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# The Impact of Mining Activities on Land Use and Land Cover Change in Rwamagana District, the Case of Muhazi Sector, Rwanda

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## Abstract

The main purpose of this study was to examine the impacts of mining activities on land use and land cover in Rwamagana District. Thus, this study is guided by specific objectives that are; to analyze the spatial and temporal LULC change induced by mining activities from 2000 up to 2020 in the study area, to examine the impact of mining activities and operations on different identified LULC types and to assess the community perceptions on the impacts of mining activities and land use and cover in the study area. Primary and secondary sources were involved in the data collection process, these include field observations, satellite image and focus group discussion with communities. The research design integrates quantitative and qualitative methods to provide a comprehensive assessment. Geographic Information System (GIS) technology was used to analyze spatial data, mapping spatio-temporal LULC conditions before and after mining activities. The land use/cover classes were classified as tree-covered, grassland and sparse, wetland, water body, and built ups, The most notable changes occurred in grassland & sparse areas, which experienced a significant gain of 1241 ha, resulting in a net change of 1163 ha reflecting a 460.7% net increase. Conversely, tree-covered areas suffered a substantial loss of 609 ha especially in the southern edge where mining activities are undertaken, resulting in a net change of -422 ha, representing a 59.3% decrease. Cropland also experienced a considerable gross loss of 1305 ha, mitigated by a gain of 467 ha, resulting in a net change of -838 ha, representing a 19.8% decrease. Wetlands exhibited a gross loss of 71 ha, with a minor gain of 22 ha, resulting in a net change of -49 ha, representing a 65.8% decrease. Water bodies, on the other hand, experienced a net gain of 43 ha, showing an 8.5% increase. Built-up areas experienced no gross loss and a gain of 104 ha, resulting in a 100% net increase. These changes illustrate the dynamic shifts in land cover within Muhazi sector, reflecting a variety of environmental and anthropogenic influences over the two- decade period. Practical regulations and policies for the rehabilitation of the damaged environment are not sensitized. Therefore, the enforcement of policies and guidance to rehabilitate the degraded environment should be considered while developing professionalism mining with modern equipment.

**Keywords**: *Mining activities, LULC, MMB, Muhazi, GIS, Satellite image.*

## 1. Introduction

Global land use and land cover patterns are shaped by a complex interplay of natural processes and human activities, impacting essential ecosystem services crucial for human well-being, such as clean water, air quality, and climate regulation (Ali, 2009). Human activities including population growth, urbanization, agriculture, industry, and mining have profound implications for these patterns (Reed, 2009). Understanding the dynamics of land use and land cover (LULC) globally is essential for addressing environmental challenges, fostering sustainable development, and mitigating the impacts of human actions on Earth's ecosystems (Hailu, 2020).

Over the past three decades, the global forest area as a percentage of total land area has declined from 32.5% to 30.8%, amounting to a net loss of 178 million hectares (FAO and UNEP, 2020). Despite this decline, the rate of net forest loss has slowed by approximately 40% between 1990-2000 and 2010-2020, driven by reduced losses in some regions and gains in others (FAO and UNEP, 2020). Agricultural expansion remains the primary driver of forest loss, while efforts such as reforestation and afforestation contribute to forest area gains.

Mining activities, particularly in developing nations, are significant contributors to environmental degradation and public health concerns (Spiegel, 2018). Governments globally face the challenge of balancing economic benefits from resource extraction with environmental conservation imperatives (Tietenberg, 2018). The mining industry, traditionally focused on resource extraction and economic benefits, is increasingly scrutinized for its environmental impacts (Reed, 2009). The Sustainable Development Goals (SDGs), launched in 2015, provide a framework for achieving equitable and sustainable development worldwide, including addressing challenges posed by extractive industries like mining (World Economic Forum, 2014).

Rwanda exemplifies these challenges and opportunities within the mining sector. With a history of mining spanning nearly a century, Rwanda's mining industry has expanded significantly in recent years, particularly in artisanal and small-scale operations (Dusengemungu, 2022). Despite policy frameworks like the National Environment Policy and mining laws aimed at environmental protection and rehabilitation (REMA, 2012), the sector faces persistent challenges including unsustainable practices and inadequate compliance.

In Rwamagana District, where the Muhazi Mining Business (MMB) operates, concerns over environmental impacts are pronounced. Observations reveal widespread issues such as abandoned mining sites, inadequate waste management, and adverse effects on nearby agricultural land and communities. This study aims to assess the impacts of mining activities on LULC in this context, focusing on understanding changes in land use and cover driven by mining operations and the effectiveness of existing environmental policies and practices.

### 1.1 Research Objectives

#### 1.1.1 General objective

The main objective of this study is to assess the impact of mining activities on land use and land cover change in Rwamagana District.

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### 1.1.2 Specific Objectives

(i) To analyze the spatial and temporal LULC change induced by mining activities in the study area from 2000 up to 2020.

(ii) To examine the impact of mining activities and operations on different identified LULC types.

(iii) To assess the community perceptions on the impacts of mining activities and land use and land cover in the study area.

