varied environments.

In LULC classification, both supervised and unsupervised approaches are important. The availability of labeled training data, the amount of precision required, and the complexity of the terrain under consideration all influence the choice between the two. To get the most accurate and comprehensive land use land cover classification, a mixture of both methodologies or semi-supervised algorithms is frequently used.

2.4.3. Accuracy assessment

Accuracy assessment is critical in determining the performance and reliability of remote sensing and geospatial analysis approaches (Chen et al., 2014; Vasuki et al., 2019). Accuracy assessment evaluates the agreement between anticipated classifications and actual ground truth data by comparing classified or derived outputs with reference data (Bizimana et al., 2021b; Gabinema, 2016). Accuracy evaluation approaches include confusion matrices, error matrices, overall accuracy, producer's accuracy, user's accuracy, kappa coefficient, and commission and omission errors (Pontius Jr and Millones, 2011). Researchers gain confidence in the validity of their results and can make informed decisions based on the performance of their models and algorithms through precise accuracy evaluation.

CHAPTER 3. RESEARCH METHODOLOGY

This chapter presents the methodology used to conduct the study. Its describe the study area, highlights the needed data and their sources as well as the methods applied to retrieve the information from the data.

3.1. Description of study area

Miyove gold mining area is located in the south of the famous Rugezi wetland in the highlands of Gicumbi and Burera Districts, Northern Province of Rwanda. The area is characterized by steep slopes (25-45%) and high altitude with and an elevation ranging from 2000m to 2400m above sea level. Mining activities in Miyove area have a very long history as they were initiated by the Belgians during the colonial era back in 1930s (UNDP, 1988). Miyove gold mining area is made of 5 concession blocks being developed by Ngali Mining Ltd since 2017. Our study area covers a big part of Ngali concessions as illustrated in Figure 1. The Miyove gold mining area is geologically underlain by rocks from the Central African Mesoproterozoic-aged Kibara Belt, which extends north-east from the Democratic Republic of the Congo (DRC) via Rwanda to the southern section of Uganda. The property contains shale, siltstone, sandstone, and uncommon conglomerate units and has basic anticlinal and synclinal fold structures (Byizigiro, 2016). The gold mineralization is linked to a number of NW-SE trending structures that host gold-bearing quartz veins and stock works. The area contains three mineralized zones named Karenda in the north, Baradega in center, and Masogwe in the south, which are all aligned along a northwest-southeast mineralization trend.

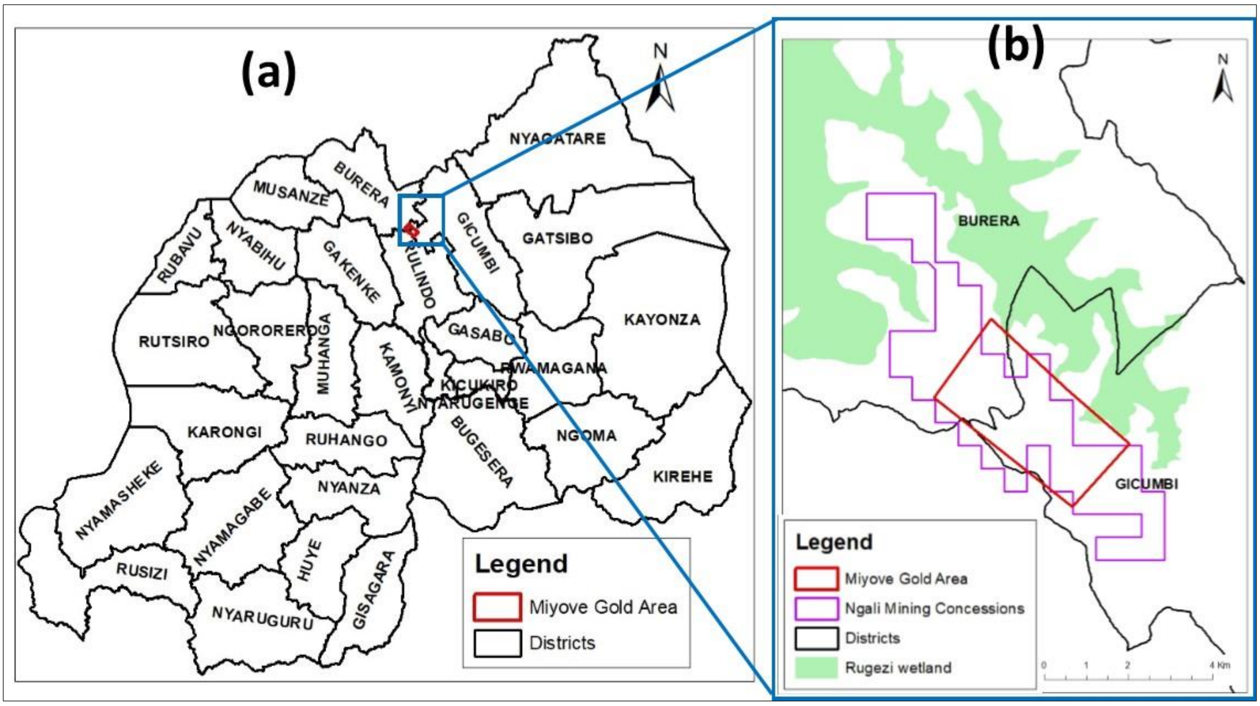


Figure 1: Miyove Gold Mining area – Study area location map (b) and administrative map of Rwanda (a). Source: NISR, 2006; RMB, 2024.

3.2. Data collection

Data collection for this research involved both primary and secondary data sources. This section presents the required data, their sources and methods used to acquire them as well as highlighting the limitations encountered while searching for the data as well.

3.2.1. Primary data acquisition

The primary data were gathered through field observations and field mapping, focusing on key features relevant to the study. During the field survey, we located and mapped numerous mine sites and related activities in order to understand the mining activities distributions in the study area and assess any possible effect of mining on the environment (Appendix 3). Additionally, using handheld GPS, we have collected GPS points of the key features such as primary schools, road junctions and market to assist the georeferencing of the satellite images.

Furthermore, we collected ground truth points using the sampling/area frame method to cover the entire study region. This approach was chosen as it is simple and efficient for conducting a land use/land cover survey over a large territory as the target population, taking into account the size and features of the units to be sampled. The sampling/area frame units are closely related with specific geographical locations. Using the sampling segment strategy, the territory was divided into regular shaped portions of about 500m by 500m (Figure 2). A total of 31 ground truth points were picked at the intersection of the grid lines inside the study area. This all-encompassing strategy resulted in the collection of accurate and dependable ground truth data, which were a useful resource for our study.

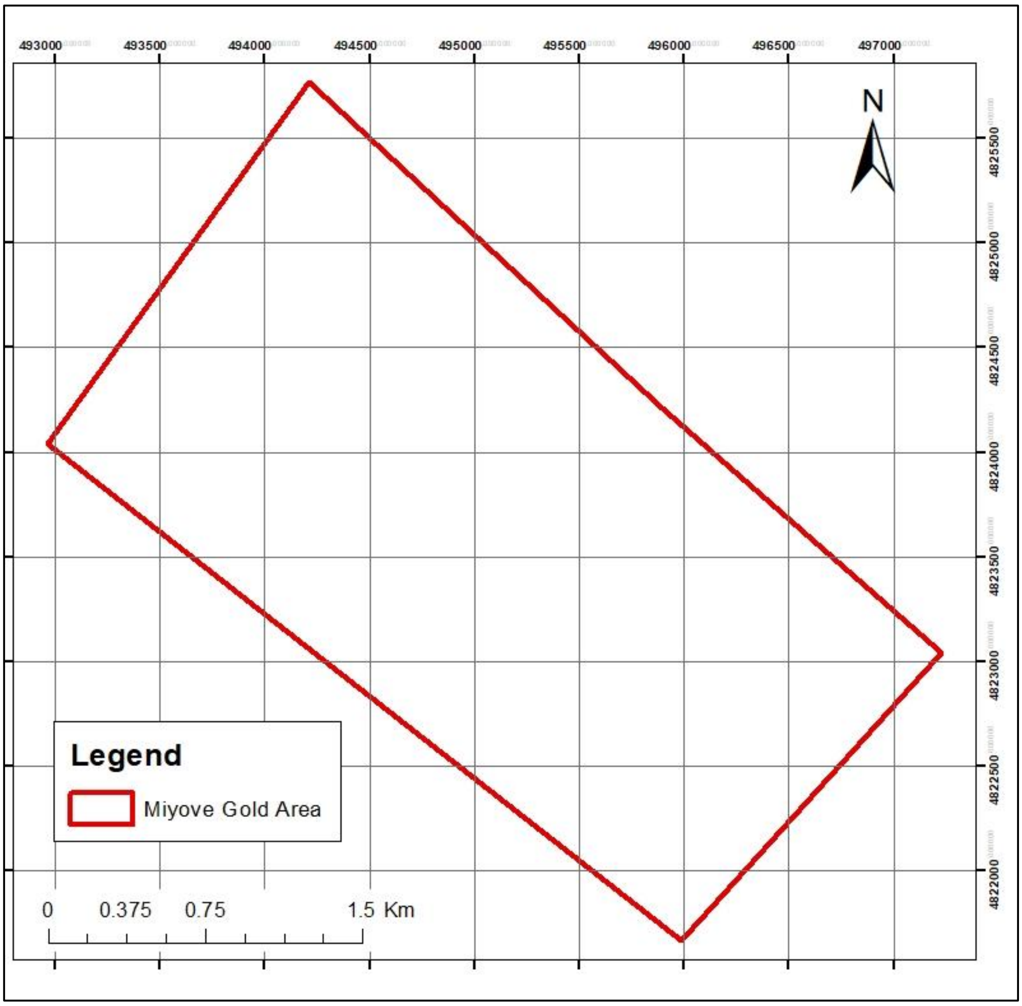


Figure 2: sampling/area frame units – 500m grid lines.
Source: Field data, 2024

3.2.1. Secondary data acquisition

Our secondary data includes two types of data: imageries and vector data in form of shapefiles. The satellites imageries used are acquired from Landsat, taken at several time intervals in our study while the vector data are made of administrative boundaries from NISR and mining license shapefiles from the Rwanda Mines Petroleum and Board portal. The use of such various datasets emphasized on the importance of having the necessary data readily available. The satellite images which were acquired as described in table 3, assisted in analysis of the changes and developments that occurred throughout study period, allowing us to conduct a thorough examination of the LULC dynamics of the study region.

Historical Landsat images were acquired from the Google Earth Engine. To ensure data quality and consistency throughout the study period, we were looking for images with cloud cover less than 5%, captured during the same period of the year, preferably sunny season (June-July-August) to avoid any bias related to comparing LULC of a rainy season with a sunny season. As results, we could find the images of year 2000 in January, year 2010 in June and year 2021 in July.

The significance of the year 2000 can be as of the most historical images that could meet our criteria, and year 2010 can be taken as the middle of our study period while the year 2021 is considered as the most recent time period due to images availability. The details of the satellite images used in this study are summarized in the table below.

Table 3: Description of the satellite images

Year	Date	Satellite Image type	Resolution	Pixel Resolution
2000	1 January	LandSat	High	0.5 meters
2010	30 June	LandSat	High	0.5 meters
2021	19 July	LandSat	High	0.5 meters

Source: USGS, 2024, https://developers.google.com/earth-engine/datasets/catalog/landsat.

The selected satellite images were pre-processed using ArcGIS Pro 2.9 software to georeference and crop the study area from the regional image. Georeferencing was conducted using GPS location points collected at key features such as Mubuga Market, road junction to Karenda and Mubuga Primary school. The pre-processed imagery was then analyzed to identify land use/land cover changes and patterns within the Landsat images across the selected study area and over different time periods. The result was the generation of land use/land cover change maps to facilitate the assessment of mining impacts on the region's sustainability and land use dynamics.

Furthermore, elevation and slope data were generated from the DEM to better understand the topography of the area.

Lastly, using the Focus Group Discussion methodology, two groups were consulted to understand the historical development of the mining activities around Miyove area over time. The first group was composed of members of "Imbereheza Bacukuzi", a Cooperative of artisanal miners of Miyove sector of Gicumbi District and the second one composed of members of "Twizamurane", a cooperative of artisanal miners of Karenda sector of Burera District (Appendix 5).

3.2.3. Data acquisition limitations

During the data acquisition process, we have encountered some limitations related to data availability and quality. Our initial plan was to assess the LULC of the last four decades, unfortunately we could only find better satellites images from year 2000 as the previous years' images were too cloudy (more than 60% cloud cover) in our study area. We have also tried to use the LULC data of 1990 from the Regional Centre for Mapping of Resources for Development (RCMRD) but we found them too regional with only two different classes (crop land and forest) over our study area.

3.3. Data processing

3.3.1. Field data processing

Several processes were required during the data processing phase to achieve accurate and dependable results. First, we entered field data thoroughly, meticulously capturing all pertinent information acquired during the survey. This was an important step in constructing a thorough database of the acquired data.

Following that, we concentrated on effective database management, structuring information in a structured and easily accessible manner. This systematic methodology will enable us to efficiently handle and analyze the data.

Statistical analysis methods were used to extract useful information from the collected data. We used Microsoft Excel to generate clustered bar of the LULC per class per period and examine trends, and correlations in the data, which improved our comprehension of the subject. Furthermore, we combined field observation data with generated spatial datasets into our analysis, the process contributed to a more comprehensive view of the research topic. We also upgraded the datasets through preprocessing techniques to ensure the quality and clarity of our findings, correcting any inconsistencies or errors that may occur during data collection or entry. Finally, using the processed and improved data, we built visuals to properly explain our findings. These graphics were helpful in expressing complex information in a clear and informative manner, allowing us to reach sound conclusions based on the study's objectives.

3.3.2. Time series land covers/uses maps generation using satellite images data classification

In this work, high-resolution Landsat images from Google Earth pro were used. The Landsat images was downloaded as individual bands in TIFF format and afterwards merged into single-color composites. Bands 1, 2, 3, 4, 5, and 7 of Landsat were combined. We sub-seted our study area and the subset process consisted of the pan-sharpened images for all time spans, within the boundaries of the Miyove gold mining area. To create land use/land cover maps we used a pixel-based approach via supervised classification. Ground truth data were collected in order to create areas of interest on multispectral images, the process was accomplished by displaying the 4-3-2 false color composite result as the RGB order combination. In ERDAS Imagine software, classification was based on demarcated training zones, allowing each pixel to be allocated a distinct land cover class.

Four significant classes identified based on shared physical properties and spectral values. First, the “forest” class, which includes dense forest, open forest and forest plantations. The second class, "artificial surface: bare soil & built-up" included barren land, roads, non-cultivated farms, and built-up land. The third class “non-forest vegetation cover” which includes grass, shrub and crops, and finally, the "mining area" class included mine site locations, and related activities such as dumping sites or washing areas.

To assure the accuracy of the classification results, an assessment process was carried out, which included the use of the ground truthing points and google earth pro images.

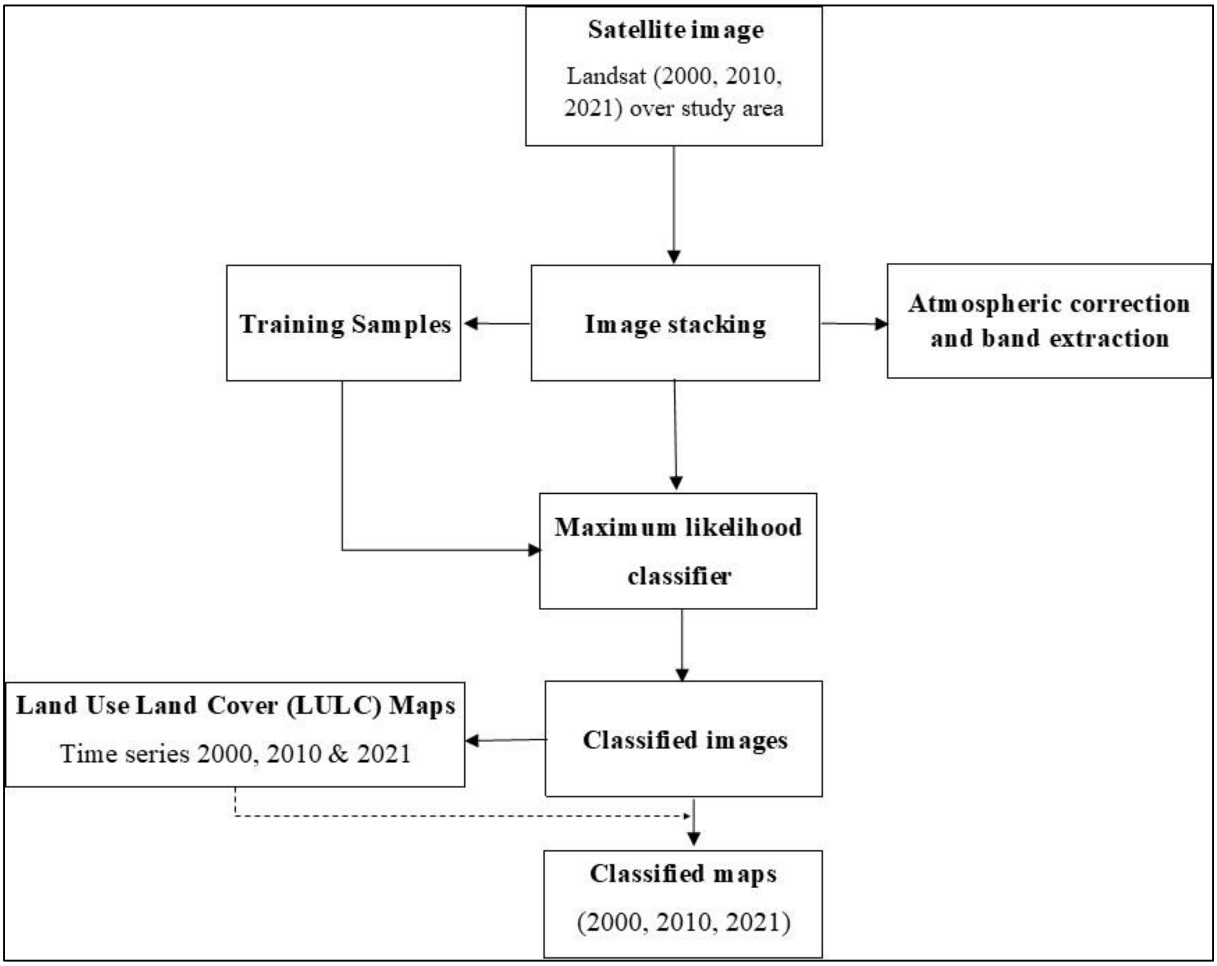


Figure 3: LULC mapping flowchart.
Source: Adapted from Gabinema, 2016.

3.3.3. Land covers Land uses change detection

Land cover Land use changes were mapped after mapping each time series separately one by one and then compare the changes made over time.

Each classified map among the distinct time periods had 4 classes including mining areas class. The change matrix was performed using map-to-map operations to identify changes in land cover classes. A change matrix was generated to quantify the transitions between different land cover types, focusing on the occupancy of each class over time. Two time spans among three were compared each other. Pixel algorithms were made for 2000-2010, 2010-2021 and the overall

2000-2021. The changes and trends of mining activities as well as for land use/land cover patterns were compared, analyzed, counted, displayed and explained.

3.3.4. Future Land use land cover prediction using Markov Chain analysis.

A spatially explicit land use change modeling tool, such as the Markov-Chain analysis (CA) methodology, assisted for the projection of multiple future scenarios. Burnham was the first to employ the Markov-Chain model for land use modeling, as documented by Mishra and Rai (2016) and Parsa et al. (2016). Markov chains represent stochastic processes, as noted by Halmy et al. (2015) and Subedi et al. (2013) and are employed with matrices to depict transitions between land use categories. This approach is grounded in the fundamental principle of historical development continuity (Koomen and Borsboom-van Beurden, 2011), and is frequently utilized for modeling and simulating changes and trends in land use and land cover (LULC), as highlighted by Halmy et al. (2015), Mishra and Rai (2016), and Parsa et al. (2016). The homogeneous Markov model, which is utilized to forecast land use changes, can be expressed mathematically, as outlined by Subedi et al. (2013). Its popularity has grown significantly with the advancements in Remote Sensing and GIS technology. This model is frequently employed to replicate landscape changes (Baker, 1989; Muller and Middleton, 1994), examine various land use types, trends, and the scale of alterations (Weng, 2002; Huang et al., 2008). Noteworthy models include the Markov chain model (Muller and Middleton, 1994) and the CA (Cellular Automata) Markov model (Clarke, 1997). In the Markov chain model, each pixel's subsequent state (land cover type) is solely dependent on its immediate previous state, without regard to any earlier states.

The Markov-CA technique was used in this work to forecast land use changes and project changes in 2050 by extrapolating present LULC trends. We intend to project the distribution of each Land Use and Land Cover (LULC) class using the Markov model (Figure 4) based on the transition probability between two LULC classes (2010 and 2021). The model Markov-CA is selected because it is a robust model approach that is more recommended for predicting land use change as it outperforms other methods (Halmy et al., 2015; Li et al., 2014; Liping et al., 2018; Onilude and Vaz, 2021; J. Wang and Maduako, 2018). Using Land change modeler (LCM) change analysis of LULC was performed and predicted land use land cover map was produced.

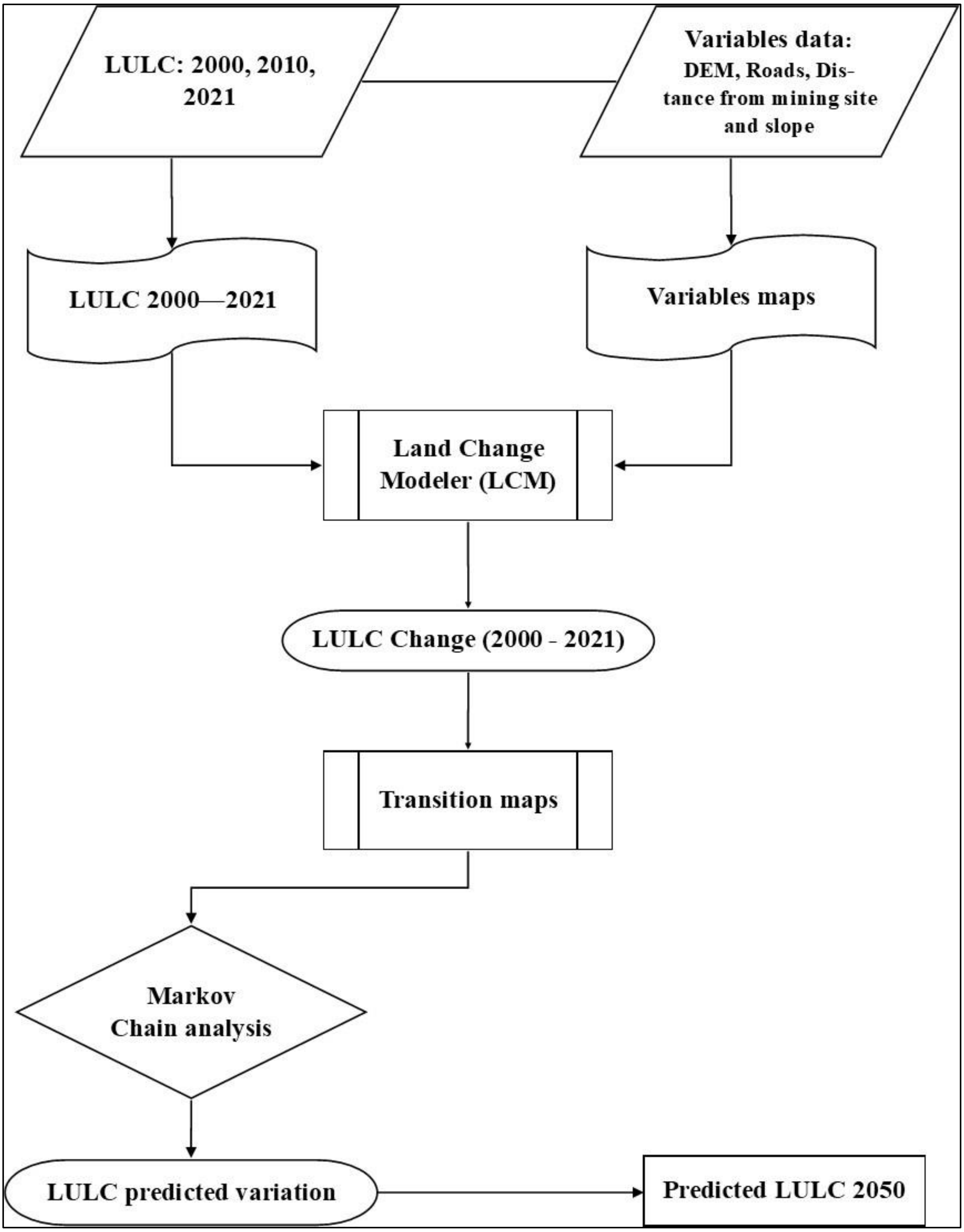


Figure 4: Flowchart Markov model.
Source: Adapted from Halmy et al., 2015.