## 2. Materials and methods

### 2.1 Profile of Rwamagana District

Rwamagana District, located in Rwanda's Eastern Province, is bordered by Kayonza to the north, Ngoma to the east, Kirehe to the south, and Gatsibo to the west. The district's topography, defined by hilly terrain and a diverse landscape, not only contributes to its natural beauty but also presents various economic opportunities. In the southern part of Muhazi, the mining site of MMB Mining Company plays a significant role in bolstering the regional economy and is set amid the area's picturesque natural landscape. The coordinates, specifically 1°56'.1 S °27'53.0 E, place the mining site within the Muhazi sector, highlighting its close proximity to the natural environment and geographical features of the region. However, it's important to note that mining activities can have detrimental effects on the landscape. Furthermore, the district is well-regarded for its agricultural and mining activities, with a substantial portion of the population engaged in these sectors.

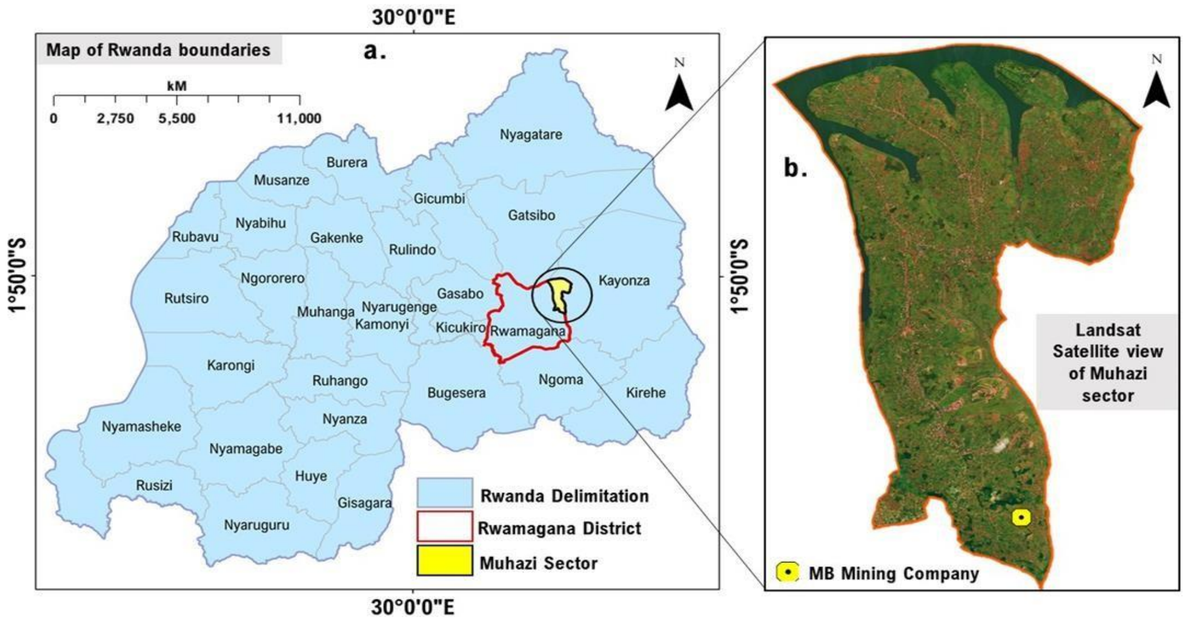


**Figure 3.1 : Map depicting the study area location and its spatial view captured from Landsat satellite with a 30×30 m extent.**

### 2.2 Research design and sampling techniques

The research employed a mixed methods approach with purposive sampling targeted areas directly affected by mining, facilitating focused data collection from MMB employees, local residents, and mining experts through three structured focus group discussions (FGDs). Primary data collection included remote sensing analysis for spatial mapping of land cover changes, field observations to document physical alterations, and qualitative insights from FGDs. Data analysis involved spatial analysis using ArcGIS to map temporal changes, supplemented by thematic and content analysis of qualitative data to identify socio-environmental impacts. The approach ensured comprehensive exploration of mining effects on land dynamics, providing valuable insights for environmental management and policy formulation.