To predict the LULC four influencing variables were selected including the Elevation, Slope, Distance to the roads and existing mining sites.

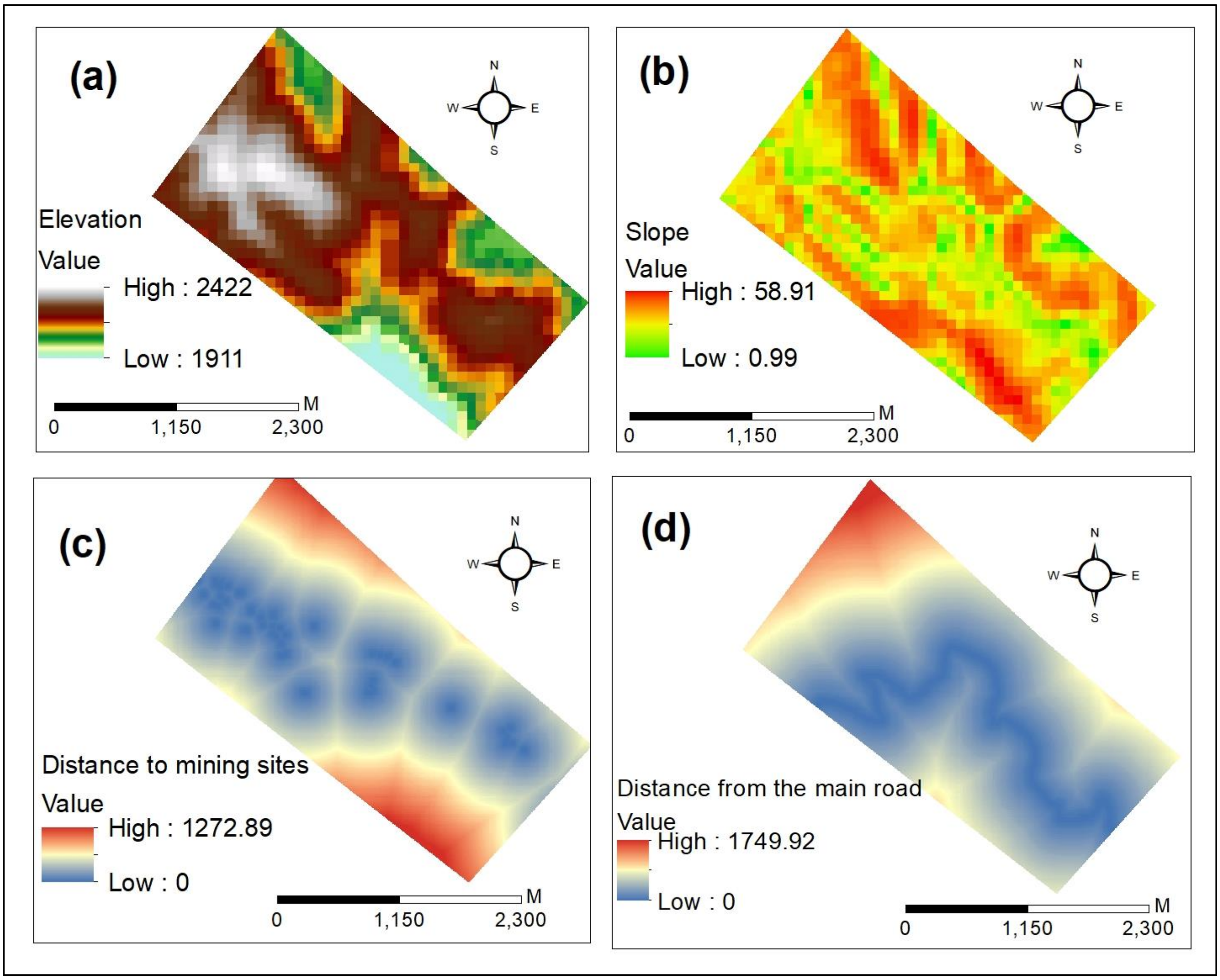


Figure 5: Visualization of the four influencing variables (a) Elevation, (b) Slope (c), Distance to mining site and (d) Distance from the main road.

The four factors highlighted in Figure 5 were chosen based on their substantial influence on both land use/land cover (LULC) dynamics and mining operations (Awotwi et al., 2018). Elevation and slope, for instance, play critical roles in shaping changes in LULC, particularly in built-up areas and other human activities (Onilude & Vaz, 2021). Additionally, proximity to mining activities is a crucial determinant, as these activities often have significant ramifications on various types of land cover. Likewise, the distance from roads emerges as a significant factor, given that road construction can strongly contribute to deforestation, while the proximity to roads often fosters the expansion of frontier residential development.

CHAPTER 4. RESEARCH FINDINGS

This chapter presents the results of the findings of our study. Its covers the classified satellites images through the studied period, the LULC changes and the predicted land use land cover of the study area in 2050.

4.1. Spatial and temporal distribution and changes of main land uses and land covers types in the Miyove gold mining area

The study area covers an approximate area of 712 ha, and the analysis of spatial and temporal changes in Figure 6 of land use and land cover (LULC) within the Miyove gold mining area reveals significant patterns over the years.

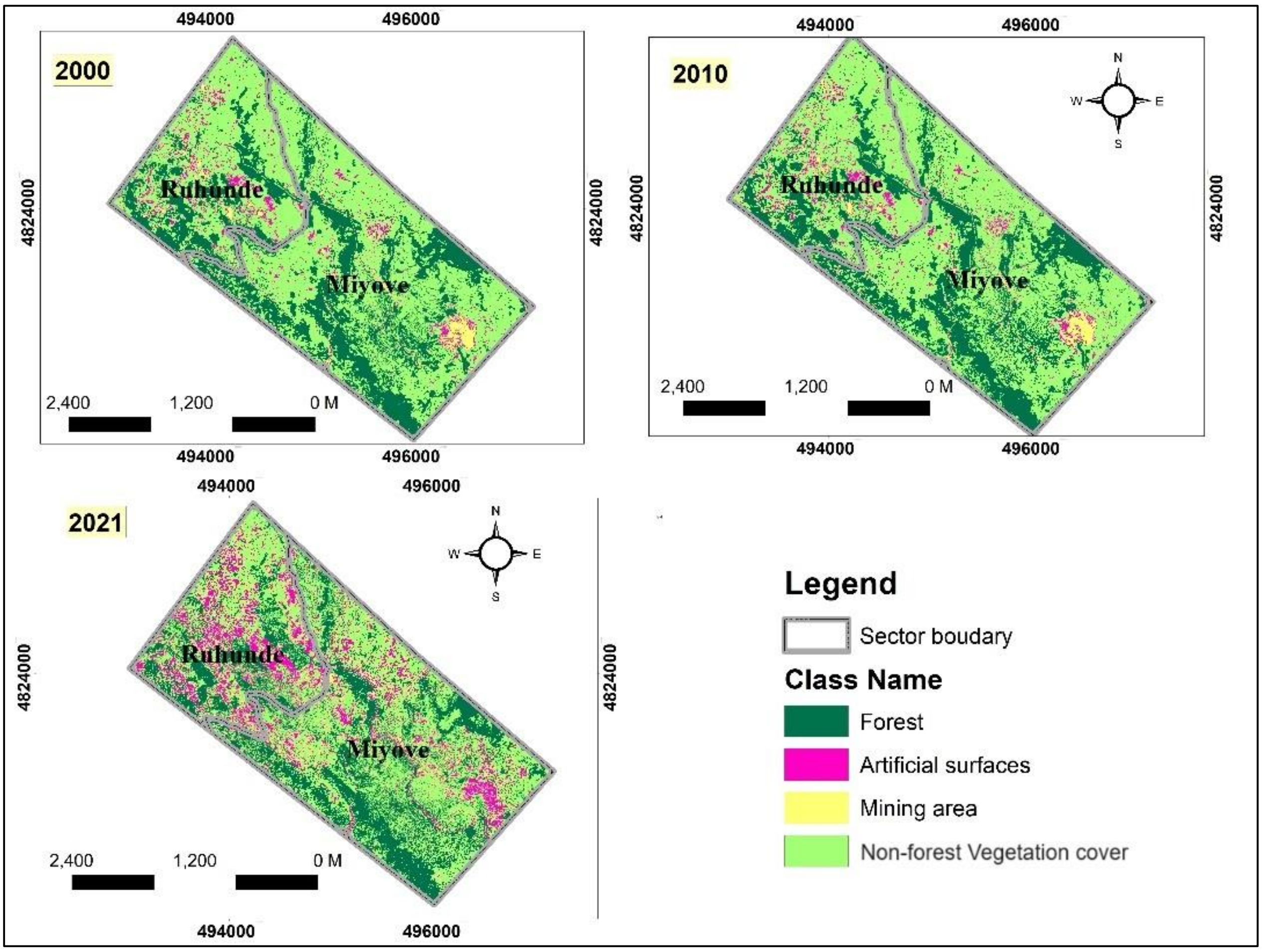


Figure 6: Land use land cover change dynamics (2000-2021)

The table below presents the distribution of Land use land cover categories across the study period, offering understandings into the dynamics of the landscape.

Table 4: Land use/land cover distribution from 2000 to 2021.

Year	LULC Category	Area (ha)	Percentage of Total Area (%)
2000	Forest	225.775	31.68
	Artificial surfaces	32.9075	4.62
	Mining area	18.8275	2.65
	Non-forest vegetation cover	434.59	61.05
2010	Forest	263.0475	36.94
	Artificial surfaces	154.47	21.69
	Mining area	28.9025	4.06
	Non-forest vegetation cover	265.68	37.31
2021	Forest	214.3175	30.10
	Artificial surfaces	95.2075	13.37
	Mining area	78.24	10.99
	Non-forest vegetation cover	324.3525	45.54

The analysis of land use and land cover (LULC) dynamics in the Miyove gold mining area, as depicted in Table 4, offers valuable insights into the spatial and temporal changes occurring in key LULC categories over the period from 2000 to 2021.

The result reveals a fluctuating trend in forest/ non-forest vegetation cover across the years. Initially, there was an increase in forest cover from 2000 to 2010 as evidenced by the increase from 225.775 ha (31.68% of the total area) in 2000 to 263.05 ha (36.94%) in 2010 and then decreased to 214.32 ha (30.10%) in 2021. The same trend was also observed for artificial surfaces which increased from 32.9 ha (4.62%) in 2000 to 154.47 ha (21.69%) in 2010 and fall to 95.2075 ha (13.37%) in 2021.

Additionally, a different form of fluctuation was noticed in non-forest vegetation cover whereby it considerably decreased almost by a half, from 434.59 ha (61.05 %) in 2000 to 265.68 ha (37.31 %) in 2010 and risen to 324.3525 ha (45.54 %) in 2021.

In contrast to the fluctuating trend observed in all other classes, we have observed a gradually increasing trend in and mining area from 18.8 ha (2.65%) in 2000 to 28.9 ha (4%) in 2010 and climbed to 78.24 ha (10.99%) in 2021.

Furthermore, in Figure 8, the net change in various and Use and Land Cover (LULC) categories, over the entire study period, reveals that artificial surfaces and mining area experienced a positive net change, amounting to 62 ha and 59 ha, respectively. Conversely, there was a negative change for forest and non-forest vegetation cover of -11 ha and 110 ha respectively.

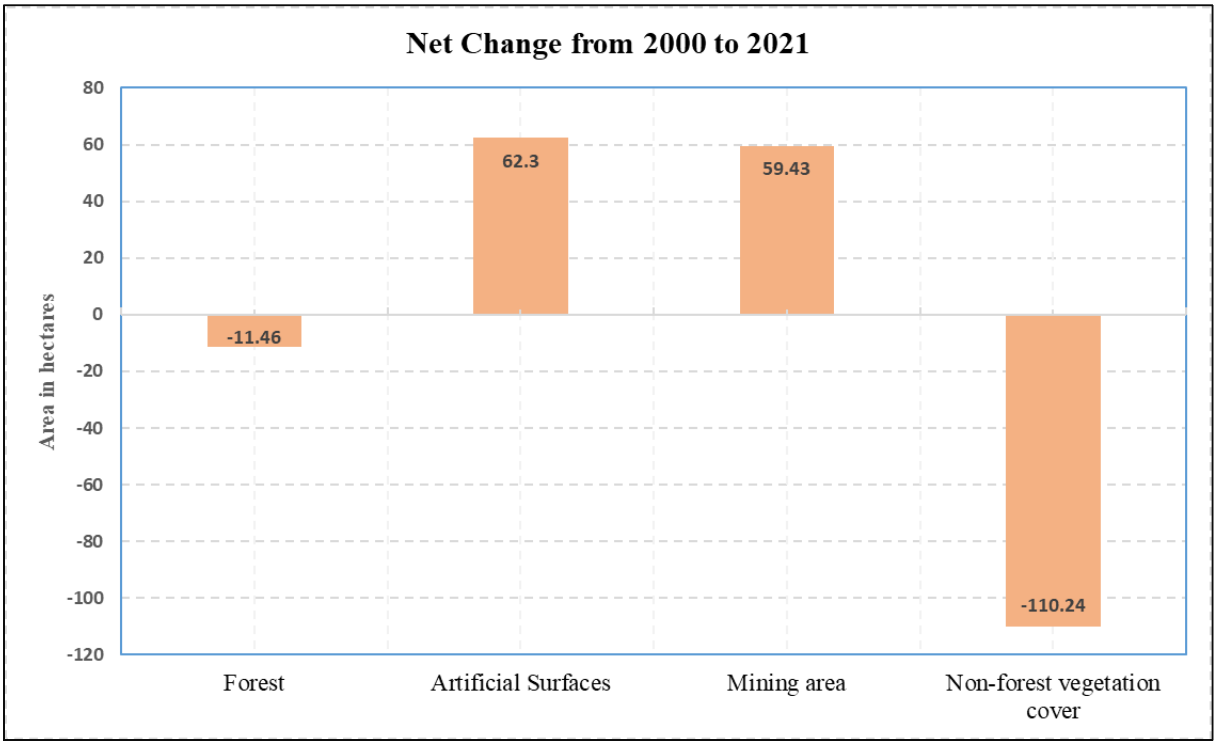


Figure 7: Net change of LULC classes (ha) from 2000 to 2021.

The results spanning from 2000 to 2021 shows a dynamic interplay between mining area and diverse land use and land cover (LULC) categories. Considerably, a tremendous part of vegetated, artificial surfaces and forested area totaling 74 ha transitioned into mining area over the entire observed duration. This shift underscores a heavy effect of mining operations on agriculture land witnessed by the fact that 75% of the total area which transitioned into mining area from the non-forest vegetation cover alone.

Simultaneously, during the last two decades we noted a negligible effort to reclaim mined lands as only 14 ha of former mining areas reverted to vegetated and forest area. This reversal shows lack of restoration tasks or natural regeneration strategies aimed toward mitigating the environmental outcomes of mining areas and fostering environment resilience. Furthermore, the results display the urbanization (settlements) pressures and land use alterations associated with mining, as evidenced by means of the conversion of vegetated area into built up or bare soil areas, encompassing approximately 64 ha.

Additionally, there are some mining activities observed at Baradega which threaten the forest and non-forest vegetation cover in the study area.

4.2. Projected land use/land cover change for the Miyove area up to the year 2050.

Examining historical shifts in Land Use and Land Cover (LULC) distributions provides insights into potential future changes based on spatial explanatory variables in Figure 5. Utilizing the Multilayer Perceptron (MLP), we produced transition potential maps for different transitions, achieving an accuracy surpassing 83% (Appendix 1). Additionally, Markov analysis was conducted on the multi-temporal land cover images spanning from 2000 to 2021, with predictions extended to 2050, as illustrated in Figure 9.

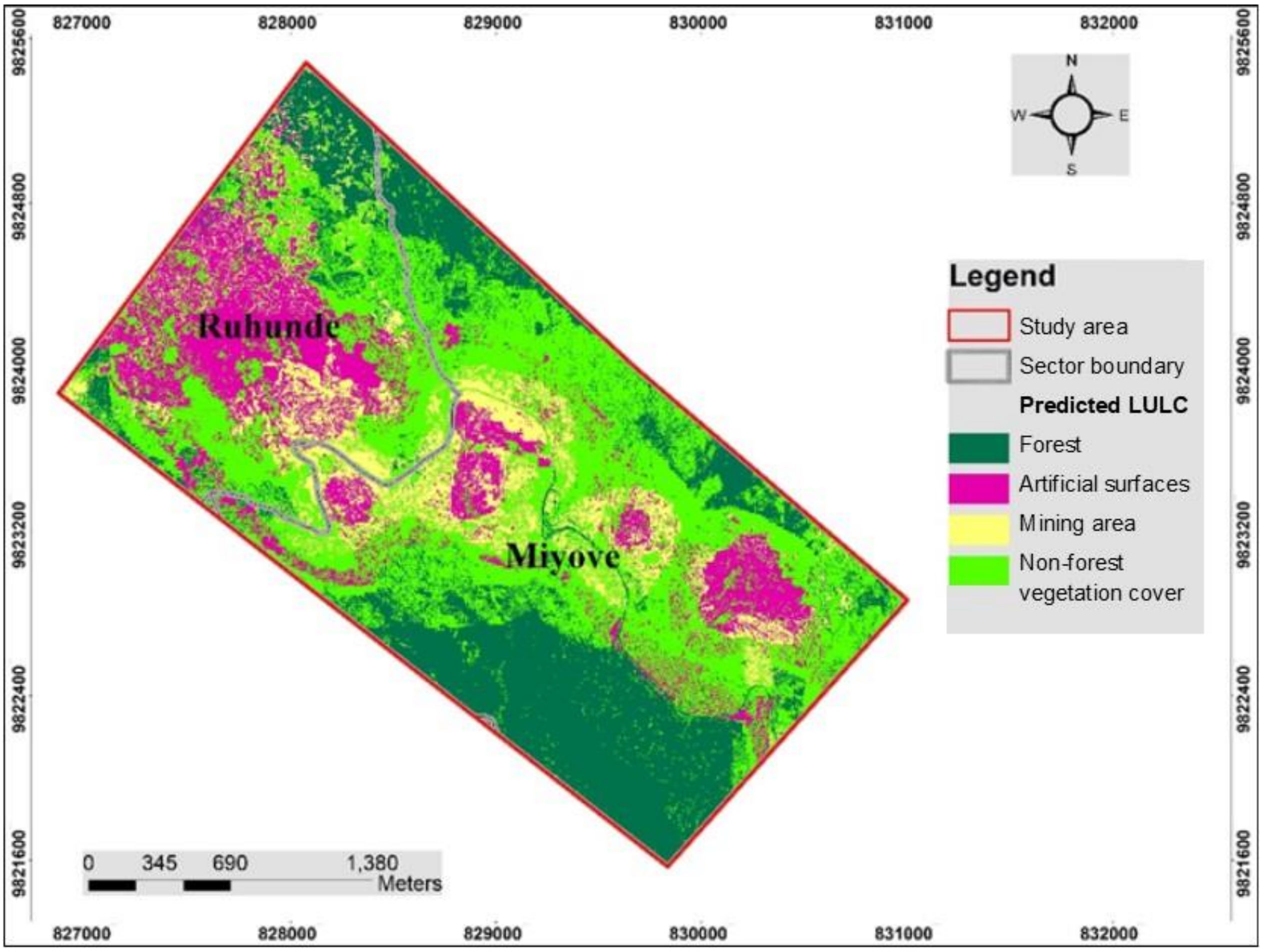


Figure 8: Predicted LULC map for year 2050.

Table 6 depicts the transition probability matrix, derived through Markov chain analysis, spanning from 2000 to 2010, with a forecast for 2050. This matrix comprises rows and columns, alongside diagonal values indicating the probability of each Land Use and Land Cover (LULC) class remaining unchanged over the specified period (Halmy et al., 2015). The outcomes indicate a fluctuation into transitions from one class to another with a relatively high probability of all other classes transitioning into non-forest vegetation cover.

Table 5: Markov transition probability matrix and LULC change for 2050.

	Forest	**Artificial Surfaces**	**Mining area**	**non-forest Vegetation cover**
Forest	49%	8%	7%	36%
Artificial Surfaces	14%	30%	17%	39%
Mining area	13%	33%	19%	34%
non-forest Vegetation cover	21%	17%	13%	49%

Both figure 9 and 10 illustrate the LULC variations from year 2000 extending to the predicted time of 2050. The graph reveals that over the analyzed period, significant shifts occurred in land use and land cover patterns. Notably, it illustrates the dynamic nature of Forest and non-forest vegetation cover, which are most likely to decrease in 2050 compared to the current situation. It also indicates a gradual expansion of the artificial surfaces and mining areas which are likely to double in 2050 compared to its initial status in 2000.

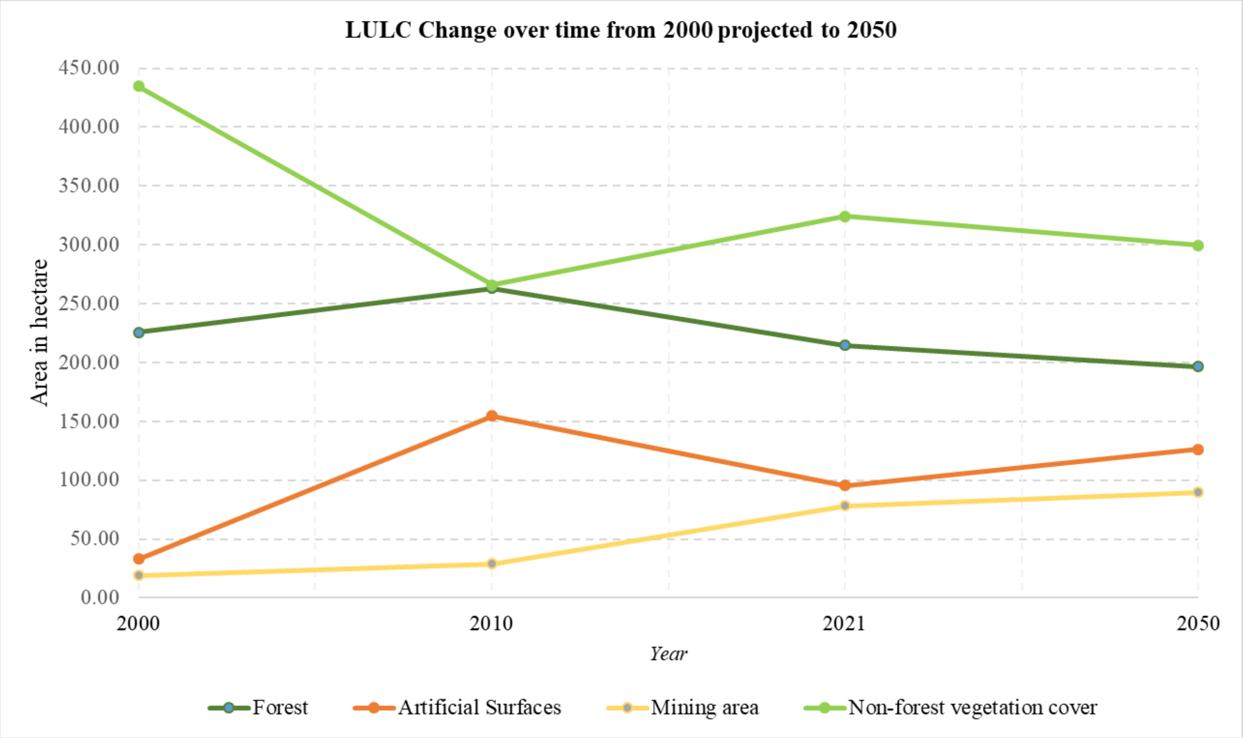


Figure 9:Land use Land cover variation from 2000 to 2021 and prediction to 2050.

Figure 10 shows clearly a consistent increase in mining areas over the study area which is associated with the increased mining activities amplified by the new discoveries and new investment brought in by the current mining license holder.