### 2.3 Illustration of research methodology

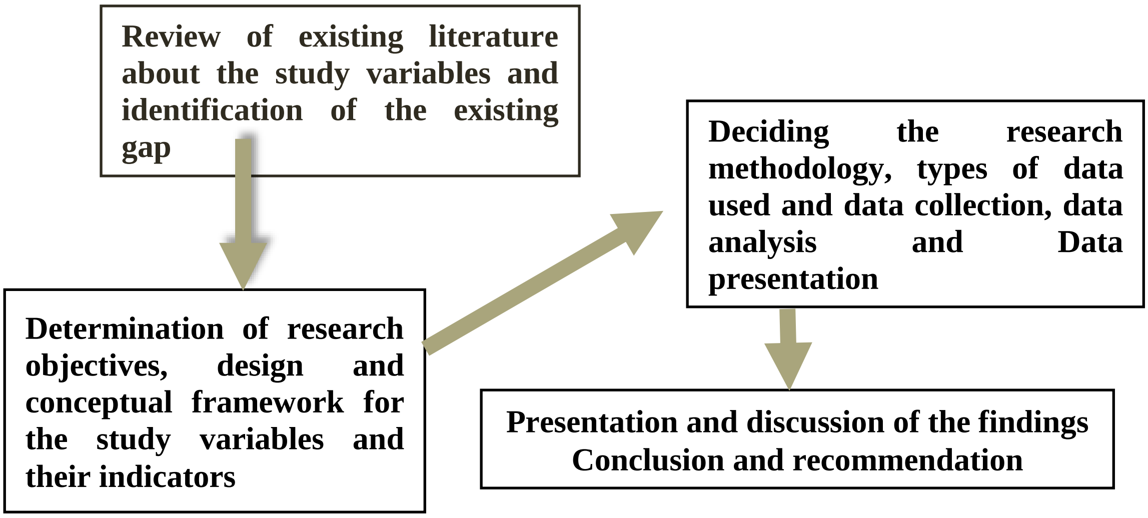


**Figure 2.1: Methodology flowchart followed by the researcher**

## 3. Results

### 3.1 Dataset preparation and processing

The study employs remote sensing, geospatial, and statistical data to examine the landscape dynamics of the Muhazi sector in Rwamagana District. In acquiring data from 2000 to 2020, 30- meter resolution Landsat images were obtained from the USGS EROS (United States Geological Survey data center Earth Resources Observation and Science) center. This high-resolution imagery enables the detection of nuanced changes in land cover, including cropping, infrastructure, deforestation, reforestation, and structural alterations within a landscape. The frequent 16-day revisit time of the Landsat imagery allows for consistent monitoring of land cover dynamics. The spatial and temporal precision of the data is well-matched to the study area, enabling careful analyses and dependable interpretation of the evolving land cover within the Muhazi sector. Additionally, it allows for tracking and visualizing the types of land changes occurring in the mining site located to the south of the study area over the specified time period. Following the image acquisition, terrain-correction for radio-geometric accuracy was accomplished using ArcGIS and TerrSet (Geospatial Monitoring and Modeling System). Subsequently, the area of interest was isolated for the purpose of land use classification. The classification of land cover types within the research area was carried out using a Hybrid Maximum Likelihood Classification (H-MLC) technique, incorporating both unsupervised and supervised methods. Renowned as one of the most effective remote sensing classification algorithms, the H-MLC technique assigns raster pixels to the class with the highest posterior probability. The theoretical underpinnings and application of this classification methodology have been rigorously developed and extensively documented (Ahmad and Quegan 2012).

**Table 4.1: Accuracy from confusion error matrix of land cover classification of Muhazi Sector 2000, 2016, 2020)**

**2000-Reference Statistics**

| | **LCLU** | Tree covered | Grass- Spars | Cropland | Wetland | Water Bodies | Built Ups |
|---|---|---|---|---|---|---|---|
| **Sampling satellite Image** | Tree Covered | 27 | 2 | 1 | 0 | 0 | 0 |
| | Grass-Sparse | 2 | 26 | 1 | 1 | 0 | 0 |
| | Cropland | 0 | 0 | 27 | 2 | 1 | 0 |
| | Wetland | 1 | 2 | 1 | 26 | 1 | 0 |
| | Water bodies | 0 | 0 | 0 | 1 | 28 | 0 |
| | Built Ups | 0 | 0 | 0 | 0 | 0 | 0 |
| | **TTV** | **134** | | | | | |
| | **TSV** | **150** | | | | | |
| | **OA** | **89.3%** | | | | | |

**2016-Reference Statistics**

| | **LCLU** | Tree covered | Grass- Sparse | Cropland | Wetland | Water bodies | Built Ups |
|---|---|---|---|---|---|---|---|
| **Sampling satellite Image** | Tree Covered | 21 | 2 | 5 | 2 | 0 | 2 |
| | Grass-Sparse | 2 | 22 | 0 | 3 | 0 | 5 |
| | Cropland | 3 | 0 | 22 | 2 | 1 | 3 |
| | Wetland | 3 | 3 | 2 | 20 | 1 | 0 |
| | Water bodies | 0 | 0 | 0 | 3 | 28 | 0 |
| | Builts Ups | 33 | 3 | 1 | 0 | 0 | 20 |
| | **TTV** | **133** | | | | | |
| | **TSV** | **150** | | | | | |
| | **OA** | **88.7%** | | | | | |

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**2020-Reference Statistics**

| Sampl Ing | LCLU | Tree covered | Grass-Sparse | Cropland | Wetland | Water bodies | Built Ups |
|---|---|---|---|---|---|---|---|
| | Tree Covered | 28 | 4 | 5 | | 2 | 2 |
| | Grass-Sparse | 2 | 25 | 0 | | 8 | 0 |
| | Cropland | 0 | 0 | 22 | | 2 | 2 |
| | Wetland | 0 | 1 | 1 | | 15 | 4 |
| | Water bodies | 0 | 0 | 0 | | 3 | 22 |
| | Built Ups | 33 | 0 | 2 | | 0 | 0 |

| | |
|---|---|
| **TTV** | **132** |
| **TSV** | **150** |
| **OA** | **88.3%** |

The study covers the period from 2000, 2016 and 2020, capturing land use changes before and after the commencement of mining activities in 2016. Despite the potential benefits of expanding the dataset to 2023, cloud cover significantly impacted Landsat scenes for 2021-2023 within the relatively small Muhazi sector, leading to the decision to focus on 2020 which provided clear- sky imagery. Additionally, unless of any further assessment, we are confident that the careful analysis conducted regarding land use change remains pertinent for the period of 2021 to 2024.

The extent of spatial temporal land use change and the diverging patterns across the Muhazi sector before and after the establishment of the MMB mining company Using historical land cover data, we utilized the Multi-Layer Perceptron (MLP) neural network method within the Land Change Model (LCM) to estimate the Net Change Rate (NCR) for various land cover typesin the study area. We also identified potential land use transitions to gain insight into the possiblechanges that may occur in the area due to mining activities. These transitions involve shifts from one land cover type to another (Rudel et al. 2005, Long et al. 2021). Examples encompass cropland expansion, deforestation, urbanization, and wetland loss or gain. For instance, the transition from forest to cropland signifies cropland expansion, while any transition to forest denotes afforestation. The LCM facilitates modelling of transitions between all land cover types, enabling the identification of events following mining activities across the study area. Furthermore, the MLP has been extensively applied to offer an automated mode that eliminates the need for user intervention(Eastman 2012). It can consolidate numerous substitutions into a single group while supplying valuable insights on multiple transitions that share the same explanatory variables, such as elevation, aspect, and slope.

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In order to obtain the output layers detailing land cover transitions or land use change events, a supervised training algorithm known as Back Propagation (BP) was utilized. This involved the incorporation of temporal land cover fractions, represented by α (pre-mining year, 2020) and β (post-mining year, 2020), as input layers in the network. In addition, explanatory variables such as elevation, slope, and aspects were incorporated into the model. The input layers consisted of neurons gathering a normalized set of input variables of ji (i = 1, 2, 3, … r0), with the hidden layers containing neurons r1 receiving a set of variables of ki (i = 1, 2, 3, …r1). These were connected to the explanatory variables' layers, which contained neurons r3 and received a set of variables of li (i = 1, 2, 3, …r2). A continuous nonlinear mapping was then performed in the ro neurons of ji variables towards the ki variables and then to the li variables to generate weights of neurons in each layer for each output of neurons of the input (Taud and Mas 2018). In general, the MLP is supplied with samples extracted from pixels that have experienced the transition during modelling or those demonstrating persistence. These collected cells are then divided into two clusters, with 50% utilized for training (training RMS) and the remaining portion for validation (testing RMS) of the potential transition, enabling the generation of a connection between transition probability and explanatory variables. The obtained weights play a crucial role in reducing errors associated with accuracy. Consequently, once the accuracy reaches its peak iteration, the probability of transition maps of the sub-model achieves the suitability of Land Cover Land Use (LCLU) categories over the simulated time. Additionally, the MLP provides a comprehensive report featuring aggregate accuracy and skill measure scores, expressed as follows (Eastman 2012):