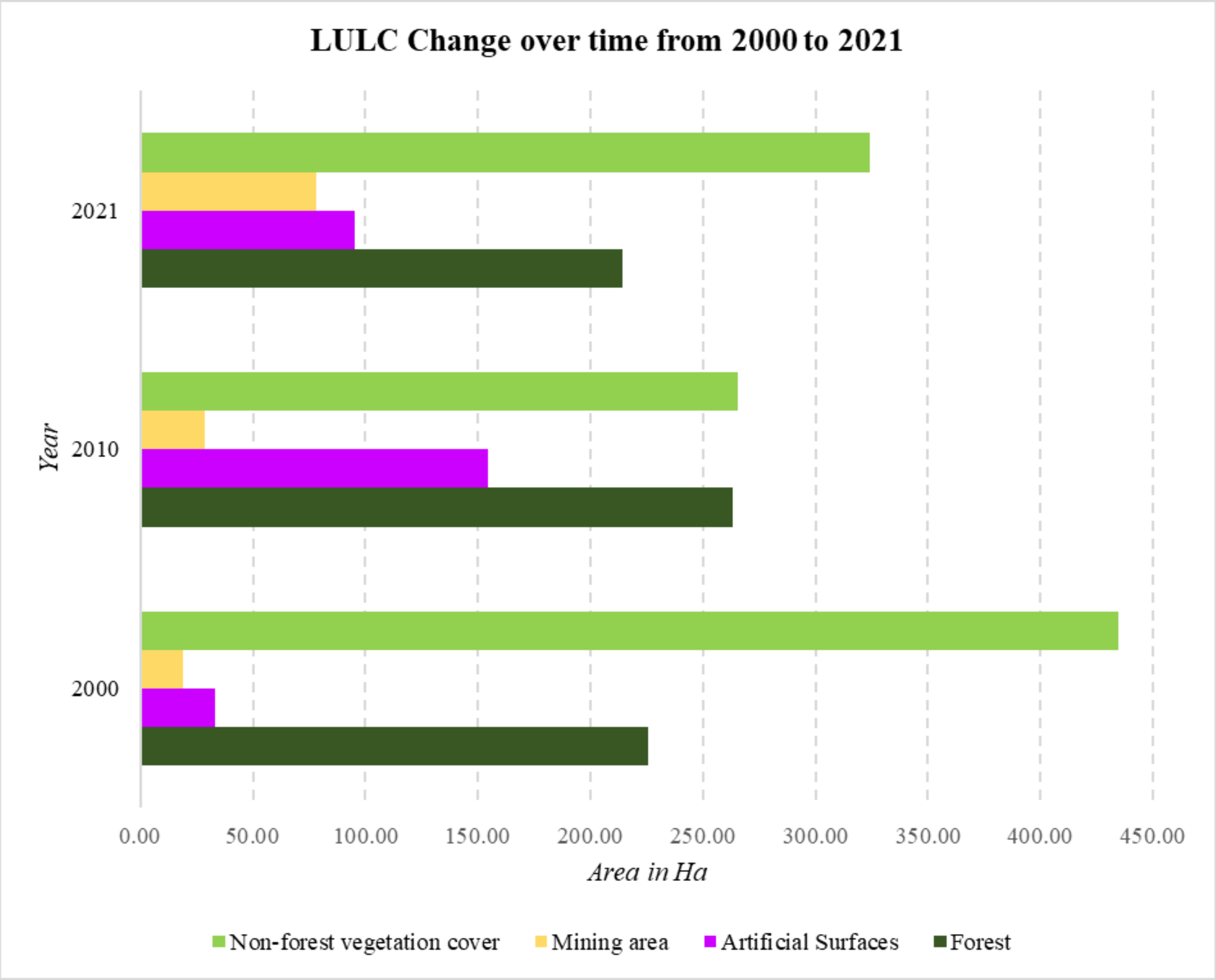


Figure 10: LULC Change over time from 2000 to 2021 and projected to 2050.

5. RESEARCH FINDINGS DISCUSSION

This chapter discusses the findings of this study as they are presented in the previous chapter. It compares the results with other similar studies and try to explain to findings based on the field observations and available literatures. The discussions are split into two main parts; the spatiotemporal LULC change of the period ranging from 2000 to 2021 in one hand and the projection of the LULC into 2050 on the other hand.

5.1. Spatio-temporal LULC change over Miyove gold mining area from 2000 to 2021

Over the period ranging from 2000 to 2021, significant shifts were observed in LULC categories. Our results are categorized based on the study period which is divided into two episodes: the first one made of the period between 2000 and 2010 and the second one between 2010 and 2021.

The first episode is characterized by a slight increase in mining areas, an increase in artificial surfaces and forest and a sharp decline in non-forest vegetation cover. The reasons behind being that the region observed a period of minimum mining activities characterized by sporadic isolated mine sites which had relatively small impact on the environment.

The second episode which runs from 2010 to 2021 is characterized by a considerable rise in mining areas from 18 to 78 ha (416% increase) accompanied with a persistent decline in the non-forest vegetation cover from 434.59 to 324.3 ha (25% decrease) due to the new gold discoveries and the recent investment in the mining sectors. Over the same period, we can also observe a fluctuation of the non-forest vegetation cover and artificial surfaces (built up and bear soil) which is linked to the new settlements and trade centers originating from the mining activities (Appendix 4). Consulted focus group of the Twizamurane Karenda has confirmed that the new trade centers are very recent. A few houses were constructed by Nzabanterura at Karenda and few other cooperative members followed the trends. It all came from the new working arrangement the cooperative concluded with Ngali Mining which boosted the mining revenues.

Despite the presence of the forest cover around the mining activities, we have noticed the mining activities that are being carried out within the forest (Appendix 4). That bad practice may hump the wellbeing of the forest and non-forest vegetation cover in the Miyove gold mining area and may lead to significant deforestation and habitat loss.

This aligns with previous research by Awotwi et al. (2018) and Davies (2023), who also reported significant reductions in forest/vegetation cover in Ghana and globally associated with mining activities. However, the extent of this impact may vary depending on factors such as regulatory frameworks, enforcement mechanisms, and ecosystem resilience. For instance, regions with strict environmental regulations may experience less severe deforestation compared to areas with weak governance structures (Amini Parsa et al., 2016; Ohwo & Abotutu, 2015; Seto et al., 2012; Suleiman et al., 2017).

Additionally, the capacity of ecosystems to recover from mining-induced disturbances plays a crucial role in mitigating habitat loss. Reclamation efforts and natural regeneration strategies can promote vegetation recovery and biodiversity conservation in post-mining landscapes (Mugiraneza et al., 2019; Nshimiyimana et al., 2023).

5.2. Predicted LULC changes to 2050

The data presents a comprehensive overview of land cover changes over the years, with a notable focus on the mining area category. In the year 2000, mining area occupied a relatively small area of 18.8275 ha, but by 2021, it expanded significantly to 78.24 ha. This expansion suggests substantial changes in land use, potentially driven by increased mining activities or land development projects. Meanwhile, other categories like Forest, artificial surfaces, and non-forest vegetation cover also underwent changes, reflecting the dynamic nature of land cover patterns.

Between 2000 and 2010, while mining area expanded, there were also increases in Forest cover and Artificial Surfaces. However, by 2021, there was a noticeable reversal in trends, with Forest cover decreasing and artificial surfaces expanding further. This shift indicates a possible trade-off between natural habitats and urbanization, with mining area serving as a key player in land transformation processes. Looking ahead to 2050, projections suggest continued expansion of mining area to 89.79 ha, highlighting its persistent influence on landscape dynamics.

The matrix in Table 5 outlines the probabilities of transitions between different LULC classes over time, reflecting the dynamic nature of landscape transformations. The outlined Markov transition probability matrix offers valuable insights into the anticipated land use/land cover (LULC) changes for 2050 in the Miyove region, aligning with similar studies in the field. For instance, research by Adedeji et al. (2022) and Wang et al. (2019) emphasized the dynamic nature of LULC transitions, particularly in regions undergoing rapid urbanization and industrialization, which resonates with the findings presented in the matrix. The relatively low but not negligible probabilities of forest and non-forest vegetation cover transitioning to built-up/bare soil and mining areas highlight the potential risks of land use conversion, consistent with the concerns raised by Kumi et al. (2024), He et al. (2019) and Hanzl et al. (2021) regarding habitat loss and ecosystem degradation associated with such transformations.

Furthermore, the matrix indicates a high likelihood of stability in mining areas, echoing findings by Awotwi et al. (2018), which underscores the persistence of mining activities over time and the challenges associated with mitigating their environmental impacts. Comparing the results to other researchers' findings reveals both consistencies and unique insights. While the probabilities of LULC transitions may vary depending on specific regional contexts and modeling methodologies, the overarching trends emphasize the significance of human-induced changes in shaping future landscapes.

Further interdisciplinary research integrating socio-economic factors, policy interventions, and stakeholder engagement, as advocated by Zhang et al. (2018), is crucial for developing holistic strategies to address the challenges posed by land use conversions and promote sustainable land management practices. Thus, while the Markov analysis provides valuable predictive capabilities, its interpretation within the broader context of existing research highlights the complexities of LULC dynamics and underscores the need for concerted efforts to ensure the long-term ecological integrity and resilience of landscapes. Moreover, while mining activities often result in significant reductions in non-forest vegetation and forest cover, effective land management strategies are essential for minimizing adverse effects and promoting sustainable land use practices in mining regions.

In summary, the findings underscore the significant impact of mining area on land cover changes over time. Its expansion reflects ongoing mining activities and land development efforts, which may have implications for ecosystem health and biodiversity. Understanding these trends is crucial for implementing sustainable land management strategies that balance economic development with environmental conservation, ensuring the long-term resilience of ecosystems in the studied area.

6. CONCLUSION AND RECOMMENDATIONS

This study has assessed the spatiotemporal LULC changes over the Miyove gold mining area for the period between 2000 and 2021 and predicted the possible changes in 2050 using Markov chain. Landsat images of 2000, 2010 and 2021 were classified to map the LULC and compared between them to retrieve the LULC changes over the studied period. Furthermore, we have predicted the LULC into 2050 using the Markov chain analysis.

The data present a comprehensive overview of land cover changes over the years, with a notable focus on the mining area category. In the year 2000, mining areas occupied a relatively small area of 18.8275 ha, but in 2021, it expanded significantly to 78.24 ha. This expansion suggests substantial changes in land use, potentially driven by increased mining activities or land development projects. Meanwhile, other categories like forest, artificial surfaces, and non-forest vegetation cover also underwent changes, reflecting the dynamic nature of land cover patterns.

The results have revealed that between 2000 and 2010, while mining area expanded, there were also an increase in forest cover and artificial surfaces. However, in 2021, there was a noticeable reversal in trends, with forest cover decreasing and artificial surfaces expanding further. This shift indicates a trade-off between natural habitats and urbanization, with mining area serving as a key player in land transformation processes. That trade-off was confirmed by the consulted focus group discussions with some members of the two cooperatives of miners operating in the study area.

Looking ahead to 2050, projections suggest continued expansion of mining area from 18.82 to 89.79 ha, highlighting its persistent influence on landscape dynamics.

After having observed that mining activities occur in some forest within the study area, we recommend further an interdisciplinary research integrating various environmental factors to develop holistic strategies to address the challenges posed by land use conversions in mining areas. We believe that prioritizing environmental management practices and encouraging mining adaptive technological approaches will help to mitigate the adverse effects of mining activities and promote the sustainable use of natural resources for the benefit of present and future generations, in the Miyove gold mining area and elsewhere in the mining regions.

7. REFERENCES

Abbas, Z., & Jaber, H. S. (2020). Accuracy assessment of supervised classification methods for extraction land use maps using remote sensing and GIS techniques. *IOP Conference Series: Materials Science and Engineering*, *745*(1). https://doi.org/10.1088/1757-899X/745/1/012166

Adedeji, O. H., Tope-Ajayi, O. O., Abegunde, O. L., Wahyudi, A., Liu, Y. Y., Eastman, J. R., Eastman, Shen, Z., Zeng, J., Fan, J., Liu, Q., Ren, Z., Chen, Z., Li, W., Yu, Y., Zhou, Y., Hu, X., Qian, Y., Pickett, S. T. A., … Huang, X. (2022). Analysis of Landscape Pattern Bases on the CA-Markov Model. *Applied Geography*, *112*(September), 301–318. https://doi.org/10.1016/j.apgeog.2019.102081

Amini Parsa, V., Yavari, A., & Nejadi, A. (2016). Spatio-temporal analysis of land use/land cover pattern changes in Arasbaran Biosphere Reserve: Iran. *Modeling Earth Systems and Environment*, *2*(4), 1–13. https://doi.org/10.1007/s40808-016-0227-2

Asr, E. T., Kakaie, R., Ataei, M., & Tavakoli Mohammadi, M. R. (2019). A review of studies on sustainable development in mining life cycle. *Journal of Cleaner Production*, *229*, 213–231. https://doi.org/10.1016/j.jclepro.2019.05.029

Awotwi, A., Anornu, G. K., Quaye-Ballard, J. A., & Annor, T. (2018). Monitoring land use and land cover changes due to extensive gold mining, urban expansion, and agriculture in the Pra River Basin of Ghana, 1986–2025. *Land Degradation and Development*, *29*(10), 3331–3343. https://doi.org/10.1002/ldr.3093

Barreto, M. L., Jennifer, H., & Felix, H. (2018). *Economic Contributions of Artisanal and Small-Scale Mining in Rwanda: Tin, Tantalum, and Tungsten* (Issue January).