### 4.1 The extent of spatial temporal land use change and the diverging patterns acrossthe Muhazi sector

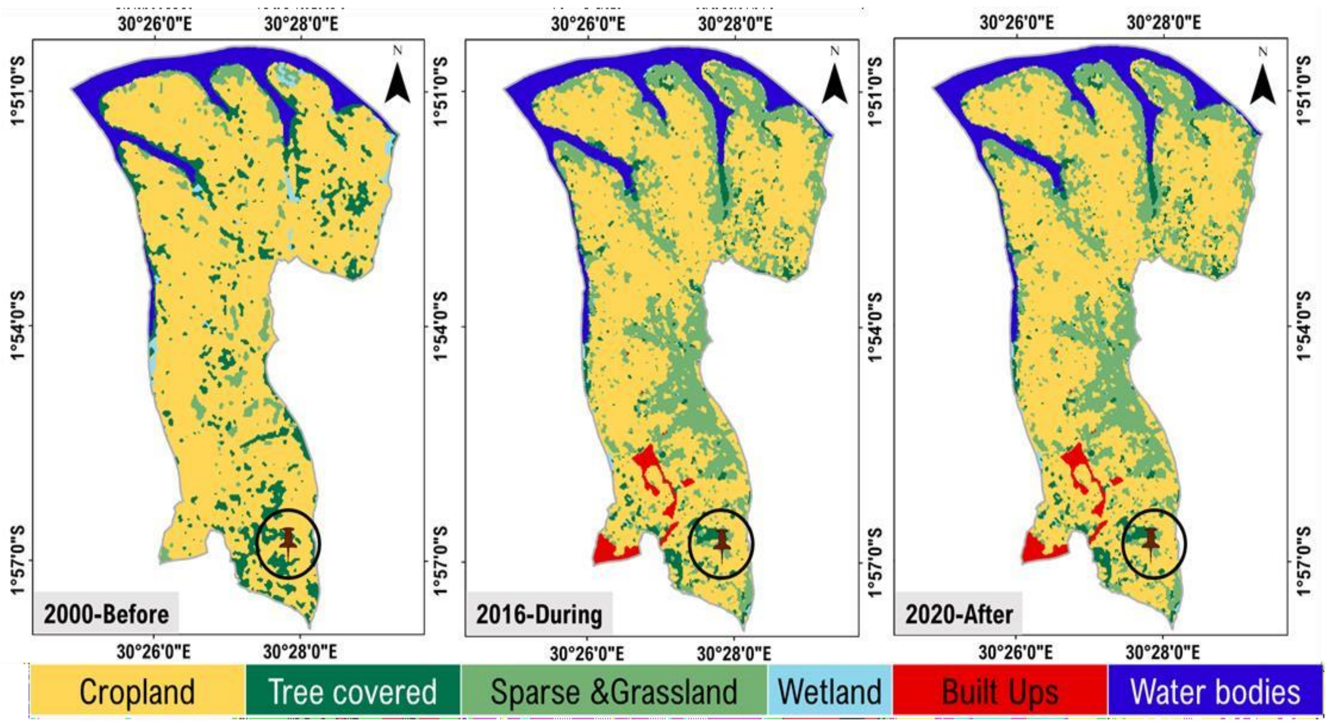


**Figure 4.1: Spatial temporal land cover dynamics in Muhazi Sector before, during and after mining activities.**

The pin shows one of the locations of where most of mining activities are undertaken.

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**Table 4.2 : Statical distribution of land cover areas in different period**

| LC | 2000 | 2016 | 2020 |
|---|---|---|---|
| | Extent [Hectares, ha] | | |
| Tree Covered | 711.54 | 171.09 | 289.4 |
| Grassland & Sparse | 252.45 | 1192.41 | 1415 |
| Cropland | 4232.88 | 3553.65 | 3394.9 |
| Wetland | 74.52 | 94.59 | 26.0 |
| Water bodies | 505.08 | 633.06 | 546.6 |
| Built Ups | 0 | 131.58 | 103.9 |
| **Total** | **5776** | **5776** | **577** |

The findings indicate significant changes in land cover within Muhazi sector from 2000 to 2020. There was a notable decrease in tree-covered areas from 711.54 ha in 2000 to 171.09 ha in 2016, followed by a slight increase to 289.44 ha in 2020. This decline suggests a potential loss of tree cover over the years. Additionally, grassland and sparse areas expanded substantially from 252.45 ha in 2000 to 1192.41 ha in 2016, and further to 1415.7 ha in 2020, indicating a considerable increase in these land cover types. Cropland experienced a gradual reduction from 4232.88 ha in 2000 to 3553.65 ha in 2016, and a slight decrease to 3394.98 ha in 2020, reflectinga conversion of cropland to other land cover types or a decrease in overall agricultural activities in the region. Wetland areas fluctuated, reaching a peak of 94.59 ha in 2016 and declining to 26.01 ha in 2020, signifying potential changes in the wetland ecosystem. Water bodies also fluctuated, with an increase from 505.08 ha in 2000 to 633.06 ha in 2016, followed by a decreaseto 546.66 ha in 2020. Built-up areas emerged, with 131.58 ha in 2016 and 103.95 ha in 2020, indicating urban development or infrastructure expansion within the sector. These changes could have implications for the sector's ecosystem, biodiversity, and overall land use patterns. Moreover, these changes highlight the potential deforestation linked to mining activities, supported by the spatial context indicating mining activities in the southern edge of the study area. The expansion of grassland and sparse areas also suggests the impacts of mining activities, potentially leading to land clearance and altered land use patterns. Additionally, the reduction in cropland indicates potential changes in agricultural activities possibly influenced by the proximity of mining operations.