Berhane, T. M., Lane, C. R., Wu, Q., Anenkhonov, O. A., Chepinoga, V. V., Autrey, B. C., & Liu, H. (2018). Comparing pixel- and object-based approaches in effectively classifying wetland-dominated landscapes. *Remote Sensing*, *10*(1). https://doi.org/10.3390/rs10010046

Bhattacharyya, R., Ghosh, B. N., Mishra, P. K., Mandal, B., Rao, C. S., Sarkar, D., Das, K., Anil, K. S., Lalitha, M., Hati, K. M., & Franzluebbers, A. J. (2015). Soil degradation in india: Challenges and potential solutions. *Sustainability (Switzerland)*, *7*(4), 3528–3570. https://doi.org/10.3390/su7043528

Bizimana, J. P., Nduwayezu, G., Gabineza, C., & ... (2021a). Spatial and Temporal Analysis of the Land Use and Land Cover Changes in Gatumba Mining Landscape, Rwanda. *... and Environment*, *4*(I), 1–27.

Bizimana, J. P., Nduwayezu, G., Gabineza, C., & ... (2021b). Spatial and Temporal Analysis of the Land Use and Land Cover Changes in Gatumba Mining Landscape, Rwanda. *... and*

Environment, *4*(I), 1–27. https://www.ajol.info/index.php/rjeste/article/view/221067

Bowman, J., Jaeger, J. A. G., & Fahrig, L. (2010). Dispersal distance of mammals is proportional to home range size. *Ecology*, *83*(7), 2049–2055. https://doi.org/10.1890/0012-9658(2002)083[2049:DDOMIP]2.0.CO;2

Byizigiro, R. V. (2016). *Geomorphic Processes Associated with Small-Scale Opencast Mining and Mitigation Measures : Case Study of the Gatumba Mining District in the Western Highlands of Rwanda* (Issue September).

Chen, L., Jin, Z., Michishita, R., Cai, J., Yue, T., Chen, B., & Xu, B. (2014). Dynamic monitoring of wetland cover changes using time-series remote sensing imagery. *Ecological Informatics*, *24*, 17–26. https://doi.org/10.1016/j.ecoinf.2014.06.007

Davies, M. (2023). *The impact of land use and land cover changes on land surface*. *8*(4).

Duncan, A. E. (2020). The Dangerous Couple: Illegal Mining and Water Pollution - A Case Study in Fena River in the Ashanti Region of Ghana. *Journal of Chemistry*, *2020*. https://doi.org/10.1155/2020/2378560

Gabinema, C. (2016). *Spatio- temporal assessment of land use and land cover changes due to mining activities in Gatumba Region , Rwanda.* (Issue May).

Government of Rwanda. (2019). Rwanda Natural Capital Accounts - Minerals resource flows. In *Rwanda Natural Capital Accounts* (Issue December).

Gudo, A. J. A., Deng, J., & Qureshi, A. S. (2022). Analysis of Spatiotemporal Dynamics of Land Use/Cover Changes in Jubek State, South Sudan. *Sustainability (Switzerland)*, *14*(17). https://doi.org/10.3390/su141710753

Halmy, M. W. A., Gessler, P. E., Hicke, J. A., & Salem, B. B. (2015). Land use/land cover change detection and prediction in the north-western coastal desert of Egypt using Markov-CA. *Applied Geography*, *63*, 101–112. https://doi.org/10.1016/j.apgeog.2015.06.015

Hanzl, M., Chen, J. J. J., Chen, J. J. J., Liao, A., Cao, X., Chen, L. D., Chen, X., He, C., Han, G., Peng, S., Lu, M., Zhang, W., Tong, X., Mills, J., Jokar Arsanjani, J., Tayyebi, A., Vaz, E., Arowolo, A. O., Deng, X., … Mishra, V. N. (2021). Monitoring urbanization and environmental impact in Kigali, Rwanda using Sentinel-2 MSI data and ecosystem service bundles. *International Journal of Applied Earth Observation and Geoinformation*, *109*(1), 137–144. https://doi.org/10.1016/j.jag.2022.102775

He, C., Liu, Z., Gou, S., Zhang, Q., Zhang, J., & Xu, L. (2019). Detecting global urban expansion over the last three decades using a fully convolutional network. *Environmental Research Letters*, *14*(3). https://doi.org/10.1088/1748-9326/aaf936

Hossain, A. K. M. A., Mathias, C., & Blanton, R. (2021). Remote sensing of turbidity in the tennessee river using landsat 8 satellite. *Remote Sensing*, *13*(18).

https://doi.org/10.3390/rs13183785

Jamal, S., & Ahmad, W. S. (2020). Assessing land use land cover dynamics of wetland ecosystems using Landsat satellite data. *SN Applied Sciences*, *2*(11), 1–24. https://doi.org/10.1007/s42452-020-03685-z

Jimoh, R., Afonja, Y., Albert, C., & Amoo, N. (2018). Spatio-Temporal Urban Expansion Analysıs in a Growing City of Oyo Town, Oyo State, Nigeria Using Remote Sensing And Geographic Information System (GIS) Tools. *International Journal of Environment and Geoinformatics*, *5*(2), 104–113. https://doi.org/10.30897/ijegeo.354627

Jog, S., & Dixit, M. (2016). Supervised classification of satellite images. *Conference on Advances in Signal Processing, CASP 2016*, *X*, 93–98. https://doi.org/10.1109/CASP.2016.7746144

Kumar, V., Chandra, A., & Usmani, Z. (2017). Impact of coal mining on soil properties and their efficient eco-restoration. *International Journal of Energy Technology and Policy*, *13*(1–2), 158–165. https://doi.org/10.1504/IJETP.2017.080613

Kumi, S., Addo-Fordjour, P., Fei-Baffoe, B., Adjapong, A. O., & Asamoah, F. B. (2024). Dynamic influence of mining-induced land use land cover changes on avifauna community over a mining landscape, Ghana. *Trees, Forests and People*, *15*(February), 100515. https://doi.org/10.1016/j.tfp.2024.100515

Laurance, W. F., Camargo, J. L. C., Luizão, R. C. C., Laurance, S. G., Pimm, S. L., Bruna, E. M., Stouffer, P. C., Bruce Williamson, G., Benítez-Malvido, J., Vasconcelos, H. L., Van Houtan, K. S., Zartman, C. E., Boyle, S. A., Didham, R. K., Andrade, A., & Lovejoy, T. E. (2011). The fate of Amazonian forest fragments: A 32-year investigation. *Biological Conservation*, *144*(1), 56–67. https://doi.org/10.1016/j.biocon.2010.09.021

Li, M., Zang, S., Zhang, B., Li, S., & Wu, C. (2014). A review of remote sensing image classification techniques: The role of Spatio-contextual information. *European Journal of Remote Sensing*, *47*(1), 389–411. https://doi.org/10.5721/EuJRS20144723

Liaqat, M. U., Mohamed, M. M., Chowdhury, R., Elmahdy, S. I., Khan, Q., & Ansari, R. (2021). Impact of land use/land cover changes on groundwater resources in Al Ain region of the United Arab Emirates using remote sensing and GIS techniques. *Groundwater for Sustainable Development*, *14*(August 2019), 100587. https://doi.org/10.1016/j.gsd.2021.100587

Lin, L., Hao, Z., Post, C. J., Mikhailova, E. A., Yu, K., Yang, L., & Liu, J. (2020). Monitoring land cover change on a rapidly urbanizing island using google earth engine. *Applied Sciences (Switzerland)*, *10*(20), 1–16. https://doi.org/10.3390/app10207336

Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PLoS ONE*, *13*(7), 1–23. https://doi.org/10.1371/journal.pone.0200493

Lv, J., Jiang, W., Wang, W., Wu, Z., Liu, Y., Wang, X., & Li, Z. (2019). Wetland loss identification and evaluation based on landscape and remote sensing indices in Xiong'an new area. *Remote Sensing*, *11*(23). https://doi.org/10.3390/rs11232834

Macháček, J., Schlossarek, M., & Lindagato, P. (2022). The Livelihood of Artisanal and Small-Scale Miners and Awareness of the Use of 3T Minerals in Rwanda—A Case Study in the Rutsiro District: A Qualitative Assessment. *International Journal of Environmental Research and Public Health*, *19*(19). https://doi.org/10.3390/ijerph191912570

Mathewos, M., Lencha, S. M., & Tsegaye, M. (2022). Land Use and Land Cover Change Assessment and Future Predictions in the Matenchose Watershed, Rift Valley Basin, Using CA-Markov Simulation. *Land*, *11*(10). https://doi.org/10.3390/land11101632

Mohd Hasmadi, I., Pakhriazad, H. Z., & Shahrin, M. F. (2009). Evaluating supervised and unsupervised techniques for land cover mapping using remote sensing data. *Malaysia NJournal of Society and Space*, *5*(1), 1–10.

Mugiraneza, T., Ban, Y., & Haas, J. (2019). Urban land cover dynamics and their impact on ecosystem services in Kigali, Rwanda using multi-temporal Landsat data. *Remote Sensing Applications: Society and Environment*, *13*, 234–246. https://doi.org/10.1016/j.rsase.2018.11.001

Mugiraneza, T., Eodomir, Nascetti, A., Couch, C., Leontidou, L., Petschel-Held, G., Al-Hameedi, W. M. M., Chen, J., Faichia, C., Al-Shaibah, B., Nath, B., Kafy, A. Al, Hu, G., Al-Aizari, A., Chang, X., Wang, D., Xing, Y., Wang, J., & Gong, W. (2021). Continuous Monitoring of Urban Land Cover Change Trajectories with Landsat Time Series and LandTrendr-Google Earth Engine Cloud Computing. *Urban Sprawl in Europe: Landscapes, Land-Use Change & Policy*, *13*(10), 1–273. https://doi.org/10.1002/9780470692066

Mugiraneza, T., Nascetti, A., & Ban, Y. (2020). Continuous monitoring of urban land cover change trajectories with landsat time series and landtrendr-google earth engine cloud computing. *Remote Sensing*, *12*(18). https://doi.org/10.3390/RS12182883

Nshimiyimana, A. R., Niyigena, E., Nyandwi, E., & Ngwijabagabo, H. (2023). Spatial Assessment of Urban Growth on Green Spaces in Rwanda : An insight from Rebero Mountain Landscape in Kicukiro District , City of Kigali. *Rwanda Journal of Engineering, Science, Technology and Environment*, *5*(I), 1–24.

Ohwo, O., & Abotutu, A. (2015). Environmental Impact of Urbanization in Nigeria. *British Journal of Applied Science & Technology*, *9*(3), 212–221.

https://doi.org/10.9734/bjast/2015/18148

Oluku, S., & Asikhia, M. O. (2021). Geospatial Assessment of the Impacts of Sand Mining Activities in Benin City, Edo State Nigeria. *Journal of Geography, Environment and Earth Science International*, *25*(1), 46–57. https://doi.org/10.9734/jgeesi/2021/v25i130267

Onilude, O. O., & Vaz, E. (2021). *Urban Sprawl and Growth Prediction for Lagos Using GlobeLand30 Data and Cellular Automata Model agricultural agricultural*. 1–21.

OS, B., & AA, A. (2016). Change Detection in Land Surface Temperature and Land Use Land Cover over Lagos Metropolis, Nigeria. *Journal of Remote Sensing & GIS*, *5*(3). https://doi.org/10.4172/2469-4134.1000171

Oyekola, M. A., & Adewuyi, G. K. (2018). Unsupervised Classification in Land Cover Types Using Remote Sensing and GIS Techniques. *International Journal of Science and Engineering Investigations*, *7*(72), 11–18.

P.O, L. (2011). Effects of Sand/Gravel Mining in Minna Emirate Area of Nigeria on Stakeholders. *Journal of Sustainable Development*, *4*(1). https://doi.org/10.5539/jsd.v4n1p193

Patra, S., Sahoo, S., Mishra, P., & Chandra, S. (2018). Impacts of urbanization on land use / cover changes and its probable implications on local climate and groundwater level. *Journal of Urban Management*, *April*, 1–15. https://doi.org/10.1016/j.jum.2018.04.006

Paul Nkundabose, J., Nshimiyimana, F., Twagirayezu, G., & Irumva, O. (2021). Employing Remote Sensing Tools for Assessment of Land Use/Land Cover (LULC) Changes in Eastern Province, Rwanda. *American Journal of Remote Sensing*, *9*(1), 23. https://doi.org/10.11648/j.ajrs.20210901.13

Pohl, W. L., Biryabarema, M., & Lehmann, B. (2014). Early neoproterozoic rare metal (Sn, Ta, W) and gold metallogeny of the Central Africa Region: A review. *Transactions of the Institutions of Mining and Metallurgy, Section B: Applied Earth Science*, *122*(2), 66–82. https://doi.org/10.1179/1743275813Y.0000000033

REMA. (2021). RWANDA STATE OF ENVIRONMENT AND OUTLOOK. In *Ministry of Natural Resources* (Issue June). http://www.arcosnetwork.org/uploads/2018/03/Rweru-Mugesera_assessment_Report.pdf

Romero, A., Gatta, C., & Camps-Valls, G. (2016). Unsupervised deep feature extraction for remote sensing image classification. *IEEE Transactions on Geoscience and Remote Sensing*, *54*(3), 1349–1362. https://doi.org/10.1109/TGRS.2015.2478379

Schluter, T. (2008). Geological Atlas of Africa. In *Economic Geology* (Vol. 103, Issue 6). https://doi.org/10.2113/gsecongeo.103.6.1379

Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(40), 16083–16088. https://doi.org/10.1073/pnas.1211658109

Suleiman, M. S., Wasonga, O. V., Mbau, J. S., & Elhadi, Y. A. (2017). Spatial and temporal analysis of forest cover change in Falgore Game Reserve in Kano, Nigeria. *Ecological Processes*, *6*(1). https://doi.org/10.1186/s13717-017-0078-4

Tehrany, M. S., Pradhan, B., & Jebur, M. N. (2013). Spatial prediction of flood susceptible areas using rule based decision tree (DT) and a novel ensemble bivariate and multivariate statistical models in GIS. *Journal of Hydrology*, *504*, 69–79. https://doi.org/10.1016/j.jhydrol.2013.09.034

Turner, W., Rondinini, C., Pettorelli, N., Mora, B., Leidner, A. K., Szantoi, Z., Buchanan, G., Dech, S., Dwyer, J., Herold, M., Koh, L. P., Leimgruber, P., Taubenboeck, H., Wegmann, M., Wikelski, M., & Woodcock, C. (2015). Free and open-access satellite data are key to biodiversity conservation. *Biological Conservation*, *182*, 173–176. https://doi.org/10.1016/j.biocon.2014.11.048

UNEP. (2010). *Rwanda: From Post-Conflict to Environmentally Sustainable Development.* http://www.zaragoza.es/contenidos/medioambiente/onu/issue07/1117_eng_ch9.pdf

Uwizeyimana, L. (1988). *L'activité minière au Rwanda : d'une exploitation marginale à l'effondrement. Talence : Centre de recherche sur les espaces tropicaux*. 1–205.

Vasuki, Y., Yu, L., Holden, E. J., Kovesi, P., Wedge, D., & Grigg, A. H. (2019). The spatial-temporal patterns of land cover changes due to mining activities in the Darling Range, Western Australia: A Visual Analytics Approach. *Ore Geology Reviews*, *108*, 23–32. https://doi.org/10.1016/j.oregeorev.2018.07.001

Wang, J., & Maduako, I. N. (2018). Spatio-temporal urban growth dynamics of Lagos Metropolitan Region of Nigeria based on Hybrid methods for LULC modeling and prediction. *European Journal of Remote Sensing*, *51*(1), 251–265. https://doi.org/10.1080/22797254.2017.1419831

Wang, X., Wu, Y., Gong, J., Li, B., & Zhao, J. J. (2019). Urban planning design and sustainable development of forest based on heat island effect. *Applied Ecology and Environmental Research*, *17*(4), 9121–9129. https://doi.org/10.15666/aeer/1704_91219129

Werner, T. T., Bebbington, A., & Gregory, G. (2019). Assessing impacts of mining: Recent contributions from GIS and remote sensing. *Extractive Industries and Society*, *6*(3), 993–1012. https://doi.org/10.1016/j.exis.2019.06.011

Yin, Z., Li, X., Tong, F., Li, Z., Jendryke, M., Keshtkar, H., Voigt, W., Shi, Z. H., Chen, L. D., Hao, J. P., Wang, T. W., Cai, C. F., Trivedi, J., Sareen, H., Dhyani, M., & United Nations.,

U. (2009). The effects of land use change on environmental quality in the red soil hilly region, China: A case study in Xianning County. *Modeling Earth Systems and Environment*, *12*(1), 295–306. https://doi.org/10.4103/0019-5545.43623

Zhang, Z., Liu, F., Zhao, X., Wang, X., Shi, L., Xu, J., Yu, S., Wen, Q., Zuo, L., Yi, L., Hu, S., & Liu, B. (2018). Urban Expansion in China Based on Remote Sensing Technology: A Review. *Chinese Geographical Science*, *28*(5), 727–743. https://doi.org/10.1007/s11769-018-0988-9

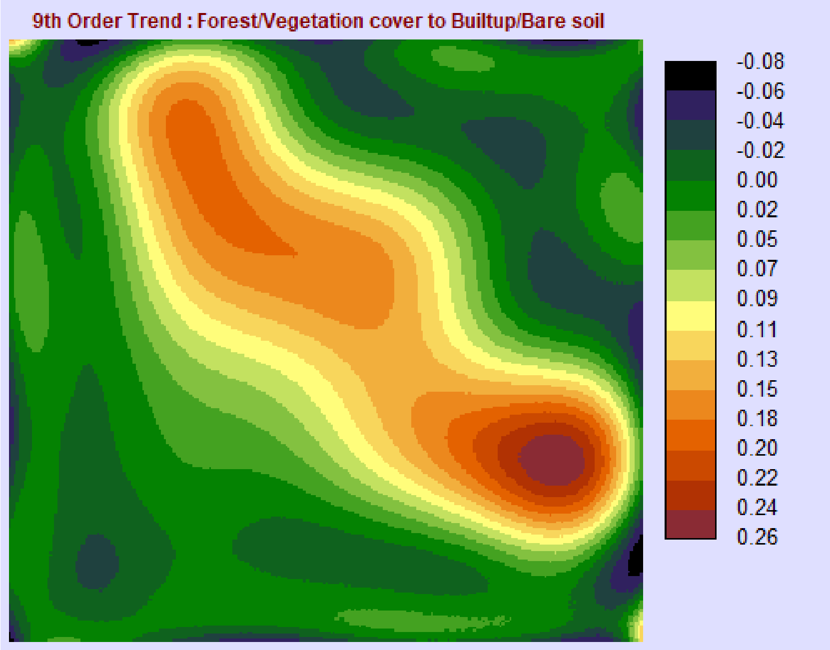
Zhou, W., Cao, F., & Wang, G. (2019). Effects of spatial pattern of forest vegetation on urban cooling in a compact megacity. *Forests*, *10*(3), 17–20. https://doi.org/10.3390/f10030282

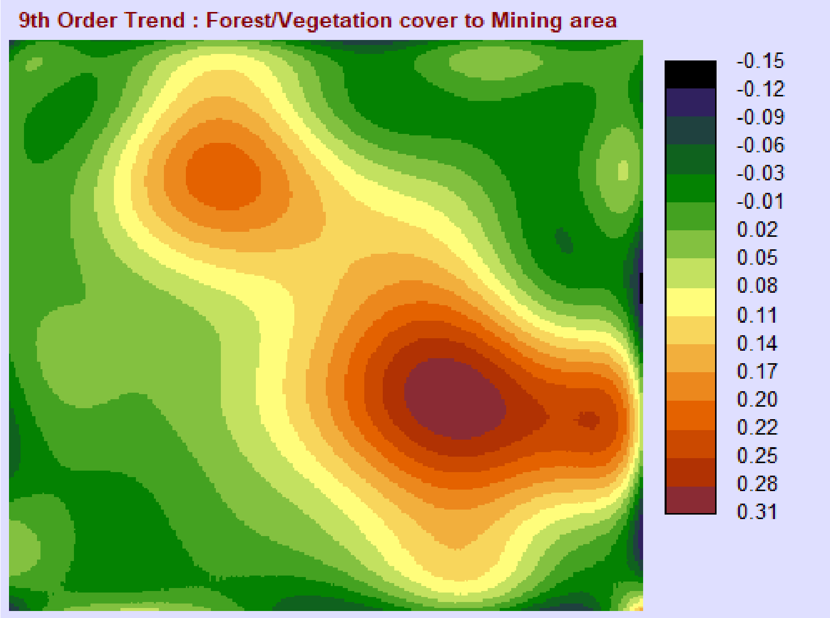
8. APPENDICES

APPENDIX 1: Accuracy Assessment table

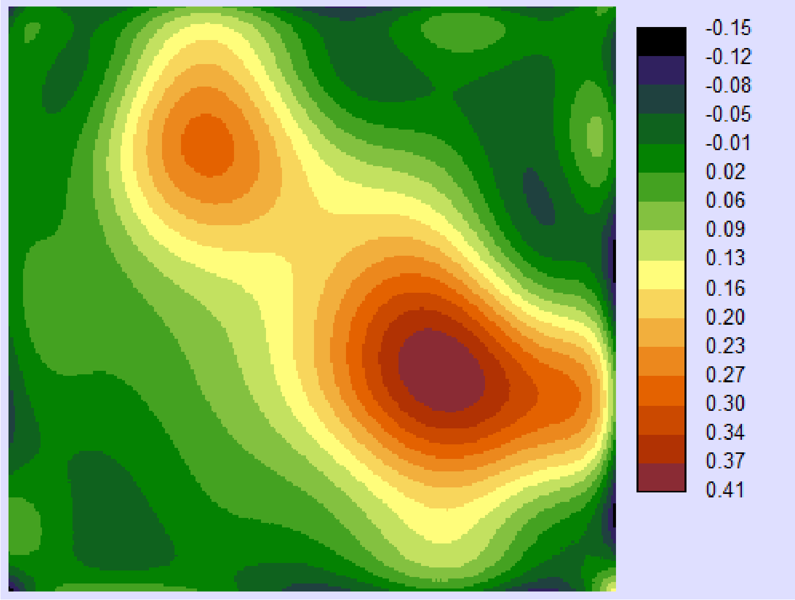
Year	Overall accuracy (%)	Kappa Coefficient (%)
2000	83	73.45
2010	90	86.05
2021	87	79.02

APPENDIX 2: Spatial trend maps

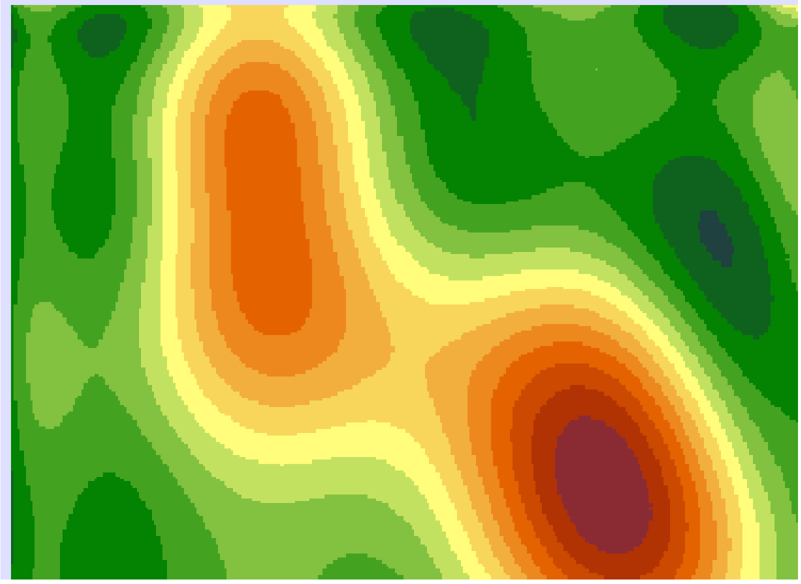




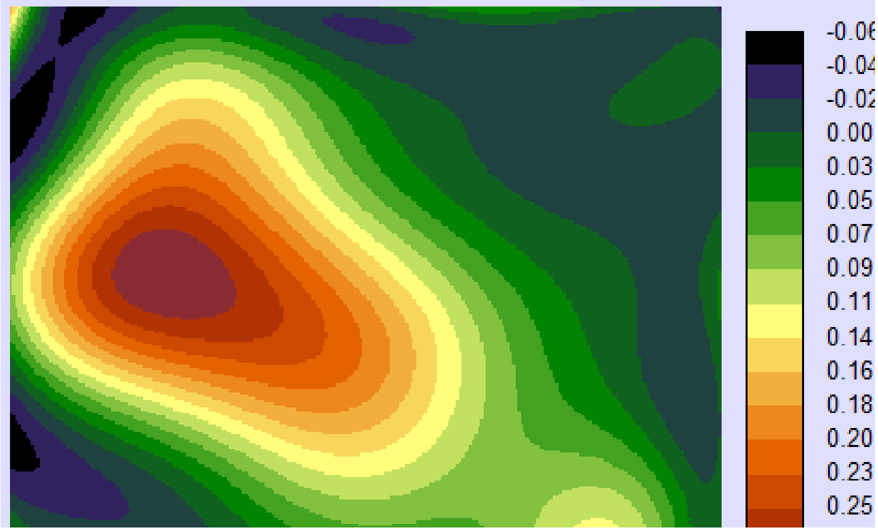
9th Order Trend : All to Mining area



9th Order Trend : Builtup/Bare soil to Mining area



9th Order Trend : Mining area to Builtup/Bare soil



APPENDIX 3: Mining activities (tunnels and wash points).