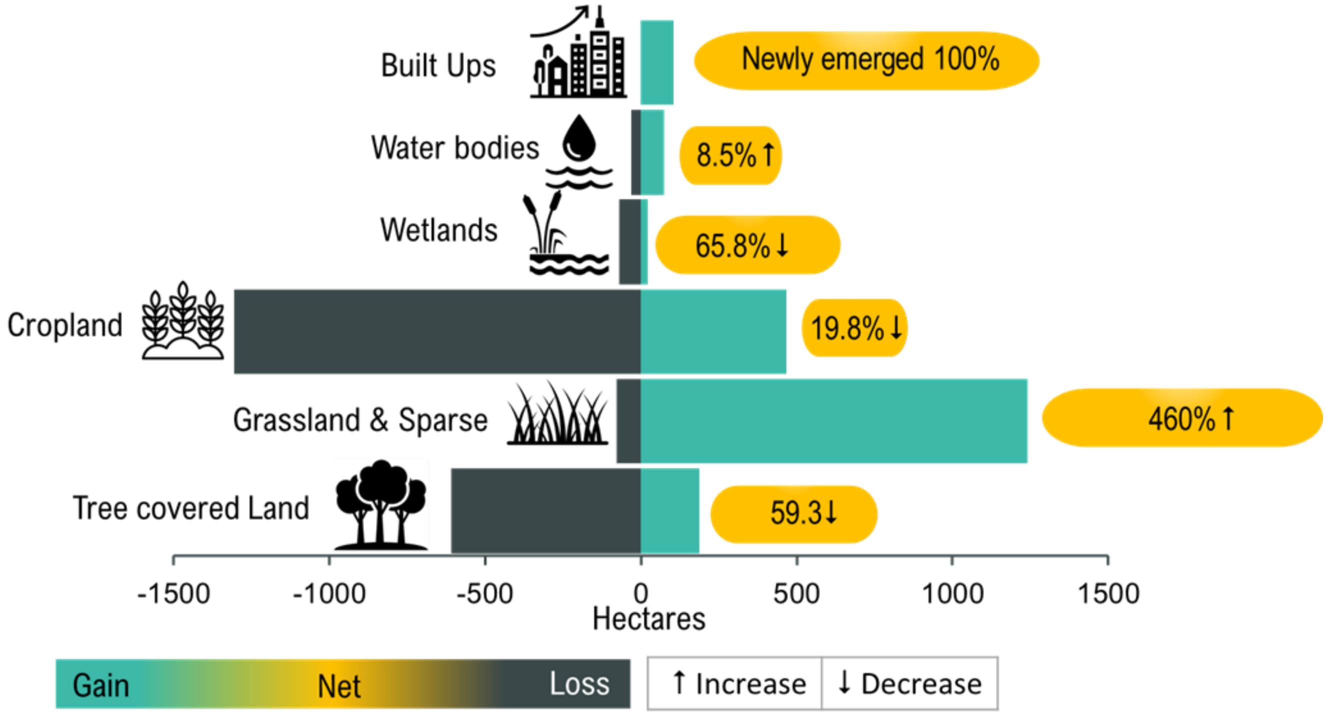


**Figure 4.2 : Changes in land cover, comprising Gains, Net, and Loss, were observed in Muhazi sector 2000-2020**

The Satellite Dataset Classification Algorithm for Land Cover and Land Use plays a crucial role in analyzing and categorizing different land cover types based on satellite imagery. This algorithm utilizes advanced image processing techniques to identify various features like vegetation, water bodies, bare land, and built-up areas. Specifically focused on detecting built-up areas, the algorithm uses specific criteria such as high reflectance and geometric shapes to accurately pinpoint urban developments. However, the absence of built-up areas in the 2000 dataset suggests that the algorithm did not identify significant traces of urban development during that period. However, the emergence of built-up areas in subsequent datasets indicates a dynamic shift in the landscape, underscoring the algorithm's sensitivity to changes in land use patterns over time (Table 4.2 – Figure 4.2).

These analyses indicate substantial changes over the two-decade period. The most notable changes occurred in grassland & sparse areas, which experienced a significant gain of 1241 ha, resulting in a net change of 1163 ha reflecting a 460.7% net increase. Conversely, tree-covered areas suffered a substantial loss of 609 ha especially in the southern edge where mining activities are undertaken, resulting in a net change of -422 ha, representing a 59.3% decrease. Cropland also experienced a considerable gross loss of 1305 ha, mitigated by a gain of 467 ha, resulting in a net change of -838 ha, representing a 19.8% decrease. Wetlands exhibited a gross loss of 71 ha,with a minor gain of 22 ha, resulting in a net change of -49 ha, representing a 65.8% decrease. Water bodies, on the other hand, experienced a net gain of 43 ha, showing an 8.5% increase. Built-up areas experienced no gross loss and a gain of 104 ha, resulting in a 100% net increase. These changes illustrate the dynamic shifts in land cover within Muhazi sector, reflecting a variety of environmental and anthropogenic influences over the two-decade period.

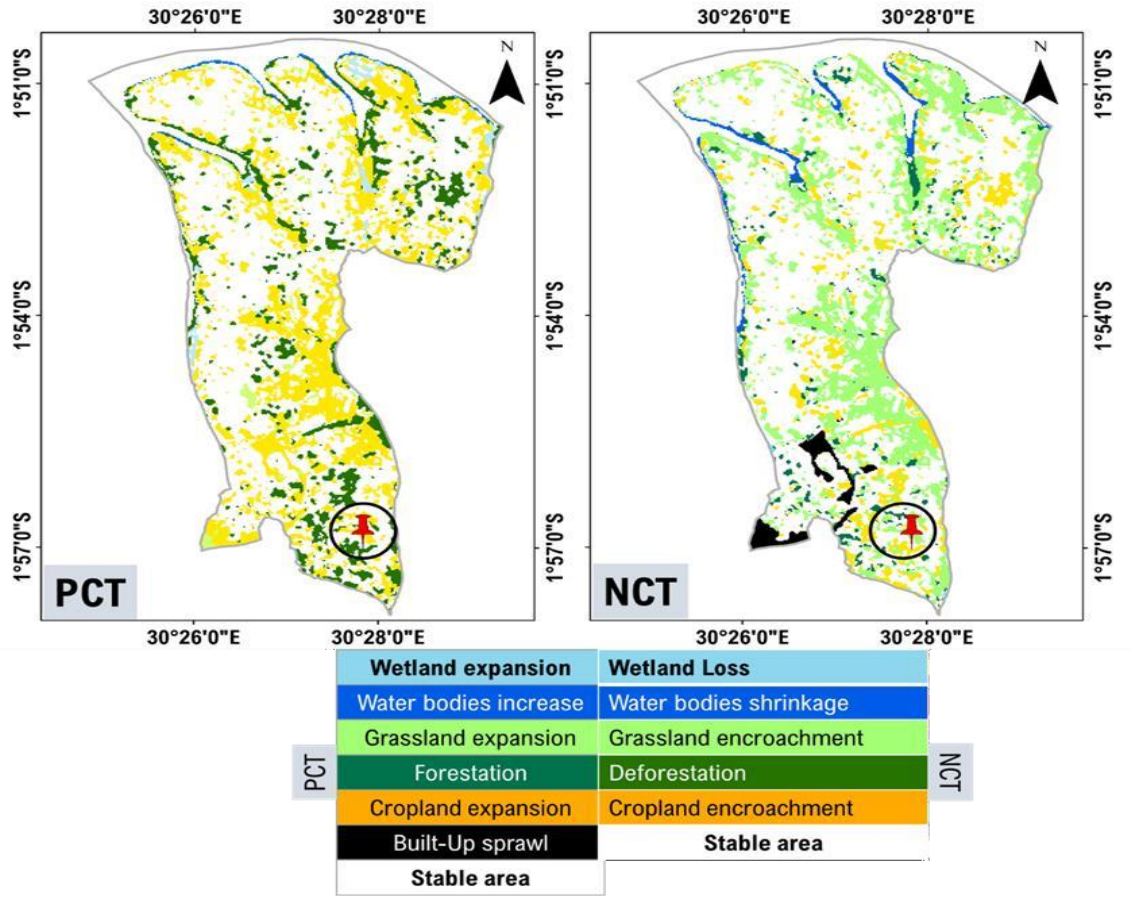


**Figure 4.3: Potential transitions across Muhazi sector 's land cover types (2000-2020)**

It is worth to understand that in spatial analysis, "stable land" relates to areas where there is persistence, gain, loss, or a combination of these factors. It refers to land areas that have maintained their original land cover without significant alterations or transitions. Gain signifies areas where new vegetation or land cover types have emerged, often due to natural processes or human intervention. Thus, spatially, significant transitions have been modeled within the study area, indicating various positive and negative changes in land use events. Positive transitions encompass wetland expansion, increasing water bodies, expanding grasslands, afforestation, cropland expansion, and urban development. Conversely, negative change transitions involve wetland loss, reduction in water bodies, encroachment of grasslands, deforestation, and cropland encroachment. It is notable that grassland expansion dominates the positive change transitions, while the negative change transitions are dominated by cropland encroachment following deforestation. In the context of land cover transitions, the prevalence of grassland expansion in positive change transitions signifies a natural shift towards grassland vegetation, potentially driven by ecological factors or land management practices. On the other hand, the dominance of negative change transitions characterized by cropland encroachment following deforestation suggests the human-induced conversion of forested areas into agricultural land, presenting a concerning trend in terms of habitat loss and ecosystem disruption. With a focus on the Muhazi sector's ongoing mining activities, the observed land cover transitions reveal consequential implications. The

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widespread deforestation indicates a substantial loss of forested areas, leading to diminished biodiversity and ecological services. Concurrently, the expansion of grassland and sparse vegetation, driven by the clearing of trees, raises concerns about the alteration of local ecosystems and potential effects on soil stability, water retention, and carbon sequestration. Moreover, cropland encroachment resulting from deforestation signifies a direct impact on agricultural practices and land productivity, with ramifications for local livelihoods and food security. These shifts in land cover underscore the substantial environmental impact of mining activities in the Muhazi sector, highlighting the need for comprehensive environmental assessments and sustainable land management strategies to mitigate ecological disturbances and promote long-term environmental resilience.

Upon identifying the locations of ongoing mining activities within the Muhazi sector, it becomes evident that deforestation, cropland abandonment, and the expansion of grassland and sparse vegetation are occurring. This implies significant tree felling in favor of grassland and sparse vegetation as a result of these mining activities.

The implications of these mining activities are multifaceted and can have far-reaching consequences. The deforestation linked to mining activities can lead to the loss of important habitats for various plant and animal species, impacting biodiversity within the area. Additionally, the reduction in tree cover may contribute to soil erosion, environmental degradation, and alterations in local microclimates. The abandonment of cropland, potentially due to the proximity of mining operations, could have implications for local food production and agricultural livelihoods. Furthermore, the expansion of grassland and sparse vegetation may indicate a transformation of the landscape, potentially altering ecological processes and impacting the overall land use patterns in the area. These changes emphasize the need for comprehensive environmental impact assessments and sustainable land management practices to mitigate the potential negative effects of mining activities on the ecosystem and local communities. Collectively, this statistical evidence underscores the importance of comprehensive environmental monitoring, sustainable land management practices, and strategic interventions to mitigate the impacts of mining activities, restore ecological balance, and support the long-term well-being of the Muhazi sector and its surrounding areas.