TUNNEL	SITE	COORDINATES		VILLAGE	CELL	SECTOR	STATUS
		X	Y				
01KAGOTE	KAGOTE	830777	9822174	KAGOTE	MUBUGA	MIYOVE	Production
02KAGOTE	KAGOTE	830754	9822129	KAGOTE	MUBUGA	MIYOVE	Production
04 KAGOTE	KAGOTE	830957	9822045	KAGOTE	MUBUGA	MIYOVE	Production
05KAGOTE	KAGOTE	830911	9822058	KAGOTE	MUBUGA	MIYOVE	Production
06 KAGOTE	MIYOVE	831148	9821568	MUREHE	MIYOVE	MIYOVE	Production
07 KAGOTE	KAGOTE	830810	9822106	KAGOTE	MUBUGA	MIYOVE	Production
08 KAGOTE	KAGOTE	830972	9821979	KAGOTE	MUBUGA	MIYOVE	Production
09 KAGOTE	KAGOTE	830957	9822045	KAGOTE	MUBUGA	MIYOVE	Production
10 KAGOTE	KAGOTE	831008	9822319	KAGOTE	MUBUGA	MIYOVE	Primary development
11 KAGOTE	KAGOTE	831068	9822264	KAGOTE	MUBUGA	MIYOVE	Production
12 KAGOTE	KAGOTE	831013	9821947	KAGOTE	MUBUGA	MIYOVE	Production
13 KAGOTE	KAGOTE	830835	9822082	KAGOTE	MUBUGA	MIYOVE	Production
14 KAGOTE	KAGOTE	830991	9822323	KAGOTE	MUBUGA	MIYOVE	Production
15 KAGOTE	KAGOTE	830745.2	9822167	KAGOTE	MUBUGA	MIYOVE	Primary development
01MASOGWE	MASOGWE	830178	9822894	KAGOTE	MUBUGA	MIYOVE	Production
02MASOGWE	MASOGWE	830153	9822982	KAGOTE	MUBUGA	MIYOVE	secondary development
03MASOGWE	MASOGWE	830194	9822918	KAGOTE	MUBUGA	MIYOVE	Production
04MASOGWE	MASOGWE	830181	9822934	KAGOTE	MUBUGA	MIYOVE	Production
06MASOGWE	MASOGWE	830231	9822884	KAGOTE	MUBUGA	MIYOVE	Production
07MASOGWE	MASOGWE	830230	9823016	KAGOTE	MUBUGA	MIYOVE	Production
01BARADEGA	BARADEGA	829067	9823687	KIRWA	MUBUGA	MIYOVE	secondary development
02BARADEGA	BARADEGA	828925	9823385	KIRWA	MUBUGA	MIYOVE	Production
03BARADEGA	BARADEGA	829141	9823645	KIRWA	MUBUGA	MIYOVE	Production
04 BARADEGA	BARADEGA	829067	9823687	KIRWA	MUBUGA	MIYOVE	Temporary stopped
05BARADEGA	BARADEGA	829061	9823695	KIRWA	MUBUGA	MIYOVE	Production
06 BARADEGA	BARADEGA	829141	9823645	KIRWA	MUBUGA	MIYOVE	Production
07 BARADEGA	BARADEGA	828062	9823715	KIRWA	MUBUGA	MIYOVE	Production
08 BARADEGA	BARADEGA	828989	9823718	KIRWA	MUBUGA	MIYOVE	Production
9 BARADEGA	BARADEGA	828948.1	9823763	KIRWA	MUBUGA	MIYOVE	site preps
10 BARADEGA	BARADEGA	829003.1	9823718	KIRWA	MUBUGA	MIYOVE	Production
01 MUBUGA	MUBUGA	829361	9823538	KIRWA	MUBUGA	MIYOVE	site preps
2 MUBUGA	MUBUGA	829461.3	9823579	KIRWA	MUBUGA	MIYOVE	Production
3 MUBUGA	MUBUGA	829650.3	9823452	KIRWA	MUBUGA	MIYOVE	Production
1 MURAMBO	MURAMBO	828884	9823374	MURAMBO	MUBUGA	MIYOVE	Production
2 MURAMBO	MURAMBO	828909	9823424	MURAMBO	MUBUGA	MIYOVE	Production
3 MURAMBO	MURAMBO	828921	9823474	MURAMBO	MUBUGA	MIYOVE	Primary development
4 MURAMBO	MURAMBO	828923	9823726	MURAMBO	MUBUGA	MIYOVE	Primary development
5 MURAMBO	MURAMBO	828908	9823594	MURAMBO	MUBUGA	MIYOVE	site preps
6 MURAMBO	MURAMBO	828939.2	9823098	MURAMBO	MUBUGA	MIYOVE	site preps
01TETERO	TETERO	828280	9823372	TETERO	MUBUGA	MIYOVE	Production

02TETERO	TETERO	828280.1	9823372	TETERO	MUBUGA	MIYOVE	Production
03TETERO	TETERO	828361.4	9823218	TETERO	MUBUGA	MIYOVE	Production
02 KARENDA	KARENDA	827265	9824441	MUREMURE	GITOVU	RUHUNDE	secondary development
3 KARENDA	KARENDA	827306	9824407	MUREMURE	GITOVU	RUHUNDE	Primary development
05 KARENDA	KARENDA	827447	9824421	MUREMURE	GITOVU	RUHUNDE	secondary development
06 KARENDA	KARENDA	827557	9824377	MUREMURE	GITOVU	RUHUNDE	secondary development
07 KARENDA	KARENDA	827449	9824386	MUREMURE	GITOVU	RUHUNDE	secondary development
08 KARENDA	KARENDA	827491	9824375	GASURA	RUSEKERA	RUHUNDE	production
9 KARENDA	KARENDA	827489	9824404	GASURA	RUSEKERA	RUHUNDE	production
10 KARENDA	KARENDA	827484	9824358	GASURA	RUSEKERA	RUHUNDE	production
11 KARENDA	KARENDA	827474	9824176	GASURA	RUSEKERA	RUHUNDE	production
12 KARENDA	KARENDA	827496	9824273	GASURA	RUSEKERA	RUHUNDE	production
13 KARENDA	KARENDA	827539	9824214	GASURA	RUSEKERA	RUHUNDE	production
16 KARENDA	KARENDA	827867	9824080	GASURA	RUSEKERA	RUHUNDE	secondary development
17 KARENDA	KARENDA	827887	9824015	GASURA	RUSEKERA	RUHUNDE	production
18 KARENDA	KARENDA	827979	9823999	GASURA	RUSEKERA	RUHUNDE	production
19 KARENDA	KARENDA	828356	9823987	GASURA	RUSEKERA	RUHUNDE	production
20 KARENDA	KARENDA	828014	9823888	GASURA	RUSEKERA	RUHUNDE	production
21 KARENDA	KARENDA	828098	9823906	GASURA	RUSEKERA	RUHUNDE	production
22 KARENDA	KARENDA	827677	9824306	GASURA	RUSEKERA	RUHUNDE	production
23 KARENDA	KARENDA	827717	9823964	GASURA	RUSEKERA	RUHUNDE	secondary development
24KARENDA	KARENDA	828062	9823824	GASURA	RUSEKERA	RUHUNDE	production
25KARENDA	KARENDA	827984	9823926	GASURA	RUSEKERA	RUHUNDE	production
26KARENDA	KARENDA	827433	9824195	GASURA	RUSEKERA	RUHUNDE	production
27 KARENDA	KARENDA	827980	9824085	GASURA	RUSEKERA	RUHUNDE	secondary development
28 KARENDA	KARENDA	828046	9823973	GASURA	RUSEKERA	RUHUNDE	Primary development
30 KARENDA	KARENDA	828356	9823987	GASURA	RUSEKERA	RUHUNDE	production
31 KARENDA	KARENDA	828356	9823987	GASURA	RUSEKERA	RUHUNDE	production
32 KARENDA	KARENDA	828098	9823722	GASURA	RUSEKERA	RUHUNDE	production
33 KARENDA	KARENDA	827328	9824287	MUREMURE	GITOVU	RUHUNDE	Primary development
34 KARENDA	KARENDA	828536	9823830	GASURA	RUSEKERA	RUHUNDE	site preps
35 KARENDA	KARENDA	827387.6	9823821	GASURA	RUSEKERA	RUHUNDE	production
36 KARENDA	KARENDA	827532.7	9824336	GASURA	RUSEKERA	RUHUNDE	production
MASOGWE E1	MASOGWE	830354	9822820	KAGOTE	MUBUGA	MIYOVE	production
NML04	KARENDA	827445	9824021	MUREMURE	GITOVU	RUHUNDE	production
W.P 01	KAGOTE	829527.4	9822700	KAGOTE	MUBUGA	MIYOVE	2 Ball mills
W.P 02	KAGOTE	830301	9822239	KAGOTE	MUBUGA	MIYOVE	2Ball mills
W.P 03	MASOGWE	830404.8	9822408	KAGOTE	MUBUGA	MIYOVE	1 ball mills
W.P 04	KU IBANDA	829533.3	9823138	KIRWA	MUBUGA	MIYOVE	7 Ball mills
W.P 05	MUBUGA	829186.1	9823809	KIRWA	MUBUGA	MIYOVE	6Ball mills
W.P 06	MUBUGA	829189.2	9823842	KIRWA	MUBUGA	MIYOVE	5Ball mills
W.P 07	BARADEGA	829180.7	9823461	KIRWA	MUBUGA	MIYOVE	6Ball mills
W.P 08	BARADEGA	829153.1	9823587	KIRWA	MUBUGA	MIYOVE	5Ball mills
W.P 09	BARADEGA	829130.1	9823613	KIRWA	MUBUGA	MIYOVE	4Ball mills

W.P 10	BARADEGA	829055.6	9823677	KIRWA	MUBUGA	MIYOVE	5Ball mills
W.P 11	TETERO	828276.1	9823349	TETERO	MUBUGA	MIYOVE	4Ball mills
W.P 12	KARENDA	828015.2	9823841	GASURA	RUSEKERA	RUHUNDE	3Ball mills
W.P 13	KARENDA	828066.4	9823740	MUREMURE	GITOVU	RUHUNDE	2Ball mills
W.P 14	KARENDA	827893.4	9824145	GASURA	RUSEKERA	RUHUNDE	6Ball mills
W.P 15	KARENDA	827587.5	9824430	GASURA	RUSEKERA	RUHUNDE	No ball mill
W.P 16	KARENDA	827547.8	9824512	GASURA	RUSEKERA	RUHUNDE	4Ball mills
W.P 17	KARENDA	827786.2	9824872	GASURA	RUSEKERA	RUHUNDE	2Ball mills

APPENDIX 4: Field survey pictures

On the top of Karenda mountain, mines sites are very close to houses

Dumping sites at Karenda mountains

Mine site around Built-up area

Newly created trading center at Karenda resulting from gold mining revenue

Mineral washing facilities ruins the forest At Baradega

At Baradega, mining operations threatens the water channels

Effect of mining activities on forest and non-forest vegetation cover at Baradega

APPENDIX 5: List of members of Focus Group Discussion

Twizamurane Karenda Cooperative	**Imbereheza Bacukuzi Cooperative**
NYISABITEKA Francois (president)	HABINEZA Jean Marie Vianney (President)
NZABANTERURA Pierre Celestin	NTAGASIGAYE Marcel
NTABANGANYIMANA Jacqueline	NZABANTERURA Jean Baptiste
MUGIRANEZA Aimable	HABIMANA Ezekiel