### 4.1 Environmental and social impacts of mining activities

Mining activities have many environmental and social impacts, and some of them were mentioned during group discussion .Environmental and social impacts of mining activities canbe summarized by looking on what is being impacted as follow:

#### 4.1.1 Impacts of mining activities on wildlife

Mining operations remove vegetation and topsoil, which has an impact on the environment and related biota by distancing wildlife, releasing pollutants, and producing noise. These species' ability to survive may be influenced by the local climate, altitude, soil composition, and other habitat-related factors. Wildlife is harmed by mining both directly and indirectly. The disturbance, removal, and redistribution of the land surface are the main causes of the impacts. Some impacts, like the extinction or displacement of species in areas under excavation, are limited to the mine sites; others, on the other hand, might have long-term, far-reaching effects. Fish and other aquatic animals suffer greatly if streams, lakes, and ponds—which serve as the host of aquatic habitats—are filled in or drained. These aquatic and terrestrial species are disappearing, which reduces the amount of food available to predators. In general, many animal species are unable to adapt to changes brought about by

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disturbances to their natural habitats. Living space is decreased by these modifications. Habitat fragmentation caused by mining operations typically results in species declines locally or genetic effects like inbreeding. species that need extensive forested areas simply disappear.

- ***Impacts of mining activities on soil quality***

**Figure 4.4 : Exposed tailing dams in MMB which are not well managed**

**Figure 4.5: Pictures showing how land degraded due to different mining activities**

It is known that mining operations can contaminate the soil in a variety of ways. The majority of mining operations have an impact on nearby agricultural activities. The locals living close to mines claim that because mining exposes previously undisturbed earthen materials, the surrounding landscape is regularly altered. Sediment loading to surface waters and drainage channels can occur from the erosion of exposed soils as well as the erosion of tailings, other fine material, and extracted mineral ores in waste rock piles. Soil contamination can also result from hazardous material spills and leaks as well as from contaminated windblown dust deposition. There are two main types of contaminated soils that pose a risk to human health and the environment: soils contaminated by dust carried by the wind and soils contaminated by chemical spills and residues. Fertile soil that has been farmed may also be lost as a result of mining operations.

- **Impacts of mining activities on social values and human**

Although mineral development has the potential to be very disruptive, it can also be very profitable. In isolated and underdeveloped areas, mining projects may boost demand for goods and services by building roads, schools, and jobs, but the costs and benefits may not be distributed fairly. Mining projects have the potential to cause violent conflict and social unrest if local communities believe they are receiving unfair treatment or insufficient compensation. Environmental Impact Assessments may understate or even completely ignore the effects that mining projects have on the local populace in some circumstances. Documents from the group discussion reveal that some workers have diseases and injuries related to their jobs. Based on field observations, it appears that the environment surrounding MMB Mining Company is not adequately protected. For instance, poorly managed tailing dams can be found in this area. This company uses fewer personal protective equipment (PPEs). You can see the miners working underground without helmets or shoes, demonstrating how dangerous it is to not wear protective gear in light of the still-low level of safety procedures.

## 4.1 Community view about the impacts of mining activities on land use and land cover change

Community view began by consulting with members of communities around MMB mining company, miners within company and formal leaders just togather their perspectives and experiences.

### Group A: Miners at MMB mining company

The specific effects of mining operations on land that are of concern at the workplace are identified by miners from MMB Mining Company; these could include,In addition to the physical risks of accidents and collapses, mining workers also face health risks from exposure to chemicals, dust, and noise. Both the workers and the surrounding community are impacted by environmental issues such as habitat destruction, air and water pollution, deforestation, soil erosion, biodiversity loss, and soil degradation. Job insecurity can result from economic volatility brought on by volatile commodity prices, and social effects such as community dislocation and land-rights disputes can exacerbate difficulties faced by mining employees.

### Group B: communities around company

Communities near mining operations frequently experience a range of effects, both favorable and unfavorable. Development of infrastructure, the creation of jobs, and economic expansion are examples of positive effects. On the other hand, adverse effects may comprise social unrest, community dislocation, pollution-related health risks, and environmental deterioration. Conflicts over resources and land rights, as well as modifications to traditional lifestyles, can also have an impact on culture. Careful management and sustainable methods are needed to balance these effects in order to minimize harm and optimize benefits for the impacted populations.

**Group C: formal leaders at sector level**

A variety of factors, including political ideology, economic interests, and pressure from constituents and stakeholders, influence the perspectives of formal leaders regarding the effects of mining activities on land. While some may emphasize the positive economic effects of mining, such as job creation and revenue generation, others may highlight the negative social and environmental effects and advocate for stricter regulations, sustainable practices, and community engagement to mitigate negative impacts.

## 4. Conclusion

In conclusion, the study assessed the impact of mining activities on land use and cover in the Muhazi sector using remote sensing and field observations. Analysis revealed significant declines in tree-covered areas and fluctuations in wetlands and water bodies, while grassland and built-up areas expanded, indicative of urban development. Poor mining practices were identified through community discussions, highlighting environmental degradation, water pollution, and biodiversity loss. Recommendations include enhancing technical support for local stakeholders, adopting cleaner mining technologies, and promoting sustainable practices through education and collaboration with ethical organizations. Future research using advanced satellite imagery or object-based software was proposed for more precise monitoring of mining impacts over time. Stronger environmental regulations and public awareness initiatives were also suggested to mitigate mining's adverse effects and promote responsible resource management..

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